LOAN PRICING AND RISK INCENTIVES IN PRIVATE CREDIT

By

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Vienna, 26 May 2025

Zsuzsa Koós

Abstract

As a relatively new debt market, private credit has not been thoroughly studied. Due to its illiquid, opaque, and loosely governed nature, policymakers are emphasizing growing concerns about its trajectory. Few studies provide loan-level evidence comparing private credit and bank loan pricing, or examine whether fund compensation structures drive risk-taking. This thesis contributes to the emerging literature in two key ways: (1) by analyzing how private credit loan pricing differs from that of banks, and (2) by investigating whether incentive structures in business development companies (BDCs) influence risk behavior. Using global loan-level data from LSEG Refinitiv (2014-2024), I conduct regression analyses and find that private credit loans carry, on average, spreads that are 170 basis points higher than comparable bank loans. Additionally, using 10-K filings from 25 BDCs (2018-2024), I estimate panel regressions to examine how performance-based fees and leverage interact to affect credit risk. I find that after controlling for both incentive fees and leverage, their interaction term is a strong predictor of greater total gains and losses, suggesting increased risk appetite under pressure to deliver returns.

Acknowledgements

I would like to thank my sisters and friends for providing me support.

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Chapter 1

Introduction

The 2008 Great Financial Crisis (GFC) has transformed the financial system drastically. The implementation of the Dodd-Frank Act in the United States (US) and Basel III. have changed the rules for banks globally. The application of stricter capital requirements and risk-weighted asset rules, discouraged financial institutions from risk taking (Cortés et al., 2020). Consequently, lending to middle-market companies,[1] which required banks to increase their holdings under the new policies, became too expensive, thus banks pulled back from lending them credit.

Private credit (PC),[2] interchangeably used with direct lending due to its bilateral nature of credit contracts, filled this gap in the debt market (Aramonte and Avalos, 2021). By 2025, this credit market grew to over $3 trillion in assets under management (AUM) (Alternative Investment Management Association (AIMA), 2024), despite remaining relatively illiquid, opaque, and institutionally concentrated (IMF, 2024a). Private credit funds act as intermediaries, raising money from institutional investors such as pension funds, insurance companies, or sovereign wealth funds (IMF, 2024b). Due to the sophisticated nature of these investors, the market remains less regulated (IMF, 2024b). Most private credit funds operate as closed-ended funds,[3]

[1] A middle-market firm is a business typically generating $100 million to $1 billion in annual revenue, too small for public debt issuance yet requiring financing beyond the capacity of a single bank, with loans that are generally unrated (IMF, 2024b).

[2] Private credit is term mused to identify corporate loans lent by nonbank entities (IMF, 2024b).

[3] A closed-end fund is an investment vehicle with a fixed number of shares that are issued through an initial public offering and subsequently traded on an exchange, they typically use leverage in their operations and are actively managed (IMF, 2024b).

such as business development companies (BDCs). BDCs differ from other PC funds because they operate under the Investment Company Act of 1940, and are regulated by The United States Securities and Exchange Commission (SEC) (IMF, 2024b).

As private credit blossomed, its historical annual high returns have attracted many investors (Morgan, 2023; IMF, 2024b; Peter Breyer, 2024). With a surge in funding, PC expanded (Faridi, 2024), and broadened its borrower base. Initially, private credit served as a lender to borrowers who were deemed too risky for banks (IMF, 2024b). Today, however, it also competes for borrowers who have access to bank financing (Zawadowski and Albuquerque, 2025; Haque, Mayer, et al., 2024). At the same time, private credit funds increasingly rely on bank financing to support the growing demand of their loans (Haque, Jang, et al., 2025). As PC funds grow bigger, they rely more on bank funding, increasing the interconnectedness between the banking system and private credit market.

Figure 1.1 illustrates the sharp rise in private credit volumes over the past decade, making up more than 12% of all bank corporate loans in 2023. This trend underlines the growing importance of understanding the behavior, pricing, and systemic risk implications of private credit markets.

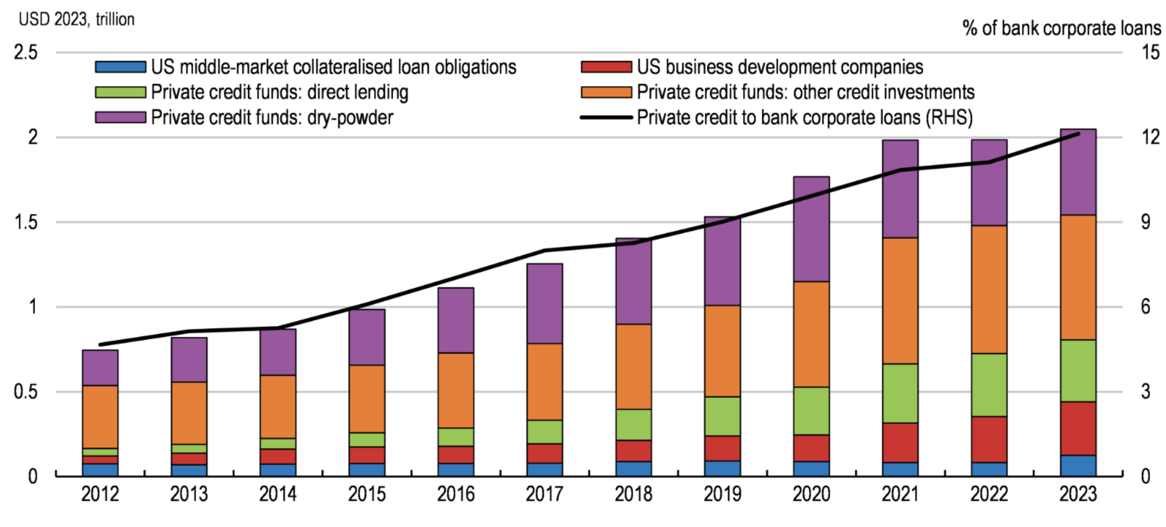


Figure 1.1: Private Credit Continues to Rise in Advanced Economies, 2012–2023. Source: OECD Economic Outlook (Dec 2024); IMF; Pitchbook; Houlihan Lokey.

As private credit's popularity is still growing, it has garnered the attention of financial regulators and researchers. The emerging consensus is that if PC continues to grow with present tendencies, systemic risk causing market failure is a valid concern (IMF, 2024b; Cai and Haque, 2024; Roulet, 2024). The drivers of this market has been thoroughly researched (IMF, 2024b; Cai and Haque, 2024; Avalos et al., 2025). Larger portions of relevant literature focuses on firm-level analysis, rather than loan specific details (IMF, 2024b; Morgan, 2023; Suhonen, 2024). Many of the existing work has been written by regulators, consulting firms, or select industry researchers but thorough academic analyses are rare. Contemporary works discuss loan interaction between private credit funds and banks (Zawadowski and Albuquerque, 2025) as well as dual borrowers of both lender types (Haque, Mayer, et al., 2024). Most recent research on private credit focuses on macroprudential risks, firm-level determinants of BDC behavior, and interactions between banks and private credit, not systematic comparisons of loan pricing across borrower types (IMF, 2024b; Cai and Haque, 2024; Zawadowski and Albuquerque, 2025). This gap motivates the first half of the thesis.

Many studies inspect BDCs (Suhonen, 2024; Chernenko et al., 2025) – the most available source of data due to regulations – to provide conclusions on private credit as a whole (Zawadowski and Albuquerque, 2025). Consequently, findings on BDC operations are notable contributions to scholarship (Suhonen, 2024; Chernenko et al., 2025; Aramonte and Avalos, 2021; Haque, Jang, et al., 2025). In such a study, Suhonen (2024) points to the possibility that incentive fee structures may influence risk-taking and returns in BDCs. Understanding the issues that stem from this and regulating them is essential for policymakers, as it directly concerns the safety of the financial system. Notwithstanding, this relationship has not been empirically explored, which inspires the second half of this thesis.

The first section of this thesis will focus on understanding pricing mechanisms of private credit loans without restrictions on borrowers. I answer the following two research questions. How does private credit loan pricing compare to that of banks? How are different types of loans within PC priced? For this analysis, I use global loan-level data. Furthermore, to better understand private credit loans, I look at private credit loan information on its own. I find that PC loans, ceteris paribus, have 170 basis points (bps) higher spreads on average,[4] than bank loans. Furthermore, this analysis finds that private credit also offers lower priced credit lines,[5] augmenting the literature, which emphasizes how borrowers prefer bank-given credit lines (Haque, Mayer, et al., 2024).

In the second part, I explore the lender side of private credit and answer further two research questions. How do compensation structures in BDCs incentivize risk-taking? Does the combination of high incentive fees and leverage make BDC managers take more risk? These questions matter because BDCs often operate with high leverage and earn performance-based incentive fees, which may push managers to invest in riskier loans. Whilst Gande and Kalpathy (2017) argue that risk-taking in financial firms were associated with compensation incentives, this has never been done for the case of private credit (Suhonen, 2024). To successfully model this, I use financial data of twenty-five BDCs. While I find no evidence that income-based fees have an unconditional effect on credit risk, I identify that the compensation structure increases the risk appetite of managers when the fund uses a high level of leverage.

This thesis is organized into five chapters. Following this introduction in Chapter 1, Chapter 2 reviews the existing literature on private credit, focusing on its historical evolution, loan pricing, fund structures, and the role of compensation in shaping risk. Chapter 3 presents the empirical analysis of loan pricing using loan-level data and regression models that compare private credit and bank loan characteristics. It discusses the implications and limitations of the results. Chapter 4 looks at BDCs, and investigates how compensation and leverage interact and influence risk behavior. Finally, Chapter 5 concludes this thesis.

[4]Spreads are the difference between a loan's interest rate and a benchmark rate, reflecting lender profit and credit risk.

[5]A credit line is a revolving loan that allows borrowers to access funds up to a set limit as needed, paying interest only on the amount drawn.

Chapter 2

Literature Review

This chapter presents the relevant literature on the rise of private credit, pricing differences between private credit and bank loans, and the structural features of private credit funds. It contextualizes the two central questions this thesis investigates: why private credit loans are priced differently from bank loans, and how fund-level incentives shape risk-taking in business development companies. Section 2.1 explores the rise in the demand for private credit and the shift in borrower composition, while section 2.2 examines differences in loan pricing and borrower characteristics compared to traditional banks. Section 2.3 focuses on the structure and incentives of PC funds and how these influence risk-taking behavior. Despite the growing literature, empirical analyses remain sparse, especially concerning the incentive mechanisms within private credit funds. This thesis contributes to closing that gap.

