

Online Appendix

Supplementary Material for:

*PIK Now and Pay Later -
How Deferred Interest Reshapes Private Credit*

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OA.1 Model Appendix

OA.1.1 Repayment rate and the equity-debtholder conflict

In the main body of the paper, we focus our analysis on repayment payoff R such that $R \in (0, V_M - D]$. A natural question is can the debtholder and equityholder negotiate a repayment rate R outside the boundaries $R \notin (0, V_M - D]$ such that the safe project becomes more attractive than the risky project for the equityholder or so that debtholder itself willing to finance the project while understanding that the equityholder would take the risky project? The short answer is "no". To see why, consider first setting the repayment rate R as high as possible to extract more rents from the good state of the risky project to boost its attractiveness. At the extreme case, the debtholder captures all the surplus in the high state by setting $R = V_H - D$. However, by Assumption 2 this would still not be enough to make the risky project dominate the liquidation option for the debtholder. Moreover, any $R > V_M - D$ would effectively remove the equityholder's incentives to take on a safe project in the first place as her payoff from the safe project would then become negative, making her prefer liquidation over the safe project. Alternatively, the debtholder could try to persuade the equityholder to take the safe project by setting R very low. Now the lowest debtholder could set R with still being at least indifferent between safe project and liquidation is $R = 0$, because setting $R < 0$, would imply that $D + R - I < \theta D$ by Assumption 3. However, this would not be enough to change equityholder's preferences toward safe projects as the first condition in Assumption 3 implies that $p(V_H - D) > V_M - D$. Clearly, changing the interest rate for the follow-up investment or lender's concessions is not enough to solve the conflict of interest between debt-and equityholder.

OA.1.2 Solutions to the equity-debtholder conflict:

We showed above how there does not exist a repayment rate R that can solve the conflict of interest between equityholder and debtholder. Thus, the equityholder would like to

give the debtholder some credible guarantee that she will choose the safe project when receiving funding, because otherwise the debtholder is forced to liquidate. We discuss two solutions to overcome inefficient liquidation, which have been identified by previous literature (see e.g. [Green \(1984\)](#)) and summarize the results in Proposition 1.

Solution 1 - An equity injection from PE sponsor: PE sponsor of the firm, here the equityholder, injects equity J into the firm. This additional equity can act as a commitment device for the equityholder because we can show that she now prefers the safe project over the risky one if

$$\begin{aligned} V_M - D - R + J - J &> p(V_H + J - D - R) + (1 - p) \min\{V_L + J - D - R, 0\} - J \\ \Rightarrow (1 - p)J &> p(V_H - D - R) - (V_M - D - R) \end{aligned}$$

The second line follows when we assume $J \leq D + R - I - V_L$, which implies $\min\{V_L + J - D - R, 0\} = 0$.¹ So intuitively when the expected loss from the equity injection (LHS of equation in the bottom row) exceeds the expected increase in equity value from choosing the risky project over the safe project (RHS of equation in the bottom row) then the equityholder can credibly commit to the safe project and debtholder is thus willing to lend.

Solution 2 - The debtholder receives a warrant: Warrants (also called "equity kickers") are a classic feature in many private debt or venture debt contracts. They are effectively call option securities issued by the company that give the holder the right (but not the obligation) to purchase company stock at a specified price within a specific period.²

In our setup, debtholder receives a warrant that gives the equity holder the right to purchase α fraction of the firm's equity at price $E_M = V_M - D - R$, where we have normalized the total number of firm shares to one. So warrant is a call option with value $W = \alpha \mathbb{E}[\max\{E - E_M, 0\}] = \alpha \mathbb{E}[\max\{V - D - R - (V_M - D - R), 0\}]$ with E and V being

¹When $J \geq D + R - I - V_L$, then the equityholder fully insures the debtholder, making the risky project safe for the lender. However, this can be an excessively costly way for the equityholder to commit to the safe project.

²While we focus on warrants, similar outcomes can be obtained using other types of securities with similar equity optionality, such as convertible debt.

random variables. The warrant gives the debtholder access to profits if the risky project is chosen and V exceeds V_M . Thus, the debtholder will exercise the warrant only in the high state when $V_H > V_M$ while in the low state the warrant expires worthless. Thus, the value of the warrant is $W = \alpha p(V_H - V_M)$.³

After giving the debtholder a warrant, the equityholder prefers the safe project over the risky one if

$$\begin{aligned} V_M - D - R &> p(V_H - D - R) - \alpha p(V_H - V_M) \\ \Rightarrow \alpha &> \frac{p(V_H - D - R) - (V_M - D - R)}{p(V_H - V_M)} = \frac{pE_H - E_M}{p(E_H - E_M)} > 0 \end{aligned}$$

As long as the debtholder's profits exceed this level, then the equityholder can commit to taking the safe project.

OA.1.3 Banks versus Private Debt lenders as liquidity providers

[Haque, Mayer, and Stefanescu \(2024\)](#) show that many private debt borrowers also rely on bank credit lines for their continuation financing. However, despite the existence of such options for borrowers, it may not be optimal for the Private Debt lender to always allow banks to do the continuation financing for them. This is because what might be good for the bank may not be optimal for the existing lender.

OA.1.3.1 Case 1: Risky project is inefficient and borrower cannot commit

To see why, let us abstract away from the use of warrant and equity injections, and assume that a private debt lender is not willing to provide continuation funding I , but a risk-neutral bank is willing to do this instead in exchange for a final payoff of R . And to show that our argument holds even when there is no direct dilution in the claim of the

³While we introduce this solution by speaking in terms of warrants, the debt contracts often include similar call option-like securities that also generate the same result, such as convertible debt and preferred shares. Thus, in the empirical part, we use the dual-holding variable as a proxy of the presence of such securities.

existing debtholder, let's assume that the bank's debt claim is junior relative to that of the private debt lender. This is typically not the case, but assuming that the two debt claims are paid at pari-passu or that the bank credit line is senior to that of the private debt lender, simply strengthens the point we make below.

With the other lender, the equityholder's analysis is the same as before. From her perspective, it does not matter whether there is one debtholder with claim $D + R$ or two debtholders with claims D and R respectively.

