Managerial Incentives and Debt Structure in Private Credit: Evidence from U.S. Business Development Companies

Part I:

Incentives, Leverage, and Portfolio Risk in Private Credit: Evidence from U.S. Business Development Companies

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Part I

Incentives, Leverage, and Portfolio Risk in Private Credit: Evidence from U.S. Business Development Companies

Abstract

Following the Global Financial Crisis and subsequent period of regulatory tightening within the financial services sector, private credit has emerged as a crucial source of credit to U.S. middle market companies. Despite the growing body of literature on private credit and direct lending, no study has yet examined whether the incentives of private credit fund managers affect their risk-taking behaviors. This thesis addresses this gap by examining whether differences in managerial fee structures help explain the cross-sectional variation in leverage, growth, and portfolio risk among Business Development Companies (BDCs). Using a panel dataset of detailed portfolio holdings, financial statement data, and hand-collected information on fee structures for 60 unique BDCs, I utilize a combination of cross-sectional and fixed effects regressions to answer two primary questions. First, whether BDCs charging management fees on gross assets are associated with higher leverage and balance sheet expansion. Second, whether income-based incentive structures encourage managers to "reach-for-yield" through riskier portfolio composition. The results point toward gross-fee BDCs operating with significantly higher leverage ratios, consistent with their incentives to "borrow-to-earn". However, no meaningful relationship can be observed between income-based incentive fees and portfolio risk outcomes. Taken together, the evidence suggests that managerial fee structures matter more for decisions on capital structure rather than portfolio risk. A likely explanation is that portfolio composition in direct lending is slow to adjust, thus limiting managers' ability to act on short-term fee incentives through changes in portfolio composition and risk.

Keywords

Private Credit, Nonbank Lending, Business Development Companies (BDCs), Managerial Incentives, Fee Structures, Risk-Taking, Leverage

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List of Abbreviations

ACR	Asset Coverage Ratio
AUM	Assets Under Management
BDC	Business Development Company
BIS	Bank for International Settlements
CIK	Central Index Key
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
EDGAR	Electronic Data Gathering, Analysis, and Retrieval
EURIBOR	Euro Interbank Offered Rate
FRED	Federal Reserve Bank of St. Louis Economic Data
GFC	Global Financial Crisis
GP	General Partner
H1	Hypothesis 1
H2	Hypothesis 2
HHI	Herfindahl-Hirschman Index
HWM	High-Water Mark
IRR	Internal Rate of Return
ISDA	International Swaps and Derivatives Association
LIBOR	London Interbank Offered Rate
LSEG	London Stock Exchange Group

NBFI	Nonbank Financial Intermediary
NII	Net Investment Income
OLS	Ordinary Least Squares
PE	Private Equity
PIK	Payment-in-Kind
R&D	Research & Development
REIT	Real Estate Investment Trust
RIC	Regulated Investment Company
ROE	Return on Equity
SBCAA	Small Business Credit Availability Act
SEC	Securities and Exchange Commission
SOFR	Secured Overnight Financing Rate
SOI	Schedule of Investments
SONIA	Sterling Overnight Index Average
SPV	Special Purpose Vehicle
STIBOR	Stockholm Interbank Offered Rate
WA	Weighted Average
WACC	Weighted Average Cost of Capital
XBRL	eXtensible Business Reporting Language

1. Introduction

During the last 15 years, the market for private credit has expanded rapidly and now represents a meaningful share of middle-market corporate borrowing. Global assets under management (AUM) in private credit funds have grown to more than $2.5 trillion (Avalos et al., 2025, p. 13), reflecting a large shift in how credit is intermediated in the financial system. Historically, the private credit market has relied on institutional capital, with little to no participation by retail investors in the asset class. However, the rapid growth of Business Development Companies (BDCs) during recent years, many of which are publicly traded, has opened the doors for retail investors to enter the otherwise opaque private credit market, who now represent approximately 13% of total private credit AUM (Aldasoro et al., 2025, p. 1). These shifts have captured the interest of researchers, policymakers, and investors to understand the underlying drivers of private credit growth, the systemic implications of an increased reliance on nonbank financial intermediaries (NBFIs) in the financial sector, and the risks associated with investing in private credit funds. However, despite the growing interest, the topic of private direct lending is relatively underexplored in academic literature compared to the vast body of research on traditional bank lending, the bond market, and private equity (Davydiuk et al., 2024).

Although lending from NBFIs dates back further than the 2008 Global Financial Crisis (GFC), the GFC and subsequent period of regulatory tightening are widely regarded as important catalysts for the NBFI sector's rapid growth. Prior studies have shown why firms choose to borrow from nonbanks (Chernenko et al., 2022), how stricter banking regulation incentivized a migration of credit from banks toward less-regulated entities (Chernenko et al., 2025; Erel and Inozemtsev, 2025), and as a result, how banks and NBFIs have adjusted and evolved to organize intermediation in mutually beneficial ways (Acharya et al., 2026). Researchers have also focused on BDCs specifically, examining their investment model, role as substitute capital providers for credit rationed firms, and their impact on target firm growth and innovation (Davydiuk et al., 2024a). Other studies provide evidence on how BDCs adjust leverage and portfolio risk in response to funding shocks (Davydiuk et al., 2024b), and how leverage constraints and regulatory changes affect their lending practices (Balloch and Gonzalez-Uribe, 2021). Despite this growing body of research, one dimension of BDC and private credit behavior remains completely unexplored,

namely whether compensation structures and fee incentives of external managers affect risk-taking behaviors among BDCs.

To understand why this avenue in particular warrants empirical research, one must consider the peculiar fee structures that govern the compensation of external BDC managers. BDCs often charge fixed management fees based on gross assets, including leverage, which creates a direct incentive to grow the fee-paying asset base using debt. Furthermore, income-based performance fees are commonly determined based on quarterly net investment income (NII) above a set hurdle rate, possibly encouraging managers to reach for yield to maximize the probability of earning above the threshold. Research in adjacent fields has established clear links between fee structure and risk-taking behaviors in externally managed funds, such as real estate investment trusts (Capozza and Seguin, 2000) and hedge funds (Goetzmann et al., 2003; Lan et al., 2013; Yin and Zhang, 2023). This thesis aims to address this gap in the private credit literature by examining whether similar mechanisms affect the risk-taking behaviors observed in the BDC sector.

Using a panel dataset comprised of detailed portfolio holdings, financial statement data, and hand-collected information on fee structures across 60 BDCs from 2015Q4 to 2025Q2, this study utilizes a combination of cross-sectional and fixed effects models to analyze whether differences in fee incentives help explain the cross-sectional variation in leverage, growth, and portfolio risk among BDCs. I find that BDCs charging management fees based on gross assets are, on average, associated with higher leverage ratios, consistent with the expectation that such managers are incentivized to take on more debt. By contrast, income-based incentive fee arrangements are not found to have a significant relationship with portfolio composition nor risk, inconsistent with the prediction that managers reach for yield to maximize their income-based incentive fees.

This paper is structured as follows. Section 2 provides the institutional background and reviews the related literature on private credit, BDCs, and the effects of incentive structures on risk within the delegated asset management industry. Section 3 describes the data, methodology, and presents summary statistics for the key variables included in the study. Section 4 reports and discusses the results obtained from the empirical tests, along with an acknowledgement of the main limitations of the study. Finally, Section 5 summarizes the main conclusions and proposes potential avenues for future research.

2. Literature Review

2.1 Institutional Background

2.1.1 The Rise of Private Credit and Nonbank Lending

Much of the existing literature has focused on explaining the growing role of nonbanks and the migration of credit from traditional banks to NBFIs. One commonly adopted view in the academic literature is that stricter banking regulation following the GFC gave rise to a form of regulatory arbitrage that incentivizes a migration of credit supply away from the regulated banking sector (see, e.g., Chernenko et al., 2022; Erel and Inozemtsev, 2025). Supporters of this view argue that, since nonbanks are required to hold less capital when investing in middle-market loans than banks, these loans become relatively more attractive, thereby shifting credit supply towards the less-regulated nonbank lending.

Chernenko et al. (2022) provide systematic evidence on the mechanisms affecting the decision by firms to borrow from nonbanks. They utilize a hand-collected dataset of loans to middle-market firms and find evidence that firms with negative EBITDA, or high levels of leverage in relation to their EBITDA, are more likely to borrow from NBFIs instead of banks. After controlling for observable differences between banks and NBFIs, such as loan techniques and pricing, and unobservable factors affecting the risk and decisions of borrowers, their results strongly suggest that bank regulation is the most important driver for nonbank lending. This perspective is corroborated by Erel and Inozemtsev (2025, p. 1235), who document a 45% decrease in the volume of small business loans by commercial banks following the GFC, and that this lending gap was subsequently filled by the increased participation of NBFIs.

However, a more recent study by Chernenko et al. (2025) challenges the idea of regulatory arbitrage being the primary driver of private credit growth. They argue that nonbank lenders, specifically BDCs, are extremely well capitalized according to bank capital frameworks. The authors show that these entities maintain a 36% median risk-based capital ratio, which far exceeds the regulatory requirements faced by banks (p. 2). Rather than regulatory arbitrage being the primary driver, they suggest a “supervisory arbitrage” channel, in which banks prefer lending to private credit funds rather than managing risky middle-market loans on their own balance sheets.

By doing this, banks avoid the high supervisory costs, or "shadow costs", associated with risky balance sheet lending. They can instead apply lower risk-weights in their calculation of regulatory capital by investing in cheaper, over-collateralized loans to private credit funds through bankruptcy-remote special purpose vehicles (SPVs), allowing them to achieve a higher return on equity (ROE) on their investments.

The view that banks utilize NBFIs and direct lenders as vehicles to bypass the regulatory and supervisory costs of balance-sheet lending is broadened by Acharya et al. (2026). Rather than viewing banks and NBFIs as operating in parallel or as substitutes, they provide empirical evidence supportive of a "transformation view", in which banks and NBFIs have evolved to organize intermediation by minimizing regulatory costs and constraints while retaining the liquidity benefits of the banking industry. As a result, instead of engaging in middle market lending directly, banks provide senior credit to NBFIs, which is used to fund riskier and more junior loans to, e.g., middle-market companies, and then banks provide NBFIs with additional credit lines for short-term liquidity. This view is consistent with Chernenko et al. (2025), implying that although banks carry less direct lending risk, they remain indirectly exposed to middle-market lending due to the growing interconnectedness with the NBFI lending sector.

Researchers from the Bank for International Settlements (BIS) offer complementary perspectives on the rise of private credit globally by exploring cross-country patterns in private credit underwriting and using loan-level data to systematically study the underlying drivers of the industry's growth. First, Avalos et al. (2025) find that private credit underwriting is higher in countries with lower policy rates, less efficient banking systems, and more stringent banking regulation. The authors list two potential reasons why lower interest rates could result in higher levels of private credit underwriting. For one, the "low-for-long" interest rate environment might have prompted investors to search for yield by tilting their portfolios more toward private credit funds, leading to lower funding costs for these entities. Alternatively, decreasing interest rates could have acted as a suppressant to traditional loan supply by eroding the profitability of bank lending. As rates fall, the spread between a bank's assets and liabilities compresses due to the slow-moving nature of deposit rates. Such a spread compression would not affect private credit funds, which are financed at market rates and primarily extend floating-rate loans to their

borrowers. Second, loan portfolios of private credit funds tend to be heavily concentrated in terms of industry exposure, possibly yielding screening and monitoring benefits that improve credit availability for riskier firms, but simultaneously exposing funds to sector-specific downturns. Third, by studying the cost of capital of banks and publicly listed BDCs, the authors find that the weighted average cost of capital (WACC) between the groups has converged post-GFC, suggesting that the rise in BDC lending may at least partly be explained by a decline in the cost of funding relative to banks.

2.1.2 Business Development Companies: Characteristics and Empirical Evidence

A Business Development Company (BDC) is a U.S. invention, structured as a closed-end investment company and created as part of the Small Business Investment Incentive Act of 1980 to stimulate investments in small- and middle-sized private companies (Cai and Haque, 2024). BDCs are legally required to hold at least 70% of their investments in "eligible assets", primarily consisting of cash, government securities, and eligible portfolio companies. Eligible portfolio companies are defined as U.S. operating companies that are not publicly traded, or publicly traded companies with a market capitalization of less than $250 million.[1] Although BDCs are allowed to make both equity and debt investments, the majority share of BDC portfolios are made up by debt securities, with equity investments constituting less than 25% in terms of fair values (Davydiuk et al., 2024a, pp. 6-7). Regardless of investment type, BDCs are also required to offer significant managerial assistance to their portfolio companies. Similar to real estate investment trusts (REITs), most BDCs bypass corporate income taxes by electing to be treated as regulated investment companies (RIC), whereby they are required to distribute at least 90% of their taxable income as dividends (Jang, 2024). As such, BDCs are legally constrained in their ability to grow organically, causing them to be heavily reliant on public capital markets to finance growth.

[1] Section 55(a) of the Investment Company Act of 1940 contains detailed information on which investments are considered eligible.

Prior to 2018, BDCs were subject to a statutory leverage limit requiring a 200% asset coverage ratio (ACR), roughly equivalent to a 1:1 debt-to-equity ratio. In 2018, the passing of the Small Business Credit Availability Act (SBCAA) lowered this requirement to 150%, allowing BDCs to increase their debt-to-equity to 2:1 contingent on approval by the shareholders or board of directors. Notably, BDC leverage has tripled during the last 15 years (Aldasoro et al., 2025, p. 1), and a gradual increase in leverage was observed in the years following the enactment of the SBCAA (Balloch and Gonzalez-Uribe, 2021, p. 20).

The compensation structure to managers of externally managed BDCs exhibits notable differences compared to other types of investment vehicles. Similar to, e.g., hedge funds and private equity funds, fees generally consist of a fixed management fee and a performance-based incentive fee. However, unlike private equity and venture capital funds, BDCs typically charge management fees based on gross assets, including leverage, rather than the committed or invested equity capital in the fund. Performance-based incentive fees generally consist of two separate fees: one based on net investment income and another based on net realized capital gains plus unrealized losses.

A key reason why private credit has remained relatively understudied in the academic literature is the sector's high opacity and lack of reliable data. However, BDCs represent a notable exception. As regulated entities under the Securities Exchange Act of 1934 and Investment Company Act of 1940, BDCs are required to file periodic and current reports to the Securities and Exchange Commission (SEC), which provide researchers and market participants with a glimpse into the otherwise opaque private credit market (Davydiuk et al., 2024a). These filings include detailed information on BDC portfolio holdings, such as investment type, industry, maturity, interest rate, and reported loan values, among other things.

Furthermore, the literature emphasizes other characteristics that support the use of BDCs as a useful empirical laboratory to study private credit and direct lending more broadly. First, BDCs collectively make up one of the largest groups of direct lenders, managing assets of approximately $440 billion as of 2024Q4 and accounting for approximately 40% of all direct lending in the United States (Chernenko and Scharfstein, 2025, p. 1). Second, by leveraging survey evidence collected from private credit fund managers, Block et al. (2024) document that BDCs share many traits and characteristics of other types of private credit funds. They show that the difference in the amount

of leverage deployed by BDCs is somewhat higher, but not significantly different, from that of non-BDC private credit funds in the U.S. They also document that BDCs and non-BDCs both target approximately the same gross returns and rely heavily on private equity sponsors for deal flow, with 75% of the average invested capital across BDCs and 81% across non-BDCs being made up by PE-sponsored deals (Block et al., 2024, p. 350). These similarities suggest that the findings and conclusions derived from examining BDCs can likely be applied to other types of private credit funds as well.

However, Block et al. (2024) also document some key differences between BDCs and other direct lending vehicles. Size, as measured by AUM, and experience in the private credit industry are two notable examples, with BDCs being significantly larger and more experienced on average (p. 343). Furthermore, the survey responses indicate that BDCs spend considerably less time on due diligence in the pre-investment phase, amounting to roughly half of what was observed in non-BDC funds (p. 349). These differences may limit the external validity of the findings from studying BDCs to the broader private credit industry.

One of the first comprehensive studies on BDCs in the academic literature, conducted by Davydiuk et al. (2024a), studies the rise of direct lending and the role of BDC capital in the post-GFC financial system. Using a novel database of BDC investments, private debt deals, and firm-level borrower data, the authors show that BDCs have a higher propensity to enter markets experiencing a shortage of traditional credit, while disproportionately allocating capital toward high-tech and R&D-intensive borrowers. These findings support the view that private credit acts as a substitute for traditional bank funding, enabling riskier middle-market firms lacking traditional funding sources to obtain credit.[2] BDC loans are also documented to carry interest rates that are roughly 400-500 basis points higher than comparable bank loans (Davydiuk et al., 2024a, p. 7), consistent with the findings of Chernenko et al. (2022, pp. 4924-4925), and possibly explained by the greater flexibility, quicker deal execution, and looser covenants commonly observed in BDC loans. Finally, the authors frame BDCs as a hybrid of traditional banks and private equity funds, given

[2] This substitution view contrasts the findings of e.g., Acharya et al. (2026), as discussed above.

that BDCs can provide both debt and equity funding and are required to provide substantial managerial assistance to their portfolio companies. Consistent with this characterization, they find that greater managerial attention is associated with increased employment growth in portfolio firms, suggesting that non-financial factors may also contribute to the real economic benefits of private credit. BDC-funded firms also exhibit increased patenting activity, highlighting the broader role of private credit in stimulating innovation and supporting growth.

While the above studies primarily shed light on the characteristics and lending practices of BDCs, Davydiuk et al. (2024b) provide novel evidence on private credit market discipline and how BDCs adjust their portfolio composition and capital structures in response to shocks. Their work is one of the closest academic contributions to the topic examined in this paper. By exploiting the exclusion of BDCs from major U.S. stock indexes and subsequent sell-off by institutional shareholders,[3] the authors document that BDCs primarily respond to adverse funding shocks by adjusting their portfolio risk exposure rather than changing their capital structure. Following the shock, as raising new equity became more expensive, BDCs did not adjust their capital structure toward increased leverage. Instead, affected BDCs exhibited a "flight-to-quality" response by shifting portfolio exposure away from riskier instruments, such as equities and subordinated debt, toward safer senior debt investments. This effect was more pronounced for BDCs subjected to stricter market discipline from their creditors, suggesting that creditor oversight and market forces can serve as effective disciplining mechanisms for NBFIs.

Related evidence on how BDCs respond to regulatory shocks is offered by Balloch and Gonzalez-Uribe (2021). They exploit the passing of the 2018 SBCAA to examine how the relaxation of leverage limits affected credit supply and the subsequent responses by affected BDCs. The authors compare constrained and unconstrained BDCs, classified by their distance to the regulatory

[3] The index exclusion event refers to the 2014 exclusion of 32 publicly traded BDCs from the S&P and Russell Indexes. This was an unintended consequence of the 2006 Acquired Fund Fees and Expenses ("AFFE") disclosure requirements imposed by the SEC, causing a substantial decrease in liquidity and institutional ownership of BDC stocks. See Davydiuk, Marchuk, and Rosen (2024b) for more information.

leverage limit, and find that constrained BDCs tend to overreport loan values to exploit "regulatory slack" and relax leverage constraints, both in good and bad times. The intuition is that because leverage constraints are calculated based on reported loan values, overreporting loan values effectively relaxes the leverage constraint. Not surprisingly, constrained BDCs were faster and 30% more likely to adopt the relaxed leverage limits following passage of the SBCAA (pp. 26-27). These BDCs also exhibited a gradual increase in leverage following adoption, which is consistent with the predictions of Davydiuk et al. (2024b), who anticipate higher optimal leverage as capital requirements decrease. Furthermore, shortly following adoption, previously constrained BDCs marked down their loan values and reported larger unrealized losses, suggesting that loan values were previously overstated. These findings carry important implications for the research design applied in this paper. Specifically, measures derived from reported fair values must be used with caution to avoid potential bias that could distort empirical inference.

Finally, Balloch and Gonzalez-Uribe (2021) explicitly discuss the peculiar compensation structure of BDCs and the associated incentive problems that are explored in this thesis. First, they highlight that the ability of BDCs to charge management fees on gross assets, including leverage, creates natural incentives to borrow and differs from the common practice seen in the hedge fund and broader private credit industry. Second, the typical performance fee structure combined with the fact that BDCs report their own loan values create incentives for managers to reach for yield in loan origination and continuously collect fees from "bad" loans in current periods, even if such loans would entail realized losses in the future. These mechanisms constitute the primary focus of this thesis, and the above discussion helps motivate the hypotheses explored later in this paper.

2.2 Contract Design and Lending Technologies in Direct Lending

To capture and understand the nuances of risk-taking in private credit, this section aims to provide a brief overview of the typical lending technologies deployed by private credit funds and direct lenders. Assessing credit risk requires looking at both ex-post credit outcomes, such as defaults, non-accruals, and write-downs, as well as ex ante indicators embedded in the contractual design of the loans and portfolio composition. Due to the illiquid nature of private credit and the absence

of an active secondary market for loans, the availability of market-based measures of risk is limited, whereas self-reported loan values pose a threat of bias, as documented by Balloch and Gonzalez-Uribe (2021). As such, understanding how these funds structure and design their loans can offer direct insights into the risk embedded in their portfolios, especially in the absence of market-based measures of risk.

Various studies have documented notable differences between the lending technologies deployed by banks and direct lenders. Jang et al. (2025) show that almost 80% of loans issued by direct lenders are secured by so-called "blanket liens", which represent a claim on all of the borrower's assets rather than a particular type of collateral such as property or equipment. In comparison, they find that the corresponding share amounts to only 15% for loans issued by banks (pp. 27-28). Such blanket liens can be viewed as claims on the going-concern cash flow value (i.e., continuation value) of a company in the case of default (Lian and Ma, 2020), as opposed to the liquidation value of separable assets.

The strong reliance on blanket liens is likely a result of direct lending being highly dependent on the private equity industry for deal flow, as highlighted by Block et al. (2024). PE-backed companies often have higher leverage ratios and greater default probabilities than non-PE-owned firms, and prior studies have shown that PE ownership is strongly associated with the use of blanket liens (Haque et al., 2022). Another explanation could be that direct lenders are better positioned to capture the continuation value of a borrower in the case of a default, as highlighted by Jang et al. (2025). While banks are constrained in their ability to retain equity positions in non-financial companies,[4] direct lenders face fewer regulatory constraints, thus making them more willing and able to make enterprise value bets on riskier and more leveraged companies.

One of the most comprehensive studies on direct lending technologies and contract design is by Jang (2024), who uses a novel dataset of loan agreements to examine whether direct lenders behave more like banks or arm's-length investors. In terms of monitoring, Jang (2024) finds that nearly

[4] The Bank Holding Company Act of 1956 generally prohibits bank holding companies (BHCs) from owning or controlling more than 5% of the voting shares in non-financial companies.

all loans issued by direct lenders include financial covenants, often based on cash flow metrics and capital expenditures (p. 3). These loan agreements also tend to carry stricter negative covenant limits on debt issuance and investments compared to traditional bank loans to similar firms. If covenants are violated, direct lenders are also more likely to make amendments that enforce stricter covenant limits on EBITDA and liquidity, while frequently relying on additional equity injections from PE sponsors in the case of distress. As a result, covenant violations by "direct" borrowers are often associated with divestments, reduced investment rate, lower debt issuance, and increased cash holdings. These results show that direct lenders engage in strict monitoring through contractual design, especially in the form of financial and negative covenants.

Jang (2024) extends his analysis by examining the role of relationships in direct lending by exploiting the liquidity shock induced by the COVID-19 pandemic. He finds that direct lenders were more flexible in renegotiation compared to bank lenders for equally distressed borrowers. Specifically, direct borrowers were more likely to obtain payment deferrals, significantly less likely to end up in bankruptcy proceedings, and more likely to receive additional equity injections by PE sponsors. Not surprisingly, these results highlight the importance of the relationship between direct lenders and PE sponsors. As PE sponsors make up the vast majority of direct lending deal flow, direct lenders are incentivized to engage in flexible out-of-court renegotiations to avoid bankruptcy proceedings and preserve the relationship with equity sponsors. At the same time, sponsors are incentivized to inject additional equity in times of distress to provide downside protection and maintain the relationship with lenders. This notion of a strong mutual relationship is empirically validated by the evidence that direct lenders are more likely to extend future loans to PE sponsors who previously injected additional equity in times of distress.

Another common contractual feature deployed by direct lenders is the use of payment-in-kind (PIK) provisions, which allow borrowers to defer cash interest payments by adding the accrued interest to the outstanding principal amount. Rintamäki & Steffen (2025) study the prevalence and use of PIK arrangements and find that they are often used by struggling firms, serving as a form of liquidity substitute during periods of economic distress. Furthermore, they find that PIK usage strongly predicts increased future credit deterioration and borrower bankruptcy, and that banks are unwilling to provide funding to BDCs who use PIK components excessively. As such, the degree

to which a direct lending portfolio relies on PIK-paying assets could be a good ex-ante indicator of underlying portfolio risk.

2.3 Fee Structures and Managerial Incentives in Delegated Asset Management

A fundamental premise of this thesis is that the behavior of delegated asset managers is, at least in part, governed by the compensation structures and fee arrangements under which they operate. A substantial body of literature studies how fee structures and managerial compensation in alternative investment funds, most notably within the hedge fund and private equity industry, affect incentive alignment between managers and investors, and if such alignment issues translate into observable differences in risk-taking among managers. However, despite the rapid growth of private credit and the increasing role of asset managers in the broader NBFI lending sector, this topic has received virtually no attention in the empirical research on private credit. This represents a notable gap, especially seeing as typical BDC fee arrangements exhibit differences from those of hedge funds and private equity funds, which could potentially have implications for how BDC managers allocate capital and manage portfolio risk. This section reviews the broader literature on fee structures and managerial incentives in delegated asset management, drawing on research from hedge funds, private equity, and real estate investment trusts (REITs) to motivate the research questions and hypotheses examined in this paper.