2.1 A closer look into private credit

Three factors contribute to the significant increase in the number of private credit borrowers. Firstly, private credit lends to firms who cannot access bank loans due to their high-risk profile (IMF, 2024b; Block et al., 2024). Secondly, regulatory reforms, particularly Basel III. and stress testing, have decreased the risk tolerance of banks. As a result, borrowers who have relied on banks migrated to PC. Avalos et al. (2025) and Erel and Inozemtsev (2024) highlight that post-GFC constraints made middle-market lending require significant capital for banks, while non-bank lenders, unconstrained by such rules, stepped in. Thirdly, Zawadowski and

Albuquerque (2025) argue that for borrowers who have the option of both lenders, PC offers better incentives, thus elevating PC as the preferred lender. While Zawadowski and Albuquerque (2025) state that this transfer of borrowers have moved credit risk from the banking to the private credit sector, Acharya et al. (2024) finds that the risks are rather knitted together due to the interconnection between sectors. At present, a growing number of banks provide loans to PC funds (Roulet, 2024), establishing a financial stake in private credit (Chernenko et al., 2025). As of 2023, about 37% of private credit funds relied on bank credit lines, up from just 3% in 2010 (Roulet, 2024), reflecting growing interdependence between banking and shadow banking systems [6].

Private credit is also evolving institutionally, shifting from bilateral lending to funds combining power to allow syndicated lending (Faridi, 2024). While this will broaden funding options for borrowers, it also increases risks of transparency between lenders and borrowers. Lenders are not able to fully observe borrower risk, this asymmetric information presents itself in higher loan prices. Ellias and Fontenay (2025) describe a “market going dark” phenomenon, that the growth of private debt has led significant information loss into the debt market. This growing asymmetric information between borrower and lender is making it increasingly difficult for not only investors but also regulators to evaluate creditworthiness and systemic risk. Valuation methods are also concerning. The Öesterreichische Nationalbank (OeNB) (2024) warns that many PC funds report internal rate of returns (IRR) based on mark-to-model estimates, not real-time market values, potentially masking risk and performance. This institutional opacity makes asymmetric information a central theoretical concern in understanding how private credit loans are priced.

2.2 Private credit loan characteristics

Asymmetric information is a well-known problem in the credit markets (Akerlof, 1970). In private credit loans: the lack of public disclosure, secondary markets, and standardized contracts

[6] Shadow banking refers to lending and financial activities done by nonbank institutions, like private credit funds, that are not as tightly regulated as traditional banks.

increase this information gap. In markets with limited transparency, lenders cannot fully observe borrower quality or monitor behavior ex post. As a result, private credit loans often carry higher margins, stricter covenants, and are secured by collateral to mitigate the risks lenders cannot see. A typical PC loan uses floating rate,[7] and offers loans spanning 5 to 8 years to middle-market borrowers (Avalos et al., 2025). Most PC loans are secured in the private credit market – meaning collateral is provided to protect lenders in case of borrower default – to reduce credit risk (Aldasoro and Doerr, 2025; Block et al., 2024). Furthermore, PC loans carry highly customized covenants with flexible renegotiation terms that protects both sides (Ellias and Fontenay, 2025).

Empirical research shows that private credit loans are more expensive than comparable bank loans. Haque, et al. (2024) found that for dual borrowers, where firms borrow simultaneously from both bank and private credit, PC loans have higher margins by 200 basis points. These borrowers obtained riskier, longer-term credit from PC funds, while relying on banks for safer, more liquid funding. This thesis corroborates the findings that private credit lenders charge a risk premium to compensate for both borrower quality and limited observability.

The presence of private equity (PE) sponsors further complicates pricing: in the US, 78% of PC loans involve PE-backed firms, compared to 41% in Europe (Block et al., 2024). Haque, et al. (2024) report that 80% of PC borrowers were owned by PE companies. This is not coincidental, many PE firms operate PC funds, such as business development companies, and they use them as lenders for the companies they acquire (IMF, 2024b; Cai and Haque, 2024). This allows PE firms to control both sides of the lending relationship. They are the owners of the lenders and the managers of the borrowers. This raises a concern about the possibility of conflicts of interest (IMF, 2024b), and how lender strategies are affected.

[7] A floating rate loan is a loan with an interest rate that adjusts periodically based on a benchmark reference rate, such as SOFR or EURIBOR, plus a fixed spread.

2.3 Private credit fund structures and business development company incentives

Private credit funds, especially closed-end funds such as BDCs, operate under structural constraints and incentives that shape their investment decisions. Unlike banks, which hold long-term capital and relationships, BDCs must meet investor return expectations within a fixed timeline (Cai and Haque, 2024). This short duration creates pressure to originate loans with high yields and faster execution (Cai and Haque, 2024). Lalafaryan (2024) finds that institutional debt investors increasingly benchmark fund managers by performance, which may further intensify short-term profit pressures. Aramonte and Avalos (2021) suggest that even in the absence of liquidity pressures, fund managers continually seek to outperform prior periods, thus increasing their exposure to credit risk in pursuit of higher profits. This raises the question whether BDCs are structured in a way that rewards risk-taking.

2.3.1 Performance incentives

While asymmetric information characterizes the borrower-lender dynamic, the design of incentive compensation reflects the principal-agent problem between investors and fund managers (Grossman and Hart, 1983). The goal of such compensation structure is to align manager's interest to is to create a stake for the managers and take part of bearing the risk the investors face. In business development companies, managers are compensated through a mix of base and performance-based fees, often tied to net investment income or total return benchmarks (Cai and Haque, 2024). As a result, they may prefer riskier loan portfolios with higher yield potential, especially when investor expectations are tied to set returns.

Suhonen (2024) finds that historical out-performance in the BDC sector was often not driven by skill but by regulatory arbitrage and favorable market timing. The wide dispersion in fund returns suggests inconsistent internal controls and potential misalignment between managerial incentives and investor interests. Similarly, Erel, Flanagan, and Weisbach (Erel, Flanagan, et al., 2024) show that after adjusting for risk, private credit returns are statistically insignificant from traditional fixed income products, implying that returns are more driven by market conditions rather than manager's skill.

These risk-taking incentives have broader macro-financial consequences. As business development companies grow and increase their use of leverage, they become more vulnerable to market shocks (Roulet, 2024). During periods of financial stress, they may be forced to liquidate illiquid assets or withdraw credit from borrowers, therefore raising procyclical volatility in the real economy (Brooke, 2019; Gara, 2023). As BDCs depend on short-term credit to finance their loans, they face refinancing risk. If in economic downturns banks stop lending to them, BDCs may be unable to roll over their debt, and this would cause a fire-sale of assets (Haque, Jang, et al., 2025). Consequently, as BDCs stop giving out credit to the ones that need it the most, they amplify market stress.

Chapter 3

Private Credit Loans vis-à-vis Bank Loans

In this chapter, I answer the following research questions: How do loan pricing dynamics differ between private credit and traditional bank loans? How are different types of loans priced within the PC market? Firstly, I will present the base models that capture pricing tendencies for PC and bank loans. Secondly, I will introduce the loan-level dataset spanning eleven years on which the models are performed, and present the important loan characteristics. Thirdly, I report the achieved results: PC loans carry higher spread than bank loans, and within PC loans, credit lines have lower premiums than term loans. Lastly, I discuss these findings.

3.1 Models

The following hypotheses serve as basis for my modeling process. I use margin as the loan price proxy. Depending on the loan's other characteristics, such as tenor, security, seniority, this margin will change (IMF, 2024b). I assume, that in a dataset including both PC and bank loans, once controlling for these characteristics, the difference in credit prices will be explained by characteristics inherent to PC loans. As I mentioned previously, PC loan characteristics such as risky lending, speed, and personalized covenants come with a higher price than bank loans (IMF, 2024b). Due to these suppositions, my hypothesis is that PC loans will have higher loan premiums than a bank given loan with identical characteristics. Furthermore, a PC loan will have a higher margin if it has longer maturity, but lower one if the loan amount is larger. Given these presumptions, I built a regression model as follows.

The dependent variable is the spread on a loan, which adds to the profit a lender earns through the transaction. Using loan spreads to identify pricing patterns is a practice in the literature (Cowling and Yang, 2024; Camba-Mendez and Mongelli, 2021; Haque, Mayer, et al., 2024). The subsequent Equation 3.1 provides the basis of all pricing models that I introduce in this chapter.

$$\text{Spread}_i = \beta_0 + \beta_1 \cdot \text{PC}_i + \beta' \cdot \mathbf{X}_i + \varepsilon_i, \tag{3.1}$$

where i denotes an individual loan transaction. PC_i is a binary indicator equal to 1 if the lender is a private credit fund, and 0 if the lender is a bank. $\mathbf{X}_i$ is the vector of loan characteristics control variables β' is the corresponding vector of coefficients, and ε_i is the idiosyncratic error term. In β', I input tenor, security, seniority, and loan amount, since I argue all of these attributes influence pricing.

As my model has several potential limitations (discussed in Section 3.4.2), I define other models, with different explanatory variables as a way to test the robustness of the results. As I look at trends, and the loan transactions span a longer time period, I will include time-fixed effects to account for time-varying macroeconomic conditions. This is shown in Equation 3.2:

$$\text{Spread}_i = \beta_0 + \beta_1 \cdot \text{PC}_i + \sum_t \gamma_t \cdot \text{Year FE}_{it} + \varepsilon_i, \tag{3.2}$$

Since the focal point of this thesis is private credit, I created a model that specifically only examines PC loans. I assume that the loan-data will be severely imbalanced since PC is relatively new and data access is limited. In Equation 3.3, in a PC-only sample I look at the spreads on different loan types and what the change in margin due to loan specifications (tenor, loan amount).

$$\text{Spread}_i = \beta_0 + \beta' \cdot \mathbf{X}_i + \varepsilon_i, \tag{3.3}$$

where i indexes individual private credit loan transactions. $\mathbf{X}_i$ is the vector of loan characteristic control variables: tenor, and loan type and β' is the corresponding vector of coefficients, and ε_i is the error term as before.

3.2 Data

To implement Equations 3.1, 3.2, and 3.3, I use a dataset covering loan transactions over a significant period of time to capture true trends.