We need to show that the bank may be willing to provide (junior) continuation funding for the borrower even when the private debt lender would prefer liquidation. Since the borrower cannot commit to abstaining from the risky project, the bank is willing to lend only if the project generates a positive NPV for him, that is, when

$$pR - I \geq 0 \tag{1}$$

Since we have assumed that bank debt is junior to PD debt, then in the low state of the risky project, the remaining asset value V_L goes to the existing debtholder in its entirety. Now, the PD lender is happy to let the risky project go on with the benefit of the bank-provided continuation financing, only if

$$pD + (1 - p)V_L \geq \theta D \tag{2}$$

but in the main body of the paper, we showed that under reasonable values of R ,

$$pD + (1 - p)V_L + pR - I < \theta D \tag{3}$$

which implies that $pD + (1 - p)V_L < \theta D$ when $pR - I \geq 0$ leading to a contradiction.

The important takeaway is that when the risky project is inefficient and dominated by liquidation and there are no credible commitment from the borrower from abstaining from it then even if the new lender would be willing to provide continuation financing for the borrower (with rate R such that $pR - I \geq 0$) then this transaction should be blocked by

the old lender (e.g. with covenants) and liquidate the firm instead.

OA.1.3.2 Case 2: Risky project is efficient and borrower cannot commit

Things may be different when the risky project is a more efficient option than liquidation. That is, let us replace Assumption 2 and instead assume that

Assumption 1. $\theta D < pV_H + (1 - p)V_L - I$

As there exists a surplus over the liquidation option, the existing lender can now directly negotiate a rate R that allows the lender to break even. We can abstract away from the safe project for now by assuming the borrower cannot commit to it. Lender is indifferent between liquidation and a risky project as long as that

$$\begin{aligned}\theta D &= p(D + R) + (1 - p)V_L - I \\ \Rightarrow R &= \frac{(\theta - p)D - (1 - p)V_L + I}{p}\end{aligned}$$

And since $R < V_H - D$, then the borrower also receives a positive payoff $V_H - R - D > 0$ from the risky project, thus avoiding the inefficient liquidation.

But [Haque et al. \(2024\)](#) observes that in many cases in the US middle market, the banks are providing the liquidity provision for borrowers that have issued term loans to PD-lenders. So why would the PD-lender be willing to let the bank provide the continuation financing?

The reason we observe arrangements where banks provide liquidity insurance in the form of credit lines, while PD-loans focus on term loans, might be because there are reasons why the banks can do liquidity provision more efficiently relative to PD-lenders. A simple way to capture this comparative advantage of banks is to assume that the investment I_{PD} from the PD lender involves some origination costs that are transferred to the borrower. Still, the bank can avoid these costs so the investment it needs to provide to keep the firm

alive are strictly lower than what it would be if PD-lender were to provide it $I_B < I_{PD}$.⁴ Then, as long as the following conditions hold

$$pR - I_B \geq 0 \tag{4}$$

$$pR - I_{PD} < 0 \tag{5}$$

$$pD + (1 - p)V_L \geq \theta D \tag{6}$$

It is beneficial for both types of lenders to let the bank provide the continuation financing. The first line ensures that the bank finds it attractive to make the investment. The second line ensures that PD lender prefers to let bank do the follow-up investment rather than do it herself, as it also implies $p(D + R) + (1 - p)V_L - I_{PD} < pD + (1 - p)V_L$. The third line ensures that letting the risky project go on is a better option than liquidating the firm. We can collapse these equations to just two conditions

$$I_{PD} > I_B \tag{7}$$

$$p + (1 - p)\frac{V_L}{D} \geq \theta \tag{8}$$

These conditions suggest that PD-lender is willing to let the bank provide the continuation financing when the bank can provide the continuation financing more efficiently and the PD-lender's payoff from the risky project is sufficiently good that it exceeds the value of debt at liquidation.

⁴One could think these costs $I_{NB} - I_B$ arise from the fact that PD lender may not have that extra cash lying around. Thus, it needs to raise additional funding from its investors, sell existing assets, or withhold from other attractive investments. Bank on the other hand, keeps a high level of cash reserves due to the complementarities between deposits and credit lines and can relatively easily provide continuation financing (i.e., let credit lines be drawn) (Kashyap, Rajan, and Stein, 2002).

OA.2 Data Appendix

OA.2.1 Sample Construction

This appendix outlines the data cleaning steps applied to a BDC Collateral’s investment dataset, ensuring consistency, accuracy, and completeness. The process includes handling missing values, standardizing variable names, merging datasets, categorizing loan and investment types, and creating unique identifiers.

We construct the loan identifier using four identifying information: lender, borrower, seniority (e.g. "First Lien Senior Secured"), and loan type (e.g. "Term loan", "Revolver," etc). This identifier then allows us to track each loan across time. Typically, this tuple of four identifies a single loan, but in the rare cases when we observe multiple observations with the same identifier in the same year-quarter, we group these loans by summing the *Fair*, *Par* and *Cost* values of affected loans and calculating other loan characteristics as the par-value-weighted average of the loan characteristics.⁵

For seniority categorization, we rely on pre-existing BDC Collateral’s **securitytype** classification. When creating a loan type categorization, we again mainly rely on the existing **securityclassnormalized** variable of BDC Collateral. However, due to a number of missing observations, for this category, we fill in the missing variables based on the textual information in the **securitytyperaw** variable in BDC Collateral. This variable often has textual information that helps to assign the missing observations to BDC Collateral’s existing categories. For example, if the **securitytyperaw** variable contains the strings "Delay" and "Draw", we set the missing **securityclassnormalized** to "Delay Draw Term Loan". We do the same for term loans, revolvers, ABL loans, bonds, unitranche loans, and letters of credit.

⁵For example, for two loans (call them 1 and 2) with the same identifiers in the same period the new *Fair/Par* ratio is calculated as $\frac{Fair}{Par} = \frac{Fair_1}{Par_1} \frac{Par_1}{Par_1 + Par_2} + \frac{Fair_2}{Par_2} \frac{Par_2}{Par_1 + Par_2}$. In most cases these loan characteristics within a tuple are typically identical or very similar anyway.