One important early contribution to the hedge fund literature, which provides a valuable starting point in the discussion of managerial compensation structures, comes from Goetzmann et al. (2003), who study the high-water mark (HWM) provision in performance fee contracts and its implications on the division of wealth between investors and hedge fund managers. They show that, because the performance fee has an option-like payoff structure, hedge fund managers have incentives to increase portfolio risk when the fund's asset value is near but below the high-water mark, as greater volatility raises the probability of the contract being “in the money” and triggering a fee payment. Conversely, as the fund's asset value approaches the liquidation boundary,

managers have an incentive to reduce portfolio risk to maximize the probability of fund survival and protect future fee income.

Although BDCs and private credit funds do not incorporate HWM provisions in their performance fee structures, the paper by Goetzmann et al. (2003) highlights a few relevant and important considerations. First, the authors establish a clear link between the value of a fund manager's compensation contract and their incentive to take on risk. Second, they highlight a crucial consideration, namely that hedge fund managers are inherently reluctant to grow the fund's size to scale the fixed management fee, by nature of the diminishing returns to scale and limits to arbitrage in the hedge fund industry. The same is not true for, e.g., managers of mutual or pension funds, who can increase their fixed compensation by growing the fund's AUM without sacrificing future returns given the absence of capacity constraints. This difference in managers' ability to increase compensation through fund growth highlights an interesting trade-off between performance-driven risk-taking motives (to maximize future performance fees) and precautionary survival motives (to protect future management fees). In short, while the classic hedge fund model may incentivize managers to increase portfolio volatility to trigger future performance fees, managers in more scalable fund structures may oftentimes be more motivated to protect their future management fees by prioritizing fund survival.

Yin and Zhang (2023) capture this element and provide a natural next step to understand the link between managerial compensation structures and risk-taking by studying how risk-taking is affected by the relative importance of future management fees in hedge fund managers' total compensation structures. They document that for the average fund in their sample, 40% of total future compensation is attributable to management fees, representing the largest share of income for the average hedge fund manager (pp. 920-921). Furthermore, when the contribution of future management fees to the total compensation increases, hedge fund managers take on less risk. This effect is more pronounced for large funds subjected to greater capacity constraints. They also show that the fund's termination probability decreases when future management fees become the dominant factor of total compensation, suggesting a primary driver behind managers' de-risking choices is to increase the survival probability to protect future income.

With this in mind, even though hedge funds are more constrained in their ability to increase fund size to scale their fixed compensation component, management fees remain the most important contributor to the average manager's income, which incentivizes de-risking behavior. This is corroborated by Lan et al. (2013), who study hedge fund managers' optimal leverage choices against the cost of fund liquidation, thus capturing another dimension related to financial risk in the capital structure of the fund. Their model treats leverage as an endogenous choice that maximizes the combined present value of AUM-based management fees and HWM-based incentive fees and finds that managers have a precautionary motive to de-risk in favor of preserving the fund's "going-concern" value to protect future management fees. As such, a risk-neutral manager becomes endogenously risk-averse following poor performance.

In the private equity industry, Metrick and Yasuda (2010) provide complementary findings by documenting that, on average, about two-thirds of total GP revenues in both venture capital and buyout funds are derived from fixed management fees that are not contingent upon performance (p. 2328). This reliance on management fees is notably higher than the 40% average estimated for hedge funds by Yin and Zhang (2023, pp. 920-921). Metrick and Yasuda (2010) also document that buyout funds are highly scalable, with positive excess performance even as the funds grow and deal values increase. The close interconnectedness between the private equity and private debt industries, as documented by Block et al. (2024), combined with the rapid growth of both segments following the GFC, suggests similar levels of scalability for BDCs and private debt funds. As such, the expectation that BDC managers, like private equity buyout fund managers, rely on fixed management fees as their primary source of income is reasonable.

The literature on REITs sheds additional light on managerial compensation structures and incentives from a more comparable institutional context. Capozza and Seguin (2000) study the underperformance of externally managed REITs by comparing them to their internally managed counterparts. The key difference between the two classes of trusts, which also applies to BDCs, is that external managers rely on asset- and income-based fees instead of salaries and traditional performance-based incentives. They find that externally managed REITs adopt higher leverage and raise debt at unfavorable rates relative to both their internally managed counterparts and the current yield of the projects purchased with the acquired funds. The interest rate differential

remains even after controlling for the greater leverage deployed in externally managed trusts, indicating that external managers make suboptimal decisions on behalf of investors. Furthermore, building upon the findings of previous studies showing that externally managed trusts are associated with higher systematic risk, the authors find no discernible differences in business risk between the two classes. As such, they conclude that differences in systematic risk between externally and internally managed REITs are solely attributable to higher financial risk. These results are interpreted as evidence that external managers, whose compensation is tied to AUM-based management fees and income-based incentive fees, are incentivized to use leverage to expand the asset base, even if it entails more financial risk and reduced cash flows available to shareholders. Given the similarities in fee arrangements between externally managed REITs and BDCs, these findings provide direct motivation for examining whether similar incentives exist within BDCs in the private credit sector.

Bringing these strands together, the above literature highlights how compensation design creates competing incentives for delegated asset managers, which ultimately affect the choices they make on behalf of their investors. Management fees based on gross AUM incentivize fund growth and additional leverage, particularly in scalable fund structures where capacity constraints are limited. Income-based incentive fees may encourage yield-seeking and riskier portfolio allocations, whereas a greater reliance on fixed management fees and liquidation risk may counteract this effect in favor of more precautionary incentives to ensure fund survival. As such, the central implication is that specific compensation structures do not entail a single predictable outcome on the risk-taking incentives of managers. Instead, the outcome relies on several dynamic forces whose net effect depends on which component is economically dominant at each point in time. This paper fills a large gap and expands the literature by examining how these competing forces shape managerial risk-taking in the private credit industry, which has not been subjected to any empirical investigation before.

2.4 Synthesis and Hypothesis Development

The reviewed literature provides the institutional context and conceptual background needed to motivate the research focus of this paper. Importantly, these papers highlight two broad dimensions: first, the role of BDCs in the broader private credit market, and second, the mechanisms through which managerial incentives may shape the decisions and risk-taking behaviors of fund managers. This section summarizes and brings together the core literature to motivate the research focus and hypotheses explored in this paper.

The use of BDCs as empirical subjects to study the otherwise opaque private credit market is well-established and motivated in the existing literature. Various papers highlight the institutional design of BDCs, particularly the regulatory disclosure requirements, to motivate why the BDC sector serves as a natural empirical setting (see, e.g., Davydiuk et al., 2024a; Davydiuk et al., 2024; Chernenko et al., 2025). Apart from being a convenient data source, BDCs have grown to represent a large and meaningful share of the direct lending sector (Chernenko and Scharfstein, 2025), highlighting the economic relevance and further validating the decision to study this particular segment in more detail. Moreover, in terms of external validity, the literature suggests that findings related to BDCs are likely informative about the broader private credit sector as well. Block et al. (2024) document that BDCs share several core characteristics with other private credit funds, whereas Davydiuk et al. (2024a) and Chernenko et al. (2025) highlight similarities in investment strategies and overall portfolio composition.

Beyond motivating the empirical setting, a recurring implication from the reviewed literature is that compensation structures tied to fund size create incentives for managers in scalable funds to increase the fee-paying asset base. As highlighted by Balloch and Gonzalez-Uribe (2021), this is especially true for BDCs, where management fees are charged based on gross assets and managers have economic incentives to increase leverage and regulatory constraints that pressure them to continuously invest the proceeds. The evidence from REITs highlights how compensation structures in externally managed REITs may encourage fund growth through increased leverage, even if it leads to higher financial risk and suboptimal investment decisions (Capozza and Seguin, 2000). Finally, the scalability and strong reliance on management fees documented in private equity funds by Metrick and Yasuda (2010) suggest that BDCs may similarly have incentives to

prioritize AUM-growth to increase the fixed portion of their fee arrangements. Taken together, these findings provide a strong foundation and motivation for the first hypothesis explored in this thesis, namely the *borrow-to-earn incentive.*

Hypothesis 1: Borrow-to-Earn Incentive

BDCs with stronger AUM-based fee incentives are associated with higher leverage and greater balance sheet expansion.

Another theme that is present in the related literature is that "option-like" performance fees, such as those commonly found in BDC fee arrangements, may incentivize managers to allocate capital towards riskier assets. The broader hedge fund literature establishes a clear link between performance fees and risk-taking, although from a different institutional context (see, e.g., Goetzmann et al., 2003; Yin and Zhang, 2023; Lan et al., 2013). However, although the hedge fund literature generally emphasizes that performance fees may induce higher risk-taking, it's important to note that this is highly contingent upon external factors such as the risk of fund liquidation. As such, the implication is not that performance fees always encourage higher risk-taking, but rather that income-based incentives can tilt managers toward riskier investments, especially when precautionary motives are less salient.

In the context of BDCs, Balloch and Gonzalez-Uribe (2021) provide the broader argument that the typical performance fee structure encourages managers to search for yield and misreport loan values to accrue compensation even from "bad" loans that generate current accounting income but will likely result in future losses. At the same time, Davydiuk, Marchuk, and Rosen (2024b) show that these risk-taking behaviors are likely to be expressed through portfolio composition, rather than capital structure. Although no prior study has examined the link between performance fees and risk-taking in a private credit setting, the related literature provides a clear basis for expecting that income-sensitive compensation does affect risk-taking in terms of portfolio composition in BDCs. As such, the second hypothesis explored in this paper refers to the *reach-for-yield incentive.*

Hypothesis 2: Reach-for-Yield Incentive

BDCs with stronger income-based fee incentives are associated with higher-yielding portfolios and riskier portfolio composition.

Importantly, the first and second hypotheses do not explicitly account for external factors which may activate the precautionary motives highlighted in the related literature. The evidence presented by Davydiuk et al. (2024b) shows that BDC managers de-risk by adjusting their portfolio composition following adverse funding shocks. This flight-to-quality response is broadly consistent with the hedge fund literature, including Goetzmann et al. (2003), Yin and Zhang (2023), and Lan et al. (2013), which suggests that hedge fund managers may become endogenously risk-averse and should optimally de-risk as the continuation risk of the fund increases. Hence, the related literature points toward the existence of strong survival motives among delegated asset managers when the preservation of future compensation becomes more important. Applied to the context of BDCs, one would expect that any observed positive associations between fee-incentives and risk-taking would be expected to weaken, or potentially reverse, in the presence of heightened continuation risk. Although not being within the scope of this paper, it serves as a natural next step in the research on fee incentives in private credit funds.

Taken together, this thesis addresses a notable gap in the private credit literature. Existing studies have shown why private credit has expanded, how BDCs and direct lenders differ from traditional bank lenders, and how they respond to funding shocks and leverage constraints. However, unlike the literature on other alternative asset classes, there is still no direct evidence on whether differences in compensation structures help explain the cross-sectional variation in portfolio risk and capital structure within the BDC sector itself. By doing so, this thesis extends the existing literature on incentives and risk-taking in delegated asset management to the private credit setting and contributes to the growing body of research on BDCs and direct lending.

3. Empirical Framework

This section outlines the empirical framework and provides an overview of the data and methodology used to study the hypotheses put forward in Section 2.4. Given the limited previous research on the effects of managerial incentive structures in private credit, the empirical framework is inspired by design elements from adjacent literatures where comparable incentive structures have been studied. Specifically, the comparison of gross-asset and net-asset-based fee structures in Hypothesis 1 is motivated by the REIT literature, most notably Capozza and Seguin (2000), who test the impact of an external management indicator on leverage. The distance-to-hurdle design used to test Hypothesis 2 is inspired by the hedge fund literature, where the proximity to incentive fee thresholds has been used to study dynamic risk-taking incentives (see, e.g., Goetzmann et al., 2003; Yin and Zhang, 2023; Lan et al., 2013). Incorporating these design elements and extending the scope to the private credit setting allows me to exploit a combination of reported financial data, manually collected contractual fee data, and detailed portfolio holdings to examine how compensation structures shape both capital structure decisions and portfolio risk-taking within the private credit sector.

The remainder of this section is structured as follows: Section 3.1 describes the data sources, sample construction, and variable definitions, Section 3.2 outlines the empirical strategy, and Section 3.3 reports summary statistics for the key variables included in the sample.

3.1 Data & Variable Definitions

3.1.1 Data Sources & Sample Construction

The empirical analysis is based on data from four primary sources, with the core dataset consisting of quarterly BDC portfolio holdings data from Preqin's "BDC Holdings" database. Given the regulatory disclosure requirements governing all entities under the Investment Company Act of 1940 and Securities Exchange Act of 1934, BDCs are required to file periodic reports that include a Schedule of Investments (SOI) with detailed information on portfolio holdings. The data from Preqin is compiled from the SOI in periodic filings and contains details on investment type, lien

position, fair value, amortized cost, principal amount, acquisition and maturity dates, along with contractual features such as reference rate, spread, reported coupon, and PIK provisions, for each investment. Leveraging this data allows me to construct a detailed sample consisting of quarterly observations on portfolio holdings for 60 unique BDCs covering the period from 2014Q4 to 2025Q2. As BDCs are U.S. entities by legal definition, the sample is restricted to the United States by construction.

The data from Preqin closely resembles other data sources used in previous research on BDCs. Various studies rely on LSEG's BDC Collateral database (formerly Refinitiv) to obtain a similar BDC-quarter panel compiled from mandatory SEC filings (see, e.g., Balloch and Gonzalez-Uribe, 2021; Jang, 2024; Jang et al., 2025). Both datasets compile detailed portfolio holdings from the same underlying filings, and the key variables included in the data are broadly comparable. The primary difference is that the LSEG BDC Collateral dataset offers improved coverage, dating back to 2012Q3 and comprises 190 unique traded and non-traded BDCs (Haque et al., 2025, p. 8). Furthermore, it offers additional BDC financial statement data, whereas the Preqin dataset does not. Due to data availability reasons, this thesis utilizes the Preqin database for BDC portfolio holdings data, supplemented by financial data compiled from Compustat and SEC EDGAR datasets, described more in detail below. Nonetheless, the use of Preqin as a data source is not expected to materially affect the conclusions of this study for two main reasons. First, since both providers compile the data from the same underlying filings, the data quality is expected to be comparable between the two. Second, although the number of unique BDCs differs across providers, the 60 BDCs included in my sample jointly managed approximately $328 billion in assets as of 2024Q4, which represents approximately 74% of the BDC sector's total AUM as reported by Chernenko and Scharfstein (2025, p. 1), suggesting that the sample captures the economically dominant part of the sector.

Several measures were taken to clean and prepare the data before using it for empirical analysis. First, initial quarters in which fewer than 10 unique BDCs had data coverage were excluded to mitigate the risk of bias stemming from a small and unrepresentative sample in earlier periods with poor data coverage. Second, all portfolio investments with a fair value of less than $1m were dropped from the sample. These holdings constituted less than 0.5% of the total fair value in any

quarter and were therefore determined to have a negligible impact on the representativeness of the sample. Third, the sample was restricted to only include investments for which the yield could be directly observed or manually computed. This required either (1) a reported coupon rate, or (2) sufficient information to manually compute the yield, based on either a reference rate and spread pair or a stated standalone PIK rate. Fourth, to facilitate data collection, the sample was restricted to loans with reference rates that appear at least 1,000 times across the full dataset. As a result, the remaining loans are either fixed-rate or quoted in reference to SOFR, LIBOR, Prime, EURIBOR, SONIA, or STIBOR, while disregarding less common reference rates that appear infrequently in the data.

Quarterly data on benchmark rates for SOFR, LIBOR, EURIBOR, SONIA, and STIBOR were collected from LSEG Workspace (Workspace), and the Bank Prime Loan Rate (Prime) was collected from the Federal Reserve Bank of St. Louis (FRED). To account for the fact that a meaningful share of the loans are quoted in reference to LIBOR even after its official discontinuation, the LIBOR rate is proxied using the ISDA LIBOR fallback rate, sourced from Workspace and applied to replace LIBOR during the entire sample period.[5] Using the fallback rate to replace LIBOR during the entire sample period is a simplification, and may cause minor measurement errors in the constructed yield for LIBOR-quoted loans prior to discontinuation in June 2023. However, this limitation only affects the yield-based outcome variables and is unlikely to have a material impact on any of the other key variables used in this study.

Quarterly financial statement data for publicly traded BDCs between 2015Q4 and 2025Q2 is obtained from Compustat North America using the Central Index Key (CIK) corresponding to each unique BDC. For each BDC-quarter observation, data on total assets, liabilities, equity, and total debt is collected. Furthermore, since Compustat does not include net investment income (NII) as a standalone variable, data on total revenues, operating expenses, and interest expenses is collected in order to manually compute the quarterly NII for each BDC in the sample. The NII variable is constructed by subtracting interest expenses and operating expenses from total revenue.

[5] The ISDA LIBOR fallback rate is a replacement rate by the International Swaps and Derivatives Association (ISDA), constructed based on SOFR and adjusted by a fixed spread based on the historical difference between the two rates.

This construction was validated against a random sample of 10-Q filings and found to accurately match reported NII in all sampled cases.

To obtain financial data for non-traded BDCs, I utilize the SEC EDGAR Business Development Company Data Sets (hereby referred to as EDGAR), which consist of structured XBRL data extracted from periodic 10-Q and 10-K filings submitted to the SEC from 2022Q4 and onwards. To match the financial data with the BDCs in my sample, each data file is filtered based on the unique CIK numbers. Next, each quarterly balance sheet and income statement variable is identified and extracted based on its respective XBRL tag.[6] Several cleaning steps were then applied to ensure the accuracy of the extracted data. First, for balance sheet variables, duplicate observations were removed by only keeping the most recent filing for a given tag and BDC-quarter combination. Apart from removing duplicates, this step also ensures that any potential amendments are accurately reflected in the resulting figures. Second, for income statement variables, 10-K filings were excluded when a 10-Q filing existed for the same BDC-quarter observation, to prevent full-year income from overriding quarterly figures. In the rare cases where BDCs only reported full-year income in their annual 10-Ks and quarterly figures were absent, the annual NII was divided by four to obtain a quarterly approximation of the NII during the last quarter of the fiscal year. Third, due to inconsistencies in XBRL tagging across BDCs, some tags capture gross rather than net investment income. To address this, NII is collected using multiple tags, and when more than one tag returns a non-missing value for the same BDC-quarter observation, only the minimum value is retained.

The two datasets containing financial data from Compustat and EDGAR are subsequently merged into a single panel dataset, covering both publicly traded and non-traded BDCs. In cases where both sources provide data for the same BDC-quarter, which is the case for most publicly traded BDCs after 2022Q4, the data collected from Compustat is prioritized. As a result, Compustat represents the primary source of financial data for the publicly traded BDCs in my sample, whereas

[6] The following tags were used to collect the data: “Assets”, “Liabilities”, “StockholdersEquity”, “LongTermDebt”, “NotesPayable”, “LineOfCredit”, “NetInvestmentIncome”, “InvestmentIncomeNet”, “IncentiveFeeExpense”, “IncomeBasedIncentiveFeeExpense”.

EDGAR provides financial data on non-traded BDCs from 2022Q4 and onwards. The resulting dataset is an unbalanced panel with limited full-sample coverage before 2022Q4, which could potentially introduce bias if the results are driven by the changing composition of the sample rather than the fee structures that this thesis aims to explore. This concern is explicitly addressed in robustness analyses which are explained further in Section 3.2.1.

Data on fee structures is manually collected from SEC-filings for each of the 60 BDCs and structured in a standardized way to ensure comparability and enable empirical analysis. Contractual terms governing management and incentive fees are primarily collected from N-2 filings, which BDCs file in connection with new debt or equity issuances (Davydiuk et al., 2024a). These filings typically contain information on how external managers are compensated under the existing Investment Management Agreement (otherwise commonly referred to as the "Investment Advisory Agreement", "Investment Advisory and Management Agreement", or similar). In the absence of N-2 filings, or in cases where the N-2 filing refers directly to the most recent annual report, 10-K filings are used as substitute sources. In addition to the data on fee structures, the date at which each BDC approved the relaxed asset coverage requirements following the 2018 SBCAA is collected from the same filings. Finally, the inception date of each BDC, used to construct the age variable described later in Section 3.1.4., is collected from N-54A filings, which represent the date at which the company elected to be treated as a BDC under the Investment Company Act of 1940.

For management fees, collected variables include the fee basis (e.g., gross assets, net assets, etc.), contractual fee rates, potential leverage thresholds above which the fee rate changes, along with a dummy variable indicating whether the BDC is externally managed. For income-based incentive fees, information on the hurdle rate, hurdle basis, and the terms of any catch-up provisions are recorded. BDCs with non-standard incentive fee structures, such as those based on cumulative internal rate of return (IRR) rather than quarterly NII, are treated as missing and excluded from subsequent analyses.

As a final step, the portfolio holdings dataset is aggregated to the BDC-quarter level to obtain the same panel structure as the dataset containing BDC financials. The resulting dataset contains portfolio-level variables for each BDC-quarter observation in my sample, including the fair-value-

weighted average yield and spread, along with the share of equity investments and PIK loans as a percentage of the total fair value of the portfolio. Subsequently, BDC-quarter observations with missing or zero equity and total assets below $10 million are excluded from the sample, as these observations mainly correspond to BDCs that are in their initial formation period and have very limited investment operations. As a result, the final regression sample is an unbalanced panel consisting of 60 unique BDCs observed at a quarterly frequency over the period 2015Q4 to 2025Q2, yielding 1,298 BDC-quarter observations. The construction of all variables is described in more detail in Sections 3.1.2 through 3.1.4.

3.1.2 Dependent Variables

Hypothesis 1

The dependent variables used to test H1 capture two dimensions related to the *borrow-to-earn incentive*, namely leverage and balance sheet growth. Leverage is measured using two alternative ratios based on book values obtained from Compustat and EDGAR. The primary measure for leverage is the debt-to-equity ratio, which is particularly informative given its link to the statutory ACR that is used to govern the leverage capacity of BDCs.[7] As an alternative measure, the debt-to-assets ratio is used as a useful robustness check. Although the two measures are mechanically linked, the debt-to-assets ratio is bounded and differs in scale, thus limiting the influence of extreme debt-to-equity observations that may arise when equity is small or close to zero.

Balance sheet growth is measured using the one-quarter log asset growth rate. For each BDC *i* observed in quarter *t*, the following formula is used to compute the growth:

$$\textit{Asset Growth} = 100 \times [\text{Log}(\text{Assets}_{i,t}) - \text{Log}(\text{Assets}_{i,t-1})] \quad (1)$$

[7] The statutory Asset Coverage Ratio (ACR) is formally defined as total assets less liabilities that are not senior securities, divided by the value of senior secured debt. As stated by Balloch and Gonzalez-Uribe (2021), this ratio can instead be expressed in terms of a leverage ratio based on total debt relative to the value of net assets (i.e., equity).

To further examine the underlying sources of asset growth, two additional variables are created, equity growth and debt growth, defined as a percentage of lagged total assets. Unlike the log asset growth rate in Equation (1), these variables are not defined as logarithmic differences. This is to ensure that both measures are directly comparable in magnitude and can be interpreted as the contribution of debt and equity growth to total balance sheet growth, respectively.

$$\text{Equity Growth}_{i,t} = 100 \times \frac{\text{Equity}_{i,t} - \text{Equity}_{i,\,t-1}}{\text{Assets}_{i,\,t-1}} \tag{2}$$

$$\text{Debt Growth}_{i,t} = 100 \times \frac{\text{Debt}_{i,t} - \text{Debt}_{i,\,t-1}}{\text{Assets}_{i,\,t-1}} \tag{3}$$

Adding these variables complements the results derived from the asset growth specification by enabling separate identification of the underlying drivers of balance sheet growth, specifically whether any observed differences in asset growth are driven primarily by the issuance of debt or equity.

Hypothesis 2

The dependent variables used to test H2 capture various measures of risk within each BDC's portfolio. The primary measure used is the fair-value-weighted average yield across all debt investments for a given BDC *i* in quarter *t*:

$$\text{Weighted Average Yield}_{i,t} = \frac{\sum_j y_{i,j,t} \times \text{FV}_{i,j,t}}{\sum_j \text{FV}_{i,j,t}} \tag{4}$$

Where $y_{i,j,t}$ represents the total yield on investment *j* and $\text{FV}_{i,\,j,\,t}$ its fair value. As noted in Section 3.1.1, the total yield is either directly observed from the data or manually constructed as follows. For each loan, if a reported coupon is available in the data, this rate is directly used. For floating-rate loans without a reported coupon, the yield is constructed as the sum of the quoted reference rate and the reported spread. For such loans, if a contractual interest rate floor also exists in the data, this floor is applied to the reference rate when calculating the total yield. For PIK-only loans

without a reported spread or reference rate (treated as a fixed PIK loan), the PIK rate is used directly. For loans with both a stated reference rate and a reported PIK rate (treated as a floating PIK loan), the yield is defined as the sum of the reference rate and the PIK rate.