3.2.1 Data source

I used LSEG Refinitiv Workspace (2025) to download global loan-level data between the periods of 2014 January 1st and 2024 December 31st. During these 11 years, 85546 loans were reported. For each transaction, I extracted key loan characteristics including issue and maturity dates, margin over base rate, tenor, tranche amount, currency, borrower, domicile, sector, seniority, and security status. Important loan features are defined in Table A.1 in the Appendix. To distinguish between bank and private credit lenders, I classified each transaction based on the lender's name. Using a set of identifying keywords, I manually assigned each lender to either the bank or private credit category. This classification allowed me to analyze differences in loan characteristics across the two lending types.

3.2.2 Variables and their descriptive statistics

Category: The classification of lenders is the backbone of this analysis. Separating private credit and bank lenders is essential in order to uncover their discrepancies. The dataset is unbalanced in the quantity of private credit and bank loans. This could be due to the opaque nature of private credit (IMF, 2024b). It contains 1721 loans from PC funds compared to 76998 borrowed from banks. Moreover, a number of loan characteristics are missing for PC loans, which additionally decreases the sample. I will address these limitations in section 3.4.2.

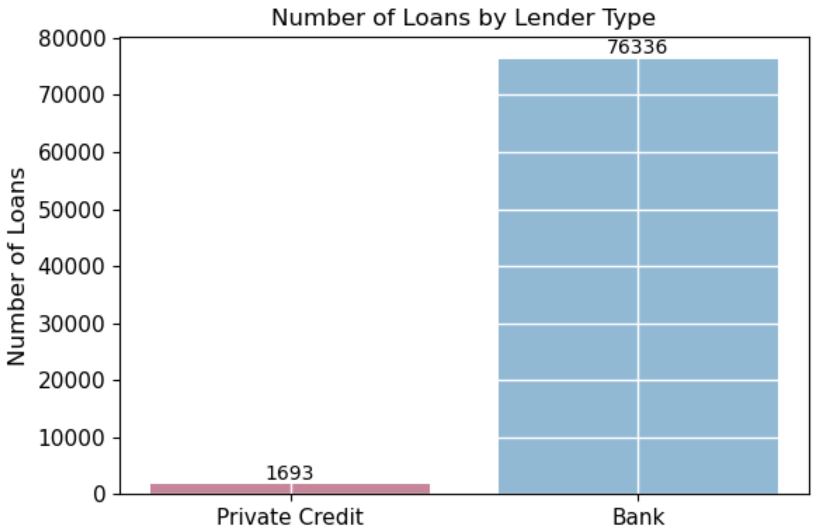


Figure 3.1: Loan Amounts by Category

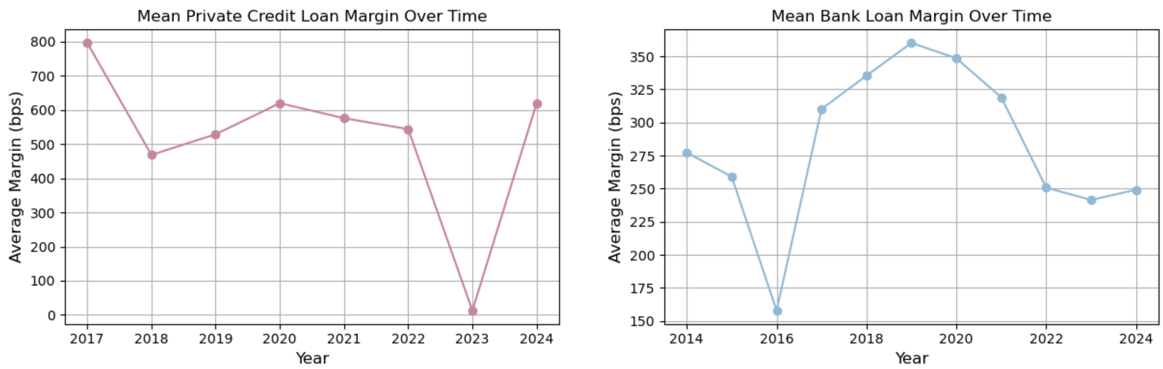
Margin: The dependent variable of this analysis is the margin on top of the base interest rate. Private credit loans, as I mentioned before, use floating interest rates which is tied to a base rate, changing with it simultaneously, hence the name ”float”. The most common floating rates are the Secure Overnight Financing Rate (SOFR) and London Interbank Offered Rate (LIBOR).

In this study, the spread is given by the margin on top of the base rate, Haque et al. (Haque, Mayer, et al., 2024) have estimated spread the same way. Thus, margin reflects the credit risk premium charged over a base rate therefore, in this analysis I use margin/spread/premium synonymously. It’s important to note that since I use margin and not the cost of loan themselves in a way I implicitly control for the interest rate (assuming that it affects all the loans unanimously).

Table 3.1 shows that only 357 PC loans include margin data (10375 bank). The average margin for private credit is approximately 270 basis points higher, with lower standard deviation, suggesting consistent but higher pricing. In contrast, bank loan margins show greater variance, with a long right tail.

Figure 3.2 shows the average loan margins over the years for PC and bank loans. Plot 3.2a shows that PC loans carry significantly higher average margins (other than 2023 due to no data). Plot 3.2b shows that bank loan margins have been more stable over time, fluctuating within a narrower band between 250 and 350 basis points. These trends visually confirm the broader empirical finding that private credit loans are priced at a significant premium relative to traditional bank loans (IMF, 2024b; Haque, Mayer, et al., 2024).

Table 3.1 supports this observation with summary statistics. On average, private credit loans carry a margin of 569 bps, nearly double of bank loans at 299 bps. Interestingly, while both distributions include a minimum margin of 0, the maximum margin for bank loan is 5690 bps, an extreme value likely driven by distressed or highly specialized deals. In contrast, the maximum private credit loan spread is 875 bps, which still places them well above the mean bank loan.



(a) Average Margin for Private Credit Loan

(b) Average Margin for Bank Loan

Figure 3.2: Loan Margins Over Time

Table 3.1: Descriptive Statistics of Margin (bps) and Tenor

Variable	**Lender**	**Count**	**Mean**	**Std. Dev.**	**Min**	**25%**	**Median**	**75%**	**Max**
Margin (bps)	Private Credit	357	569.12	122.97	0.0	500.0	575.0	650.0	875.0
	Bank	10375	298.73	208.90	0.0	145.0	250.0	425.0	5690.0
Tenor (months)	Private Credit	1555	63.83	16.51	2.0	54.0	69.0	72.0	96.0
	Bank	70643	87.77	77.84	1.0	54.0	60.0	96.0	10836.0

Tenor: The tenor is the length of the loan in terms of months. Private credit loans tend to be similar in length, shown by its standard deviation, whereas bank loans tend to be longer on average and more versatile, aligning with past literature (Block et al., 2024).

Security: Collateralized loans are safer for lenders, since they are backed by an asset and more common in private credit (Aldasoro and Doerr, 2025). Figure 3.3 shows that in the use data sample 99.91% private credit and 92.88% bank loans are secured.

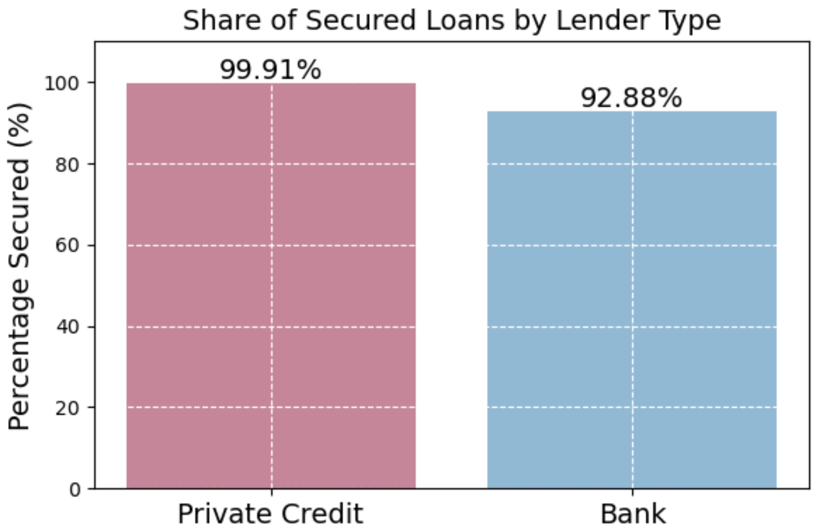


Figure 3.3: Loan Security by Category

Tranche Type: Tranche type defines the loan type. For clearer analysis, I grouped the loan structures into five common categories, they are individually defined in Table A.2 in the Appendix.

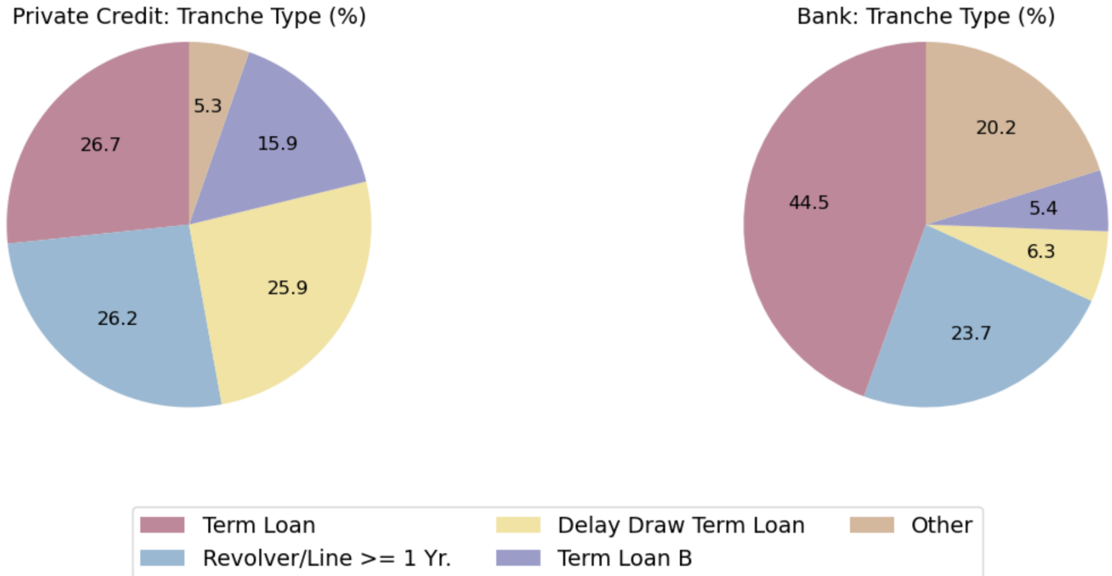


Figure 3.4: Tranche Type Across Categories

Figure 3.4 shows that private credit (PC) uses a more diverse set of loan structures than banks. While banks rely heavily on standard term loans (44.5%), PC loans are split across Revolver/Lines (26.2%), Delay Draws (DDTL) (25.9%), and other flexible types. This suggests that PC funds offers term loans and credit lines. (The bank loan type chart sums up to 100.1% due to rounding.)