Finally, since this `securityclassnormalized` has several categories with only a handful of observations, such as "Aircraft Loan" with only 19 observations, we group these miscellaneous items into a larger group called "Other". After this step, we have five security class categories called "Delay Draw Term Loan", "Revolver", "Term Loan", "Unitranche" and "Other". For observations with no security class information available, we allocate them to "Term Loan" category, which represents most of the loans.

We also use BDC Collateral's column `investmenttype` to classify loans into different control investment categories: "Controlled/Affiliated Investment", "Non-Controlled/Affiliated Investment", and "Non-Controlled/Non-Affiliated Investment". In rare cases where the same borrower-lender pair is allocated to more than one category in the same quarter, we set the control category to N/A. We follow this conservative approach also when assigning industry information and PE-sponsor identity: if there is conflicting information regarding the same borrower for the same period, we set the characteristic to N/A.

Since our main focus is on private credit, we drop three BDCs that do not fit this description. We drop MacKenzie Realy Inc and Terra Income Fund 6, which operate mainly as REITs and provide commercial real estate loans, and Newtek Business Services, which operates as a bank for a large part of the sample.⁶ Even at their largest, these companies covered less than 0.7% of the total market, so dropping them has little significance on the representativeness of the sample. After dropping these three, we are left with 215 BDCs.

When calculating fund age, we rely primarily on information about the date of incorporation or founding date from Pitchbook, and S&P Global. However, in the absence of information from these sources, we collect the dates of BDC inception date from SEC Edgar or internet searches and use those.

We also correct a few data errors in the BDC Collateral datasets. First, we manually

⁶Unlike most other BDCs that typically have approximately 100 borrowers in the portfolio, Newtek Business Services originates hundreds of tiny business loans, overwhelming the other loans in terms of number but not in economic importance. Including these loans would create unnecessary bias in any OLS estimate toward Newtek's portfolio.

check for rounding errors and other reporting errors for several investment-level variables. For example, when the interest rates have been reported as 500% typically the correct number is 5%. Similarly, there are cases of misreporting in the "all-in yield". We correct for this by calculating the all-in-yield ourselves using its definition ($All-in-yield = \max(Base\ rate, Floor) + Cash\ Spread + PIK\ Spread$) and our knowledge of the values of left hand side of the equation. In cases where no base rate is not reported at all, we assign the loan to be a fixed-rate loan, and our manual inspection verifies that the reported all-in-yield for these loans do not change between periods, even when typical reference rates like LIBOR experience shifts in levels. We also winsorize all the financial ratios (leverage, ROE, fair-to-par, etc) at 1% and 99% level.

OA.2.2 Pithbook based variables

We construct several variables using data from Pitchbook and then match them to BDC Collateral data. We can find a Pitchbook ID counterpart for 13201 firms out of 16562 unique borrower IDs in the BDC Collateral investment dataset.⁷

First, we control for borrowers' access to bank financing by tracking deals in Pitchbook where one of the lenders is classified as "Commercial Bank" or "Investment Bank". If the borrower has obtained a bank loan in the past five years, including the current quarter, then the variable "Has bank financing" takes a value of one, and zero otherwise.

Second, we use this deal information to find cases when the borrower has gone through a bankruptcy (either Chapter 11 restructuring or Chapter 7 liquidation). Dealtypes called "Out of Business", "Bankruptcy: Liquidation", or "Bankruptcy: Admin/Reorg" are classified as bankruptcy events. This allows us to construct a variable that takes a value of one

⁷Manual inspection of the unmatched firm IDs in BDC Collateral indicates that, from the matches that fail, often the reason is that there exists no firm name in BDC Collateral to match against, or the ID is associated with a CLO or another fund vehicle, for which Pitchbook does not offer a match. This is reassuring since our main focus is on the nonfinancial borrowers within the BDC portfolios, for which we find a match with high probability.

if the borrower experiences a bankruptcy at any future date, and zero otherwise, which we use in the Table 6.

Third, we construct a variable "PE Sponsored" that tracks a borrower's status as a private equity-backed company. We construct this variable by using the 2024Q2 snapshot of all the firms in Pitchbook (both active and inactive ones). First, we shrink the number of potentially PE-backed firms to those firms that are assigned as "Formerly PE-backed" or "Private Equity-Backed" that is, those that were PE-backed at any point in the sample. Then we render those "Formerly PE-backed" firms as non-PE-backed from the date their ownership status changes to something else (either "Acquired/Merged", "Acquired/Merged (Operating Subsidiary)", "In IPO Registration", "Out of Business", "Privately Held (no backing)", or "Publicly Held").

OA.2.3 Industry Classification

For industry information, we primarily use Pitchbook’s existing industry categories called `primaryindustrysector`. However, since we are unable to match all the companies between BDC Collateral and Pitchbook, for the remaining unmatched firms we augment these industry categories using industry information provided by BDC Collateral. Specifically, the investment dataset of BDC Collateral reports industry information associated with each portfolio company, but this information is not standardized and contains typos. We use ChatGPT to allocate these industries to Pitchbook’s `primaryindustrysector` categories to fill in the industry information for the remaining firms. Table A1 shows the mapping file generated by ChatGPT (after manually fixing the typos from the Industry column).

OA.2.4 Collecting information about PIK restrictions

In this section, we describe how we collect information about PIK-related restrictions in bank lending contracts to BDCs using a large language model.

We set up a multi-agent workflow that applies Retrieval Augmented Generation (RAG) to pull Paid-in-Kind (PIK) data from every 10-K and 10-Q filed by Business Development Companies. A parsing agent ingests each filing, and an indexing agent stores every page as a separate record in a document store; this page-level document store lets a keyword retriever return the full page whenever it finds terms such as “paid in kind” or “PIK,” keeping the exact source (income statement, cash-flow statement, narrative, or table) intact for later checks.