A fair-value-weighted average spread is also computed using Equation (4) by substituting the total yield with the reported spread associated with the loan. The weighted average spread variable serves as a useful alternative to yield-based measures, as it separates the credit risk premium component by isolating it from movements in the underlying reference rate. This makes it a clean alternative to measure deliberate risk-taking in loan portfolios, since it is not affected by the prevailing interest rate environment to the same extent as total yield. However, the spread variable is unable to compare loans that are quoted against different reference rates, making it insufficient to use on a standalone basis.[8]

Finally, two alternative measures of portfolio composition are created: *PIK share*, defined as the share of total portfolio fair value attributable to investments with a PIK component, and *equity share*, defined as the share of total portfolio fair value attributable to equity investments. Using the equity share as a proxy variable for portfolio risk is motivated by Davydiuk et al. (2024b), who use the share of equity investments as a direct proxy for portfolio risk. A higher equity share represents a shift towards subordinated investments and should thus be interpreted as an increase in overall portfolio risk. The PIK share is motivated as a portfolio risk measure by the observation that PIK components are generally associated with subordinated debt and weaker borrower characteristics (Balloch and Gonzalez-Uribe, 2021), which is supported empirically by Rintamäki and Steffen (2025) who document that increased PIK usage predicts higher bankruptcy rates and realized portfolio losses. As such, a higher PIK share reflects a riskier portfolio composition and greater exposure to potential future credit losses. All dependent variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers, and all growth variables are treated as missing in cases with non-consecutive BDC-quarter observations.

[8] Davydiuk et al. (2024) use the reported spread as a dependent variable in panel regressions, but control for the reference rate limitation by only considering LIBOR-denominated loans.

3.1.3 Independent Variables

Hypothesis 1

The primary independent variable for H1 is *GrossFee*, a binary variable indicating whether a BDC charges management fees based on gross asset values that are not adjusted for leverage.[9] The *GrossFee* variable is zero for internally managed BDCs and those that charge management fees on the basis of net assets. The intuition behind using this dummy variable is that for net-fee BDCs, only growth in net assets increases the management fee base, whereas for gross-fee BDCs, both equity and debt-financed growth contribute to expanding the management fee base. As such, the *GrossFee* variable captures this differential incentive to use leverage to expand the fee-paying asset base.

Many BDCs apply non-linear elements to their management fee structures. A common example is to include leverage-based thresholds tied to the ACR or a multiple of NAV, which adjust the applicable management fee rate depending on the magnitude of existing leverage. To extend beyond the binary logic and capture this non-linear variation in fee incentives, an alternative independent variable, *MarginalFee,* is constructed. *MarginalFee* measures the incremental management fee rate (in percentage terms) associated with a $1 increase in gross assets, thus capturing any potential leverage thresholds that exist in the management fee structure. Similar to the *GrossFee* variable, *MarginalFee* is zero for net-fee and internally managed BDCs. For gross-fee BDCs without any leverage-based thresholds, *MarginalFee* is equal to the contractual management fee rate. For gross-fee BDCs with leverage-based thresholds, the applicable fee rate depends on whether the BDC is above or below the threshold at each point in time:

$$MarginalFee_{i,t} = \begin{cases} 0 & \text{if net-fee or internally managed} \\ r_{\text{above}} & \text{if gross-fee and above threshold} \\ r_{\text{below}} & \text{if gross-fee and below threshold} \end{cases} \tag{5}$$

[9] The GrossFee variable is also equal to 1 for a few BDCs charging management fees on the total fair value of their investments.

where r_{above} and r_{below} represent the contractual management fee rates above and below the threshold. To illustrate, consider a BDC that charges management fees on gross assets at a rate of 1.50% above a 200% ACR threshold and 1.00% below. At one point in time, the BDC has $100 million in total assets and $40 million in total debt, corresponding to an ACR of 250%, placing it above the ACR threshold. At this level, the *MarginalFee* for an incremental $1 of assets would equal 1.50%. Now, consider another point in time where the BDC still has $100 million in total assets, but $60 million in total debt. The ACR is now roughly 167%, placing it below the leverage-based threshold. As a result, the *MarginalFee* for an incremental $1 of assets would equal 1.00%.

Hypothesis 2

The primary independent variables used to test H2 share the same logic as the variables included for H1, namely to capture the structure and magnitude of fee-based incentives. However, these variables shift the focus away from the management fee and instead towards the income-based component within a BDC's incentive fee arrangement. Three sets of variables are constructed, each reflecting a different aspect of the incentive fee structure.

First, two contractually determined variables are used. *HurdleRate* is defined as the annualized hurdle rate and represents the minimum annualized return that a BDC must achieve before any incentive fees are paid to the advisor, expressed as a percentage of net assets. *IncentiveFeeRate* is defined as the share of excess NII (i.e., all NII that exceeds the hurdle) that is attributable to the external manager.[10] The *IncentiveFeeRate* thus resembles the "carry" component commonly found in private equity compensation arrangements, although it is based on quarterly income rather than realized capital gains. Both variables are time-invariant within BDCs, as they are both collected from the terms of the investment management agreement. A higher *HurdleRate* implies that the

[10] All BDCs in the H2 sample include full catch-up provisions, with the exception of one BDC that applies a 50% catch-up rate. Due to the limited variation across BDCs, these provisions are not included in any of the models.

manager must achieve higher returns before accruing any incentive fees, whereas a higher *IncentiveFeeRate* corresponds to a higher share of excess NII being owed to the manager.

Second, I construct another set of variables that measure the distance between a BDC's NII and its required hurdle income in each quarter. The hurdle income is first constructed by calculating the minimum NII required to trigger the incentive fee in each quarter.

$$Hurdle\ Income_{i,t} = \frac{HurdleRate}{4} \times Net\ Assets_{i,t} \tag{6}$$

Subsequently, the *Distance-to-Hurdle* variable is defined as the difference between realized NII and hurdle income in each quarter, which is then divided by net assets to ensure comparability across BDCs of different sizes. The resulting variable measures how far above or below the hurdle threshold each BDC is in each quarter, expressed as a percentage of net assets.

$$Distance\text{-}to\text{-}Hurdle_{i,t} = NII_{i,t} - Hurdle\ Income_{i,t} \tag{7}$$

$$Distance\text{-}to\text{-}Hurdle\ (\%)_{i,t} = \frac{Distance\text{-}to\text{-}Hurdle_{i,t}}{Net\ Assets_{i,t}} \times 100 \tag{8}$$

As noted in Section 3, this variable design is inspired by the hedge fund literature (e.g., Goetzmann et al., 2003; Yin and Zhang, 2023; Lan et al., 2013) and aims to measure dynamic incentives based on the proximity to a hurdle, above which a manager starts accruing performance-based compensation. A positive *Distance-to-Hurdle (%)* indicates that the BDC is earning excess NII above the hurdle, implying that the manager is entitled to income-based incentive fees. Conversely, a negative value implies that the BDC manager is not entitled to any performance-based compensation. Lagged values of these variables are also computed to address endogeneity concerns, discussed further in Section 3.2.2.

Finally, a third set of categorical variables are created, designed to classify BDCs into four distinct groups based on the observed *Distance-to-Hurdle (%)* at each quarter. For each BDC-quarter observation, BDCs are either classified as: *FarBelow*, *NearBelow*, *NearAbove*, or *FarAbove* the hurdle. The near below and near above groups are defined as being within +/- 1% of the hurdle, with observations outside this range being classified as either far below or far above. The intuition

behind including these categorical variables is that income-based fee incentives are likely more pronounced near but below the hurdle, where the marginal payoff to additional income is higher, consistent with an incentive to reach-for-yield when approaching the threshold.

3.1.4 Control Variables

Five primary control variables are used to control for differences in observable characteristics among BDCs. The first variable, *Size*, controls for BDC size and is defined as the natural logarithm of total assets. There may exist systematic differences between large and small BDCs in terms of leverage capacity, portfolio composition, access to external financing, among other things, making size an important control variable to include in all regression specifications. The second variable, *Age,* is defined as the natural logarithm of a BDC's age in years and is constructed based on the inception date collected from N-54A filings. Controlling for age captures differences related to which stage a given BDC is in its lifecycle. Younger BDCs are likely to be in different growth stages compared to older and more established BDCs, which may affect both leverage decisions and portfolio composition independently of fee structures.

The third control, *PostSBCAA,* is a binary variable equal to one from the quarter in which a BDC adopted the relaxed 150% asset coverage limit, following shareholder or board approval of the new rules introduced under the SBCAA. This variable absorbs any mechanical increase in leverage that emerged as a result of the relaxed regulatory constraint, ensuring that any differences in leverage between BDCs are not confounded by differences in SBCAA adoption timing.

To capture elements associated with portfolio composition that may independently affect growth and leverage, the fourth control variable captures the degree of industry concentration within each BDC's portfolio, using the Herfindahl-Hirschman Index (HHI) based on the primary industry associated with each target company. *HHI* is calculated for each BDC-quarter observation by squaring the fair-value-based share of each industry in the portfolio and summing across all industries, as shown in Equation (9).

$$HHI_{i,t} = \sum_{j=1}^{J} s_{ij,t}^2 \tag{9}$$

A higher value of *HHI* implies greater portfolio concentration with respect to industry, which could amplify the effects of sector-specific shocks that may have an impact on growth, overall portfolio risk, and the value of assets and liabilities which would mechanically affect leverage. Controlling for portfolio concentration using the *HHI* is motivated by, e.g., Capozza and Seguin (2000), who utilize Herfindahl-indices to control for portfolio concentration within REITs across region and property type. Furthermore, Ávila et al. (2013) document that the HHI is a particularly robust measure of concentration risk and one of the most important causes of credit losses within banks' portfolios, which warrants the use of this metric when studying private credit funds as well.

The fifth control variable, *Senior Share,* measures the share of the portfolio invested in senior debt, which is a useful proxy for the riskiness of a given BDC's lending strategy. BDCs with a higher *Senior Share* face lower expected credit losses and may therefore be better positioned to sustain higher leverage, independently of their fee structure. Both *Senior Share* and *HHI* are incorporated with one-quarter lags across all regression specifications to mitigate simultaneity concerns, as portfolio composition, risk, and leverage may be jointly determined within the same quarter.

3.2 Methodology

The following section describes the empirical approaches and regression specifications used to test each hypothesis. Despite differences in design and identification strategy across the different models, a few common elements of the empirical design apply throughout. First, all specifications include quarter fixed effects to account for time-varying unobserved characteristics affecting all BDCs each quarter. Fluctuating credit market conditions such as policy interest rate movements

and common macroeconomic shocks are examples of effects absorbed by the inclusion of quarter fixed effects.

Second, BDC outcomes such as portfolio composition, yields, leverage, and growth rates are not independently measured at each quarter within the same fund, as they partly reflect the overall investment strategy and the accumulated decisions that have been made in the past. This implies that residuals are likely to be serially correlated within each BDC over time, which limits empirical inference under the standard OLS assumptions. Petersen (2009) shows that when residuals are correlated both within entities and across time, one can control for time effects parametrically by including time fixed effects while addressing firm effects by clustering standard errors within entities. As such, beyond adding quarter fixed effects, standard errors are also clustered at the BDC level across all specifications. Following Petersen (2009), the validity of this approach is confirmed by comparing the size of clustered and heteroskedasticity-robust (White) standard errors across selected regressions. Appendix **D** reports the results of these tests, revealing consistently larger clustered standard errors which is consistent with the presence of a firm effect in the panel.

3.2.1 Hypothesis 1: Borrow-to-Earn Incentive

To test Hypothesis 1, I begin by estimating a pooled OLS regression using the following specification:

$$Y_{i,t} = \beta_1 GrossFee_i + \beta Controls_{i,t} + \delta_t + \varepsilon_{i,t} \quad (10)$$

where $Y_{i,t}$ represents one of the dependent variables; *Debt-to-Equity*, *Debt-to-Assets*, *Asset Growth*, *Debt Growth*, or *Equity Growth*, for BDC *i* in quarter *t*. *GrossFee* is the primary independent variable of interest, and $Controls_{i,t}$ represents a vector of control variables, including *Size*, *Age*, *PostSBCAA*, *Senior Share,* and *HHI*. δ_t denotes quarter fixed effects and $\varepsilon_{i,t}$ is the associated error term. Standard errors are clustered at the BDC-level to mitigate the impact of serial correlation within entities over time. Across all specifications, *Size, Senior Share,* and *HHI* are lagged by one quarter to avoid simultaneity between the control variables and the dependent variable. The regression specification in Equation (10) is then repeated using *MarginalFee* as the

primary independent variable, to see whether estimates are consistent after introducing additional variation in fee incentives across BDCs.

While the construction of *MarginalFee* allows for additional variation, examining the data reveals that BDCs rarely breach their contractual leverage thresholds, resulting in limited variation within this variable over time. As such, BDC fixed effects are excluded from all specifications, given that both *GrossFee* and *MarginalFee* are largely time-invariant and would therefore be absorbed by the inclusion of BDC fixed effects. Importantly, this implies that identification is cross-sectional, with the estimated coefficients capturing the average difference in leverage and growth between gross-fee and net-fee BDCs, after absorbing common time trends and controlling for observable characteristics.

For robustness, all the models are re-estimated based on an alternative sample restricted to the post-2022Q4 period, during which both publicly traded and non-traded BDCs are well-represented in the data. This is done to ensure that none of the observed results from the full-sample models are driven by a composition effect stemming from the entry of non-traded BDCs into the sample from 2022Q4 and onwards.

3.2.2 Hypothesis 2: Reach-for-Yield Incentive

To test Hypothesis 2, three separate estimation approaches are used, all of which focus on different parts of the income-based incentive fee structure. Each set uses the same dependent variables: *Weighted Average Yield, Weighted Average Spread, Equity Share,* and *PIK Share,* and include the same control variables, including lagged *Size* and *HHI*, *Age,* and the *PostSBCAA* dummy. *Senior Share* is excluded as a control from all H2 specifications as portfolio composition is closely related to the outcome variables and would likely absorb part of the effect that the models aim to identify.

The first approach is comprised of two separate regression specifications, defined in Equation (11) and (12), and uses the contractual *HurdleRate* and *IncentiveFeeRate* as primary independent variables. The effect of each variable is estimated separately to avoid the issue of multicollinearity

based on the high positive correlation observed between the contractual hurdle rate and incentive fee rate.[11]

$$Y_{i,t} = \beta_1 HurdleRate_i + \beta Controls_{i,t} + \delta_t + \varepsilon_{i,t} \quad (11)$$

$$Y_{i,t} = \beta_1 IncentiveFeeRate_i + \beta Controls_{i,t} + \delta_t + \varepsilon_{i,t} \quad (12)$$

Since both *HurdleRate* and *IncentiveFeeRate* are time-invariant at the BDC-level, BDC fixed effects are excluded from both models. As a result, identification is cross-sectional, and the interpretation of the estimated coefficients follows the same logic as for the models used to test H1, in Section 3.2.1.

The second approach utilizes the lagged *Distance-to-Hurdle (%)* as the primary treatment variable, thus capturing a more dynamic relationship between income-based fee incentives and the portfolio-level outcome variables. Unlike the contractual variables used in the previous approach, the *Distance-to-Hurdle (%)* is calculated independently across each BDC-quarter observation, causing it to vary within BDCs over time. As such, BDC fixed effects can be included in the model to identify whether BDCs, on average, exhibit riskier portfolio composition following quarters when they were further below the hurdle, after controlling for unobservable effects that vary across BDCs but not over time. As shown by Equation (13), the model is estimated using both BDC and quarter fixed effects (α_i and δ_t), with standard errors clustered at the BDC-level.

$$Y_{i,t} = \beta_1 \textit{Distance-to-Hurdle(\%)}_{i,\,t-1} + \beta Controls_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (13)$$

Finally, the third approach replaces the continuous *Distance-to-Hurdle (%)* by a set of lagged categorical variables, indicating whether a given BDC was *FarBelow*, *NearBelow*, *NearAbove*, or *FarAbove* the hurdle in the previous quarter. BDC fixed effects are included and *NearBelow* serves as the omitted reference category. As such, the estimated coefficients on the remaining categories measure whether a BDC is associated with more or less portfolio risk in the subsequent quarter compared to when it was previously near but below the hurdle.

[11] The observed correlation between *HurdleRate* and *IncentiveFeeRate* is ρ = 0.69.

$$Y_{i,t} = \beta_1 FarBelow_{i,t-1} + \beta_2 NearAbove_{i,t-1} + \beta_3 FarAbove_{i,t-1} + \beta Controls_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t} \quad (14)$$

By dividing BDCs into groups and allowing the intercepts to vary, the estimates can be directly compared to the theoretical prediction that the BDCs closest to (but below) the hurdle have the strongest incentives to increase portfolio risk. However, since the outcome variables reflect the level of portfolio risk, and not the change across quarters, it is possible that an endogeneity problem exists between each category and the outcome variables. Since the hurdle group is determined by NII, BDCs with temporarily higher portfolio risk may be more likely to exceed the hurdle in a given quarter. If the elevated level of portfolio risk persists across several quarters, the estimated coefficients could capture these pre-existing differences instead of the deliberate risk-taking decisions made by BDC managers. To address this, a second model using quarterly first differences of the outcome variables is used, which measures the association between lagged hurdle groups and subsequent changes in portfolio risk, rather than the observed level.

3.3 Summary Statistics

Table 1 reports key BDC characteristics across the entire sample period, including full-sample statistics along with groups based on whether a given BDC charges management fees on gross or net assets. The full sample consists of 1,298 BDC-quarter observations, with the average BDC managing $3.6 billion in total assets with a debt-to-equity ratio of 0.98. The observed leverage is notably higher than what has been observed in prior studies, which is expected given that the sample is primarily concentrated in the post-SBCAA period. As such, much of the gradual increase in leverage documented by Balloch and Gonzalez-Uribe (2021) is reflected in the debt-to-equity ratios observed in this sample.

Splitting the sample based on fee structure reveals a few interesting observations. First, gross-fee BDCs are smaller on average, although the distributions suggest that net-fee BDCs are more dispersed and that the average is largely driven by a small number of very large entities. As such, the median size is a more informative measure, which shows a more modest, but still meaningful difference in size between gross-fee ($1.7bn) and net-fee ($2.3bn) BDCs.

Table 1 - Summary Statistics: BDC Characteristics

Variable	N	Mean	S.D.	P25	P50	P75
Full Sample						
Assets ($m)	1,298	3,627	6,416	695	1,822	3,326
Equity ($m)	1,298	1,813	3,228	356	885	1,613
Total Debt ($m)	1,257	1,484	2,150	314	812	1,598
Debt-to-Equity	1,257	0.98	0.38	0.74	0.97	1.22
Age (Years)	1,298	9.39	6.70	4.18	8.42	12.84
NII (% of Assets)	1,265	1.24	0.39	1.03	1.27	1.47
Gross-fee BDCs						
Assets ($m)	1,032	3,148	4,399	580	1,684	3,171
Equity ($m)	1,032	1,539	2,109	277	820	1,482
Total Debt ($m)	1,019	1,520	2,241	297	777	1,696
Debt-to-Equity	1,019	1.03	0.37	0.78	1.03	1.26
Age (Years)	1,032	9.18	5.06	5.17	8.66	12.46
NII (% of Assets)	1,011	1.21	0.38	1.01	1.23	1.43
Net-fee BDCs						
Assets ($m)	266	5,486	11,037	1,418	2,344	4,121
Equity ($m)	266	2,878	5,678	726	1,245	2,169
Total Debt ($m)	238	1,328	1,702	560	926	1,522
Debt-to-Equity	238	0.76	0.33	0.60	0.82	1.00
Age (Years)	266	10.20	10.94	1.73	4.23	15.71
NII (% of Assets)	254	1.38	0.39	1.20	1.41	1.59

Table 1 presents summary statistics for key BDC characteristics across the entire sample period, reported separately for the full sample, gross-fee, and net-fee BDCs.

This presence of large net-fee BDCs is confirmed by Appendix **A.2,** which shows the ten largest BDCs along with information on their management fee structures. As of 2024Q4, net-fee BDCs represent the largest group in terms of size, with the biggest (Blackstone Private Credit Fund) being more than 2.5 times the size of its closest competitor. Interestingly, the management fee rate is observed to be higher among the large BDCs that charge management fees based on gross assets, which suggests that these managers have amplified incentives to grow the asset base using additional leverage.

To account for the changing composition of the sample after 2022Q4, Appendix **A.1** offers complementary insights by showing cross-sectional summary statistics for the same BDC characteristics as of 2024Q4. Looking at the age variable reveals that gross-fee BDCs are considerably older, with a mean (median) age of 10.8 (11.7) years compared to 5.8 (3.0) years for

net-fee BDCs. This difference can also be observed when comparing the interquartile ranges of the two groups, with the middle 50% of gross-fee BDCs being between 6.0 and 13.8 years old, ranging only from 1.8 to 4.2 years for net-fee BDCs. The right-skewed distribution of age among net-fee BDCs suggests that a small number of older BDCs exist within this group, which may correspond to the larger and more established entities observed earlier.

Importantly, the observed differences in debt-to-equity between the two groups are consistent across the full panel and the 2024Q4 cross-section. Gross-fee BDCs maintained a mean (median) debt-to-equity ratio of 1.03 (1.03) over the sample period, compared to 0.76 (0.83) for net-fee BDCs. A similar difference can also be observed in the 2024Q4 cross-section. While not controlling for any other variables, these results provide preliminary evidence in favor of Hypothesis 1, suggesting that the higher leverage observed in gross-fee BDCs may in part reflect the structural differences in incentives between the two groups.

Table **2** provides an overview of fee structure variables for each BDC in the sample. Of the 60 unique BDCs, 38 (63%) charge management fees on gross assets, whereas only three (5%) are internally managed and the remaining 19 (32%) base their fees on net assets. The average management fee rate is 1.30% with a narrow interquartile range between 1.25% to 1.50%, suggesting a limited dispersion in management fee rates across BDCs. Of the gross-fee BDCs in the sample, only ten (17%) apply some form of leverage-based threshold that adjusts the fee rate depending on their level of leverage.

Table 2 - Summary Statistics: Fee Structure Variables

Variable	N	Mean	S.D.	P25	P50	P75
Management Fee						
Management Fee Rate (%)	57	1.30	0.33	1.25	1.25	1.50
Gross-fee BDC (Y/N)	60	0.63				
Leverage Threshold (Y/N)	60	0.17				
Income-Based Incentive Fee						
Hurdle Rate (%)	54	6.41	1.09	5.25	6.00	7.00
Incentive Fee Rate (%)	54	16.18	3.65	12.50	17.50	20.00
Catch-up (Y/N)	60	0.88				
Net Assets Hurdle Basis (Y/N)	60	0.83				

Table 2 presents summary statistics for variables related to fee structure. Management fee characteristics include the applicable management fee rate (in %) and binary variables indicating whether a BDC charges management fees on gross assets or applies a leverage-based threshold. Income-based incentive fee characteristics include the annualized hurdle and incentive fee rate (in %), and binary variables indicating whether a BDC has a catch-up provision or uses net assets as the hurdle basis. "(Y/N)" indicates binary variables.

Table 2 also reports details on incentive fee structures, showing the average fund using an annualized hurdle and incentive fee rate of 6.4% and 16.2%, respectively. As stated in Section 3.2.2, these variables exhibit a strong positive correlation ($\rho = 0.69$), indicating that BDCs applying a higher hurdle rate tend to compensate their external managers by offering a greater share of the excess NII. The vast majority of BDCs include catch-up provisions in their income-based compensation arrangements (88%) and calculate the required hurdle income on the basis of net assets (83%).

Table 3 reports portfolio-level variables across the full sample period. The average BDC portfolio exhibits a weighted average yield of 10.2%, with floating-rate loans averaging a spread of 6.8%. The average yield is slightly higher than what has been observed in other studies. Balloch and Gonzalez-Uribe (2021, p. 16) document an average all-in yield of 8.9% as of 2017Q4 based on a sample of 77 BDCs. However, this difference is largely attributable to the sample period, with the majority of observations in this study being concentrated within the post-2022 period following the Federal Reserve's monetary policy tightening cycle. The average share of loans with PIK provisions is 13%, which is consistent with the results obtained by Rintamäki and Steffen (2025, p. 51). Furthermore, the average share of senior loans (76%) and low average share of equity

investments (3%) point towards BDCs primarily engaging in senior direct lending to their portfolio companies. Again, to address the composition effect affecting the sample after 2022Q4, Appendix **A.3** provides an overview of the same portfolio-level variables as of 2024Q4, which shows no meaningful deviations from the full-sample statistics.

Table 3 - Summary Statistics: Portfolio Variables

Variable	N	Mean	S.D.	P25	P50	P75
Weighted-Average Yield (%)	1,260	10.24	2.35	8.94	10.28	11.47
Weighted-Average Spread (%)	1,223	6.76	1.23	5.93	6.50	7.52
PIK Share	1,260	0.13	0.13	0.03	0.09	0.17
Equity Share	1,260	0.03	0.06	0.00	0.00	0.02
Senior Share	1,260	0.76	0.28	0.68	0.86	0.96
Industry HHI	1,260	0.23	0.09	0.17	0.21	0.26

Table 3 presents full-sample summary statistics for portfolio-level outcome variables and selected control variables used to test Hypothesis 2. Weighted-Average Yield and Spread are weighted based on fair value. PIK Share and Equity Share represent the fair-value-based share of loans with PIK provisions and proportion of equity investments in the portfolio. Senior Share measures the fair-value-based proportion of senior loans in a BDC's portfolio, while Industry HHI represents the Herfindahl-Hirschman Index based on target company industry, which measures the degree of portfolio concentration.

4. Results & Discussion

This section presents and discusses the results obtained from the empirical analysis described in Section 3.2. The section is divided into three parts. Section 4.1 presents and discusses the results associated with each hypothesis separately, followed by robustness tests and a brief discussion of the key findings. Section 4.2 synthesizes and compares the key findings related to each hypothesis and provides a general discussion on the implications of the results. Finally, Section 4.3 acknowledges and discusses the key limitations of the study.