The tenor distribution across private credit loans types shown in Table A.3 in the Appendix is similar, the average for each is between 63 to 65 months. This suggests that borrowers take out credit lines along with their term loans.

Seniority: Nearly all private credit and bank loans are senior, providing repayment priority in the event of default. Table A.4 in Appendix shows what percentage of loans in the sample have what seniority.

3.3 Results

I have estimated 5 different OLS regressions on the base models (Equations 3.1, 3.2, and 3.3). The main variable of interest is the coefficient of β_1, it captures the difference of a PC loan margins compared to a bank loan. To adjust to the dataset, I modified the base models as the following.

$$\begin{aligned}\text{Model 1:}\quad \text{Margin}_i = \beta_0 + \beta_1 \cdot \text{PrivateCredit}_i + \beta_2 \cdot \text{Secured}_i + \beta_3 \cdot \text{Seniority}_i \\ + \beta_4 \cdot \text{Tenor}_i + \beta_5 \cdot \text{TrancheAmount}_i + \varepsilon_i\end{aligned} \tag{3.4}$$

In Equation 3.4, I use security, seniority, tenor, and the loan amount as control variables. I turned the first two into dummy variables. A secured loan takes the value of 1, 0 otherwise. Senior loans equals 1, 0 otherwise. PC loans in this sample are homogeneously secured and senior, those control variables will only reflect bank loan information.

Model 2 applies a log transformation to both the margin and tranche amount variables. As shown in Figure A.1 in the Appendix, Tranche Amount (USD) is heavily right-skewed, while its logarithmic transformation approximates a normal distribution. This improves model interpretability and reduces heteroskedasticity in the residuals. The updated equation is the following:

$$\text{Model 2:}\quad \ln(\text{Margin}_i) = \beta_0 + \beta_1 \cdot \text{PrivateCredit}_i + \beta_2 \cdot \text{Secured}_i + \beta_3 \cdot \text{Seniority}_i + \beta_4 \cdot \text{Tenor}_i + \beta_5 \cdot \ln(\text{TrancheAmount}_i) + \varepsilon_i \tag{3.5}$$

As a further robustness check of my results, I drop the control variables – which may be biased since both the margin and loan characteristics are determined by the lender – and replace them with time fixed-effects shown in Equation 3.6.

$$\text{Model 3:}\quad \text{Margin}_i = \beta_0 + \beta_1 \cdot \text{PrivateCredit}_i + \beta_2 \cdot \ln(\text{TrancheAmount}_i) + \sum_{t=2014}^{2024} \gamma_t \cdot \text{Year FE}_t + \varepsilon_i \tag{3.6}$$

These three models have the same observation sample with both PC and bank lenders. The regression results of Equations 3.4, 3.5, and 3.6 are presented in Table 3.2.

Table 3.2: Regression Results to Capture Pricing Differences between PC and Bank Loans

Variable	**Model 1**	**Model 2**	**Model 3**
Category: Private Credit	169.99^{***} (8.23)	0.5391^{***} (0.017)	167.10^{***} (8.28)
Secured	218.83^{***} (7.05)	0.9148^{***} (0.037)	—
Seniority	-167.36 (122.09)	-0.4555 (0.429)	—
Tenor	-0.5944^{***} (0.042)	-0.0022^{***} (0.000)	—
Tranche Amount	$-2.22e{-}08^{***}$ (2.94e-09)	—	—
Ln(Tranche Amount)	—	0.0227^{***} (0.005)	-3.1856^{**} (1.57)
Year FE	—	—	Yes
Constant	368.15^{***} (122.40)	5.0382^{***} (0.442)	317.50^{***} (36.95)
Observations	5942	5853	5942
R-squared	0.118	0.139	0.127
Adjusted R-squared	0.117	0.139	0.125
F-statistic	451.0	436.1	92.15
Heteroskedasticity-Robust SEs	HC3	HC3	HC3

Robust standard errors in parentheses. $^{***}p<0.01$, $^{**}p<0.05$

The coefficient of the PC loan is positive and statistically significant at the 1% level ($p < 0.001$) in all three models. This suggests that private credit loans, holding everything else equal, come with significantly higher margins than traditional bank loans. Based on Model 1, I conclude that private credit loans have approximately 170 bps higher margins than bank loans, controlling for loan characteristics. Except for seniority, all variables show statistically significant results. Secured loans have higher margins by 218 bps. Tenor increase affects the margin negatively.

Model 2 shows that margins of PC loans, ceteris paribus, are 71.4% higher than of bank loans. Security and seniority remain as in Model 1. Tranche amount has low positive effect.

Model 3, which includes year fixed effects and excludes potential endogenous controls, yields almost identical results to Model 1, that PC loans, ceteris paribus, have approx. 167 bps higher margins than bank loans. 1% increase in tranche amount decreases the margin by 0.032 bps.

Next, taking a sample consisting only of private credit lenders, and using Equation 3.3, I have defined Equation 3.7 and 3.8 to look at how pricing changes within PC based on loan types. Loan types were converted into dummy variables, using the most popular Term Loan as the baseline. This was due to the fact that literature unanimously agrees that it is the most common PC loan. I have excluded seniority and security, since all loans were identical in these aspects. I have estimated both log and linear models for thorough comparison.

$$\text{Model 4:} \quad \ln(\text{Margin}_i) = \beta_0 + \beta_1 \cdot \text{TrancheType}_i + \beta_2 \cdot \text{Tenor}_i + \beta_3 \cdot \ln(\text{TrancheAmount}_i) + \varepsilon_i \tag{3.7}$$

$$\text{Model 5:} \quad \text{Margin}_i = \beta_0 + \beta_1 \cdot \text{TrancheType}_i + \beta_2 \cdot \text{Tenor}_i + \beta_3 \cdot \ln(\text{TrancheAmount}_i) + \varepsilon_i \tag{3.8}$$

Table 3.3 presents the regression results for Model 4 and 5.

Table 3.3: Regression Results: Private Credit Loans

Variable	**Model 4**	**Model 5**
Tenor	0.0032** (0.001)	1.6355*** (0.460)
Ln(Tranche Amount)	-0.0346** (0.015)	-23.4948*** (4.792)
Tranche: Delay Draw Term Loan	-0.8738 (1.121)	-94.0208*** (14.809)
Tranche: Revolver/Line $\geq$ 1 Yr.	0.0036 (0.030)	-99.2951*** (16.172)
Tranche: Term Loan B	-0.1068*** (0.029)	-146.0943*** (12.958)
Tranche: Other	0.1556*** (0.026)	-195.5743 (172.405)
Constant	6.7297*** (0.294)	971.9439*** (87.428)
Observations	352	352
R-squared	0.281	0.343
Adjusted R-squared	0.269	0.332
F-statistic	26.86	28.35
Heteroskedasticity-Robust SEs	HC3	HC3

Robust standard errors in parentheses. ***$p<0.01$, **$p<0.05$

Model 4 presents that longer tenor increases the margin on a private credit loan by approximately 0.32%, holding other factors constant. Similarly, a 1% increase in the tranche amount decreases the margin by around 0.035%. These effects are small, but statistically significant. The coefficients of the tranche type dummies are relative to Term loans. A Term Loan B has lower margins by 10.7% then a Term Loan. The two credit line types have statistically insignificant results.

Model 5 confirms Model 4's results. A one-month increase in tenor is associated with a 1.64 bps higher margin, while a 1% increase in tranche amount reduces the margin by roughly 0.235 bps. Compared to Term loans, margins are 146 bps lower for term loan B, 94 bps lower for DDTLs, and 99 bps lower for Revolver/line facilities. All three effects are highly statistically significant. The Other loan type has insignificant results.

The presence of heteroskedasticity violates the classical OLS assumption of constant error variance, rendering conventional standard errors invalid. For robustness, I used heteroskedasticity-consistent (HC) standard errors. I have applied the HC3 estimator, which adjusts the OLS residuals by inflating them according to each observation's leverage. This correction reduces the influence of high-leverage points and has been shown to perform well even in small samples (Long and Ervin, 2000).

3.4 Discussion

This section will interpret the achieved results, and discuss its implications. Afterwards, it will cover data and model limitations.

3.4.1 Interpretation and implications

This analysis finds that the growing amount of private credit loans carry significantly higher rate margins (170 bps), even after controlling for loan characteristics. This premium may partly reflect non-price advantages of private credit, such as greater flexibility, faster execution, and a higher certainty of funding (IMF, 2024b). A logical explanation is the presence of asymmetric information between borrower and lender. Since PC functions as lender to a borrower base that tend to carry a notable amount of debt (IMF, 2024b), the lender needs to mitigate credit risk[8]. This is also backed by how longer PC loans have higher margins. For lenders to carry this loan longer, they raise the risk of default, thus a higher risk premium is set, in this case that mirrors in the margin. These findings support Haque et al. (Haque, Mayer, et al., 2024), who also find a 200 bps higher premium for PC loans among dual borrowers. However, while in their sample private credit loans held longer maturities, I found that private credit loans usually last 5 to 7 years. This difference is most likely due to the fact that their intended purpose is different, as credit lines usually are shorter than term loans.

Moreover, the difference of premiums within private credit loans across tranche types raises important implications. Term loans carry the highest margin, even though the tenor between loan types are similar (shown in Table A.3). This pricing difference suggests that lenders may either perceive credit lines as less risky than term loans or, in more likelihood, that the bundling

[8]Credit risk refers to the possibility that a borrower will fail to meet its obligations to repay their the loan to the lender.

of credit lines with term loans helps reduce costs and risk exposure. This bundling may also help lessen information asymmetries between lender and borrower by increasing transparency between them. If lenders gain better visibility into a borrower's credit profile and need, they may be more willing to offer lower spreads on revolving facilities.