After retrieval, an extraction agent that uses GPT-4o Mini reviews the pages and produces structured items containing the date, PIK variable, value, and a source label. These items are grouped by company and reporting period, then passed to a summarization

Table A1: Industry Classification Table

Primary Industry Sector	Industry
Business Products and Services (B2B)	Business Services
Business Products and Services (B2B)	Services
Business Products and Services (B2B)	Shipping
Business Products and Services (B2B)	Transportation
Business Products and Services (B2B)	Wholesalers
Consumer Products and Services (B2C)	Beverage Food & Tobacco Processing
Consumer Products and Services (B2C)	Consumer
Consumer Products and Services (B2C)	Hotel & Gaming
Consumer Products and Services (B2C)	Leisure & Entertainment
Consumer Products and Services (B2C)	Restaurants
Consumer Products and Services (B2C)	Retail & Supermarket
Consumer Products and Services (B2C)	Textiles & Apparel
Energy	Energy
Energy	Oil & Gas
Energy	Utilities
Financial Services	Financial Services
Financial Services	Real Estate
Financial Services	REITS
Healthcare	Healthcare
Information Technology	Broadcasting
Information Technology	Media
Information Technology	Technology
Information Technology	Telecommunications
Materials and Resources	Aerospace & Defense
Materials and Resources	Agriculture
Materials and Resources	Automotive
Materials and Resources	Chemical Plastic & Rubber
Materials and Resources	Construction
Materials and Resources	Manufacturing
Materials and Resources	Mining
Materials and Resources	Paper & Packaging

agent that runs GPT-4o. GPT-4o merges overlapping filings, decides whether each figure relates to the firm’s own debt or to portfolio investments, and writes a concise JSON record for the company.

A validation agent handles quality control. It spots duplicate entries with the same CIK, quarter, and variable but with different values and asks GPT-4o to choose the most consistent number. Only the resolved results are kept. The finished dataset lists CIK, year, quarter, variable, value, page reference, whether the source came from a table or text, and whether it concerns debt or investments, giving analysts a clear, audit-ready

view of PIK obligations.

In the last step, we manually analyze the data and find that the word-pair "borrowing base" is consistently the best way to identify a case where the sentence in the regulatory filing contains information about the PIK usage dependent covenant structure. We identify all the BDCs that have these restrictions in place and use them in the analysis in Table 10.

OA.3 In what types of deals are PIKs used?

We use deal information and the BDC holding data from Pitchbook to conduct additional analysis. PIK usage varies across deal types. Table A2 shows PIK usage share for different deal types, focusing on deal types with at least 100 loans. Debt issued for general purposes such as working capital (*Debt - General*) is the largest category, followed by *Buyout/LBO* and *Debt Refinancing*. All three categories account for about 82% of loans in BDCs' portfolios. PIK usage shares range between 11% and 31% percent across these deal types, and riskier loans (such as those related to LBOs or leveraged recapitalizations) have higher usage shares.

Table A2: PIK Usage by Debt Type

This table shows the frequency of different deal types of BDC portfolio loans. *PIK share* is the fraction of loans for which borrowers have switched from cash to PIK payment. The data is from Pitchbook.

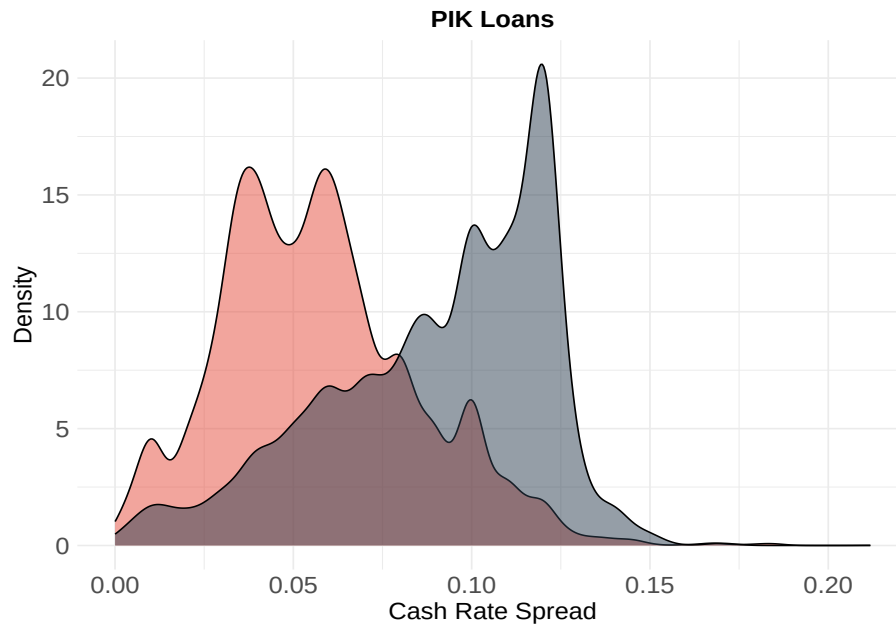
	Deal Type	PIK share	# of Loans
1	Debt - General	0.12	7,975
2	Buyout/LBO	0.16	2,850
3	Debt Refinancing	0.11	2,056
4	PE Growth/Expansion	0.20	860
5	Mezzanine	0.31	624
6	Dividend Recapitalization	0.11	455
7	Later Stage VC	0.19	219
8	Leveraged Recapitalization	0.16	160
	...		
	Other		478
	Total loans		15,677