4.1 Regression Results & Robustness Tests

4.1.1 Hypothesis 1: Borrow-to-Earn Incentive

Table 4 presents the results obtained from the leverage regressions used to test Hypothesis 1. Models (1) and (3) use *GrossFee* as the independent variable while models (2) and (4) use *MarginalFee* to test the effect of the management fee structure on the debt-to-equity and debt-to-asset ratios.

The coefficient on *GrossFee* is positive and statistically significant in both the debt-to-equity and debt-to-assets specifications. These estimates suggest that gross-fee BDCs are, on average, associated with a 0.245 higher debt-to-equity ratio and a 0.067 higher debt-to-asset ratio compared to their net-fee counterparts within the same quarter, after controlling for size, age, SBCAA adoption, as well as the concentration and risk associated with their portfolios. Replacing *GrossFee* with *MarginalFee* as the main independent variable reduces the model's explanatory power and the magnitude and significance of the coefficients across both specifications. The estimate is lower, but weakly significant ($p < 0.1$), in the debt-to-equity specification, which is consistent with the prediction of Hypothesis 1. However, the coefficient loses all significance when tested against the debt-to-asset ratio.

Table 4 - H1 Regression Output: Leverage

	Debt-to-Equity		Debt-to-Assets	
Model:	(1)	(2)	(3)	(4)
$GrossFee_i$	0.245***		0.067**	
	(0.069)		(0.027)	
$MarginalFee_{i,t}$		0.125*		0.034
		(0.072)		(0.023)
$Size_{i,t-1}$	-0.050	-0.045	-0.0005	0.001
	(0.031)	(0.033)	(0.009)	(0.010)
$Age_{i,t}$	0.089**	0.086**	0.036***	0.035**
	(0.038)	(0.041)	(0.013)	(0.015)
$Post\text{-}SBCAA_{i,t}$	0.327***	0.346***	0.093**	0.098**
	(0.103)	(0.095)	(0.042)	(0.040)
$HHI_{i,t-1}$	0.120	0.082	0.037	0.029
	(0.494)	(0.476)	(0.133)	(0.129)
$SeniorShare_{i,t-1}$	0.091	0.107	0.025	0.029
	(0.096)	(0.094)	(0.027)	(0.025)
Fixed Effects				
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,167	1,159	1,167	1,159
R^2	0.36043	0.33889	0.28628	0.27189
Within R^2	0.20013	0.17257	0.17336	0.15553

Table 4 reports the results of pooled OLS regressions estimating the association between management fee structures and BDC leverage. The dependent variables are the Debt-to-Equity ratio and the Debt-to-Assets ratio. All specifications include quarter fixed effects and the same set of control variables. Coefficient estimates are reported alongside clustered standard errors in parentheses, where standard errors are clustered at the BDC level. All dependent variables are winsorized at the 1st and 99th percentiles. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Taken together, the results imply that the binary classification of gross versus net-fee BDCs is more informative compared to the added variation of the *MarginalFee* variable, as the extra variation may simply be adding noise rather than any meaningful information. To interpret this, it

is important to first acknowledge that *MarginalFee* captures two different sources of variation simultaneously, namely the gross versus net-fee distinction (the same as *GrossFee*) and the variation in fee rates within the gross-fee group itself. The reduction in both significance and magnitude suggests that the variation in management fee rates does not appear to be a meaningful determinant of leverage across BDCs.

In terms of control variables, the coefficients on *Age* and *PostSBCAA* are positive and significant across all specifications, with similar magnitude regardless of which independent variable is used. The positive coefficient on *PostSBCAA* implies that BDCs carry significantly more leverage after adopting the relaxed asset coverage requirements introduced by the SBCAA, consistent with the findings of Balloch and Gonzalez-Uribe (2021). The positive coefficient on the lagged *Age* variable suggests that older and more established BDCs tend to operate with higher leverage. This is consistent with the notion that a longer track-record improves access to debt capital markets.

Table **5** presents the results obtained from the growth specifications used to test Hypothesis 1. Columns (1), (3), and (5) tests the relationship between *GrossFee* and the one-quarter log asset growth, debt growth, and equity growth, respectively, whereas Columns (2), (4), and (6) uses the *MarginalFee* as the main independent variable of interest. Debt growth and equity growth are both scaled using one-quarter lagged assets, implying that coefficients are interpreted as the percentage point change in debt or equity in relation to total assets in the previous quarter.

Interestingly, the coefficients on both *GrossFee* and *MarginalFee* are negative and statistically significant across all growth specifications. These results imply a direct opposite effect compared to the prediction of Hypothesis 1. BDCs that base their management fee on gross assets are associated with an approximately 5.5 percentage point lower asset growth rate compared to their net-fee counterparts within the same quarter, after controlling for lagged size, age, SBCAA-adoption, portfolio risk, and portfolio concentration. Additionally, the coefficients on debt and equity growth suggest that the effect is driven by a combination of lower debt and equity growth, with equity exhibiting a somewhat larger effect.

Table 5 - H1 Regression Output: Growth

	Asset Growth		Debt Growth		Equity Growth	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$GrossFee_i$	-5.54***		-2.46**		-3.64***	
	(1.85)		(1.08)		(1.09)	
$MarginalFee_{i,t}$		-3.85***		-1.88***		-2.25***
		(1.21)		(0.669)		(0.718)
$Size_{i,t-1}$	0.272	0.119	0.258	0.165	0.198	0.118
	(0.587)	(0.575)	(0.294)	(0.289)	(0.354)	(0.358)
$Age_{i,t}$	-5.81***	-5.66***	-2.64***	-2.55***	-3.78***	-3.73***
	(1.06)	(1.09)	(0.634)	(0.632)	(0.691)	(0.720)
$PostSBCAA_{i,t}$	2.71**	2.28	2.38***	2.16**	0.386	0.134
	(1.33)	(1.42)	(0.859)	(0.918)	(0.858)	(0.859)
$HHI_{i,t-1}$	1.96	2.88	0.227	0.670	2.42	2.97
	(5.60)	(5.09)	(3.30)	(3.18)	(3.78)	(3.55)
$SeniorShare_{i,t-1}$	-1.57	-2.21	-0.733	-1.15	-0.700	-0.999
	(1.60)	(1.55)	(1.11)	(1.11)	(0.926)	(0.870)
Fixed Effects						
Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,199	1,191	1,163	1,155	1,199	1,191
R^2	0.31965	0.32319	0.18383	0.18983	0.33437	0.33145
Within R^2	0.26359	0.26727	0.12868	0.13521	0.25716	0.25323

Table 5 reports the results of pooled OLS regressions estimating the association between management fee structures and BDC growth. The dependent variables are the Asset Growth, defined as the log difference in assets, debt growth and equity growth. Debt and equity growth are expressed as percentages of lagged assets. All specifications include quarter fixed effects and the same set of control variables. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. All dependent variables are winsorized at the 1st and 99th percentiles. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

However, the observed differences between gross-fee and net-fee BDCs presented in Section 3.3 reveal an important identification challenge. Table 1 shows that net-fee BDCs are, on average, substantially younger than gross-fee BDCs. This difference is particularly relevant for the growth specifications, since younger BDCs in their early development phases are more likely to exhibit

higher growth rates compared to older, more established BDCs, independently of fee structure. Including age as a control variable intends to capture this lifecycle effect, and the negative and significant coefficient on age supports the expectation that growth decreases as BDCs grow older. For robustness, Appendix **C.1** shows the effects of omitting age from the leverage and growth regressions. Excluding age causes the coefficient on *GrossFee* to decrease from -5.5 to -7.2 in the asset growth specification, suggesting that the effect is absorbed when age is omitted. This points toward age being a confounding variable, as it is likely correlated with *GrossFee* and simultaneously associated with BDC growth. Attempts to resolve this issue by restricting the sample above a minimum age (e.g., 5 years) or including dummy variables for different age groups were unsuccessful due to data constraints. Restricting the sample left too few net-fee BDC observations for reliable inference, whereas the age group approach suffered from insufficient representation of net-fee BDCs in the older age groups. As such, the coefficients from the growth specification are considered inconclusive and should be interpreted with caution as the effect cannot be cleanly separated from age-related lifecycle effects.

By contrast, Appendix **C.1** further shows that the leverage specification is less sensitive to the inclusion of age. Omitting the age control only result in a small increase in the *GrossFee* coefficient, from 0.245 to 0.261, with no meaningful change in the significance of the *GrossFee* coefficient. As a result, the evidence suggests that while age is a meaningful control, it does not seem to confound the relationship between *GrossFee* and leverage to the same extent as in the growth specification.

To ensure that the changing composition of the sample does not materially affect the estimated coefficients, Appendix **C.2** and **C.3** present the results obtained by re-estimating the leverage and growth models using a sub-sample restricted to the post-2022Q4 period. In terms of leverage, Appendix **C.2** shows that the *GrossFee* coefficient remains positive and statistically significant in the debt-to-equity specification, confirming that the previously observed result is not primarily driven by a composition effect. The coefficient remains positive but loses statistical significance in the debt-to-asset specification. The weakly significant *MarginalFee* coefficient observed in the debt-to-equity specification also loses its statistical significance after restricting the sample.

Similarly, Appendix C.3 shows how the coefficients in the growth specification changes when re-estimating the growth model using the post-2022Q4 subsample. The negative and significant *GrossFee* coefficient decreases in magnitude but persists for asset growth (-3.84) and equity growth (-3.20), while debt growth loses significance. The same pattern is also observed for *MarginalFee*. Nonetheless, the broad persistence in results across the restricted and unrestricted models indicate that the observed effects are not purely driven by a composition effect, which reinforces the inconclusive interpretation of the growth specifications, as discussed above.

4.1.2 Hypothesis 2: Reach-for-Yield Incentive

Table 6 reports the results obtained from examining the effect of the contractual hurdle rate on the weighted average yield, spread, PIK share, and equity share. The results in Column 3 indicate that BDCs with higher annualized hurdle rates tend to hold a larger proportion of PIK loans. Specifically, a one percentage point increase in the annualized hurdle rate is, on average, associated with a 5.4 percentage point increase in the share of loans with PIK provisions, as a proportion of fair value.

The explanation most consistent with the prediction of Hypothesis 2 is that managers resort to higher-yielding PIK loans as a way to increase portfolio yield and improve the likelihood of earning above the hurdle. Davydiuk et al. (2024a, p. 21) document average yields across different loan types, and show that loans that include PIK provisions are, on average, significantly more expensive than loans with conventional floating or fixed interest rates.[12] However, if this explanation is true, one would expect a corresponding positive effect on the weighted average yield, which is not observed. This, combined with the fact that none of the other dependent variables exhibit any significant relationship with the hurdle rate, implies a weak relationship between the hurdle rate and overall portfolio risk, providing limited support to Hypothesis 2.

[12] Table D.2 in Davydiuk et al. (2024a, p. 21) documents that ”PIK-only” and ”PIK and/or cash” loans carried average interest rates of 11.95% and 13.56%, respectively, as of 2017Q4. This is notably higher than the 9.06% and 8.26% observed for ”Cash only” and ”Base + Spread” in the same period.

Table 6 - H2 Regression Output: Hurdle Rate

Model:	WA Yield (%) (1)	WA Spread (%) (2)	PIK Share (3)	Equity Share (4)
$HurdleRate_i$	-0.806	-0.015	0.054**	0.009
	(0.556)	(0.199)	(0.024)	(0.009)
$Size_{i,t-1}$	-0.799**	-0.310***	0.018*	0.0004
	(0.381)	(0.106)	(0.010)	(0.006)
$Age_{i,t}$	1.06**	0.326	-0.003	0.011
	(0.514)	(0.199)	(0.021)	(0.010)
$PostSBCAA_{i,t}$	0.714	-0.112	-0.085*	-0.015
	(0.643)	(0.287)	(0.043)	(0.015)
$HHI_{i,t-1}$	-0.597	-0.774	0.073	0.134*
	(2.04)	(1.01)	(0.169)	(0.076)
Fixed Effects				
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,047	1,014	1,047	1,047
R^2	0.40325	0.52744	0.18660	0.14054
Within R^2	0.18534	0.18512	0.15113	0.12440

Table 6 reports the results of pooled OLS regressions estimating the association between income-based incentive fee structures and portfolio risk. WA Yield (%) & WA Spread (%) represent the fair-value-weighted yield and spread of the loans in the portfolio. Hurdle rate is expressed in annualized percentage terms. PIK Share (%) and Equity Share (%) represent the fair-value-based proportion of loans with PIK components and equity investments. Size is defined in log-difference terms. All specifications include quarter fixed effects and the same set of control variables. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. All dependent variables are winsorized at the 1st and 99th percentiles. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix **B.1** reports the results obtained from the cross-sectional models examining the effect of the contractual incentive fee rate on the same four dependent variables. None of the coefficients on the incentive fee rate are statistically significant, providing no evidence of a relationship between the contractual incentive fee rate and overall portfolio risk. Similarly, Appendix **B.2** presents the results obtained from the fixed effects panel specifications using the lagged *Distance-to-Hurdle (%)* as the independent variable of interest. The coefficients on *Distance-to-Hurdle (%)* are statistically insignificant across all outcome variables, except the *PIK Share*, where a positive and weakly significant result can be observed. However, although the coefficients of interest reveal

little meaningful information about the statistical relationship with the dependent variables, the large differences between the overall R^2 and within-R^2 observed in all models suggest that a meaningful share of the total variation in the dependent variables is explained by persistent and time-invariant BDC characteristics. As such, including fixed effects on the BDC-level seems to be of significant importance when examining the determinants of portfolio composition and risk.

Table 7 reports the results obtained from the third approach, using the hurdle group dummies as treatment variables and including both quarter and BDC fixed effects. The results imply limited evidence in relation to Hypothesis 2. The coefficients on *FarBelow* are negative across all models but only exhibit a statistically significant relationship with the share of PIK loans in the portfolio. Specifically, if a given BDC was far below the hurdle in the previous quarter, its next-quarter PIK share would, on average, be 8.1 percentage points lower compared to quarters following a near-below classification. This is consistent with the H2 prediction that BDCs have stronger incentives to reach-for-yield following periods in which they were just below the hurdle threshold.

Conversely, the coefficients on *NearAbove* are exclusively positive across all models, but statistically significant at the 10% level only for the models using weighted average yield and spread as outcome variables. This is the opposite of what H2 predicts, as it indicates that quarters following a *NearAbove* classification are associated with higher subsequent portfolio risk compared to quarters following a *NearBelow* classification. One possible explanation for the ambiguous results is that the coefficients may partly reflect pre-existing differences in portfolio risk rather than the actual changes in portfolio composition, as mentioned in Section 3.2.2. Even after controlling for time-invariant BDC fixed effects, temporary differences in portfolio risk may still be captured by the estimated coefficients. This problem arises because portfolio risk is measured in levels, rather than changes in the outcome variables from one quarter to another.

Table 7 - H2 Regression Output: Hurdle Group

Model:	WA Yield (%) (1)	WA Spread (%) (2)	PIK Share (3)	Equity Share (4)
$FarBelow_{i,t-1}$	-0.121	-0.272	-0.081***	-0.014
	(0.345)	(0.186)	(0.021)	(0.017)
$NearAbove_{i,t-1}$	0.329*	0.330*	0.032	0.010
	(0.183)	(0.183)	(0.031)	(0.013)
$FarAbove_{i,t-1}$	0.227	0.283	0.039	0.012
	(0.216)	(0.193)	(0.038)	(0.013)
$Size_{i,t-1}$	-0.142	0.121	0.028	0.007
	(0.437)	(0.248)	(0.027)	(0.006)
$Age_{i,t}$	0.308	0.193	0.057	0.001
	(0.599)	(0.284)	(0.047)	(0.015)
$PostSBCAA_{i,t}$	0.144	-0.147	-0.045*	-0.015*
	(0.248)	(0.235)	(0.024)	(0.008)
$HHI_{i,t-1}$	-2.05	-0.293	0.235	0.127*
	(1.45)	(1.02)	(0.247)	(0.072)
Fixed Effects				
CIK	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,028	995	1,028	1,028
R^2	0.82990	0.81952	0.63939	0.64398
Within R^2	0.02668	0.05830	0.09629	0.05448

Table 7 reports the results of fixed effects panel regressions estimating the association between proximity to the income-based incentive fee hurdle and portfolio risk outcomes. BDCs are classified into four groups based on their lagged Distance-to-Hurdle (%), defined as the difference between realized NII and the quarterly hurdle income and expressed as a percentage of net assets. *NearBelow* serves as the reference category. All specifications include both BDC and quarter fixed effects. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. All dependent variables are winsorized at the 1st and 99th percentiles. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

To address this issue, Table **8** reports the results from running additional robustness models in which all outcome variables are transformed into first differences. Both quarter and BDC fixed effects are included, with standard errors being clustered at the BDC level. The results show no statistically significant relationship between the hurdle groups and changes in portfolio risk outcomes. Although most coefficients turn negative, which is directionally consistent with Hypothesis 2, the lack of significance suggests that the groups cannot be statistically

distinguished from *NearBelow* in terms of changes in the outcome variables.

Table 8 - Robustness Test: H2 Hurdle Group Regressions (First-Differences)

Model:	Δ WA Yield (%) (1)	Δ WA Spread (%) (2)	Δ PIK Share (3)	Δ Equity Share (4)
$FarBelow_{i,t-1}$	0.003	-0.434	-0.036	-0.030
	(0.205)	(0.275)	(0.026)	(0.025)
$NearAbove_{i,t-1}$	-0.054	-0.033	0.004	-0.007
	(0.109)	(0.028)	(0.006)	(0.008)
$FarAbove_{i,t-1}$	-0.158	-0.070	0.0007	-0.001
	(0.143)	(0.042)	(0.007)	(0.008)
$Size_{i,t-1}$	-0.019	-0.030	-0.001	-0.003
	(0.042)	(0.030)	(0.003)	(0.003)
$Age_{i,t}$	0.070	0.043*	-0.0003	-0.002
	(0.071)	(0.024)	(0.004)	(0.004)
$PostSBCAA_{i,t}$	-0.156	-0.133**	0.004	-0.000
	(0.128)	(0.063)	(0.007)	(0.006)
$HHI_{i,t-1}$	-0.422	-0.535*	-0.027	-0.037
	(0.532)	(0.302)	(0.039)	(0.033)
Fixed Effects				
CIK	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,025	985	1,025	1,025
R^2	0.18787	0.11250	0.09713	0.06184
Within R^2	0.00389	0.03077	0.01145	0.01092

Table 8 reports the results of panel regressions replicating the hurdle group specifications using first-differenced outcome variables. Taking first differences removes time-invariant BDC-level heterogeneity and shifts the interpretation from levels to quarter-on-quarter changes in portfolio risk. *NearBelow* serves as the reference category. All specifications include both BDC and quarter fixed effects and the same set of control variables as the baseline. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively

4.2 Summary & Comparison of Results

Taken together, the results presented in this study suggest that the relationship between fee structures and risk-taking within BDCs is more nuanced than what was predicted by the initial hypotheses. Comparing the findings point towards a more asymmetric relationship, in which fee incentives appear to be more consequential for capital structure decisions than portfolio risk-taking

decisions. The leverage specifications used to test the first hypothesis provide the clearest and most robust evidence. The results indicate that gross-fee BDCs are associated with higher leverage ratios compared to their net-fee counterparts, consistent with the borrow-to-earn hypothesis that predicts a higher use of leverage among BDC managers charging fees on gross assets. Importantly, these results are broadly robust even after controlling for potential endogeneity concerns stemming from the positive correlation with age and issues related to the changing sample composition.

In contrast, the broadly insignificant results from the marginal fee regressions suggest that differences in the actual management fee rate between gross-fee BDCs offer no meaningful explanation for the observed cross-sectional differences in leverage. Examining the effects of contractual components in the income-based incentive fee reveals similar results. Neither differences in the hurdle rate nor the incentive fee rate are useful in explaining the cross-sectional variation in portfolio composition or risk. As such, the lack of conclusive evidence points toward contractual fee rates being largely unrelated to a manager's decision to increase leverage and portfolio risk. One likely explanation for the lack of evidence in the contract variable specifications is that these variables fail to capture the complexities of incentive structures when evaluated on a standalone basis. The observed positive correlation between the hurdle rate and incentive fee highlighted in Section 3.3 indicates that BDCs determine these components jointly, rather than independently. A manager subject to a higher hurdle is likely to be compensated by a larger share of the excess profits. Assuming managers evaluate their incentives holistically before making decisions, the individual effect of each standalone component likely fails to capture the overall incentives facing the manager, making it difficult to measure the effects of these isolated components.

The more dynamic specifications used to test Hypothesis 2 similarly provide no conclusive evidence of fee incentives being associated with reach-for-yield behavior. The large explanatory power of adding BDC fixed effects suggests that portfolio composition and risk are largely stable within BDCs over time, rather than driven by quarterly fluctuations in the proximity to the hurdle threshold. Examples of such stable and unobserved effects include each BDCs investment mandate and overall risk culture, which are likely determined early in the fund's lifecycle and have evolved and persisted over time. The interpretation that these persistent factors are particularly important

drivers of portfolio outcomes makes economic sense when considering the institutional context and characteristics of the private credit market, as outlined in Section 2. Direct lending portfolios primarily consist of illiquid investments that cannot easily be bought and sold in active secondary markets. Unlike managers in hedge funds or other liquid asset classes, direct lending fund managers do not have the same ability to dynamically adjust their portfolios in response to short-term fluctuations that could impact the size of their compensation package. Instead, BDC managers are faced with stickier portfolios that adjust more naturally over time, as new loans are bought or originated and old loans mature. With income-based incentive fees typically determined at a quarterly frequency, BDC managers are therefore significantly constrained in their ability to reach for yield in response to elevated fee-incentives. This interpretation not only explains why persistent factors such as risk culture and mandate are important structural drivers of portfolio risk, but also why the estimated coefficients fail to capture any meaningful relationships between short-term fee incentives and long-term portfolio outcomes.

By contrast, leverage decisions are not subject to the same timing constraint, which can help explain why the leverage models produce clearer and more robust evidence consistent with the borrow-to-earn incentive. Acharya et al. (2026) argue that banks and NBFIs are closely intertwined, with banks often providing senior credit and short-term liquidity funding to nonbank lenders. The willingness of BDC managers to increase leverage when the opportunity emerges has also been documented by Balloch and Gonzalez-Uribe (2021) and is supported by the results of the leverage regressions used in this study. Combined, the easy access to capital and observed willingness to take on debt could suggest that the necessary conditions exist for managers to make decisions based on their fee-incentives. This distinction, based on what BDC managers can and cannot easily do provides a coherent interpretation of the results obtained in this study.

4.3 Limitations

This study is subject to several limitations which may affect the reliability and interpretability of the estimated models and results. First, the largely cross-sectional research design limits the extent to which reliable interpretations can be made about the observed relationships obtained from

regression models. Since the primary treatment variables across both Hypotheses 1 and 2 are time-invariant, BDC fixed effects cannot be included to control for unobserved heterogeneity without absorbing the effects stemming from the treatment variables. As such, these models are unable to establish causality, as unobserved differences may be present but cannot be ruled out.

Second, the estimates obtained from the growth specifications tested under Hypothesis 1 are likely subject to a confounding effect from the age variable, as it is positively correlated with the *GrossFee* and *MarginalFee* variables while simultaneously being a key determinant of growth. In other words, younger and smaller BDCs in their early stages are likely to exhibit mechanically higher growth compared to older and more mature BDCs. As such, the relationship between the independent variables and age-related lifecycle effects cannot be fully separated.

Third, a number of data-related issues may also affect the reliability of the results. Since Compustat does not provide coverage for non-traded BDCs, this data had to be collected from XBRL datasets obtained from the SEC EDGAR database, which were only available from 2022Q4 and onwards. For one, this resulted in a significant restriction of the sample period, implying that a large part of the sample is concentrated only within the post-2022Q4 period following the Federal Reserve's monetary policy tightening cycle. The lack of observations across multiple policy regimes may affect the external validity of the results. Furthermore, the SEC EDGAR data required extensive cleaning to match it with the data from Compustat, which may have translated into added measurement error in the variables of interest.

Finally, as discussed in Section 4.2, the data and outcome variables used to test Hypothesis 2 are unlikely to fully capture deliberate risk-taking decisions made by BDC managers, as they primarily reflect pre-existing loans and portfolio choices that have already been made in the past. Using data on new loan originations would allow for more accurate detection of reach-for-yield behavior, suggesting an interesting avenue to explore in future studies.

5. Conclusions

The rapid growth of the private credit industry and the increased role of direct lenders as capital providers to the U.S. middle market have sparked a growing interest within the academic literature to understand the characteristics, lending practices, and systemic implications of private credit funds and other nonbank financial intermediaries. Despite this growing body of research, no study has yet been conducted to understand the link between managerial incentive structures and risk-taking behaviors within this industry. Adjacent fields in the broader literature on delegated asset management have since long established that compensation structures shape managerial decision making in significant ways, particularly regarding risk. The lack of understanding about whether similar dynamics exist within the private credit industry represents a notable gap, which limits the ability of investors and regulators to fully assess the risks associated with these funds and the systemic implications of a rapidly growing direct lending sector.