Despite tighter regulations, banks can still provide credit lines.This is due to the fact that credit lines often remain off a bank's balance sheet until used, and therefore carry lower capital charges (Berrospide and Meisenzahl, 2015). Donaldson et al. (2024) argue that in bank lending, credit lines help reduce the need for future debt issuance, although they increase the borrower's risk by committing to future debt. Applying this framework to private credit lending helps explain both the findings of this study and those of Haque et al. (2024). The borrowers who do not have access to bank-given credit lines due to high-risk profiles turn to PC lenders for both term loans and liquidity provisions. Paul Hastings (2025) reports that significant volumes of BDC lending now involve revolving credit facilities and delayed draw term loans.

3.4.2 Limitations

The limitations of results presented in this section are significant. Firstly, lack of access to information regarding private credit loans cause a significant challenge. Table A.5 in the Appendix shows that the used Refinitiv (Refinitiv, 2025) dataset contains only a fraction of loan transactions in direct lending, measured by the Bank of International Settlements (BIS) (Bank for International Settlements (BIS), 2025), used in the analysis of Avalos et al. (2025). Thus, this model is not performed on a completely random sample. This discrepancy can be seen below in Figure 3.5.

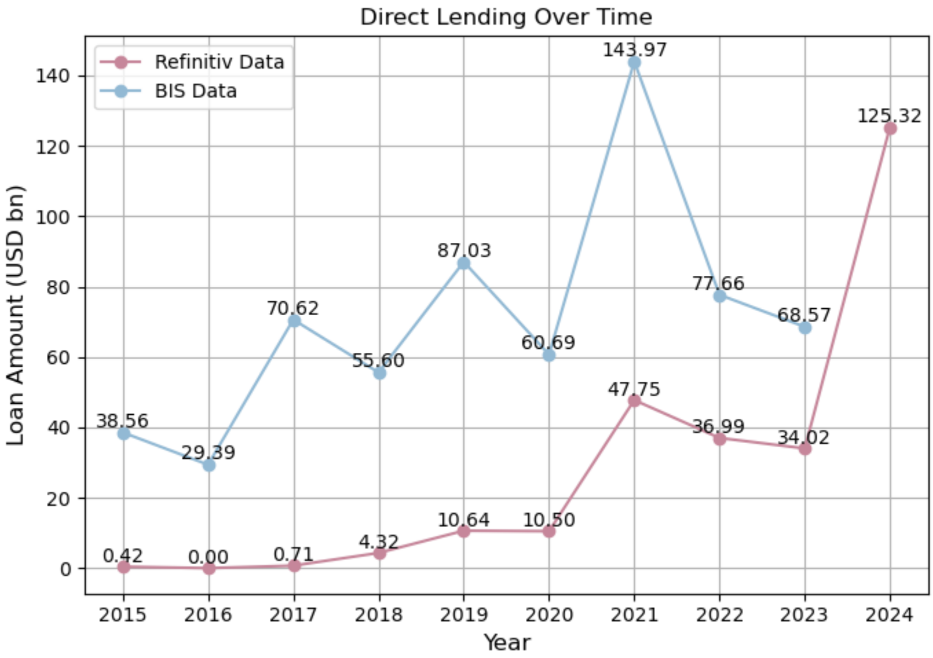


Figure 3.5: Comparing Total PC Loans Over Time

Secondly, as BDCs are publicly listed, the private credit loans are primarily lent by BDC companies. Since I do not distinguish between lender types nor for borrower characteristics (such as whether the company was sponsored by PE), omitted variable bias could affect my results. PE operates in what are called ”Leveraged Buyouts”. Figure 3.6 shows in each category of lending purpose, the number of original PC loans the dataset had, specifically the excluded ratio from the analysis due to missing margin information. Although 78% of ”Leveraged Buyouts” are removed from the regression models due to missing margin data, 97 such loans still remained. In a sample of 352 loans, these remaining loans could still influence the accuracy of the model.

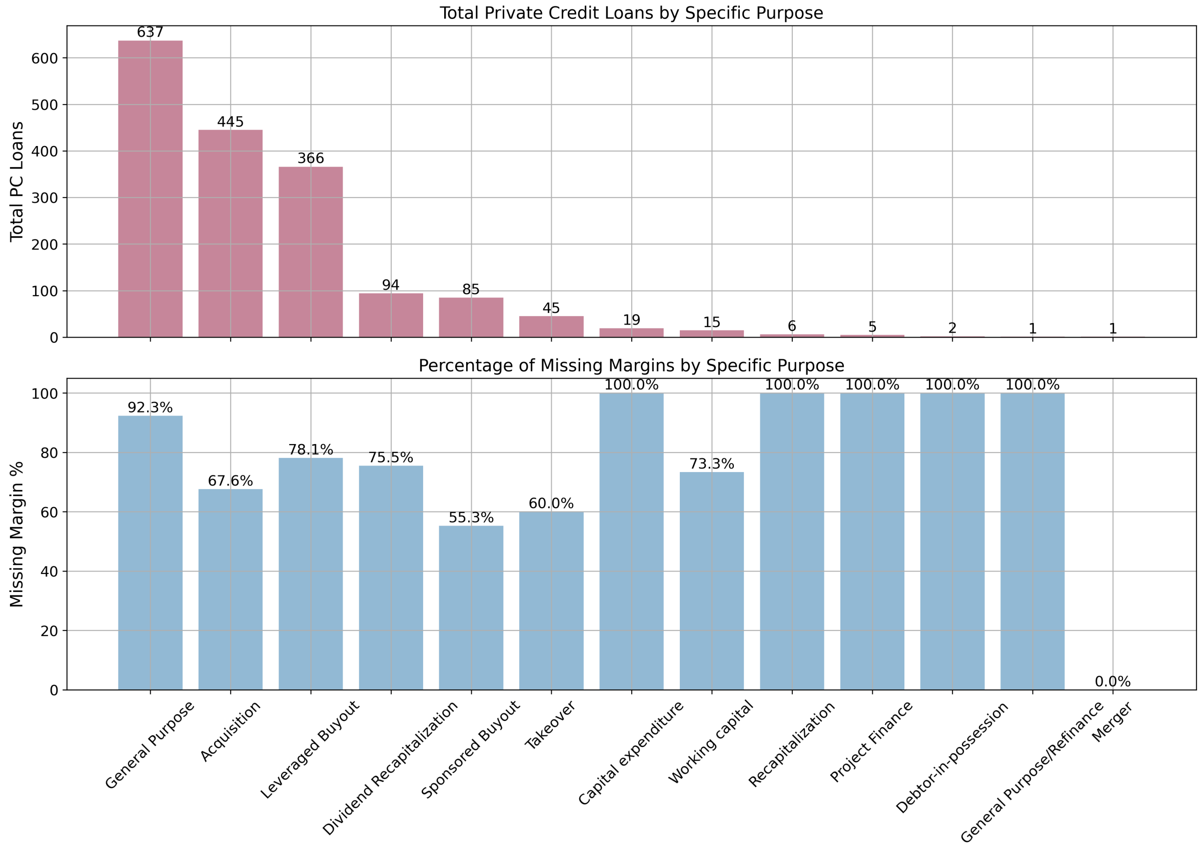


Figure 3.6: Excluded PC Loans by Purpose

Similarly, a significant portion of PC loans across all tranche types is excluded from the analysis due to missing margin information. Figure 3.7 illustrates this: the top panel shows the total number of PC loans, while the lower panel displays, for each tranche type, the percentage of loans left out due to missing margins. In the four most popular categories, more than 60% of loans are omitted, which limits the accuracy of Model 4 and 5.

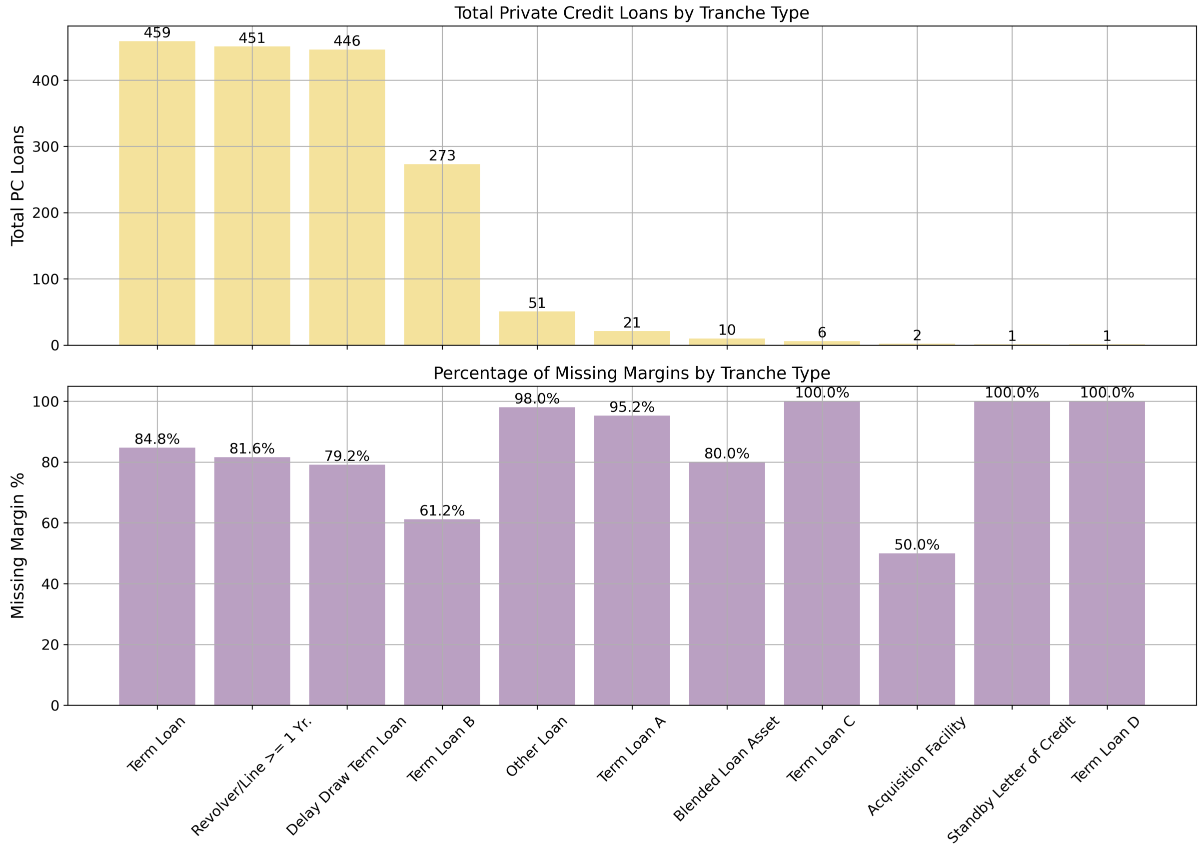


Figure 3.7: Excluded PC Loan Types

Whilst this chapter provides strong evidence of pricing differences across loan types and between bank and private credit lenders, it is restricted by missing margin data and lack of borrower-specific controls. The opacity of private credit markets results in the difficult identification of loan-level pricing drivers. To better understand lender behavior in the private credit market, the next chapter shifts focus to the risk-taking incentives of private credit funds themselves.