OA.4 COVID-19 and PIK Usage

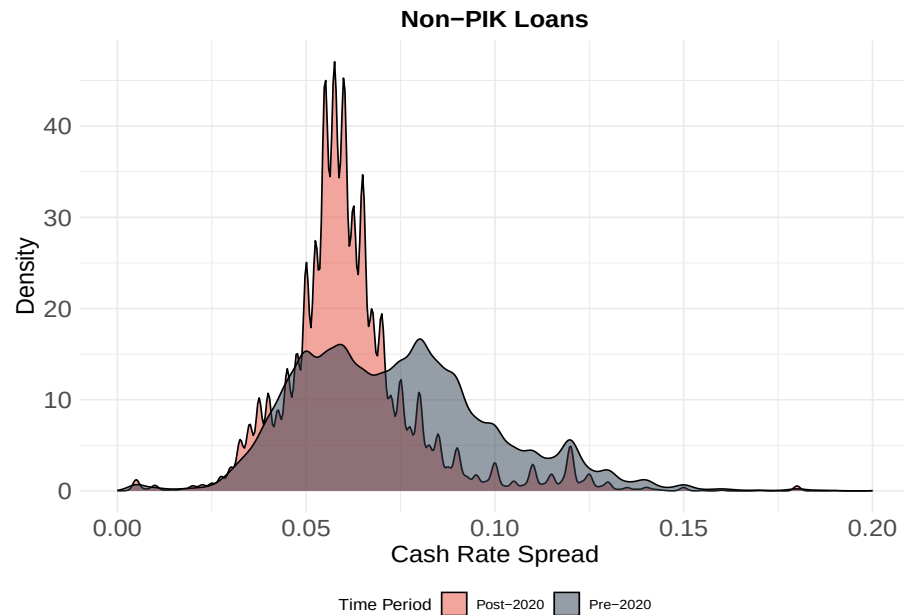
Figure A1: Use of PIK is moving to less risky borrowers

This figure shows the distribution of cash rate spread component of the loan for PIK- and Non-PIK-loans for pre- and post-2020 periods. We exclude loans with zero cash rate spread from both samples.

Panel A - PIK loans



Panel B - Non-PIK loans



OA.5 BDC Capital Structure

This section documents changes in the debt structure of BDCs over the period 2001Q1 to 2024Q4. To construct our time-series, we merge the Capital IQ and CRSP/Compustat databases. Following [Colla, Ippolito, and Li \(2013\)](#), we exclude BDC-quarter observations for which total debt reported in Compustat deviates by more than 10% from the sum of debt types reported in Capital IQ. This procedure yields a matched sample of 83 BDCs, providing detailed quarterly data on drawn and undrawn credit lines, term loans, bonds, and commercial paper issuances.⁸

Panel A of Online Appendix Figure [A2](#) illustrates the quarterly mean share of different on-balance-sheet debt items. Bank term loans and subordinated debt have traditionally played a minor role in BDC debt structures. As of 2024Q4, they account on average for about 10% of total BDC debt. BDCs predominantly finance themselves using drawn credit lines and corporate bonds, as discussed previously in the main text. Until 2009, drawn credit lines accounted for up to 70% of the BDC balance sheet. However, after the Global Financial Crisis (GFC), this share declined steadily while bond financing became increasingly prominent. Online Appendix Table [A3](#) quantifies this shift. Between 2001 and 2009, credit lines (bonds) accounted for 52% (31%) of total debt, whereas from 2010 to 2024, credit lines (bonds) accounted for 35% (53%), respectively. The observed shift between these two periods is highly statistically significant.

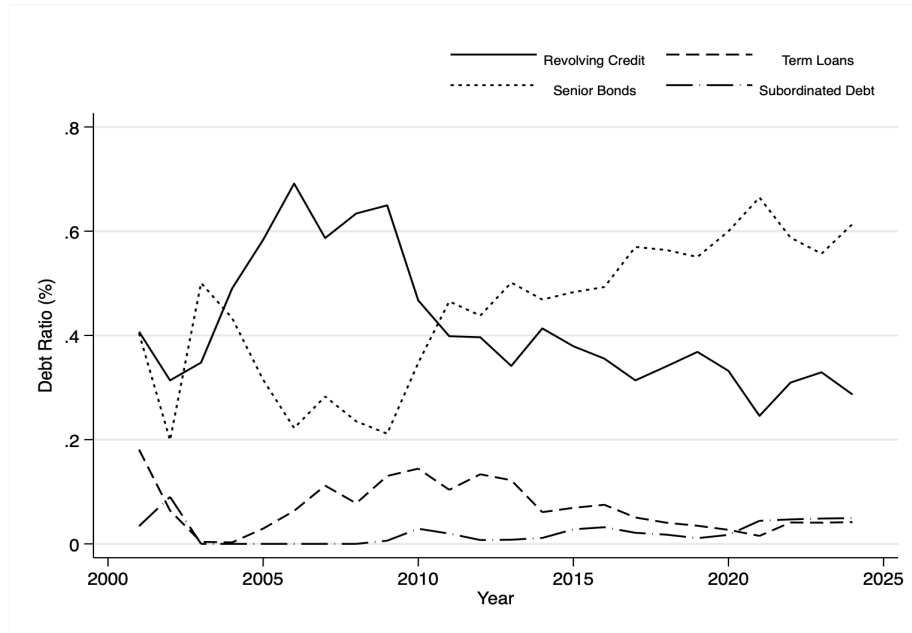
Panel B of Online Appendix Figure [A2](#) shows drawn and undrawn credit lines, both expressed as percentages of total debt. Notably, undrawn credit lines have also declined significantly. Before 2010, undrawn credit even exceeded total balance-sheet debt, but it declined to approximately 50% by the end of our sample period. Despite this reduction, undrawn credit remains substantial and, as discussed earlier, continues to play a crucial role in BDC liquidity management.

⁸Note that this analysis does not require merging with the BDC Collateral dataset.

Figure A2: BDC Debt Capital Structure

Panel A shows the average share of different debt structure items relative to total debt over the 2001 to 2024 period. Panel B shows drawn and undrawn credit lines (both as a percentage of total debt).