By combining detailed portfolio holdings, financial data, and hand-collected contractual fee data for 60 BDCs observed over the period 2015-2025, this thesis addresses this gap by examining whether differences in managerial incentive structures can help explain the cross-sectional variation in leverage, growth, and portfolio risk within the BDC sector. The central finding is that fee structures seem to matter most for capital structure decisions, rather than portfolio risk-taking. BDCs charging management fees based on gross assets are, on average, associated with higher leverage ratios compared to net-fee BDCs, suggesting that managers act on the elevated incentives to borrow when adding debt increases the fee-paying asset base. Conversely, portfolio composition and risk seem to be largely unaffected by both contractually determined and dynamic income-based incentive fee measures, providing no conclusive evidence that managers reach for yield by adjusting the composition and risk of their portfolios.

However, although the results are not uniformly consistent with the initial hypotheses, they are not necessarily uninformative. The most probable explanation offered in this thesis has to do with the characteristics and institutional context of the private credit market. I argue that since direct lending portfolios largely contain illiquid investments and portfolio composition is slow to adjust, portfolio risk cannot be rapidly adjusted within the quarterly horizons in which incentive fees are

typically determined. As such, private credit managers are constrained in their ability to act on their incentives by reaching for yield, which would explain the weak relationship observed between fee incentives and portfolio risk outcomes observed in this study. On the other hand, BDC managers have easy access to external debt financing through close relationships with banks, and their willingness to increase leverage was observed following the relaxation of leverage constraints induced by the 2018 SBCAA. This implies that leverage decisions are likely not subject to the same constraint, which would explain the significant and robust association between BDCs charging management fees on gross assets and higher leverage.

However, several limitations exist that may limit the reliability of the results showcased in this study. Due to data constraints, financial data for non-traded BDCs is limited in the pre-2022Q4 period, causing imbalances in the panel structure across the earlier parts of the sample period. As a consequence, a disproportionate share of the observations used to identify the effects of incentive structures are concentrated in periods characterized by tighter monetary policy, which may not yield representative results across different policy regimes. Furthermore, heterogeneity in reporting quality entailed that extensive cleaning and manual variable construction had to be conducted to replace missing observations in key variables, potentially introducing a degree of measurement error in the dependent variables used for analysis. The cross-sectional identification strategy used in the absence of within-entity variation also cannot establish causality and are thus interpreted as associations rather than cause-effect relationships. Finally, the possibility of other unobserved factors confounding the relationship between fee structures and risk outcomes limits the extent to which definitive conclusions can be made.

A variety of interesting avenues for future research exist that would address the limitations and build on the results obtained in this study. Examining ex-post credit outcomes would be a valuable complement to the ex-ante portfolio risk measures used in this study, to see if differences in managerial incentive structures affect realized credit losses within the private credit industry. Second, using data on new loan originations would bypass the timing-constraint stemming from the stickiness of private credit loan portfolios and allow researchers to obtain better estimates on whether dynamic fee incentives translate into increased risk through deliberate portfolio adjustments. Third, expanding the data coverage and extending the analysis to cover multiple

countries and credit cycles would significantly improve the external validity of the results. Finally, examining whether any precautionary survival incentives exist, moderating the effects of fee-based incentives on risk-taking, would be highly valuable and provide a more complete picture of how private credit managers act upon their incentives. The hedge fund literature has documented strong evidence consistent with the existence of such motives, serving as a good source of inspiration for how such studies could be designed.

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Appendix

A.1 Summary Statistics: BDC Characteristics as of 2024Q4

Table 9 - Summary Statistics: BDC Characteristics as of 2024Q4

Variable	N	Mean	S.D.	P25	P50	P75
Full Sample						
Assets ($m)	59	6,132	10,476	1,856	2,597	6,001
Equity ($m)	59	3,166	5,602	828	1,353	3,342
Total Debt ($m)	53	2,272	2,827	848	1,318	2,203
Debt-to-Equity	53	0.97	0.35	0.75	1.03	1.22
Age (Years)	59	8.96	7.22	3.19	6.40	13.59
NII (% of Assets)	58	1.24	0.37	1.06	1.22	1.42
Gross-fee BDCs						
Assets ($m)	37	4,310	5,533	1,164	2,344	4,305
Equity ($m)	37	2,078	2,607	656	1,186	2,060
Total Debt ($m)	35	2,168	2,856	471	1,118	2,093
Debt-to-Equity	35	1.06	0.37	0.97	1.14	1.30
Age (Years)	37	10.84	5.68	5.97	11.67	13.75
NII (% of Assets)	36	1.26	0.35	1.07	1.25	1.40
Net-fee BDCs						
Assets ($m)	22	9,194	15,328	2,122	4,011	7,568
Equity ($m)	22	4,995	8,332	1,124	2,016	4,532
Total Debt ($m)	18	2,474	2,841	916	1,890	2,495
Debt-to-Equity	18	0.78	0.21	0.63	0.76	0.91
Age (Years)	22	5.80	8.48	1.82	2.97	4.23
NII (% of Assets)	22	1.21	0.40	1.02	1.19	1.41

Table 9 presents summary statistics for key BDC characteristics as of 2024Q4, reported separately for the full sample, gross-fee, and net-fee BDCs.

A.2 Top 10 Largest BDCs by Total Assets as of 2024Q4

Table 10 - Top 10 BDCs by Total Assets as of 2024Q4

BDC	Assets ($m)	Fee Basis	Base Fee Rate (%)	Leverage Threshold
Blackstone Private Credit Fund	71,284	Net	1.25	No
Ares Capital Corp.	28,254	Gross	1.50	Yes
Blue Owl Credit Income Corp.	28,064	Net	1.25	No
HPS Corporate Lending Fund	16,630	Net	1.25	No
Apollo Debt Solutions BDC	15,235	Net	1.25	No
FS KKR Capital Corp.	14,219	Gross	1.50	No
Blue Owl Capital Corp.	13,866	Gross	1.50	Yes
Blackstone Secured Lending...	13,472	Gross	1.00	No
Ares Strategic Income Fund	12,150	Net	1.25	No
Golub Capital BDC Inc.	9,009	Gross	1.38	No

Table 10 lists the 10 largest BDCs in the sample by total assets as of 2024Q4. Assets are reported in millions of USD. Fee Basis indicates whether the management fee is charged on gross or net assets. Base Fee Rate is the applicable management fee rate in periods when the BDC does not exceed any potential leverage thresholds. Leverage Threshold indicates whether the BDC's management fee structure includes a provision that adjusts the fee rate based on the level of leverage.

A.3 Summary Statistics: Portfolio Variables as of 2024Q4

Table 11 - Summary Statistics: Portfolio Variables as of 2024Q4

Variable	N	Mean	S.D.	P25	P50	P75
Weighted-Average Yield (%)	57	10.43	1.12	9.78	10.22	10.71
Weighted-Average Spread (%)	57	5.75	0.79	5.35	5.61	6.05
PIK Share	57	0.13	0.09	0.07	0.13	0.17
Equity Share	57	0.02	0.05	0.00	0.00	0.02
Senior Share	57	0.84	0.27	0.87	0.93	0.99
Industry HHI	57	0.22	0.07	0.17	0.21	0.25

Table 11 presents cross-sectional summary statistics as of 2024Q4 for the portfolio-level outcome variables and selected control variables used to test Hypothesis 2. Weighted-Average Yield and Spread are weighted based on fair value. PIK Share and Equity Share represent the fair-value-based share of loans with PIK provisions and proportion of equity investments in the portfolio. Senior Share measures the fair-value-based proportion of senior loans in a BDC's portfolio, while Industry HHI represents the Herfindahl-Hirschman Index based on target company industry, which measures the degree of portfolio concentration.

B.1 H2 Regression Output: Incentive Fee Rate

Table 12 - H2 Regression Output: Incentive Fee Rate

Model:	WA Yield (%) (1)	WA Spread (%) (2)	PIK Share (3)	Equity Share (4)
$IncFeeRate_i$	0.036	0.072	0.004	0.002
	(0.058)	(0.047)	(0.004)	(0.002)
$Size_{i,t-1}$	-0.559*	-0.254***	0.007	-0.0006
	(0.299)	(0.086)	(0.011)	(0.006)
$Age_{i,t}$	0.433	0.133	0.022	0.012
	(0.313)	(0.199)	(0.015)	(0.009)
$PostSBCAA_{i,t}$	0.327	-0.138	-0.060	-0.011
	(0.483)	(0.275)	(0.039)	(0.015)
$HHI_{i,t-1}$	-1.93	-0.622	0.179	0.154*
	(1.63)	(0.810)	(0.163)	(0.080)
Fixed Effects				
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,047	1,014	1,047	1,047
R^2	0.36030	0.53895	0.12337	0.13572
Within R^2	0.12672	0.20495	0.08515	0.11949

Table 12 reports the results of pooled OLS regressions estimating the association between income-based incentive fee structures and portfolio risk. WA Yield (%) & WA Spread (%) represent the fair-value-weighted yield and spread of the loans in the portfolio. IncFeeRate is the contractual income-based incentive fee rate expressed in percentage terms. PIK Share (%) and Equity Share (%) represent the fair-value-based proportion of loans with PIK components and equity investments. Size is defined in log-difference terms. All specifications include quarter fixed effects and the same set of control variables. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. All dependent variables are winsorized at the 1st and 99th percentiles. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

B.2 H2 Regression Output: Distance-to-Hurdle (%)

Table 13 - H2 Regression Output: Distance-to-Hurdle (%)

Model:	WA Yield (%) (1)	WA Spread (%) (2)	PIK Share (3)	Equity Share (4)
$Distance\text{-}to\text{-}Hurdle(\%)_{i,t-1}$	-0.083	0.064	0.029*	0.003
	(0.124)	(0.101)	(0.015)	(0.005)
$Size_{i,t-1}$	-0.059	0.164	0.028	0.009
	(0.425)	(0.241)	(0.026)	(0.006)
$Age_{i,t}$	0.311	0.157	0.046	-0.004
	(0.642)	(0.307)	(0.048)	(0.014)
$PostSBCAA_{i,t}$	0.089	-0.194	-0.050*	-0.016
	(0.268)	(0.248)	(0.027)	(0.010)
$HHI_{i,t-1}$	-2.21	-0.491	0.217	0.122*
	(1.33)	(0.970)	(0.224)	(0.070)
Fixed-effects				
CIK	Yes	Yes	Yes	Yes
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,016	984	1,016	1,016
R^2	0.82894	0.81262	0.64010	0.64138
Within R^2	0.02170	0.03447	0.09882	0.04837

Table 13 reports the results of fixed effects panel regressions estimating the association between a BDC's distance to the hurdle threshold in the previous quarter (as a % of net assets) and portfolio risk outcomes. All specifications include both BDC and quarter fixed effects. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. All dependent variables are winsorized at the 1st and 99th percentiles. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

C.1 Robustness Test: Effect of Omitting Age from H1 Regressions

Table 14 - Robustness test: Effect of omitting Age from H1 regressions

	Debt-to-Equity		Asset Growth	
Model:	(1)	(2)	(3)	(4)
$GrossFee_i$	0.245***	0.261***	-5.54***	-7.18***
	(0.069)	(0.073)	(1.85)	(2.45)
$Size_{i,t-1}$	-0.050	-0.037	0.272	-0.449
	(0.031)	(0.028)	(0.587)	(0.540)
$Age_{i,t}$	0.089**		-5.81***	
	(0.038)		(1.06)	
$PostSBCAA_{i,t}$	0.327***	0.324***	2.71**	2.75
	(0.103)	(0.106)	(1.33)	(1.78)
$HHI_{i,t-1}$	0.120	0.214	1.96	-4.44
	(0.494)	(0.492)	(5.60)	(7.40)
$SeniorShare_{i,t-1}$	0.091	0.069	-1.57	-0.583
	(0.096)	(0.097)	(1.60)	(2.66)
Fixed Effects				
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,167	1,167	1,199	1,199
R^2	0.36043	0.32883	0.31965	0.14402
Within R^2	0.20013	0.16061	0.26359	0.07349

Table 14 reports the results of pooled OLS regressions replicating the baseline H1 leverage and asset growth specifications, with and without the *Age* control variable. Columns (1) and (3) replicate the baseline specifications, while columns (2) and (4) omit *Age*. The purpose of this test is to assess whether the inclusion of *Age* materially affects the coefficient on *GrossFee*, given the observed correlation between BDC age and fee structure. All specifications include quarter fixed effects. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

C.2 Robustness Test: Restricted H1 Regression on Leverage (Post-2022Q4)

Table 15 - Robustness Test: Restricted H1 Regression on Leverage (Post-2022Q4)

	Debt-to-Equity		Debt-to-Assets	
Model:	(1)	(2)	(3)	(4)
$GrossFee_i$	0.201**		0.049	
	(0.081)		(0.033)	
$MarginalFee_{i,t}$		0.102		0.027
		(0.087)		(0.029)
$Size_{i,t-1}$	-0.056	-0.054	-0.004	-0.004
	(0.035)	(0.039)	(0.012)	(0.013)
$Age_{i,t}$	0.144***	0.155***	0.057***	0.060***
	(0.043)	(0.039)	(0.017)	(0.015)
$PostSBCAA_{i,t}$	0.605***	0.605***	0.208**	0.207**
	(0.196)	(0.180)	(0.088)	(0.084)
$HHI_{i,t-1}$	-0.437	-0.483	-0.197	-0.203
	(0.687)	(0.680)	(0.224)	(0.221)
$SeniorShare_{i,t-1}$	-0.046	-0.041	-0.021	-0.020
	(0.105)	(0.115)	(0.036)	(0.038)
Fixed Effects				
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	496	488	496	488
R^2	0.41519	0.39767	0.38289	0.38166
Within R^2	0.37990	0.36070	0.35389	0.35169

Table 15 reports the results of pooled OLS regressions replicating the baseline H1 leverage specifications on a restricted sample covering the post-2022Q4 period, during which both publicly traded and non-traded BDCs are well-represented in the data. The purpose of this test is to assess whether the full-sample results are driven by the changing composition of the sample as non-traded BDCs enter from 2022Q4 onwards. All specifications include quarter fixed effects and the same set of control variables as the baseline. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

C.3 Robustness Test: Restricted H1 Regression on Growth (Post-2022Q4)

Table 16 - Robustness Test: Restricted H1 Regression on Growth (Post-2022Q4)

	Asset Growth		Debt Growth		Equity Growth	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$GrossFee_i$	-3.84*		-1.31		-3.20**	
	(2.06)		(1.23)		(1.26)	
$MarginalFee_{i,t}$		-2.54*		-0.959		-2.13**
		(1.46)		(0.828)		(0.854)
$Size_{i,t-1}$	-0.869	-0.947	-0.051	-0.101	-0.613	-0.673
	(0.733)	(0.731)	(0.351)	(0.366)	(0.490)	(0.474)
$Age_{i,t}$	-7.13***	-7.22***	-3.25***	-3.26***	-4.56***	-4.62***
	(1.26)	(1.33)	(0.779)	(0.800)	(0.835)	(0.894)
$PostSBCAA_{i,t}$	6.90***	6.90***	4.62***	4.64***	3.04***	3.01***
	(1.95)	(2.24)	(1.38)	(1.50)	(0.849)	(0.997)
$HHI_{i,t-1}$	-7.08	-6.20	-1.81	-1.51	-0.607	0.282
	(10.9)	(10.5)	(6.55)	(6.38)	(7.70)	(7.40)
$SeniorShare_{i,t-1}$	-3.58	-3.54	-2.74	-2.78	-1.51	-1.51
	(2.24)	(2.14)	(1.83)	(1.78)	(1.30)	(1.23)
Fixed Effects						
Quarter	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	529	521	494	486	529	521
R^2	0.45377	0.45843	0.25833	0.26223	0.43124	0.43571
Within R^2	0.42946	0.43401	0.23122	0.23557	0.39996	0.40387

Table 16 reports the results of pooled OLS regressions replicating the baseline H1 growth specifications on a restricted sample covering the post-2022Q4 period, during which both publicly traded and non-traded BDCs are well-represented in the data. The purpose of this test is to assess whether the full-sample results are driven by the changing composition of the sample as non-traded BDCs enter from 2022Q4 onwards. All specifications include quarter fixed effects and the same set of control variables as the baseline. Coefficient estimates are reported alongside clustered standard errors in parentheses, with standard errors clustered at the BDC level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

D Diagnostics Test: Comparing Clustered & White Standard Errors

Table 17 - Diagnostics Test: Comparing Clustered & White Standard Errors

	Clustered SE		White SE	
Dependent Variables:	Debt-to-Equity	WA Yield (%)	Debt-to-Equity	WA Yield (%)
Model:	(1)	(2)	(3)	(4)
$GrossFee_i$	0.245***		0.245***	
	(0.069)		(0.025)	
$Distance\text{-}to\text{-}Hurdle(\%)_{i,t-1}$		0.567		0.567***
		(0.376)		(0.103)
$Size_{i,t-1}$	-0.050	-0.651**	-0.050***	-0.651***
	(0.031)	(0.299)	(0.009)	(0.058)
$Age_{i,t}$	0.089**	0.528**	0.089***	0.528***
	(0.038)	(0.207)	(0.013)	(0.054)
$PostSBCAA_{i,t}$	0.327***	0.199	0.327***	0.199
	(0.103)	(0.400)	(0.046)	(0.224)
$HHI_{i,t-1}$	0.120	-1.45	0.120	-1.45*
	(0.494)	(1.94)	(0.128)	(0.839)
$SeniorShare_{i,t-1}$	0.091		0.091***	
	(0.096)		(0.032)	
Fixed Effects				
Quarter	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,167	1,018	1,167	1,018
R^2	0.36043	0.38320	0.36043	0.38320
Within R^2	0.20013	0.16235	0.20013	0.16235

Table 17 reports the results of two baseline specifications using alternative standard error estimators, following Petersen (2009). Columns (1) and (3) present the baseline H1 leverage specification with *GrossFee* as the independent variable and Debt-to-Equity as the dependent variable. Columns (2) and (4) present the baseline H2 specification with lagged Distance-to-Hurdle (%) as the independent variable and WA Yield as the dependent variable. Columns (1) and (2) use standard errors clustered at the BDC level, while columns (3) and (4) use heteroskedasticity-robust White standard errors. Both specifications include quarter fixed effects and the same set of control variables as the baseline. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

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ChatGPT	Support with programming and refining the formulation of sentences.	Sporadically throughout the thesis.
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Part II

Debt Structure and Refinancing Risk in Business Development Companies: A Descriptive Study

Abstract

Private credit has grown to become a crucial source of financing for U.S. middle-market companies, with Business Development Companies (BDCs) emerging as a central and increasingly retail-facing part of the sector. Despite the growing body of literature on private credit and direct lending, relatively little attention has been directed toward how these institutions finance themselves. This descriptive study addresses this gap by examining the debt structure and maturity profile of publicly traded BDCs. Combining instrument-level debt data with detailed portfolio holdings over the 2015Q1 to 2024Q4 period, I document that BDCs operate with a persistent negative maturity gap, holding assets that, on average, repay before their debt obligations fall due. This gap has narrowed substantially over time, driven by a contraction in debt maturities across the sector. Looking forward, the publicly traded BDC sector faces a significant concentration of debt maturities in the short- to medium-term, largely driven by maturing unsecured notes that were issued at historically low rates during the 2020 to 2021 period. As this debt is refinanced at prevailing rates, publicly traded BDCs face heightened refinancing risk in public debt markets, pointing toward a vulnerability that the maturity gap alone does not reveal.

Keywords

Private Credit, Business Development Companies (BDCs), Debt Structure, Maturity Structure, Refinancing Risk

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1. Introduction

Over the past 15 years, the market for private credit has expanded rapidly and now represents a meaningful share of middle-market corporate borrowing. Business Development Companies (BDCs) have been central to this growth, and as many of them are publicly listed, they have opened the private credit sector to retail investors and provided a window into the otherwise opaque private credit sector. This has attracted the attention of researchers, policymakers, and investors alike, to understand how these entities operate and the systemic implications of a growing nonbank financial sector. However, despite the growing interest, the topic of private direct lending is relatively underexplored in academic literature compared to the vast body of research on traditional bank lending, the bond market, and private equity (Davydiuk et al., 2024).

Prior studies have shown why firms choose to borrow from nonbanks (Chernenko et al., 2022), how stricter banking regulation incentivized a migration of credit from banks toward less regulated entities (Chernenko et al., 2025), and as a result, how banks and NBFIs have adjusted and evolved to organize intermediation in mutually beneficial ways (Acharya et al., 2026). Many have focused on BDCs specifically, examining their investment model, role as substitute capital providers for credit rationed firms, and their impact on target firm growth and innovation (Davydiuk et al., 2024a). Other studies provide evidence on how BDCs adjust leverage and portfolio risk in response to funding shocks (Davydiuk et al., 2024b), and how leverage constraints and regulatory changes affect their lending practices (Balloch and Gonzalez-Uribe, 2021). Despite this growing body of research, little attention has been directed toward the liability side of BDC balance sheets, and in particular toward the maturity structure of BDC debt and how it relates to the maturity of the assets that it finances.

This study addresses this gap by combining instrument-level debt data with detailed data on portfolio holdings for publicly traded BDCs during the period 2015Q1 to 2024Q4. Using a descriptive study design, I document how these institutions structure their liabilities, how the maturity of their assets and liabilities compares, and how the resulting maturity profile has evolved over time. In contrast to traditional banks, I find that BDCs operate with a persistent negative maturity gap, holding assets that, on average, repay before their debt obligations fall due. This gap

is shown to have narrowed over time, driven by a contraction in debt maturities while the maturity of assets remains broadly constant. In terms of instrument mix, publicly traded BDCs rely on a mix of fixed-rate unsecured notes and revolving credit facilities to finance their predominantly floating-rate loan portfolios, making their net investment income sensitive to fluctuating interest rates. Looking forward, the sector faces a substantial concentration of maturing notes over the coming years, much of it issued at historically low rates during the 2020 to 2021 period. As this debt is refinanced at prevailing rates, the low funding costs locked in during that period will progressively unwind, leaving publicly traded BDCs notably exposed to refinancing risk in the near- to medium-term.

The remainder of this paper is structured as follows. Section 2 provides the institutional background and reviews the related literature on BDCs, private credit growth, and the asset-liability management of financial intermediaries. Section 3 describes the data sources used for the descriptive analysis. Section 4 presents and discusses the results from the descriptive empirical analysis, along with an acknowledgement of the main limitations of the study. Section 5 concludes and proposes avenues for future research.

2. Institutional Background and Literature Review

2.1 Business Development Companies

2.1.1 Structure and Role as Private Credit Intermediaries

BDCs are structured as closed-end investment companies and were created as part of the Small Business Investment Incentive Act of 1980 with the purpose of stimulating investments in small- and medium-sized private companies in the United States (Cai and Haque, 2024). Although most BDCs focus predominantly on debt investments, they are also allowed to make investments in equity and hybrid instruments (Davydiuk et al., 2024), with the condition that at least 70% of the total portfolio consists of so-called "eligible assets". Eligible assets primarily refer to debt or equity investments in private U.S. operating companies or public companies with a market capitalization of less than $250 million, as well as cash and government securities. In addition, to extend the purpose of BDCs beyond only acting as capital providers, BDCs are required to offer substantial managerial assistance to their portfolio companies and have been documented to enhance employment growth and patenting activity in portfolio companies (Davydiuk et al., 2024a).

Concurrent with the growth of the broader private credit sector, BDCs have grown to become one of the most prominent groups of direct lenders, managing assets of approximately $440 billion as of late 2024 and accounting for approximately 40% of all direct lending in the United States (Chernenko and Scharfstein, 2025). While the broader private credit sector is characterized by a high degree of opacity, making it difficult for outside investors, regulators, and other market participants to obtain reliable information about the asset class, BDCs provide a much more transparent window into the private credit landscape. Due to the regulatory disclosure requirements imposed on BDCs by the Investment Company Act of 1940 and Securities Exchange Act of 1934, BDCs are required to file periodic and current reports to the Securities and Exchange Commission (SEC). Apart from financial information, these filings include detailed Schedules of Investments (SOI) which provide detailed investment-level information on the portfolio holdings of BDCs. As a result, much of the recent literature on private credit and direct lending utilizes BDCs as empirical subjects to gain insights that likely extend to the broader sector as well.

Apart from offering transparency, prior studies have documented several similarities between BDCs and other types of private credit funds, suggesting that findings obtained from researching BDCs may also be broadly representative of the private credit sector as a whole. Block et al. (2024) use survey responses from private credit fund managers and document that both BDCs and non-BDC funds rely extensively on private equity sponsors for deal flow, averaging 75% and 81% of total invested capital for each group, respectively. They also show that both groups tend to target the same gross returns and deploy similar amounts of leverage, although BDCs tend to be significantly larger and more experienced than non-BDC funds on average.

Although sharing traits with other types of private credit funds, BDCs exhibit meaningful differences from traditional bank lenders. Typical BDC portfolios predominantly consist of senior "direct" loans, meaning loans that are bilaterally negotiated between the borrower and a lender, or a small group of lenders, without bank syndication (Block et al., 2024). In contrast to the bank-syndicated loan market, direct lenders typically originate loans with the intent of keeping them on their own balance sheets and holding the loans until maturity. Jang (2024) documents that less than 20% of BDC loans are sold within a year of origination, whereas more than 50% of bank-syndicated term loans are traded off within days of origination. Furthermore, direct loans are usually floating-rate "cash-flow-based" loans, relying primarily on the cash generation from the borrower's operations rather than collateral (Avalos et al., 2025). Approximately 80% of direct loans are secured by so-called "blanket liens" (Jang et al., 2025), representing a claim on the going-concern cash flow value (i.e., enterprise value) of the firm rather than the liquidation value of a particular type of collateral (Lian and Ma, 2020). The corresponding share for traditional banks amounts to less than 15%, with banks being more likely to place liens on separately identifiable assets. The frequent use of blanket liens in direct lending is likely a result of the borrower base, typically consisting of unprofitable and highly leveraged private equity-backed firms (see e.g., Chernenko et al., 2022; Block et al., 2024; Jang et al., 2025), which have been documented to rely more on cash flow-based debt compared to non-PE-backed firms (Haque et al., 2022). Taken together, these differences suggest that BDCs and direct lenders operate in a segment of the credit market where asset-based bank lending may be less suitable.