Chapter 4

Risk-Taking and Incentives in BDCs

The analysis of BDC performance to research private debt is a methodology used by the growing literature such as Chernenko et al. (2025), Suhonen (2024), Munday et al. (2018), and Haque, Jang, et al. (2025). This chapter examines how incentive structures in Business Development Companies influence their risk appetite, and whether larger, more leveraged firms are further prone to this risk. Firstly, it presents two models that capture the risk-taking incentives set by significant PC funds in their compensation structure. Then, it shows the data used to estimate the mentioned models. After reporting the results, this chapter concludes with the significance and limitations of its findings.

4.1 Models

There are several presuppositions that I hold true for the creation of this chapter's models. I use BDCs as a proxy for a PC fund, and presume that operations are similar to the other. While Zawadowski and Albuquerque (2025) shows that BDCs act more like banks in this aspect and they can roll over loans, my model aligns more closely with Suhonen's (2024) framework. Thus assumes a finite fund horizon, leading managers to maximize short-term returns. Moreover, I suppose relative operational homogeneity across BDCs. Their compensation structures, leverage strategies, and reporting practices need to be similar for an accurate estimation. Although some heterogeneity exists, I control for unobservable firm-specific differences using fixed effects. Thereafter, I assume causal directionality. Risk levels are affected by compensation structures and leverage, not vice versa. If this inference is violated, and managers adjust their compensation structures in response to anticipated risk, it leads to biased estimates due to simultaneity bias.

I hypothesize that compensation structures in BDCs, encourage fund managers to take on more risk. These incentives become more powerful when combined with higher leverage. In this setup, managers benefit financially if returns exceed a target but face limited downside if performance weakens. This imbalance motivates them to pursue higher-yielding, and often riskier, investments to maximize their compensation. The model builds on the principal-agent problem, where the goals of investors and fund managers are not perfectly aligned. When compensation emphasizes upside without penalizing downside, managers are more likely to engage in behavior that increases volatility. As leverage rises, the consequences of these decisions become more significant, since small changes in asset values can lead to large movements in returns. This creates a reinforcing cycle, where the pursuit of strong returns leads to riskier strategies. The following equation estimates two panel regressions.

$$\begin{aligned}\text{Risk}_{it} &= \beta_0 + \beta_1 \cdot \text{Incentive Fee}_{it} + \beta_2 \cdot \text{Leverage}_{it} \\ &\quad + \beta_3 \cdot (\text{Incentive}_{it} \times \text{Leverage}_{it}) + \beta' \cdot \mathbf{X}_{it} + \gamma_i + \delta_t + \varepsilon_{it},\end{aligned} \tag{4.1}$$

where i notes a private credit fund and t the year. γ_i controls for fund fixed effects, δ_t for time fixed effects, and ε_{it} is the error term. The interaction term, $(\text{Incentive Fee}_{it} \times \text{Leverage}_{it})$, estimates whether the combination of incentives and high leverage leads to different risk-taking behavior than either factor alone. The vector $\mathbf{X}_{it}$ includes a set of control variables such as fees, and expenses.

The main variables of interest are the Incentive Fee, the performance-based compensation of the fund manager, and Leverage. Leverage is defined as:

$$\text{Leverage}_{it} = \frac{\text{Total Debt}_{it}}{\text{NAV}_{it}} \tag{4.2}$$

where,

$$\text{NAV}_{it} = \text{Assets}_{it} - \text{Liabilities}_{it}$$

Based on Equation 4.1, two models are created. The first model (Equation 4.3) measures credit risk directly, using Non-accrual Loans (%) of the fund's portfolio. These are the loans which have unpaid principal or interest payments for more than 30 days or loans where there is probability of default (Ares Capital Corporation, 2025). This variable is used as a direct proxy for credit risk.

$$\begin{aligned}
\text{Model 1:}\quad \text{Non-accrual}_{it} = {} & \beta_0 + \beta_1 \cdot \text{Income Based Fee}_{it} + \beta_2 \cdot \text{Leverage}_{it} + \\
& + \beta_3 \cdot (\text{Income Based Fee}_{it} \times \text{Leverage}_{it}) + \\
& + \beta_4 \cdot \text{Base Management Fee}_{it} + \beta_5 \cdot \text{Operating Expenses}_{it} + \\
& + \gamma_i + \delta_t + \varepsilon_{it}, \qquad (4.3)
\end{aligned}$$

The second model (Equation 4.4) is estimated using the sum of Realized and Unrealized Gains/Losses. It shows how much the investment's value changed because of market prices and decisions the company had made (Ares Capital Corporation, 2025). Furthermore, changes in total realized and unrealized gains/losses can be used as a proxy for managerial decision-making and risk-taking. Barth et al. (2001) argue that fair value based gains and losses reflect the decisions made by managers.

$$\begin{aligned}
\text{Model 2:}\quad \text{Gains/Losses}_{it} = {} & \beta_0 + \beta_1 \cdot \text{Income Based Fee}_{it} + \beta_2 \cdot \text{Leverage}_{it} + \\
& + \beta_3 \cdot (\text{Income Based Fee}_{it} \times \text{Leverage}_{it}) + \\
& + \beta_4 \cdot \text{Base Management Fee}_{it} + \beta_5 \cdot \text{Operating Expenses}_{it} + \\
& + \gamma_i + \delta_t + \varepsilon_{it}, \qquad (4.4)
\end{aligned}$$

Due to the use of panel data, both models include fixed effects for firm and year, to control for unobserved heterogeneity across entities and time. The interaction term tests whether the effect of compensation on risk intensifies under higher leverage. I used mean-centering to improve interpretation and reduce multicollinearity between the interaction and its constituent term. The control variables for both models were Management Fee, and Total Operating Expenses. Since each of these factors can influence credit risk independently, controlling for these confounding variables is necessary for a robust model.

4.2 Data

In the last chapter, 94.4% of private credit loans in the used loan-level data occurred in the United States.

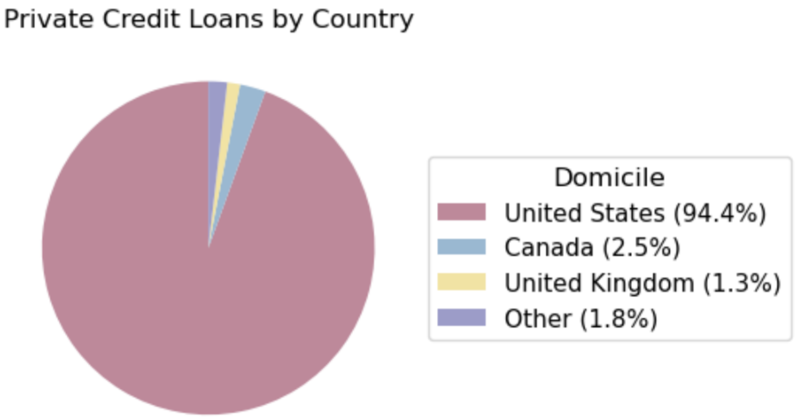


Figure 4.1: Private Credit Loans by Country

Furthermore, Avalos et al. (Avalos et al., 2025) reports that 20% of the PC market are occupied by BDCs. Additionally, since publicly available filings exist for BDCs, they are commonly used to draw conclusions about an otherwise data-scarce part of private credit markets (IMF, 2024b; Chernenko et al., 2025; Suhonen, 2024; Zawadowski and Albuquerque, 2025).

4.2.1 Data source

I produced a panel data from 10K Annual Filings of 25 publicly listed business development companies from 2018 to 2024. These companies were chosen based on Suhonen (2024) and Cai and Haque's (Cai and Haque, 2024) sample of BDCs used in their analysis. These funds include the largest BDCs in the U.S. direct lending space, such as Ares Capital Corporation, FS KKR, and Blue Owl Capital. The list of BDCs taken into account is presented in Table B.1 in Appendix. One BDC (Saratoga Capital Corp.) lacks data of 2024, resulting in a panel of 174 observations.

4.2.2 Variables and descriptive statistics

The used financial term definitions are defined in Table B.2 in Appendix B. The most important variables are outlined below. *Income Based Fee:* It is a performance-based fee, usually a bonus, that BDC managers earn if their fund's Net Investment Income exceeds a threshold (called hurdle rate). This variable will be the Incentive Fee modeled in Equation 4.1

Non-accrual Loans (%): It is the percentage of loans that are in default compared to the firm's total portfolio. High percentage of Non-accrual Loans mean high credit risk. Figure 4.2 shows the average share of non-accrual loans. There is a significant increase in 2020 and 2022, which could reflect shocks such as the pandemic, or the sharp increase of interest rates in 2022. Overall, this trend suggests that PC is sensitive to macroeconomic changes, in accordance with literature (Aramonte and Avalos, 2021).

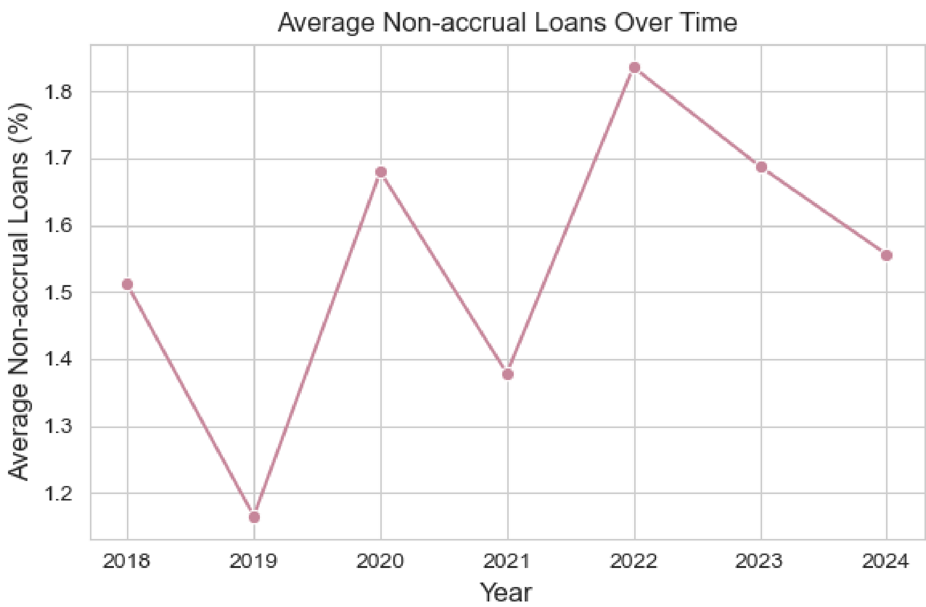


Figure 4.2: Average Non-accrual Loans between 2018-2024

Leverage: The use of leverage intensifies the changes in returns in both directions. In 2018, the

Small Business Credit Availability Act (SBCAA) allowed business development companies to have 1:2 leverage ratios. After, most BDC's increased their use of leverage. Figure 4.3 shows how leverage and non-accrual loans relate in a scatterplot. There is no visible strong correlation, which suggests here leverage does not explain credit risk fully. The scatter plot also shows that on three occasions, the BDC used higher leverage than it is allowed.