Panel A - Debt structure



Panel B - Credit line commitments

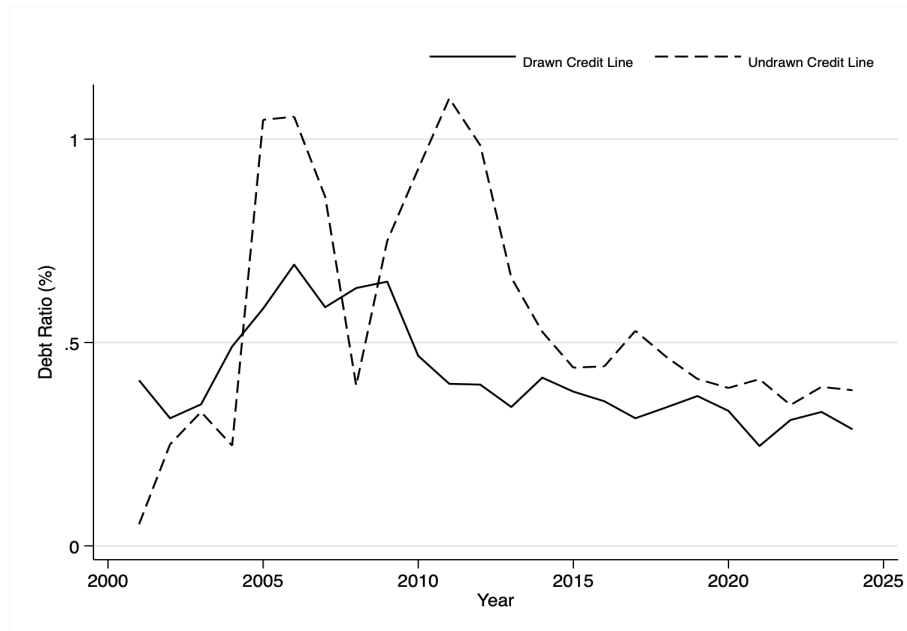


Table A3: BDC Capital Structure Over Time

This table shows the main capital structure components of BDCs (all relative to total debt). These include: Drawn credit lines (*Drawn CL*), *Term Loans*, *Senior Bonds* and Subordinated Bonds (*Sub. Bonds*). We show the mean for each year and then averages for the 2001 to 2009 and 2010 to 2024 periods, as well as the difference between both periods.

Year	Drawn CL	Term Loans	Senior Bonds	Sub. Bonds
2001	0.41	0.18	0.40	0.03
2002	0.31	0.06	0.20	0.09
2003	0.35	0.00	0.50	0.00
2004	0.49	0.00	0.43	0.00
2005	0.58	0.03	0.31	0.00
2006	0.69	0.06	0.22	0.00
2007	0.59	0.11	0.28	0.00
2008	0.63	0.08	0.24	0.00
2009	0.65	0.13	0.21	0.01
2010	0.47	0.14	0.35	0.03
2011	0.40	0.10	0.47	0.02
2012	0.40	0.13	0.44	0.01
2013	0.34	0.12	0.50	0.01
2014	0.41	0.06	0.47	0.01
2015	0.38	0.07	0.48	0.03
2016	0.36	0.08	0.49	0.03
2017	0.31	0.05	0.57	0.02
2018	0.34	0.04	0.56	0.02
2019	0.37	0.03	0.55	0.01
2020	0.33	0.03	0.60	0.02
2021	0.25	0.02	0.66	0.04
2022	0.31	0.04	0.59	0.05
2023	0.33	0.04	0.56	0.05
2024	0.29	0.04	0.61	0.05
(1) 2001-2009	0.52	0.07	0.31	0.01
(2) 2010-2024	0.35	0.07	0.53	0.03
$\Delta(2) - (1)$	-0.17***	-0.01	0.22***	0.01

OA.6 Other results

OA.6.0.1 Deferred interest at the intensive margin

Here, we restrict the sample to loans with a PIK option and focus on the intensive margin by examining whether a greater usage of PIK interest among PIK users leads to worse borrower outcomes. We construct a new variable $PIK\ Spread_{blkt}$ to capture the additional debt as our new explanatory variable.

We estimate the following regression using OLS.

$$NonAccrual_{blk,t+1} = \beta_1 PIK\ Spread_{blkt} + Controls + Fixed\ Effects + e_{blkt} \quad (9)$$

Using this specification, we test whether loans with higher PIK spreads are more likely to become delinquent compared to loans with lower PIK spreads—specifically, whether β_1 is positive. Table [A4](#) reports the results.

Column (1) shows a positive and statistically significant relationship between higher PIK spreads and borrower delinquency. To address the concern that unobservable borrower risk differences might drive this result, we introduce fixed effects, controlling for loan and borrower characteristics, and include *All-in-yield* as a control to ensure the finding is not merely due to higher overall interest rates. Further, restricting the analysis separately to PIK notes (columns 4-6) and PIK toggles (columns 7-9) confirms that higher PIK spreads consistently predict higher delinquency across both types of loans. Economically, the effect is substantial: Column (1) indicates that a 1 percentage point increase in PIK spread raises the probability of non-accrual status by 0.63 percentage points within four quarters.

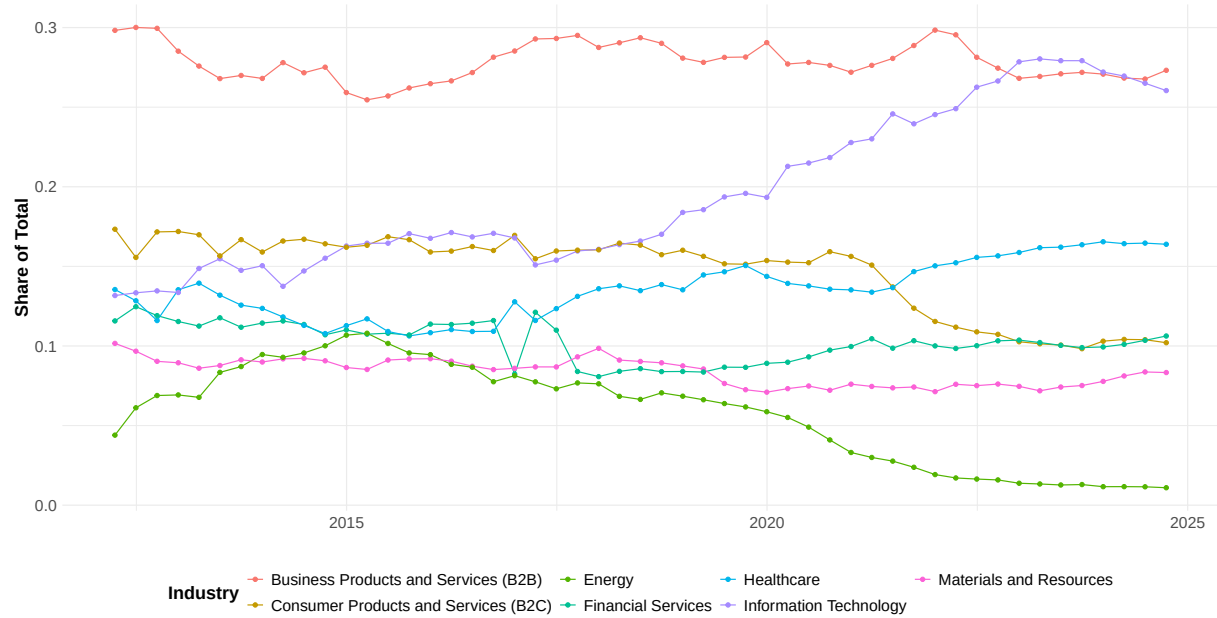
Table A4: PIKs and Loan Delinquency at the Intensive Margin