The borrower base and typical lending technology of BDCs can be better understood by considering the broader migration of credit from banks to nonbank financial intermediaries (NBFIs). Much of the existing private credit literature has focused on explaining the underlying drivers of this credit migration, oftentimes highlighting the stricter banking regulation following the Global Financial Crisis (GFC) as a primary catalyst for this shift. Stricter capital requirements made it more costly for banks to hold risky middle-market loans on their own balance sheets, thus reducing credit supply to riskier firms and creating room for less-regulated nonbank lenders to fill this gap. Consistent with this "regulatory arbitrage" view, Chernenko et al. (2022) show that unprofitable and highly leveraged firms are significantly more likely to borrow from NBFIs, with banking regulation being the most important driver for nonbank lending. Erel and Inozemtsev (2025) document a 45% decrease in small-business lending volume by large commercial banks following the GFC, and that this lending gap was subsequently filled by NBFIs. Similarly, Davydiuk et al. (2024a) find evidence of BDCs disproportionately targeting areas experiencing a shortage of traditional financing and that BDC lending acts as a substitute for more conventional sources of funding.

The existing literature primarily focuses on examining the asset side of BDCs and other private credit vehicles, examining their lending technologies, portfolio composition, how they respond to shocks, and the role they play in the post-GFC financial system and broader private credit sector. Although many of these studies also highlight facts and provide brief discussions on the composition of leverage within BDCs, relatively little systematic evidence has been put forward on the liability management and typical debt structure within these funds. The following section therefore shifts attention from the asset side to the funding side of BDCs, focusing on the capital structure and funding constraints that shape their use of debt.

2.1.2 External Financing and Leverage Constraints

The BDC business model is structurally dependent on external financing and access to capital markets to finance portfolio growth. Most BDCs elect to be treated as regulated investment companies (RICs) which allows them to bypass corporate taxation as long as they distribute at

least 90% of their taxable income to their debt- and equityholders (Davydiuk et al., 2024b). As a result, BDCs are legally constrained in their ability to grow organically and must instead primarily rely on new debt and equity issuances to scale their investment operations. However, issuing new equity is subject to certain frictions, as BDCs looking to issue shares at prices below their net asset value (NAV) generally require additional approval from existing shareholders. As a result, when market valuations are weak, access to debt capital becomes a particularly important factor for maintaining portfolio growth and credit supply for BDCs.

To examine how BDCs respond to equity funding shocks, Davydiuk et al. (2024b) exploit the exclusion of BDCs from major stock indexes and subsequent sell-off by institutional shareholders and find that BDCs primarily adjusted their portfolio risk exposure, rather than capital structure, when equity capital became more expensive. Following the index exclusion, BDCs adjusted their portfolio composition away from equity and subordinated debt and toward safer senior debt investments, consistent with a "flight-to-quality" response. On the financing side, affected BDCs experienced significantly lower growth in the book value of equity and a decline in new equity issuances after the shock. Interestingly, however, treated BDCs did not substitute the missing equity capital by issuing new debt, but instead experienced a significantly lower growth in debt as well. In total, the equity funding shock impeded the overall asset growth and investment activity of affected BDCs, leaving capital structure largely unaffected but resulting in reduced credit supply to portfolio firms.

Davydiuk et al. (2024b) argue that the unchanged capital structure is explained by the presence of two offsetting forces: (1) capital requirements, and (2) market discipline exerted by well-informed creditors through fairly priced debt. Following an equity shock, the BDC optimally de-risks the portfolio to reduce capital costs and increase the probability of preserving the fund's continuation value. In the presence of market discipline alone, this de-risking would lower the cost of debt and incentivize BDCs to issue cheap new debt to replace the missing equity. However, the presence of capital requirements simultaneously incentivizes the BDC to maintain equity buffers to avoid costly future recapitalizations near the statutory leverage limit. As a result, the presence of these two opposing forces causes the effects to cancel out, yielding no change in the capital structure of the BDC following the equity funding shock.

In practice, the capital requirements discussed by Davydiuk et al. (2024b) come in the form of a statutory leverage limit, defined as a minimum required asset coverage ratio (ACR). Prior to 2018, BDCs were required to maintain a 200% ACR, corresponding approximately to a maximum debt-to-equity ratio of 1:1. In 2018, the Small Business Credit Availability Act (SBCAA) relaxed this constraint by decreasing the statutory ACR requirement to 150%, effectively allowing BDCs to increase their debt-to-equity ratio to 2:1 contingent upon approval from shareholders or the board of directors. Balloch and Gonzalez-Uribe (2021) exploit this relaxation of the statutory leverage limit to study how leverage limits affect lending, credit supply, and loan valuations within BDCs. They document a gradual increase in leverage among treated BDCs following adoption of the relaxed asset coverage requirement under the SBCAA. Furthermore, their findings suggest that constrained BDCs, defined as those operating close to the statutory leverage limit, exploit "regulatory slack" by overreporting loan values to relax the leverage constraint before subsequently marking down their loan books following adoption of the new rules under the SBCAA.

Although leverage has tripled within the sector during the last 15 years (Aldasoro et al., 2025), prior studies have documented that BDCs are well-capitalized according to bank capital frameworks. Chernenko et al. (2025) show that BDCs maintain a 36% median risk-based capital ratio, which is significantly above the regulatory requirements faced by traditional banks. These findings challenge the view that the migration of credit supply from banks to NBFI is simply a result of regulatory arbitrage, with the results implying that BDCs hold significantly larger capital buffers compared to banks. Instead, Chernenko et al. (2025) propose a more nuanced explanation by arguing that stricter banking regulation may have changed how banks choose to obtain exposure to riskier middle-market lending. They argue that rather than holding risky middle-market loans directly on their own balance sheets, stricter capital requirements combined with costly regulatory and supervisory oversight make it more profitable for banks to provide senior financing to private credit funds instead. Such loans to private credit funds, often structured as senior overcollateralized credit facilities through wholly owned, bankruptcy-remote special purpose vehicles (SPVs), enable banks to apply significantly lower risk weights when calculating capital requirements. As a result, banks can achieve a higher return on equity (ROE) by issuing more senior claims to private credit

funds, making them well suited as capital and liquidity providers to the nonbank intermediaries holding the riskier junior claims.

This interpretation is consistent with the "transformation view" proposed by Acharya et al. (2026), who argue that the growth of private credit is not simply due to credit migrating away from the traditional banking sector, but rather a result of a reorganization of the sector and a transformation of risks between banks and NBFIs. According to their view, banks and NBFIs have evolved to organize credit intermediation based on the relative advantages of each sector, making their risks increasingly intertwined. Banks enjoy low-cost deposit financing and access to safety nets[13], whereas NBFIs are less regulated. As such, banks are well-positioned to provide senior loans and liquidity facilities to intermediaries such as BDCs, while these entities take on the role of holding the junior and more risky claims against their borrowers. This argument offers useful insights in multiple ways. First, it could help explain the mechanisms behind the rapid growth of private credit and direct lending. Second, it highlights issues related to financial stability by showing that even though banks engage in less risky middle-market lending, they are still indirectly exposed through their commitments to NBFIs. Finally, it provides a useful perspective to understand the structure of BDC financing by highlighting the interplay between banks and NBFIs, which ultimately affects how BDCs are financed and manage their assets and liabilities.

2.1.3 Descriptive Evidence on BDC Capital Structure and Financing Mix

In accordance with the leverage constraints governing the capital structure and financing mix of BDCs, these entities generally operate with substantial equity buffers. Davydiuk et al. (2024b) document that the median BDC operates with a book equity-to-assets ratio between 55% and 70%. Consistent with this, Rintamäki and Steffen (2025) show that the share of equity has decreased from approximately 70% in 2012 to around 55% by the mid-2020s. Although the relative dominance of equity financing has decreased to levels closer to the regulatory minimum over time,

[13] Safety nets include, e.g., deposit insurance and implicit too-big-to-fail guarantees (Acharya et al., 2026).

equity capital remains the dominant source of financing for BDCs. This is particularly true for non-traded BDCs, with the median debt-to-assets ratio being 8-10 percentage points lower compared to their publicly traded counterparts (Chernenko et al., 2025), suggesting that publicly traded BDCs tend to be associated with higher financial risk.

In terms of debt structure, BDCs rely on a variety of debt instruments to finance their investment operations. Chernenko et al. (2025) document a large variation in debt structures depending on whether the BDC is publicly traded or not. Their descriptive statistics reveal that publicly traded BDCs tend to rely less on lines of credit but significantly more on unsecured notes compared to non-traded BDCs. As this thesis will focus exclusively on publicly traded BDCs, the remainder of this section will primarily highlight the descriptive evidence related to publicly traded entities, unless otherwise noted.

Descriptive evidence from previous studies highlights how publicly traded BDCs rely on both public debt markets and bank financing to obtain debt capital. Unsecured notes represent the largest category, accounting for approximately 58% of total debt for the average publicly traded BDC according to Chernenko et al. (2025). This is broadly in line with Jang (2024), who documents that bonds make up the majority of total debt for public BDCs whereas the share of bank financing in the form of term loans and revolving credit facilities amounts to 13% and 31% of total outstanding debt, respectively. Although public debt markets appear to constitute the largest source of debt capital for publicly traded BDCs, bank financing remains an important secondary source of capital. Based on hand-collected data from loans agreements and SEC filings, Jang (2024) also shows that approximately 78% of the public BDCs in his sample relied on revolving credit facilities while 26% had term loans from a bank. Taken together, these findings suggest that publicly traded BDCs primarily rely on public markets to meet their financing needs but complement this with bank credit facilities that likely serve a shorter-term role to satisfy liquidity needs.

Beyond public debt issuances and traditional bank financing, BDCs may use government-sponsored debt in the form of Small Business Administration (SBA) debentures to access a cheap source of long-term debt that is guaranteed by the government. Davydiuk et al. (2024b) provide an overview of the characteristics of these debentures, including their maturity structure of 10

years or more, a fixed interest rate above the 10-year treasury bond rate, and that they are typically excluded from the asset coverage requirement of BDCs through exemptive relief from the SEC. With these characteristics in mind, this type of government-sponsored debt can be considered risk-insensitive as it is not affected or repriced based on the risk-taking activities of the borrower. Davydiuk et al. (2024b) exploit this feature by using the share of SBA debentures in a BDC's capital structure as a proxy for the level of market discipline imposed by creditors. They argue that BDCs with a higher share of risk-insensitive SBA debentures face weaker creditor discipline compared to those that rely on fairly priced debt to a larger extent. Empirically, SBA debentures account for a relatively modest average share of 4.3% of total debt for publicly traded BDCs (Chernenko et al., 2025), consistent with the fact that this form of financing is subject to certain limits and restrictions, as noted by Balloch and Gonzalez-Uribe (2021).

These findings provide a useful overview of how the liability side is structured within the average publicly traded BDC. However, the literature provides limited evidence on the more granular characteristics of BDC debt, such as maturity structure, seniority, and interest rate type, along with how these characteristics have evolved over time. Such details are important for understanding how BDCs engage in liability management and how their funding structures relates to the composition of their underlying investment portfolios.

2.2 Asset-Liability Management and Maturity Transformation

To better understand why private credit vehicles such as BDCs do not organize their intermediation practices and structure their balance sheets in the same manner as traditional banks, it is useful to first consider the structural characteristics that distinguish banks from NBFIs. This section aims to provide a brief overview of the traditional banking literature on how and why banks engage in maturity transformation and choose to manage their assets and liabilities, to establish a theoretical foundation for understanding the differences in balance sheet structures between banks and BDCs.

In many ways, the asset side of a typical BDC closely resembles that of a traditional bank. Jang (2024) concludes that direct lenders can be viewed as banks on the asset side but private equity funds on the financing side. Apart from their primary focus of extending term loans and lines of

credit to middle-market firms (Davydiuk et al., 2024a), Jang (2024) documents that direct lenders actively engage in relationship lending by building long-term relationships with borrowers and private equity sponsors, while closely monitoring borrowers through covenants and restrictions on borrower activity. However, this resemblance to banks is largely limited to the asset side. On the financing side, direct lenders behave more like private equity funds, relying on locked-up equity capital and long-term debt rather than short-term demandable deposits. To understand why this is the case, and the implications it carries, it is useful to first consider the role of short-term deposit financing that is inherent to the traditional banking model.

The banking literature has since long established how and why banks engage in maturity transformation. Diamond and Dybvig (1983) showed that by financing long-term illiquid assets with a pool of short-term demandable deposits, banks fulfill a crucial economic function by providing valuable liquidity insurance to depositors with heterogeneous liquidity needs. This way of transforming long-term illiquid investments into short-term callable deposits lies at the core of why banks exist and the objectives they serve. Without such a structure, individuals facing uncertainty in the timing of their liquidity needs would be unable to invest in long-term illiquid assets without bearing the risk of costly liquidation if their consumption needs change. By pooling deposits and providing efficient risk sharing, banks are able to offer immediate liquidity to depositors while enabling the flow of capital toward productive long-term investments. However, by internalizing this maturity mismatch on their own balance sheets, banks become highly susceptible to the risk of bank runs.

While Diamond and Dybvig (1983) highlight why maturity transformation and the use of demandable deposit contracts are valuable, fundamentally risky, yet inherent to the banking business model, Calomiris and Kahn (1991) extend the argument by showing how demandable debt acts as an effective disciplining device for bank managers. The possibility for depositors to withdraw their money on demand creates incentives to monitor the bank. The subsequent threat of a bank run occurring when a sufficiently large fraction of depositors holds negative beliefs regarding the bank's future acts as a disciplinary mechanism to align the incentives of depositors and bank managers.

Following this argument, Diamond and Rajan (2001) incorporate the notion that banks have relationship-specific skills that allow them to extract higher value from borrowers compared to outside investors. These relationship-specific skills make bank loans illiquid, because outside investors would value the loan at a discount due to their inability to utilize these skills to obtain the same value. This illiquidity becomes a problem when the lender is likely to face liquidity needs, since they may be forced to, e.g., sell the loan at a discount or liquidate the borrower inefficiently. They argue that mechanisms that commit the lender to collecting the loans create liquidity. Specifically, the use of demandable debt forces the bank to use their relationship-specific skills for the benefit of depositors without shirking or holding out on them in any way, due to the risk of a run on the bank if they do otherwise. As a result, a core argument of their paper is that the financial fragility that arises with demandable debt is a desirable consequence which promotes the creation of liquidity in the financial system.

While these three papers provide a useful theoretical foundation to understand why maturity transformation is a central feature of the banking business model, other studies highlight which institutional conditions are necessary to support these practices. Hanson et al. (2015) model the interdependencies between asset characteristics and funding strategies and find a clear link between an intermediary's access to "stable" funding sources, such as insured deposits and equity cushions, and its ability to invest in illiquid fixed-income assets. Access to stable funding enables an intermediary to act as a patient investor in long-term illiquid assets, whereas intermediaries that rely on "unstable" funding are forced to allocate a larger portion of their capital toward liquid assets to avoid runs and fire-sale losses. This highlights an important distinction between banks and private credit vehicles that is consistent with the argument of Diamond and Dybvig (1983). Banks can sustain a maturity mismatch because deposit insurance and other governmental backstops effectively stabilize their funding. Private credit funds, including BDCs, generally lack such support structures and are naturally forced to implement other mechanisms, such as lock-ups and closed-end fund structures, while relying on longer-term capital that is not immediately callable by investors.

Another important consideration in the discussion of debt maturity is how it affects refinancing risk (also known as rollover risk). He and Xiong (2012) document that when debt market

conditions deteriorate, the refinancing losses from issuing new bonds to replace maturing ones are ultimately borne by shareholders, while maturing debtholders are repaid in full. As a result of these refinancing losses, shareholders may choose to default at higher fundamental thresholds, thereby increasing the default premium. They also highlight that firms with shorter average debt maturities face greater default risk due to an increased frequency of refinancing events.

Taken together, the existing literature provides detailed discussions on the asset side of BDCs and the drivers behind private credit growth. Although many studies also provide insights into the broad composition of BDC financing and the leverage constraints that shape it, the literature lacks more detailed evidence on debt composition and the maturity structure of BDC balance sheets, and how these have evolved over time. At the same time, the literature on maturity transformation is heavily focused on traditional banks, whose reliance on demandable deposits and access to public backstops make them structurally different from private credit vehicles such as BDCs. This raises the question of how NBFIs that lack these features organize the maturity of their balance sheets. This thesis addresses this gap by documenting the debt structure, maturity profile, and resulting maturity gap of publicly traded BDCs, along with the forward-looking refinancing risk implied by the timing of their debt maturities. By doing this, it extends the descriptive evidence on BDC capital structure and bridges the literature gap between traditional banks and private credit vehicles such as BDCs.

3. Data

The empirical analysis in this thesis builds on three primary sources of data. For the liability-side analysis, detailed data on BDC debt is collected from the Capital IQ Debt Capital Structure database, which provides instrument-level information on outstanding debt obligations for publicly traded BDCs on a quarterly basis. On the asset side, quarterly data on portfolio holdings is collected from Preqin's BDC Holdings database, which is compiled from the SOI included in periodic SEC-filings. Quarterly financial statement data for publicly traded BDCs is collected from Compustat North America. All datasets are matched using the Central Index Key (CIK) assigned to each unique BDC, which serves as a unique identifier across all three datasets.

The Capital IQ debt data is structured at the instrument level and contains one observation per unique debt instrument for each BDC-quarter observation. The data covers 33 publicly traded BDCs from 2015Q1 to 2024Q4, including variables such as debt type, seniority, outstanding principal balance, interest rate, interest rate type, maturity date, among other characteristics. The debt type classification distinguishes between term loans, bonds and notes, credit facilities, debentures, repurchase agreements, and other borrowing types, while seniority and security status are reported as either senior or subordinated, and secured or unsecured, respectively. Interest rates are reported in percentage terms and classified as either fixed or variable, with variable rates being accompanied by information on the applicable benchmark rate.

Several steps were undertaken to clean the data before using it for empirical analysis. First, only the most recent observation for each BDC-quarter combination was retained to account for the possibility of amendments or restatements affecting the reported information. Second, for revolving credit facilities, rows where the reported amount referred to a maximum credit limit, rather than the outstanding drawn balance, were removed to ensure that only drawn debt obligations are included in the data. Third, debt instruments denominated in foreign currencies were removed from the sample, with multi-currency credit facilities being retained but treated as USD-denominated. Collectively, the excluded foreign currency instruments only accounted for approximately 1.7% of the total outstanding debt across the full sample, and their removal is therefore not expected to materially affect the representativeness of the sample or the accuracy of

the results. Fourth, all observations with an outstanding balance of zero were dropped before normalizing all amounts to millions of USD to ensure consistency across the sample. Finally, observations with missing information on maturity dates and interest rates were flagged and excluded from subsequent calculations of weighted averages but retained in calculations of total outstanding debt. Following these cleaning steps, the data is aggregated from the instrument level to the BDC-quarter level, resulting in a panel of debt structure variables for each entity and time period in the sample.

The Preqin BDC Holdings dataset provides investment-level portfolio data compiled from the SOI included in mandatory periodic reports to the SEC. For each BDC-quarter observation, information on the investment type, fair value, principal amount, maturity date and other contractual features such as the reported interest rate and spread over the benchmark rate are included. To clean the data, a number of measures were undertaken. First, early quarters in which fewer than 10 unique BDCs had coverage were dropped from the sample to avoid any bias stemming from an unrepresentative sample in the early part of the sample period. Second, investments with a total fair value of less than $1 million were excluded, as these constituted less than 0.5% of the total fair value in any given quarter and were therefore not expected to materially affect the results. Third, all debt investments were required to have sufficient information to directly observe or manually compute the yield, meaning that either a reported coupon rate, a benchmark rate and spread pair, or a standalone payment-in-kind (PIK) interest rate had to be available. Debt investments with missing data across these dimensions were dropped from the sample. Finally, benchmark rates appearing fewer than 1,000 times across the sample were excluded to remove unusual and rarely observed benchmark rates and facilitate data collection.

Finally, the quarterly financial statement data from Compustat includes variables such as total assets, equity, and debt for each publicly traded BDC in my sample. This data is primarily used to construct BDC-level characteristics such as size and leverage ratios which cannot be directly observed from the Capital IQ and Preqin datasets.

4. Empirical Analysis

This section presents and discusses the empirical findings on BDC debt structures among publicly traded BDCs over the sample period. The analysis is descriptive in nature and aims to provide insights related to three main themes. Section 4.1 provides descriptive evidence on how publicly traded BDCs structure their liabilities, highlighting the composition of debt across instrument and interest rate type. Section 4.2 focuses on the maturity aspect of BDC debt, examining and discussing the maturity structure of BDC liabilities relative to the maturity of their underlying investment portfolios, and documenting the forward-looking maturity profile and the refinancing risk it implies. Section 4.3 concludes by outlining the key limitations of the study.

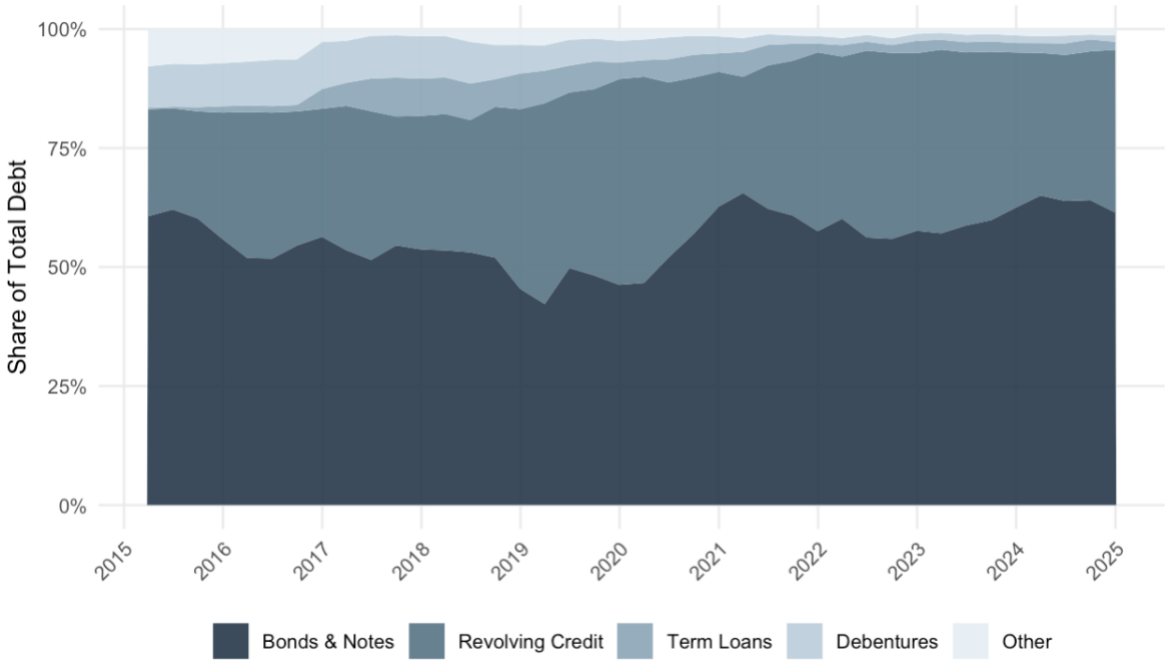
4.1 The Debt Structure of BDCs

4.1.1 Instrument Mix

Figure 1 presents the composition of total outstanding debt among publicly traded BDCs over the period 2015Q1 to 2024Q4. The shaded areas correspond to specific classes of debt instruments and show, for every quarter, the share of total outstanding debt attributable to each of the five instrument categories. Summary statistics on the full-sample debt composition are also reported in Appendix A.1. Consistent with the previous literature (e.g., Chernenko et al., 2025), bonds and notes (excl. debentures) consistently make up the largest category of debt among publicly traded BDCs, averaging 56% of total outstanding debt per quarter across the full sample period and ranging from a low of 42% in 2019Q1 to a high of 66% in 2021Q1. Revolving credit facilities make up the second largest source of debt, averaging 32% of total outstanding debt per quarter across the sample period and ranging from 21% in 2015Q2 to 43% in 2020Q1. The remaining three categories, debentures, term loans, and other borrowings, account for a quarterly average share of only 5%, 4%, and 3%, respectively.

Figure 1: *Debt Composition of Publicly Traded BDCs*

Figure 1 shows the composition of aggregate outstanding debt for publicly traded BDCs by instrument type (bonds and notes, revolving credit, term loans, debentures, and other) over 2015Q1 to 2024Q4. For each quarter, instrument shares are averaged across BDCs weighted by total outstanding debt. Shares sum to 100% in each quarter.