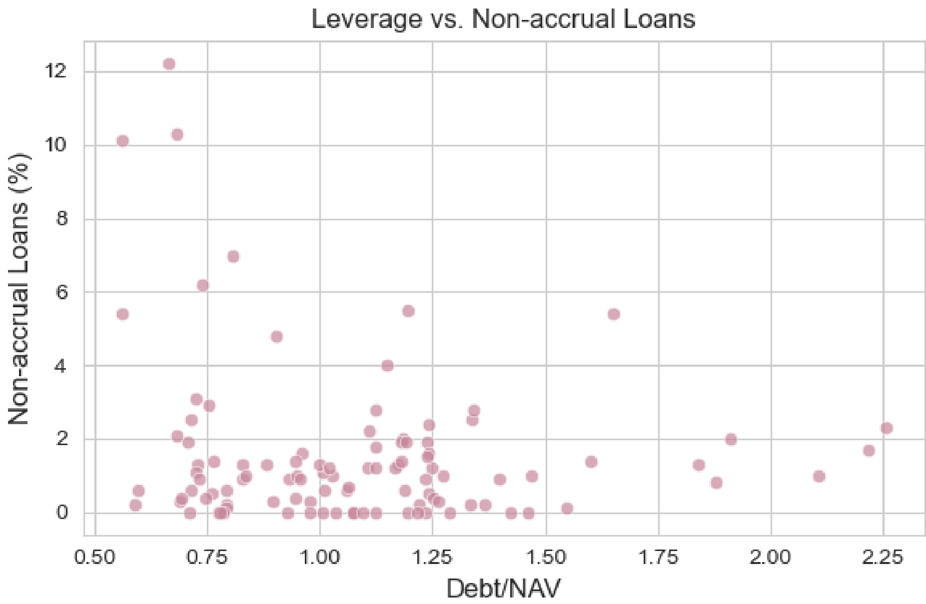


Figure 4.3: Leverage vs. Non-accrual Loans

Table 4.1 shows the descriptive statistics of significant variables in BDCs.

Table 4.1: Descriptive Statistics of Key Variables

Variable	Count	Mean	Std. Dev.	Min	25%	50%	75%	Max
Non-accrual Loans (%)	103	1.55	2.15	0.00	0.30	1.00	1.85	12.20
Total Gains/Losses (USD bn)	167	-0.02	0.19	-1.06	-0.05	-0.01	0.03	0.96
Leverage	174	1.09	0.34	0.40	0.81	1.08	1.27	2.26
Net Asset Value (USD bn)	174	1.62	2.23	0.13	0.34	0.84	1.51	13.36
Base Management Fee (USD bn)	160	0.05	0.06	0.00	0.01	0.02	0.05	0.32
Income Based Fee (USD bn)	154	0.03	0.05	-0.00	0.01	0.02	0.03	0.33
Operating Expenses (USD bn)	167	0.17	0.25	0.02	0.04	0.08	0.16	1.51

Non-accrual loan (%) shows a right-skewed distribution, suggesting low levels of loans in default for most BDCs. However, the few outliers experience substantial credit stress. The number of Non-accrual loans (103) also reflects missing observations, which will reduce the effective sample size in risk-related regressions. Leverage (Debt/NAV) shows moderate variation, with most values between 0.8 and 1.3. A few firms operate at much higher leverage ratios, potentially reflecting differing investment strategies or regulatory thresholds. Net Asset Value (USD bn) varies, with a median of 0.84 and a maximum of over 13 billion, highlighting the disparity in fund sizes within the market.

4.3 Results

I present in Tables 4.2 and 4.3 the panel OLS estimation results for Models 1 and 2, where the dependent variables are the share of non-accrual loans and total gains/losses, respectively. As I am working with panel data, serial correlation and heteroskedasticity of the errors is a concern. Therefore, I cluster robust standard errors at the entity level (Wooldridge, 2009). All models include entity and time fixed effects to account for unobserved heterogeneity across firms and over time.

Table 4.2: Model 1 Regression Result

Variables	**Full Model**		
Intercept	0.7273	0.8385	0.7837
	(1.7643)	(1.5661)	(1.7147)
Income Based Fee (USD bn)	-3.8869	2.4774	-2.5532
	(19.353)	(4.9739)	(19.520)
Leverage	0.5539	0.6829	0.6292
	(1.1364)	(1.3075)	(1.2064)
Incentive × Leverage	15.060	17.992	17.426
	(9.6689)	(12.314)	(11.659)
Base Management Fee (USD bn)	6.2142	–	5.4656
	(21.778)	–	(21.550)
Operating Expenses (USD bn)	0.6083	–	–
	(1.4475)	–	–
R-squared (within)	0.0257	0.0198	0.0210
F-statistic (robust)	0.5163	0.7908	0.6771
P-value	0.7629	0.5036	0.6104
Observations	87	87	87
Fixed Effects	Entity, Time	Entity, Time	Entity, Time

Note: Robust standard errors clustered at firm level are in parentheses. All models estimated via PanelOLS. The dependent variable is Non-accrual Loans (%).

Table 4.2 shows the results for Model 1 does not provide evidence for a link between managerial incentives and loan performance. The coefficient for Incentive×Leverage is positive and large, however given the large standard errors, these estimates are not statistically significant. Similarly, the coefficients for Income Based Fees and Base Management Fees vary and lack significance.

Table 4.3: Model 2 Regression Result

Variables	**Full Model**		
Intercept	0.0780	0.0630	0.0731
	(0.0616)	(0.0741)	(0.0676)
Income Based Fee (USD bn)	0.9940	-2.0563	0.5703
	(3.9056)	(1.6652)	(4.2344)
Leverage	0.0490	-0.0030	0.0307
	(0.0310)	(0.0275)	(0.0432)
Incentive $\times$ Leverage	4.0448***	3.0073***	3.3298***
	(0.6064)	(0.6737)	(0.6685)
Base Management Fee (USD bn)	-3.0870	–	-2.8860
	(3.1335)	–	(3.0722)
Operating Expenses (USD bn)	-0.1638	–	–
	(0.1890)	–	–
R-squared (within)	0.0953	0.0834	0.0845
F-statistic (robust)	15.573	18.624	19.971
P-value	0.0000	0.0000	0.0000
Observations	150	150	150
Fixed Effects	Entity, Time	Entity, Time	Entity, Time

Note: Robust standard errors clustered at the entity level are in parentheses. $^{***}p<0.01$. All models estimated via PanelOLS. The dependent variable is Total Gains/Losses (USD bn).

In contrast, Table 4.3 reports that 9.5% of the variation in gains/losses can be explained by the chosen variables. The regression has highly significant F-statistics and p-values across all the three versions of the model. The Incentive$\times$Leverage coefficient is consistently positive and significant across specifications, ranging from 3.3 to 4.0, with robust standard errors. This suggests that stronger incentive alignment with leverage is associated with higher realized gains. By contrast, Income-Based Fees and Base Management Fees show inconsistent signs and significance depending on the control specification, showing that they might correlate with each other or the interaction term and cause multicollinearity. Operating Expenses have no significant effect on outcomes in either model.

My findings provide mixed support for the theoretical expectation that stronger incentive structures in private credit funds are associated with greater credit risk and performance volatility. While the results for non-accrual loans (Model 1) offer no statistical evidence for risk-taking, the results from Model 2 suggest that incentive-aligned managers do achieve higher realized gains and losses, especially when leverage is high. This supports the view that fund managers, driven by performance-based compensation, may engage in more aggressive or risk-exposed strategies. Importantly, the significant interaction effects in Model 2 align with my hypothesis that incentive-driven decision-making is conditional on the level of leverage.

4.4 Discussion

This section discusses what the two models show about risk-taking incentives in BDCs, focusing on the interaction between leverage and performance-based pay. It connects the findings to recent literature. The final part outlines key limitations, including data constraints, model assumptions, and the endogeneity of leverage.

4.4.1 Interpretation and implication

The poor performance of Model 1 could be due to the few number of observations (87), and because the included fixed effects decrease the information left to estimate the model on. In contrast, Model 2 shows robust results with larger number of observations, and finds that BDC managers take higher risks when their firm is highly leveraged. One can argue that the risk that Model 2 captures eventually will affect Non-accrual loans, credit risk of a firm.

The constant effort by managers to surpass past performance (Aramonte and Avalos, 2021), the increased leverage usage (Avalos et al., 2025) predict an increased appetite for risk. Since returns are not tied to manager ability (Suhonen, 2024; Erel, Flanagan, et al., 2024) the chase for high profits will lead to riskier investment choices, especially as easier deals become scarcer. While defaults have remained low so far, this trajectory raises concerns about the long-term sustainability of current strategies. Thus, the hypothesis that risk-taking will intensify reflects not past failures, but the structural incentives and market dynamics we can observe today in private credit.

An important aspect to consider is that PE sponsorship of a BDC can influence the fund's decision-making. In my sample, the largest BDCs, Ares Capital Corp. is managed by Ares Management. Normally, regulated entities like BDCs are restricted under the Investment Company Act of 1940 from co-investing alongside affiliated funds managed by the same adviser, due to potential conflicts of interest. However, Ares and its affiliates received a "Co-Investment Exemptive Order" from the U.S. Securities and Exchange Commission (SEC) (Ares Capital Corporation, 2025). This practice is not uncommon. Haque et al. (2024) strengthens the implication of emerging conflict of interest with arguing that 80% of borrowers who acquire PC loans are owned by PE firms.