The results are based on loan-quarter level panel data. The sample for columns (1)-(3) contains all PIK loans, i.e. loans that pay PIK at any point during the loan lifetime. The sample for columns (4)-(6) contains PIK Notes, i.e. loans that pay PIK at every quarter during the loan's lifetime. The sample for columns (7)-(9) contains all PIK Toggles, i.e. loans that pay PIK at some quarters during the loan lifetime but not at every one. $PIK\ spread_t$ is a measure of the PIK component of the loan rate at time t . $NonAccrual_{t+1}$ on PIK_t and various control variables. $NonAccrual_t$ ($NonAccrual_{t+1}$) is an indicator variable that takes a value of one if the loan is reported as non-accrual for period t ($t+1$). $Maturity_t$ is the natural logarithm of the remaining time to maturity. $Fair/Par_t$ is the current valuation of the loan position. $LoanSize_t$ is the natural logarithm of the par value of the loan amount. $Fixedrate\ loan$ is an indicator variable that takes the value of one if the loan has a fixed interest rate. $Base\ rate_t$ is the loan's base rate at time t and zero if there is no base rate. $Dual\ holding_t$ is an indicator variable that takes the value of one if the BDC also has an equity stake in the borrowing firm. $PE\ Sponsored_t$ is a dummy variable that takes a value if the borrower is private equity sponsored in period t and zero otherwise. We include different fixed-effect combinations. BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter e.g. 2022Q4. $Borrower$ refers to the identity of the borrower. $Seniority$ refers to loan seniority. $LoanType$ refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, year-quarter and borrower level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variable:	NonAccrual _{t+1}								
	All PIK loans			PIK Notes			PIK Toggles		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Variables</i>									
PIK spread _t	0.35*** (0.05)	0.46*** (0.07)	0.44*** (0.07)	0.23*** (0.06)	0.70*** (0.15)	0.74*** (0.25)	0.47*** (0.07)	0.53*** (0.09)	0.52*** (0.08)
NonAccrual _t	0.87*** (0.01)	0.74*** (0.01)	0.73*** (0.01)	0.93*** (0.01)	0.72*** (0.02)	0.69*** (0.02)	0.85*** (0.01)	0.72*** (0.02)	0.71*** (0.02)
Loan Size _t	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00* (0.00)	0.01*** (0.00)	0.01** (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Base rate _t	0.06 (0.10)	0.13 (0.14)	0.08 (0.18)	-0.09 (0.13)	0.14 (0.33)	0.30 (0.52)	0.07 (0.13)	0.08 (0.18)	-0.02 (0.23)
Fixed rate loan	0.01* (0.00)	0.01 (0.00)	0.01 (0.00)	0.00 (0.01)	0.01 (0.02)	0.03 (0.02)	0.01** (0.00)	0.01 (0.00)	0.01 (0.01)
Maturity _t	-0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	-0.02*** (0.00)	-0.01** (0.01)	0.00 (0.01)	-0.01*** (0.00)	-0.01*** (0.00)	-0.01** (0.00)
Dual holding _t	-0.02*** (0.00)	-0.04*** (0.01)	-0.04*** (0.01)	-0.02*** (0.00)	-0.05*** (0.01)	-0.05** (0.02)	-0.02*** (0.00)	-0.04*** (0.01)	-0.04*** (0.01)
PE Sponsored _t	-0.01*** (0.00)	-0.03** (0.01)	-0.03** (0.01)	0.00 (0.00)	-0.04 (0.03)	-0.06* (0.03)	-0.01*** (0.00)	-0.03** (0.01)	-0.02 (0.01)
All-in-yield _t		-0.03 (0.10)	-0.02 (0.09)		-0.19 (0.15)	-0.21 (0.19)		-0.03 (0.12)	-0.01 (0.13)
<i>Fixed-effects</i>									
YearQtr	Yes	Yes		Yes	Yes		Yes	Yes	
Borrower		Yes	Yes		Yes	Yes		Yes	Yes
Seniority		Yes			Yes			Yes	
LoanType		Yes			Yes			Yes	
BDC		Yes			Yes			Yes	
YearQtr-Industry			Yes			Yes			Yes
Seniority-YearQtr			Yes			Yes			Yes
BDC-YearQtr			Yes			Yes			Yes
LoanType-YearQtr			Yes			Yes			Yes
<i>Fit statistics</i>									
Observations	52,452	52,452	52,435	10,687	10,687	10,670	41,765	41,765	41,765
Adjusted R ²	0.71	0.72	0.73	0.81	0.83	0.83	0.68	0.70	0.71

Figure A3: Industry mix in BDCs' portfolios

The figure shows the time-series of the value-weighted percentage of loans extended to different industries over the 2013Q1 to 2024Q3 period. Industries are defined in Online Appendix OA.2. Industry definitions are from Pitchbook.