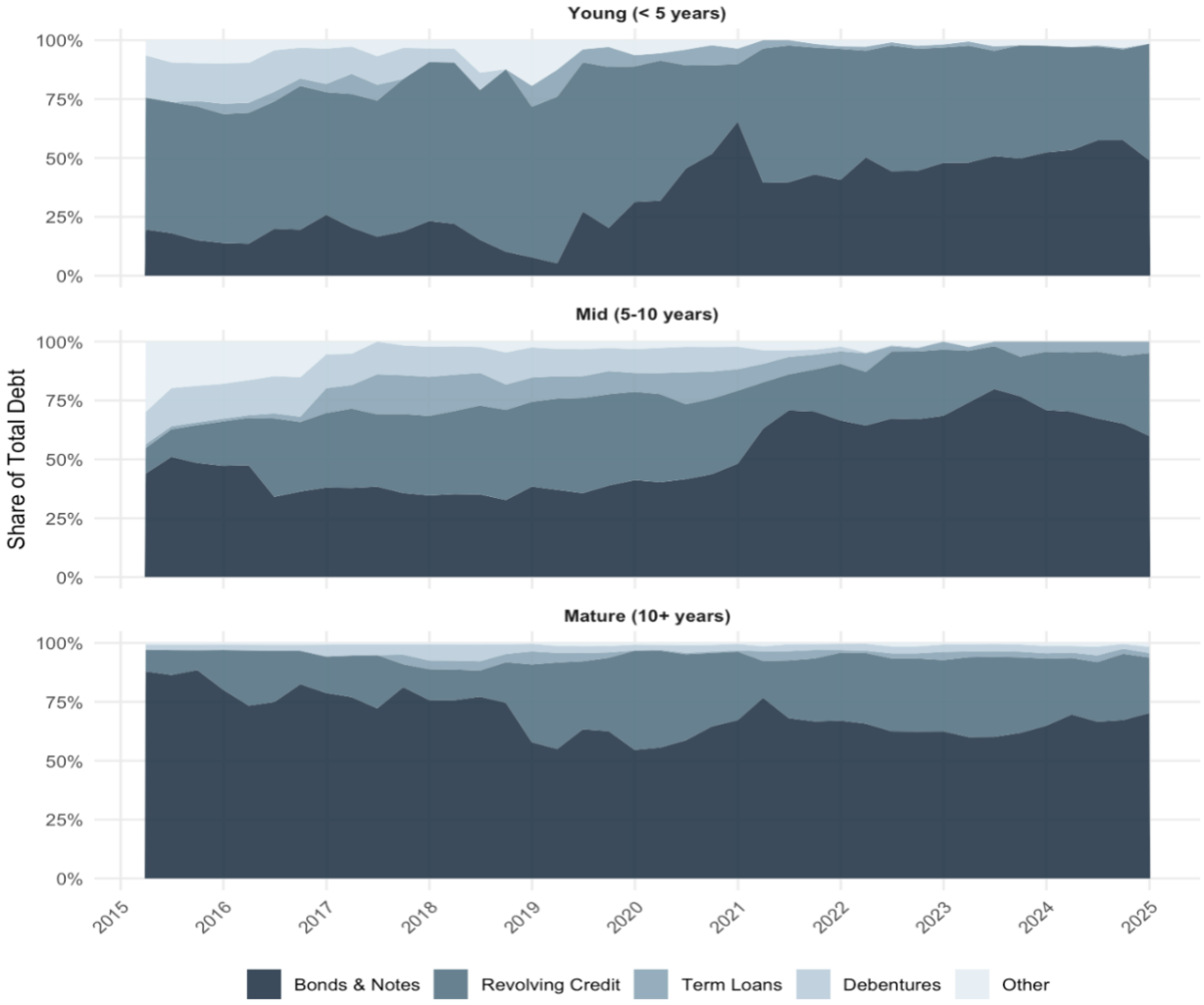
Whereas the combined share of bonds, notes, and revolving credit facilities has seen a meaningful increase during the sample period, reaching almost 96% of total outstanding BDC debt as of 2024Q4, the share of debentures, term loans, and other borrowings has dramatically decreased. However, these results should not be interpreted as evidence that BDCs have stopped relying on these sources of debt in absolute terms. Instead, this is primarily a reflection of the rapid growth in total outstanding debt driven by bond issuances and credit facilities which mechanically compresses the relative share of other debt instruments.

Building on these insights, Figure 2 examines whether these patterns related to debt composition vary across BDCs in different stages of their lifecycle. At each point in time, BDCs are classified into three distinct age groups based on the number of years since their inception. Young BDCs are classified as having less than five years of operating history, middle-aged BDCs are between five and ten years old, while mature BDCs are classified as having more than ten years of operating history. While these boundaries are chosen arbitrarily, this classification allows for a visual

representation of lifecycle-related differences that may affect debt composition among BDCs. Complementary summary statistics for each age group are reported in Appendix A.2.

***Figure 2**: Debt Composition by Age Group*

Figure 2 shows the composition of aggregate outstanding debt for publicly traded BDCs by instrument type over 2015Q1 to 2024Q4. Each graph corresponds to a different age group, measured from each BDC's inception date. For every quarter, instrument shares are averaged across BDCs weighted by total outstanding debt. Shares sum to 100% in each quarter.



Among younger BDCs, drawn credit facilities constitute the single largest category of debt, with bonds and notes accounting for a significantly lower share than what is observed for middle-aged and mature BDCs. The average share of revolving credit facilities across the full sample period is approximately 54%, whereas the corresponding share made up by bonds and notes is only 33%. As BDCs mature, this composition reverses, with bonds and notes accounting for an average share

of 52% and 70% for middle-aged and mature BDCs, respectively. These indicative results are not entirely unexpected, given that more mature BDCs are likely to have better access to public debt markets and more robust credit profiles compared to their younger counterparts.

Revolving credit facilities follow the opposite trajectory, declining from an average of 54% among young BDCs to 28% and 25% for middle-aged and mature BDCs, respectively. This inverse relationship across age groups suggests that BDCs tend to substitute bank funding with public debt issuances as they mature, which is consistent with the notion of improved capital market access discussed above.

Important to note, however, is that the results obtained from Figure 2 should be interpreted with caution. First, as the sample exclusively contains publicly traded BDCs, more mature entities will be overrepresented in the sample due to the time it takes for newly established BDCs to become publicly traded entities. Second, the composition of each age bucket changes as BDCs age, implying that the variation caused by changes in debt structure within BDCs over time cannot be isolated from the variation caused by compositional effects affecting each age group. This also implies that the number of observations decreases in the young and middle-aged groups as more BDCs become mature toward the end of the sample period. Finally, the within-group variation is sensitive to the presence, entry, and exit of large BDCs that disproportionally affect the weighted average debt composition within each group.[14] With these issues in mind, Figure 2 is best interpreted as suggestive evidence, rather than conclusive results, of lifecycle-related patterns in debt composition among publicly traded BDCs.

4.1.2 Interest Rate Structure

Having established the instrument mix of publicly traded BDCs, this section shifts the attention toward the interest rate structure associated with this debt. Table 1 documents the fixed versus

[14] For example, the large increase in the share of bonds and notes for young BDCs between 2019 and 2021 is largely driven by the rapid growth and relative size of Blue Owl Capital Corporation. After moving to the middle-aged group in 2021Q1, the weighted average share of bonds and notes decreases sharply due to a compositional effect.

variable rate composition of BDC debt, reported both as the debt-weighted average and the simple average across all BDC-quarter observations. The debt-weighted average weights each BDC-quarter observation by its total outstanding debt, thus capturing the interest rate structure of the aggregate pool of BDC debt. The simple average assigns equal weights to each observation and thus more closely reflects the interest rate structure for the typical BDC, regardless of size. Instruments with missing data on the type of interest rate structure are excluded from the average statistics. These instruments only account for approximately 1.6% of instrument-quarter observations and 0.4% of total outstanding debt, making their exclusion unlikely to materially affect the reported results.

Table 1: *Fixed and Variable Rate Composition of BDC Debt*

Table 1 presents the share of BDC debt carrying fixed versus variable interest rates, excluding instruments with missing interest rate information. Average Share (%) is calculated by giving each BDC-quarter equal weight. Weighted Average Share (%) weighs each BDC-quarter by the outstanding amount of debt. SBA debentures with no benchmark spread are treated as fixed rate.

Rate Type	Average Share (%)	Weighted Average Share (%)
Fixed Rate	51.9	54.1
Variable Rate	48.1	45.9

The composition of fixed versus variable rate debt is close to evenly split. Measured using a simple average across all BDC-quarter observations, fixed rate debt accounts for 52% of outstanding debt for the typical BDC, with the debt-weighted average being slightly higher at 54%. This difference of approximately 2 percentage points suggests that larger BDCs carry a somewhat higher share of fixed rate debt, although the difference is modest and does not indicate a large disparity in interest rate structure between BDCs of different sizes.

Whether this near 50-50 split reflects a deliberate choice to balance the exposure across different interest rate structures or if it simply follows from the types of debt instruments BDCs use is not evident from the aggregate statistics. Bonds and notes are commonly issued at fixed rates, whereas revolving credit facilities and term loans tend to be quoted against a floating benchmark rate. If this holds in the data, the higher fixed-rate share among larger BDCs would likely be traced back to their relatively greater reliance on bonds and notes rather than variations in the rate composition

within instrument categories. Table 2 presents the interest rate composition associated with each of the five debt instrument categories to examine if this is the case.

Table 2: *Interest Rate Composition by Debt Instrument Type*

Table 2 reports, for each instrument type, the number of instrument-quarter observations (N), its share of total outstanding debt, and the percentage of that instrument's debt that is fixed versus variable rate.

Instrument Type	N	Share of Debt (%)	Fixed Rate (%)	Variable Rate (%)
Bonds & Notes	5777	58.0	86.7	13.3
Revolving Credit	1853	33.9	0.0	100.0
Term Loans	287	3.1	0.7	99.3
Debentures	3793	3.2	99.6	0.4
Other	181	1.8	33.9	66.1

Table 2 shows that the interest rate structure exhibits very little variation within instrument categories. Revolving credit facilities and term loans are almost exclusively variable rate, whereas SBA debentures are effectively all fixed-rate instruments, consistent with the characteristics described by Davydiuk et al. (2024b). Bonds and notes are predominantly fixed rate, at 86.7% of outstanding value, with the remaining 13.3% largely being made up by securitized notes. Within the bonds and notes category, 99.7% of unsecured notes are fixed rate by value, whereas 87.2% of securitized notes have variable interest rates. Other debt instruments only account for a small share of total debt and primarily include repurchase agreements, SPV asset facilities and securitization structures, as well as various other secured and short-term borrowings. The larger variation in interest rate structure within this category therefore reflects the heterogeneity between the different instruments that are included in this category.

The overall lack of variation within instrument categories suggests that the aggregate composition of fixed versus variable rate debt is almost exclusively driven by the choice of debt instrument. If BDCs want to manage their exposure to fixed versus variable rate debt, it will most likely be done indirectly through the choice of debt instrument. However, the choice of debt instrument not only affects the interest rate structure, but also the associated borrowing costs, maturity, seniority, and covenant structure, among other factors which must be jointly considered.

This raises a few important considerations. First, the instrument mix is subject to constraints and cannot be freely chosen. For example, issuing unsecured bonds and notes generally requires sufficient scale and an established credit profile, whereas secured term loans and revolving credit facilities may be accessible to a much broader set of BDCs. These constraints could potentially cause BDCs to obtain a financing mix that is inconsistent with their preferences while exposing them to unwanted interest rate risks or other unfavorable outcomes.

Second, taking into account the dominance of floating-rate loans within BDCs' investment portfolios, the instrument mix and resulting interest rate structure carry important implications for their exposure to interest rate risk and earnings sensitivity. Davydiuk et al. (2024b) document that by 2017, the vast majority of new loan originations carried floating interest rates. By using roughly equal amounts of fixed and variable rate debt to finance predominantly floating-rate loan portfolios, net investment income becomes highly sensitive to changes in the policy rate whereas funding costs are more rigid. As a result, one would expect to see publicly traded BDCs engage in hedging activities to mitigate the downside risk associated with declining interest rates.

Chernenko et al. (2025) document that approximately 12%, corresponding to 13 out of the 111 BDCs in their sample, used fixed-to-floating interest rate swaps to match the interest rate exposure of fixed notes and floating portfolio loans as of 2024Q4. Initially, this number seems low but can likely be explained by the composition of their sample. Only about a third of the 111 BDCs in their sample are publicly traded, with the remaining categories being non-traded perpetual and term BDCs. The average (median) share of debt stemming from unsecured bonds and notes for the latter two categories only amounts to approximately 17% (0%) and 6% (0%), respectively. Compared to publicly traded BDCs, these types of entities rely significantly more on variable rate lines of credit, thus reducing the need to use hedging instruments to manage their interest rate exposure. Although the authors provide no information on the share of swaps attributable to publicly traded BDCs specifically, the concentration of fixed rate debt within this category suggests that the reported figure is unlikely to be representative of publicly traded BDCs. Even if all 13 BDCs that used swaps in 2024Q4 were publicly traded, they would still only represent a third of the publicly traded BDCs in the sample.

On the surface, one may be tempted to conclude that this mismatch entails that BDCs, on average, benefit from rising policy rates through the positive effects on net investment income. However, one must also take into account the adverse effects of rising interest rates on the underlying portfolio companies. As documented in prior studies (e.g., Chernenko et al., 2022), these firms are often unprofitable and highly levered, making their debt serviceability particularly sensitive to movements in the benchmark rate. Gains to net investment income may therefore be partially offset by greater nonaccrual and default rates within the loan portfolio. Consistent with this, Rintamäki and Steffen (2025) document an increase in PIK usage to alleviate temporary liquidity pressure on borrowers following the 2022 rate-hiking cycle. However, although PIK provisions may be effective in achieving temporary liquidity relief and stabilizing accounting income, their study finds that PIK usage is also a significant predictor of credit deterioration and future bankruptcy.

Finally, the interest rate structure documented above is not permanent. Fixed rate debt locks in borrowing costs only until the instrument matures, making the timing and maturity profile of BDC debt highly relevant in the discussion of interest rate exposure and asset-liability management. The following section analyzes the maturity structure of assets and liabilities in detail to provide a more complete picture of how BDCs manage their assets and liabilities and the implications of these decisions.

4.2 Maturity Structure of Assets and Liabilities

4.2.1 Asset Maturity

Table 3 reports summary statistics for the fair-value-weighted average maturity (WAM) of BDC portfolio loans across the sample period. Between 2015Q4 and 2024Q4, the average BDC held a loan portfolio with a remaining maturity of 3.89 years, which is slightly lower than the 4.25 years observed by Rintamäki and Steffen (2025) but higher than the 3.32 years reported for publicly traded BDCs as of 2024Q4 by Chernenko et al. (2025). The interquartile range suggests that the distribution is fairly tight, with the middle half of BDC-quarter observations being in the 3.24 to 4.48 range, indicating that portfolio maturity is largely a common feature across publicly traded BDCs.

Table 3: *Weighted Average Maturity (WAM) of BDC Portfolio Loans*

Table 3 reports summary statistics for the fair-value-weighted average remaining maturity (years) of BDC portfolio loans, computed at the BDC-quarter level over 2015Q4 to 2024Q4. Remaining maturity is measured from the observation date to each loan's stated maturity date. Holdings without a reported maturity date are excluded.

Variable	N	Mean	SD	P25	Median	P75
WAM, Assets	1057	3.89	0.86	3.24	3.81	4.48

Table 4 presents a complementary perspective by showing the distribution of portfolio loans across different maturity groups based on the remaining years to maturity. The typical portfolio is concentrated in the middle of the maturity range, with 43.1% of loans maturing within three to five years, 26.5% within one to three years, and 21.3% within five to seven years. The weighted average share, which accounts for portfolio size based on fair value, reveals a more skewed maturity distribution that is tilted toward longer remaining maturities. From this perspective, loans maturing in more than five years account for 36.8% of aggregate portfolio value, compared to 25.1% for the typical BDC, indicating that larger BDCs hold portfolios with relatively longer maturities.

Table 4: *Maturity Profile of BDC Portfolio Loans*

Table 4 reports the distribution of BDC portfolio loans across remaining-maturity buckets. Average Share (%) is calculated by giving each BDC-quarter equal weight. Weighted Average Share (%) weighs each BDC-quarter by portfolio fair value. Remaining maturity is measured from the observation date to each loan's stated maturity date. Holdings without a maturity date are excluded.

Remaining Maturity	Average Share (%)	Weighted Average Share (%)
$<$ 1 year	5.4	3.1
1-3 years	26.5	20.1
3-5 years	43.1	40.0
5-7 years	21.3	31.3
7+ years	3.8	5.5

The tables in Appendix B.1 and Appendix B.2 confirm the existence of a size difference in maturity profiles by sorting BDC-quarter observations into terciles based on portfolio fair values within each quarter. The weighted average asset maturity increases from 3.53 years for small BDCs to 4.41 years for larger ones, with the distribution across maturity groups displaying a similar pattern. The share of loans maturing within five to seven years rises from 13.4% for the

smallest tercile to 29.5% for the largest, driven by a consistently lower share of short-maturity loans compared to small- and medium-sized BDCs.

A variety of factors could help explain the existence of this pattern. One possible explanation is that asset maturity is shaped in part by a BDC's financing structure. Access to longer-term debt reduces the near-term financing need and may make it easier to hold portfolio assets with longer maturities, since funding a long-term loan with shorter-term debt would require refinancing before the loan fully repays. Dividing the sample into size terciles within each quarter reveals that the largest BDCs rely more heavily on bonds and notes compared to the smallest BDCs, averaging approximately 56% and 46% of total debt, respectively.[15] As such, differences in financing mix could possibly explain the observed differences in the maturity of assets. However, the direction of this relationship is ambiguous, as BDCs may equally structure their financing to match the assets they intend to hold. The maturity structure of BDC debt is examined in Section 4.2.2, after which these separate analyses are combined and the resulting maturity gap is evaluated in Section 4.2.3.

4.2.2 Debt Maturity

Table 5 reports summary statistics for the debt-weighted average maturity of outstanding BDC debt. Between 2015Q4 and 2024Q4, the average (median) BDC carried a debt portfolio with a weighted average remaining maturity of 5.73 (5.33) years. These figures indicate that the average debt maturity is substantially longer, exceeding the average asset maturity by approximately 1.8 years. Furthermore, the standard deviation of 2.4 years is almost three times larger than what was observed on the asset side, coupled with a wider interquartile range of 4.19 to 6.9 years, suggesting that the distribution of debt maturities is considerably more dispersed. Taken together, whereas asset maturity is a largely common feature across BDC-quarter observations, debt maturity is subject to much greater variation.

[15] BDC-quarter observations are sorted into size terciles within each quarter based on portfolio fair value. Bonds and Notes account for 56.1%, 42.2%, and 46.4% of total debt for the largest, middle, and smallest terciles, respectively.

Table 5: *Weighted Average Maturity (WAM) of BDC Debt*

Table 5 reports summary statistics for the amount-weighted average remaining maturity (years) of outstanding BDC debt, computed at the BDC-quarter level over 2015Q4 to 2024Q4. Remaining maturity is measured from the observation date to each instrument's stated maturity date. Instruments without a reported maturity date are excluded.

Variable	N	Mean	SD	P25	Median	P75
WAM, Debt	1057	5.73	2.4	4.19	5.33	6.9

Following the same procedure as Section 4.2.1, Table 6 presents the distribution of BDC debt across different maturity buckets. In contrast to the asset side, debt is spread across the full distribution, with each maturity bucket above one year of remaining maturity containing a sizable share of total debt for the typical BDC. Notably, 31.7% of debt carries a remaining maturity of more than seven years, whereas almost no portfolio holdings extend beyond this timeframe. This raises the question of which debt instruments give rise to such long-dated funding, and the composition described in Section 4.1.1 would suggest that bonds and notes likely account for the majority of debt within this category.

Table 6: *Maturity Profile of BDC Debt*

Table 6 reports the distribution of outstanding BDC debt across remaining-maturity buckets. Average Share (%) is calculated by giving each BDC-quarter equal weight. Weighted Average Share (%) weighs each BDC-quarter by outstanding amount. Remaining maturity is measured from the observation date to each instrument's stated maturity date. Holdings without a maturity date are excluded.

Remaining Maturity	Average Share (%)	Weighted Average Share (%)
< 1 year	4.8	6.0
1-3 years	20.3	21.5
3-5 years	26.8	25.2
5-7 years	16.4	18.6
7+ years	31.7	28.7

However, examining the composition of debt with remaining maturities above seven years tells a slightly different story. Rather than being dominated by bonds and notes, 55.4% of long-dated debt is made up by credit facilities, with bonds and notes only accounting for 35.6%. Table 7 reports the weighted average maturity associated with each instrument type, separating bonds and notes into unsecured and securitized notes due to the large difference in maturity between the two groups.

This breakdown shows that unsecured notes, which make up the largest source of debt in aggregate terms, have the shortest remaining maturity across all instrument types with an average of 3.71 years. In contrast, securitized notes carry a weighted average remaining maturity of 9.90 years but only represent a modest share of total debt. Between them lies revolving credit facilities with a weighted average remaining maturity of 6.90 years, which is somewhat longer than what the previous literature would suggest.[16]

Table 7: *Maturity Structure of BDC Debt by Instrument Type*

Table 7 reports, for each instrument type, the number of instrument-quarter observations (N), the share of total debt (%), and the amount-weighted average remaining maturity in years. Bonds and notes are separated into unsecured and securitized notes.

Instrument Type	N	Share of Debt (%)	WAM (Years)
Unsecured Notes	3778	49.8	3.71
Securitized Notes	1535	8.5	9.90
Revolving Credit	1730	34.2	6.90
Term Loans	287	3.2	5.99
Debentures	2933	2.7	6.50
Other	198	1.6	4.88

This instrument-level breakdown reveals important information regarding the sources of the aggregate maturity difference between assets and liabilities. Although BDC debt maturity exceeds asset maturity on average, this difference is largely driven by revolving credit facilities and, to a lesser extent, securitized notes. Compared to assets, unsecured notes exhibit a marginally lower WAM but represent the largest source of debt. Because these are market-based debt instruments, maintaining this debt composition would require BDCs to interact with public debt markets on a rolling basis, exposing them to refinancing risk that the aggregate figures understate. The timing and near-term concentration of these maturities is examined in Section 4.2.4 to assess whether BDCs face a near-term maturity wall and the magnitude of the associated refinancing risk.

[16] Davydiuk et al. (2024b) state that bank term loans and revolving credit facilities generally carry a maturity of 4-6 years. Balloch and Gonzalez-Uribe (2021) describe revolving credit facilities as a 'somewhat permanent source of financing with a four-five year maturity ' (p. 10).

4.2.3 Maturity Gap

Having separately established the maturity structure of BDC assets and debt, this section compares the two by examining the resulting maturity gap and how it has evolved over time. For each BDC-quarter, the difference between the weighted average remaining maturity of assets and debt is computed, with a negative value indicating that a BDC's loan portfolio matures, on average, before its outstanding debt.

Table 8 reports summary statistics for this maturity gap. The average (median) BDC-quarter exhibits a gap of -1.84 (-1.46) years, with approximately 82% of observations being negative. Even at the 75th percentile the gap remains negative at -0.47 years, suggesting that a loan portfolio maturing ahead of the debt that finances it is the norm rather than the exception within the sample of publicly traded BDCs during the 2015Q4 to 2024Q4 period. As stated in Section 2.2, this pattern is reversed compared to traditional banks, which engage in maturity transformation by financing long-term loans with short-term demandable deposits. Instead, the typical BDC holds assets that repay before their debt obligations become due.

Table 8: *Summary Statistics - BDC Maturity Gap (Years)*

Table 8 reports summary statistics for the maturity gap, defined for each BDC-quarter as the fair-value-weighted average asset maturity minus the amount-weighted average debt maturity. *N* is the number of BDC-quarter observations and *% Negative* is the percentage of BDC-quarter observations with a negative maturity gap.

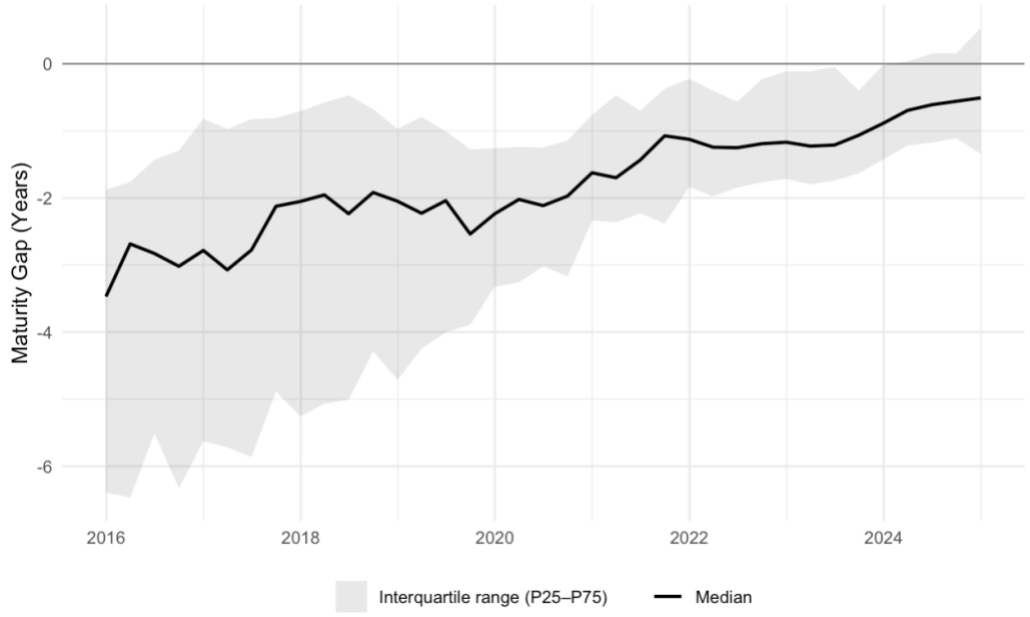
Variable	N	Mean	SD	P25	Median	P75	% Negative
Maturity Gap	1057	-1.84	2.35	-2.86	-1.46	-0.47	82.1

Figure 3 plots the median maturity gap and interquartile range over the 2015Q4 to 2024Q4 sample period. The median gap is negative for each quarter in the sample, confirming that the sign observed in the full-sample statistics is not driven by a particular point in the interest rate cycle and further strengthening the interpretation that a negative maturity gap is a persistent and common feature across BDCs over time. However, the gap narrows considerably throughout the sample period, going from a median of -3.47 years in 2015Q4 to -0.51 years in 2024Q4. At the same time, the dispersion across BDC-quarter observations decreases, indicated by the tightening of the interquartile range, suggesting that BDCs have converged toward a smaller and more uniform

maturity gap. As showcased below, this convergence appears to be largely driven by a contraction of debt maturities rather than asset maturities over time.