Debt investors increasingly care about firm performance (Lalafaryan, 2024). The returns BDCs chase, are set by their investors (Aramonte and Avalos, 2021; Cai and Haque, 2024), creating pressure to succeed. To attract capital, maintaining high returns are essential. However, this dynamic can mask hidden risks. Suhonen (2024) points out that the wide range of returns and performance persistence will hide extreme losses, thus increase tail risk.

4.4.2 Limitations

The main limitation of the analysis of compensation structure-encouraged risk-taking in this study is the lack of data in the evaluation. The first model only has 87 observation, and after controlling for fixed effects, the model does not have enough information. Furthermore, combining clustering with fixed effects in small samples can make the standard errors too big (Abadie, 2023).

Many balance sheet inconsistencies have emerged during data collection. Some BDCs did not provide explicitly provide their Non-accrual loans as a % to their whole portfolio, but as a sum of loan amounts. This inconsistent reporting decreased the total number of funds by 8. Hercules Capital, only provided the amortized cost of their non-accrual loans. Furthermore, BDCs follow different fiscal year-end reporting schedules. Most use the standard end of December, however, for example, Golub Capital BDC reports its fiscal year ending on November 30th, while Saratoga Investment Corp.'s ends at the end of February.

Furthermore, my defined models do not control for macroeconomic trends and market conditions, other than the implicit control of interest rate. Inflation, volatility, or looming recession could affect managers' decision-making, neither of which the two model take into account. Fund performance would be affected by policy changes (Aramonte and Avalos, 2021). I also did not include leveraged benchmarks or equity factors that BDC returns are sensitive to (Suhonen, 2024).

Lastly, I assume in both models, that leverage is exogenous, whereas Suhonen (2024) and Haque et al. (2024) found that BDCs can modify their leverage based on strategy, and future outlook. Thus leverage is both a cause and an effect and this creates simultaneity bias. A more robust design would require an instrumental variable that does not directly affect leverage, and use Two-Stage Least Square (2SLS) regression to have an exogenous leverage.

Chapter 5

Conclusion

This thesis investigated private credit in two ways. Firstly, it examined the disparity of pricing between loans offered by private credit funds and traditional banks, and the difference in pricing within private credit loan types. Secondly, it analyzed how compensation structures in business development companies, important PC entities, influence risk-taking behavior.

The first empirical analysis demonstrated that private credit loans carry, on average, a 170 basis point premium over comparable bank loans, even after controlling for loan characteristics such as tenor, security, and size. Term loans in private credit consistently had the highest spreads, while credit lines and alternative structures are priced lower. The large premium discrepancies between PC and bank loans suggest that there is significant asymmetric information between them. Although private credit remains difficult to regulate due to its opacity, targeted policy interventions are warranted. More transparent sharing of information should be expected both from lenders and borrowers.

The second part of the thesis revealed that compensation structures in highly leveraged business development companies increase the manager's risk appetite. While direct measures of credit risk (such as non-accrual loan rate) did not exhibit statistically robust results, the model faced severe data limitations. The performance sensitivity of BDCs indicate that private credit may mask risks not yet reflected in observed defaults. As leverage continues to rise and institutional investors seek high returns, there is a growing need to monitor how incentive structures affect funds. Without greater transparency or oversight, these structural pressures may contribute to vulnerabilities within the broader financial system.

Private credit's inherent opacity makes rigorous academic analysis difficult. Yet this is precisely why further study is essential. As this debt market grows and evolves into new areas, understanding its structure and behavior becomes increasingly important to ensure financial stability. The complexity and limited transparency of private credit should serve as motivation to investigate it more deeply. Future research should explore incentive structures in BDCs more thoroughly and rigorously using larger, standardized data. Additionally, the increasing interconnectedness of banks and private credit should be examined as it may amplify systemic vulnerabilities.

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Appendix A

Loan-level Analysis

A.1 Loan Definitions

Table A.1: Loan Features

Variable	Definition
Tranche Type	The type of loan.
Tranche Amount	The notional value of the loan tranche, expressed in US dollars for standardization.
Secured	Indicates whether the loan is backed by collateral
Seniority	The repayment priority of the loan in case of borrower default.
Tenor	The duration of the loan in months from issuance to maturity.
Margin (bps)	The interest rate spread, which represents the credit and risk premium charged to the borrower, applied over the base rate, expressed in basis points (1 basis point = 0.01%)
Category	Lender classification indicating whether the deal was made by a traditional bank or a private credit institution.

A.1.1 Loan Types

Table A.2: Definitions of Loan Types

Tranche Type	Definition
Term Loan	A loan provided for a fixed amount and duration, repaid in scheduled payments over time.
Revolver/Line $\geq$ 1 Yr	A revolving credit facility with a maturity longer than one year, borrowers can draw, repay, and redraw funds up to the loan limit.
Delay Draw Term Loan	A term loan where the borrowers can draw portions of the loan over a defined time window, allowing flexible capital use.
Term Loan B	A subtype of syndicated loans aimed at institutional investors, they tend to be more leveraged, have longer maturities, and fewer covenants compared to Term Loan A.

Table A.3: Tenor Statistics by Tranche Type within Private Credit Loans

Tranche Type	Count	Mean	Std. Dev.	Min	25%	Median	75%	Max
Delay Draw Term Loan	424	64.19	17.41	2.0	53.75	71.0	75.5	96.0
Revolver/Line $\geq$ 1 Yr.	414	63.67	14.49	12.0	58.25	72.0	72.0	90.0
Term Loan	426	63.41	17.82	10.0	51.00	67.0	72.0	96.0
Term Loan B	255	64.77	15.03	22.0	54.00	66.0	79.5	87.0

A.1.2 Seniority Type

Table A.4: Loan Seniority by Lender

Seniority Type	Private Credit	Bank
Senior	100%	99.87%
Subordinated	—	0.12%
Junior Subordinated	—	0.01%
Senior Subordinated	—	0.002%
Unclassified / Missing	—	0.02%

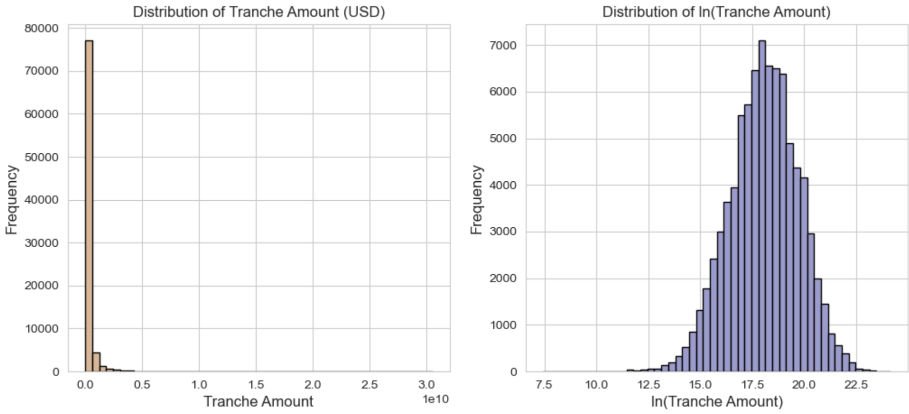

Figure A.1: Distribution of Tranche Amount vs ln(Tranche Amount)

A.1.3 Loan Amount Distributions

A.2 Direct Lending Data Comparison Over the Years

Year	Refinitiv Data (USD bn)	BIS Data (USD bn)
2015	0.42	38.56
2016	0	29.39
2017	0.71	70.62
2018	4.32	55.60
2019	10.64	87.03
2020	10.50	60.69
2021	47.75	143.97
2022	36.99	77.66
2023	34.02	68.57
2024	125.32	–

Table A.5: Private Credit Loan Amounts by Year: Comparison of Refinitiv and BIS Data

Appendix B

BDCs

B.1 BDC Sample

Table B.1: List of 25 BDCs Used

Company Name	Ticker	Company Name	Ticker
Ares Capital Corporation	ARCC	FS KKR Capital Corp	FSK
Blue Owl Capital Corporation	OBDC	Main Street Capital Corporation	MAIN
Golub Capital BDC Inc.	GBDC	Hercules Capital Inc.	HTGC
Sixth Street Specialty Lending Inc.	TSLX	Oaktree Specialty Lending Corp.	OCSL
Bain Capital Specialty Finance Inc.	BCSF	Barings BDC Inc.	BBDC
Monroe Capital Corporation	MRCC	New Mountain Finance Corp.	NMFC
Prospect Capital Corporation	PSEC	Gladstone Capital Corporation	GLAD
Gladstone Investment Corporation	GAIN	BlackRock TCP Capital Corp.	TCPC
Saratoga Investment Corp.	SAR	SLR Investment Corp.	SLRC
Stellus Capital Investment Corp.	SCM	TriplePoint Venture Growth BDC	TPVG
Horizon Technology Finance Corp.	HRZN	WhiteHorse Finance Inc.	WHF
Fidus Investment Corporation	FDUS	Crescent Capital BDC Inc.	CCAP
Oxford Square Capital Corp.	OXSQ		

B.2 BDC Balance Sheet Definitions

Table B.2: Financial Variable Definitions

Variable	Definition
Non-accrual Loans (%)	Share of the loan portfolio for which interest payments are no longer expected to be collected. This indicates borrower distress and serves as a proxy for portfolio credit risk. It is reported in BDC 10-K filings under non-performing or impaired loans.
Total Gains/Losses (USD bn)	The sum of realized and unrealized capital gains and losses, reflecting changes in the fair value of investments and actual exits. This captures both market-driven valuation changes and strategic investment performance.
Debt/NAV	Ratio of total outstanding debt to Net Asset Value (NAV), measuring financial leverage. A higher ratio indicates more reliance on debt financing relative to equity.
Net Asset Value (USD bn)	Total assets minus total liabilities, representing shareholders' equity. This is the base capital available to invest and absorb losses.
Base Management Fee (USD bn)	Annualized fixed fee earned by the BDC manager, usually calculated as a percentage of gross assets or assets under management (AUM). This represents compensation regardless of performance.
Income Based Fee (USD bn)	Variable fee component linked to investment income, typically calculated as a percentage of net investment income above a hurdle rate. Incentivizes managers to maximize recurring cash flows.
Operating Expenses Total (USD bn)	Sum of general, administrative, and operational costs not directly tied to interest or debt servicing. Includes employee salaries, legal fees, audit costs, and office expenses.