Figure 3: *Evolution of the Median BDC Maturity Gap, 2015Q4 - 2024Q4*

Figure 3 plots the median maturity gap (asset WAM minus debt WAM, in years) across BDCs in each quarter from 2015Q4 to 2024Q4, with the shaded area representing the 25th-to-75th percentile range. The horizontal line corresponds to a maturity gap of zero.



To identify which side of the balance sheet causes this convergence, Appendix C.1 plots the median weighted average remaining maturity for assets and debt separately over the sample period, with the shaded area representing the resulting maturity gap. Asset maturity remains relatively stable at approximately four years throughout the period, whereas debt maturity experiences a meaningful decline, causing the two series to converge. As such, the observed narrowing of the maturity gap can be almost exclusively attributed to a contraction of the weighted average debt maturity.

Having established the contraction over time and isolated it to the liability side, understanding whether this reflects a shift toward shorter-dated debt instruments or a natural aging of the outstanding debt stock is a natural next step. To this end, Appendix C.2 reports the debt composition across instrument types, measured at year-end intervals, to see whether the overall

debt composition exhibits any meaningful changes over time. While the instrument mix varies throughout the sample period, the share of total debt stemming from the largest categories remains broadly comparable in weight over time. Unsecured notes account for 54% of debt in 2015 and 52% in 2024, while revolving credit facilities increase from approximately 27% to 34% of total debt over the same period. These fluctuations in debt composition across instrument types are unlikely to explain the significant contraction in debt maturity, particularly given that unsecured notes, which were shown to carry the lowest WAM in Section 4.2.2, remained broadly stable across the sample period.

These results instead point toward a natural aging of the outstanding debt stock. If new debt issuances are sufficiently large and issued at similar maturities to the debt already outstanding, the weighted average remaining maturity of the total debt stock would remain steady over time. If instead new issuances are insufficient to offset the natural aging of existing debt, one would expect the average maturity of the outstanding stock to decline over time. Appendix C.3 provides a comparison of the weighted average remaining maturity of outstanding bonds and notes to that of newly issued instruments. While the maturity of newly issued bonds and notes fluctuates between five and seven years throughout the period, the maturity of the outstanding stock of bonds and notes falls steadily from 6.19 years in 2016 to 3.90 years in 2024. Since newly issued bonds and notes consistently carry longer maturities than the existing stock, yet the average remaining maturity continues to decline, the contraction cannot be explained by BDCs simply issuing shorter-dated debt. Instead, the results indicate that existing debt ages faster than new issuance replaces it.

Taken together, the descriptive results presented in this section show that BDCs operate with a persistent negative maturity gap, holding assets that, on average, repay before their debt obligations become due. This gap has narrowed during recent years, driven almost exclusively by a contraction in debt maturity that can be traced back to the natural aging of the existing debt stock. In aggregate terms, the negative maturity gap suggests that BDCs are protected against the risk of having to liquidate portfolio investments early to settle maturing debt obligations. However, this measure alone offers an incomplete picture of a BDC's refinancing position as it does not capture how those debt maturities are distributed over time. Two BDCs may exhibit identical maturity gaps yet face very different refinancing exposure depending on whether their debt maturities are

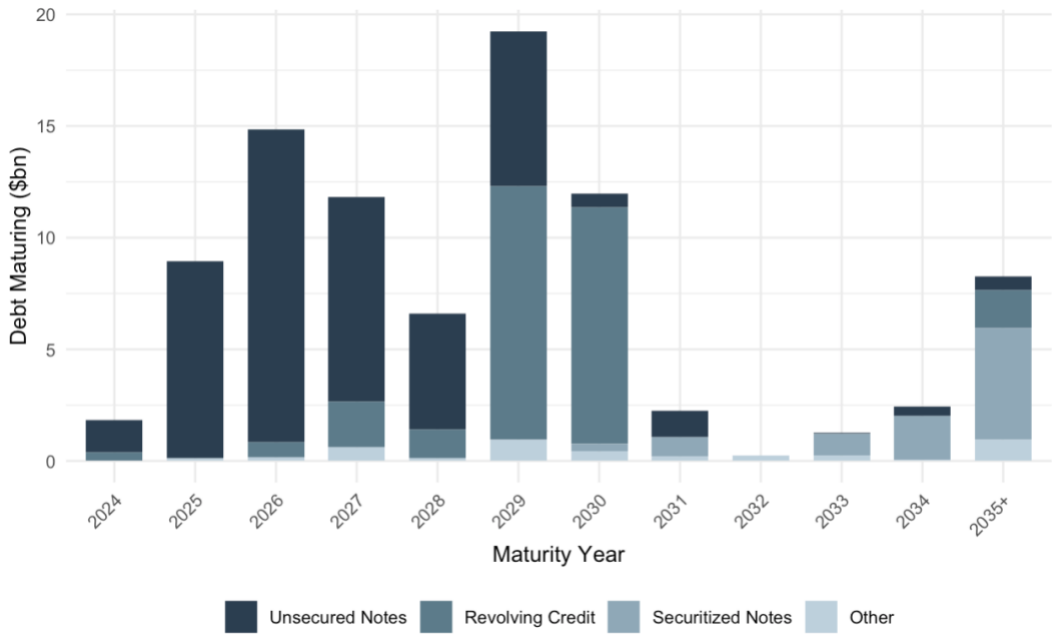
spread out over time or concentrated in particular years. The same reasoning applies to the aggregate sector, which is why the following section focuses on the aggregate maturity profile of the publicly traded BDC sector to evaluate its exposure to refinancing risk.

4.2.4 Forward-Looking Debt Maturity Profile and Refinancing Risk

Figure 4 presents the forward-looking aggregate maturity profile of all outstanding debt within the sample of publicly traded BDCs, divided by instrument type. Due to lower data availability in 2024Q4 compared to earlier periods, the analysis is anchored to 2024Q3 to ensure that the most recent quarter with representative coverage of the sector is used. Therefore, the results discussed below refer to the outstanding debt at the end of the third quarter of 2024, unless otherwise noted.

Figure 4: *Maturity Profile of Publicly Traded BDC Debt by Instrument Type (As of 2024Q3)*

Figure 4 shows the amount of outstanding debt (in $bn) as of 2024Q3, stacked by instrument type, that is maturing in each future year. Maturities beyond 2034 are grouped into a combined bucket. Instruments without a stated maturity are excluded.



As shown in Figure 4, the maturity structure of total outstanding debt is not uniformly distributed. Maturities are concentrated in the period between 2025 and 2030, with approximately 82% of all outstanding debt in the sample maturing within this window. The year with the largest amount of maturing debt is 2029, in which approximately $19 billion of outstanding debt falls due.

Decomposing the total debt by instrument type yields additional insights. Maturities are largely concentrated within the unsecured notes segment, with approximately $45.5 billion, or 94%, of unsecured notes maturing between 2024Q4 and 2029Q4. This is consistent with the short weighted average remaining maturity documented for unsecured notes in Section 4.2.2 and implies that almost the entire portion of debt that is refinanced through public debt markets must be repaid within approximately five years of the observation date.

Revolving credit facilities are concentrated somewhat later, with the majority of outstanding facilities maturing during 2029 and 2030. Across the 2025 to 2030 window, unsecured notes and revolving credit facilities make up 61% and 35% of maturing debt, respectively. As a result, the near- and medium-term aggregate refinancing needs of publicly traded BDCs depend on both prevailing credit conditions across public debt markets and banks' willingness to extend or renew existing credit facilities. However, because unsecured notes are both larger in magnitude and closer in time, a greater part of the sector’s refinancing exposure is tied to public market access rather than bank relationships.

In principle, a BDC facing a large amount of maturing debt could opt to redirect the cash flows obtained from principal repayments of their shorter-dated assets toward paying off debt, rather than refinancing it. As established in Section 2.1.2, however, BDCs are constrained in their ability to grow organically through retained earnings and depend heavily on external capital to finance their growth. As such, opting to delever would likely shrink the portfolio and the income it generates by impairing growth and new lending activity, possibly making deleveraging a costly alternative to refinancing debt.

With this said, the terms under which BDCs can refinance their maturing notes are unlikely to be comparable to those of the existing stock. Appendix D reports the outstanding amount and weighted average coupon of all fixed-rate unsecured notes maturing between 2025 and 2030,

grouped by their year of issuance. The table shows that approximately 54% of all notes maturing within this period, equivalent to $23.7 billion, were issued during the 2020 to 2021 period. These notes carry a weighted average coupon rate of roughly 4.0% and 3.1% respectively, which is substantially lower than the coupons observed in other vintage years. This implies that a meaningful share of the debt maturing within the sector was issued at historically low rates during the 2020 to 2021 period. Refinancing this debt in today's rate environment would mean substituting some of the sector's cheapest funding with more expensive debt, which ties into the interest rate exposure described in Section 4.1.2, where BDC debt was shown to be largely fixed rate while portfolio assets are predominantly floating. In short, the near- to medium-term maturity concentration of unsecured notes marks the point at which the cheap fixed-rate funding secured during the low-rate environment is gradually replaced, likely pushing up the aggregate cost of debt within the publicly traded BDC segment.

While the discussion above has focused on the refinancing risk associated with unsecured notes in public debt markets, it must also be noted that a deterioration in credit conditions is unlikely to affect a single funding channel in isolation. For example, a weaker credit environment would likely coincide with greater default rates within BDC loan portfolios, thereby weakening the collateral pledged to banks and reducing their willingness to renew and extend credit facilities. These conditions could also affect equity prices, potentially pushing prices below NAV, at which point raising new equity becomes more difficult. Viewed this way, the maturity concentration documented above is not only a question of refinancing cost, but also a potential channel through which stress in BDC funding could affect the credit supply from BDCs to the broader economy.

4.3 Limitations

This study is subject to various limitations which affect the interpretation and external validity of the results obtained from the empirical analysis. The first limitation concerns the scope of the sample. The descriptive analysis focuses exclusively on publicly traded BDCs, which differ systematically from the broader BDC universe. Prior studies document that non-traded BDCs operate with lower leverage and exhibit vastly different funding structures, relying primarily on

revolving credit facilities while bonds and notes only constitute a small share of their total debt, on average (Chernenko et al., 2025). As such, much of the evidence presented and discussed in this study should be interpreted with respect to publicly traded BDCs rather than the BDC sector as a whole.

Second, the research design is descriptive and does not establish any causal links or statistical relationships. The analysis documents how BDC balance sheets are structured and have evolved over time but does not attempt to identify the causal mechanisms behind these patterns. As such, the descriptive evidence and associated interpretations can only be seen as suggestive evidence rather than empirically tested relationships. Enriching the empirical analysis with formal tests on, e.g., the determinants of debt composition or the underlying drivers of the observed maturity gap would allow these interpretations to be tested directly, which represents a valuable extension of the descriptive results presented in this study.

Third, the forward-looking maturity analysis presented in Section 4.2.4 is limited by its reliance on a single point in time that does not necessarily reflect the current state of the BDC sector. The analysis is anchored to 2024Q3 due to limited data availability in the 2024Q4 period, which creates a notable gap between the chosen anchor date and the time of writing this study. As the composition and maturity structure of BDC debt evolve over time, the results may no longer be fully representative of the current state of the sector. Some of the debt observed will have already been refinanced or repaid, while new debt obligations have emerged that are not captured in the sample used in this study. As such, the findings should be viewed as representative of the refinancing risks faced by the publicly traded BDC sector as of late 2024, and their representativeness depends on the extent to which the conditions have persisted until today.

5. Conclusions

This study examines the debt structure and maturity profile of publicly traded BDCs, which is a topic that has received limited attention within the existing literature. While many prior studies have examined the growth of direct lending, its implications for financial stability, and the characteristics of BDCs and the lending technologies they employ, far less attention has been directed toward how these institutions manage their balance sheets, especially on the liability side. This study addresses this gap by utilizing instrument-level panel data on BDC debt and portfolio loans to document how BDCs structure their liabilities, how the maturity of their assets and liabilities compares, and how these factors have evolved over time.

Publicly traded BDCs operate with a persistent negative maturity gap, holding assets that, on average, repay before their debt obligations become due. This is the opposite of the maturity transformation that characterizes traditional banks. Although this gap has remained negative throughout the 2015 to 2024 period, it has narrowed considerably due to a contraction in debt maturities that can be traced back to the gradual aging of the existing debt stock rather than the issuance of shorter-dated instruments. However, while the maturity gap alone indicates that assets tend to repay ahead of the debt that finances them, it reveals nothing about when this debt actually falls due, which carries important implications for the refinancing needs present within the sector.

The most consequential finding concerns the forward-looking maturity profile of publicly traded BDC debt and the refinancing risk it implies. A substantial share of the sector's aggregate debt matures between 2025 and 2030, largely driven by unsecured notes that were issued at historically low rates during the 2020 to 2021 period. Because BDCs are structurally dependent on external financing, this debt must largely be refinanced rather than repaid. With the majority of this refinancing pressure stemming from unsecured notes, which constitute the single largest source of debt, publicly traded BDCs are particularly dependent on the prevailing conditions in public debt markets to refinance this debt. As unsecured notes are primarily fixed-rate instruments, the low coupons secured during the 2020 to 2021 period are only locked in until the notes mature. As such, the near- to medium-term maturity wall represents the point at which the sector's largest and

cheapest source of debt needs to be replaced, which is likely to push up the aggregate cost of debt within the sector.

Additionally, the data reveals that publicly traded BDCs finance themselves using a near 50-50 split between fixed and variable rate debt. Combined with a predominantly floating-rate asset base, this implies that a large share of the sector's funding costs is fixed while its investment income moves with prevailing rates. Moreover, the lack of variation in interest rate structure within each instrument type suggests that a BDC's interest rate exposure is largely determined by the instrument mix it deploys.

Various limitations should be kept in mind when interpreting these results. First, the analysis is descriptive in nature and does not establish any causal links or statistical relationships. As such, the results should be viewed and interpreted as suggestive, rather than conclusive evidence. Second, given that non-traded BDCs differ systematically from publicly traded BDCs, the sole focus on the latter category limits the external validity of these findings, as the sample is not fully representative of the broader BDC or private credit universe. Third, the forward-looking maturity analysis rests on the assumption that the debt outstanding as of 2024Q3 remains broadly representative of the sector's current debt profile, which may not necessarily be the case.

These limitations point toward a number of avenues for future research. A natural next step would be to extend beyond the descriptive analysis and formally test the determinants of debt structure and the underlying drivers of the observed maturity gap within BDCs. Furthermore, extending the sample to cover non-traded BDCs would offer a more complete picture of the sector as a whole. Finally, since BDCs rely on different funding channels simultaneously, including public debt markets, bank facilities, and equity issuances, evaluating the interconnectedness of these different channels would allow for a better understanding of how the sector responds to deteriorating credit conditions. Such an analysis would go beyond the more isolated focus of this study and provide valuable insights into the resilience of the BDC sector.

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Appendix

A.1 Debt Composition of Publicly Traded BDCs – Full Sample

Table 9: *Debt Composition of Publicly Traded BDCs - Full Sample*

Table 9 reports the mean, minimum, and maximum quarterly debt-weighted share (%) of each instrument type over the full sample.

Instrument Type	Mean (%)	Min (%)	Max (%)
Bonds & Notes	56.1	42.2	65.6
Revolving Credit	32.4	21.2	43.3
Debentures	5.1	1.0	9.9
Term Loans	3.7	0.3	8.1
Other	2.7	0.8	7.9

A.2 Debt Composition of Publicly Traded BDCs by Age Group

Table 10: *Debt Composition of Publicly Traded BDCs by Age Group*

Table 10 reports the mean, minimum, and maximum debt-weighted share (%) of each instrument type within each BDC age group (young, mid, mature)

Instrument Type	Mean (%)	Min (%)	Max (%)
Young (< 5 years)			
Revolving Credit	54.4	24.3	77.5
Bonds & Notes	33.2	5.3	65.5
Other	4.8	0.0	19.4
Debentures	4.7	0.0	17.9
Term Loans	3.0	0.0	11.4
Mid (5-10 years)			
Bonds & Notes	51.6	32.7	79.9
Revolving Credit	28.1	10.9	40.4
Debentures	8.1	0.0	16.8
Term Loans	7.2	1.1	17.0
Other	5.1	0.0	29.8
Mature (10+ years)			
Bonds & Notes	69.5	54.6	88.5
Revolving Credit	24.5	8.4	42.1
Debentures	3.3	2.0	7.1
Term Loans	1.9	0.0	5.5
Other	0.8	0.3	1.7

B.1 Weighted Average Asset Maturity by Portfolio Size Tercile

Table 11: *WAM of Assets by Portfolio Size Tercile*

Table 11 reports the fair-value-weighted average asset maturity (years) by within-quarter portfolio size tercile. BDC-quarters are sorted into small, medium, and large terciles by total portfolio fair value.

Portfolio Size	Mean FV ($m)	N	Mean	Median	P25	P75
Small	424	362	3.53	3.31	2.94	3.86
Medium	1,547	356	3.76	3.64	3.26	4.16
Large	7,363	339	4.41	4.38	3.94	4.93

B.2 Maturity Profile of BDC Portfolio Assets by Portfolio Size Tercile

Table 12: *Maturity Profile of BDC Portfolio Assets by Portfolio Size Tercile*

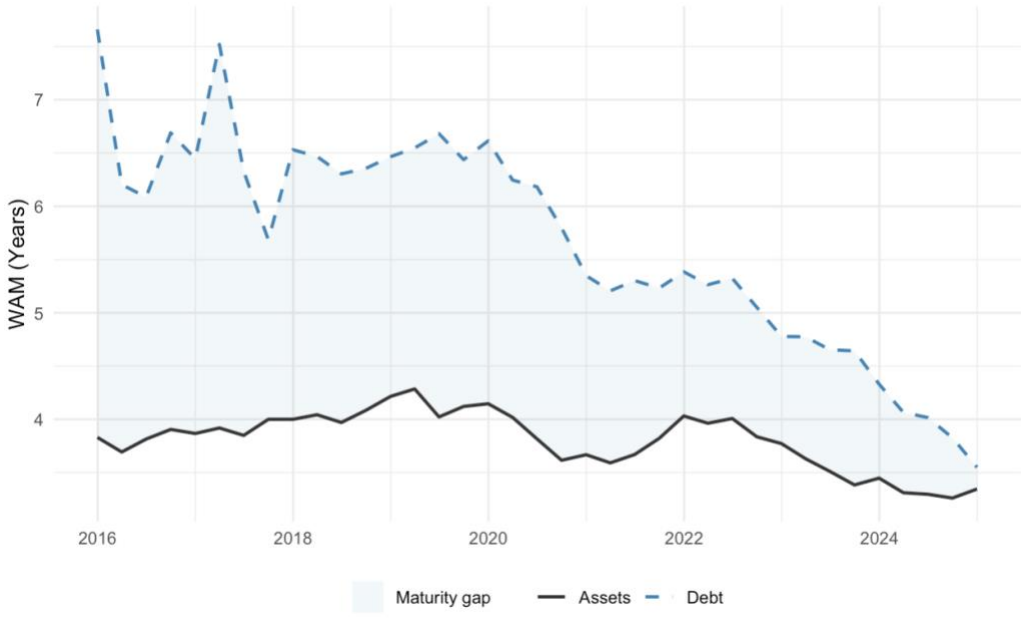
Table 12 reports the distribution of portfolio loans across remaining-maturity buckets, separately for the small, medium, and large size terciles. All figures are percentages and represent the share of portfolio loans within each maturity bucket.

Remaining Maturity	Small	Medium	Large
< 1 year	7.8	5.2	2.9
1-3 years	30.1	27.8	21.3
3-5 years	46.2	43.1	39.7
5-7 years	13.4	21.6	29.5
7+ years	2.5	2.3	6.6

C.1 Evolution of Median Asset & Debt Maturity (Years), 2015Q4 – 2024Q4

Figure 5: *Evolution of Median Asset & Debt Maturity (Years), 2015Q4 - 2024Q4*

Figure 5 plots the median fair-value-weighted asset maturity and the median amount-weighted debt maturity (years) by quarter over 2015Q4 to 2024Q4. The area between the two series is shaded to represent the maturity gap.



C.2 Year-End Debt Composition, 2015 - 2024 (% Share of Total Debt)

Table 13: *Year-End Debt Composition, 2015 - 2024 (% Share of Total Debt)*

Table 13 reports the instrument composition of aggregate BDC debt at each year-end, as the share of total debt (%) by instrument type.

Year	Unsecured	Revolving	Securitized	Term Loans	Debentures	Other
2015	54.4	26.7	2.5	1.5	7.0	7.9
2016	53.8	24.9	5.0	4.4	9.0	2.9
2017	50.0	28.9	3.8	8.2	7.6	1.5
2018	41.2	38.1	4.7	7.8	4.9	3.5
2019	38.2	42.3	8.9	3.5	4.6	2.5
2020	53.3	28.2	9.7	3.8	3.6	1.5
2021	50.6	37.9	7.6	1.8	1.6	0.4
2022	49.0	37.6	9.1	2.6	1.5	0.2
2023	52.6	32.6	10.0	2.0	1.6	1.3
2024	51.9	34.4	10.0	1.7	1.3	0.8

C.3. Outstanding-Stock and New-Issue Maturity by Instrument Type

Table 14: *Outstanding Stock & New-Issue Maturity by Instrument Type*

Table 14 reports, for bonds and notes and for revolving credit, the amount-weighted average remaining maturity of the outstanding stock (Stock WAM), the amount-weighted average remaining maturity of newly issued instruments (New-Issue WAM), and the number of new issues, by year. New issues are identified by an instrument's first appearance in the sample.

Year	Stock WAM	New-Issue WAM	New Issues (N)
Bonds & Notes			
2016	6.19	6.97	30
2017	5.01	5.02	25
2018	5.37	7.13	46
2019	5.73	6.92	58
2020	5.00	5.76	56
2021	4.34	5.72	95
2022	4.42	7.12	63
2023	3.84	6.62	48
2024	3.90	6.57	94
Revolving Credit			
2016	8.14	5.05	8
2017	6.99	3.32	7
2018	7.81	6.18	16
2019	8.28	5.95	17
2020	7.86	6.19	12
2021	7.64	7.21	31
2022	6.62	4.96	12
2023	5.94	6.85	3
2024	5.13	1.86	4

D. Fixed-Rate Unsecured Notes Maturing 2025 – 2030, by Year of Issuance

Table 15: *Fixed-Rate Unsecured Notes Maturing 2025 - 2030, by Year of Issuance*

Table 15 reports, for fixed-rate unsecured notes outstanding at 2024Q3 and maturing between 2025 and 2030, the number of notes (N), the total outstanding amount ($bn), the share of this maturing amount (%), and the amount-weighted average coupon (%), by year of issuance. Issuance year is proxied by each instrument's first appearance in the sample.

Issuance Year	N	Amount ($bn)	Share (%)	Coupon (%)
2015	1	0.35	0.8	5.25
2018	2	0.65	1.5	4.43
2019	4	1.12	2.6	4.41
2020	23	9.33	21.2	3.99
2021	38	14.40	32.7	3.08
2022	17	6.41	14.6	4.79
2023	15	3.27	7.4	7.40
2024	22	8.46	19.2	5.70

AI Appendix

What AI tools have been used and how?

ChatGPT (GPT-5) and Claude (Sonnet 4.6, Opus 4.8) have been used sporadically throughout the thesis to (1) assist with debugging and suggesting improvements to the R code, (2) improving LaTeX code for tables, (3) rephrasing long and complex sentences, and (4) proofreading the thesis to check for typos and grammatical errors.

In what ways have these tools contributed to increasing the quality of the thesis?

These tools contributed to speeding up the code-writing process, leaving more time for me to focus on reading and understanding the literature, designing and conducting the empirical analysis, and interpreting the results. Furthermore, these tools helped with improving the readability of the text while minimizing typos and other linguistic errors.

What potential risks were found using AI and what measures were taken to reduce these?

AI tools are prone to hallucinations and may generate unreliable and imprecise outputs, such as inventing fake citations to support unsubstantiated arguments. Furthermore, they tend to be biased toward agreeing with the user instead of challenging potential inaccuracies and factual errors. As such, every AI contribution of code and text was carefully checked to ensure accuracy, no AI was used in the data collection process to ensure replicability, and the cited literature was manually read to ensure that all references are correct and consistent.

What are the insights gained from using AI tools in the thesis writing process?

Using AI tools can be very effective in speeding up routine and “mindless” tasks that would otherwise require a lot of manual attention. However, it immediately became clear that one cannot blindly trust AI generated output, implying that the time saved by using AI is partly offset by the time needed for manual verification and fact-checking. In short, speed and efficiency should never take priority over accuracy and reliability in academic writing.