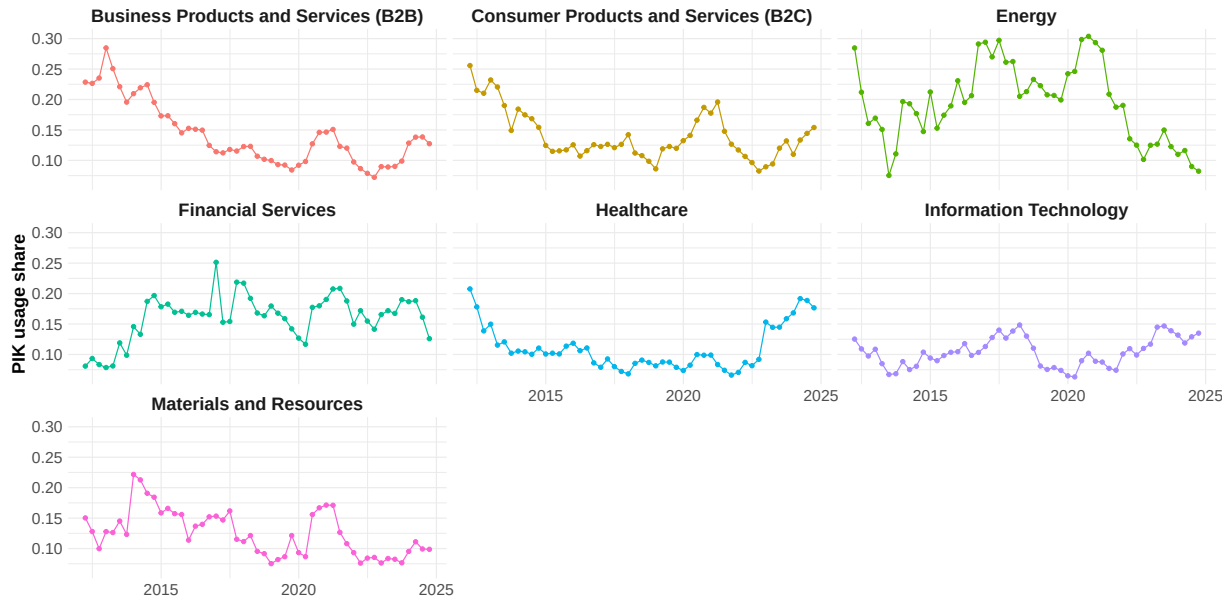
OA.6.0.2 Industry analysis

Figure A3 shows BDC portfolio composition by industry. As of 2024, almost 60% of loans are originated in two sectors, Business Products (which includes, for example, shipping, transportation or wholesale) and Service and Information Technology (which includes, for example, media, technology, or communication), followed by Healthcare and Consumer Product/Financial Services. The two most noticeable developments over time are the increase in the importance of Information Technology and the decreasing importance of Energy (including oil & gas or utility firms). Energy is a relatively small industry in BDC portfolios as of 2024Q3.

PIK usage varies notably across industries, as depicted in Figure A4. Traditionally,

Figure A4: PIK usage in different industries

The figure shows the time-series of the PIK usage share across all sample loans in different industries. PIK usage share is the value-weighted number of loans where borrowers use the PIK option relative to all loans in a given quarter.



the energy and financial services sectors exhibit higher PIK usage. The energy sector, in particular, experienced substantial spikes—with usage exceeding 30%—during both the oil and gas shock and the COVID-19 pandemic periods. However, usage rates in the energy sector declined significantly in 2023 and 2024, reflecting the reduced prominence of energy loans in overall BDC portfolios. Across all sectors, PIK adoption increased during COVID-19 and the subsequent period of elevated interest rates. As of 2024Q3, Healthcare, Consumer Products, and Information Technology display the highest average PIK usage shares.

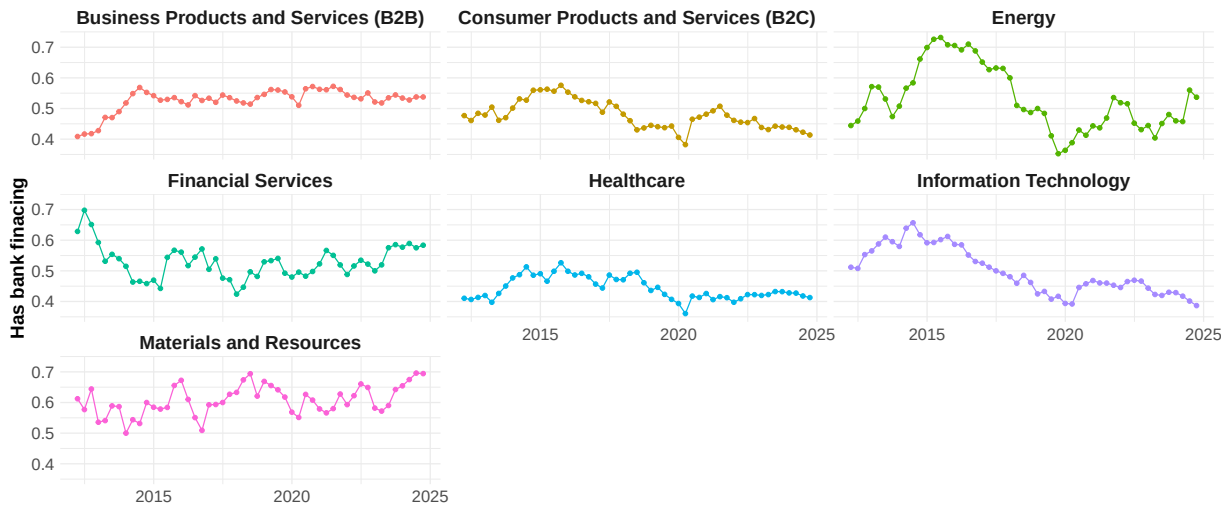


Figure A5: Share of firms that have received a bank loan in the past 5-years

OA.6.0.3 Other type of liquidity provision

BDCs can also engage in other types of liquidity provision besides offering PIK provisions, most notably being revolver loans and delayed drawdown term loans (DDTLs). Figure A6 shows the share of these items in BDC loan portfolios (in addition with Unitranche loans, which are often reported as explicit security class in BDC Collateral database, although it can be viewed as belonging more distinctly to the "Seniority" categorization of the data). The figure excludes the "Term loan" category that stands over 80% of value and thus dwarfs other loan type categories in magnitude.

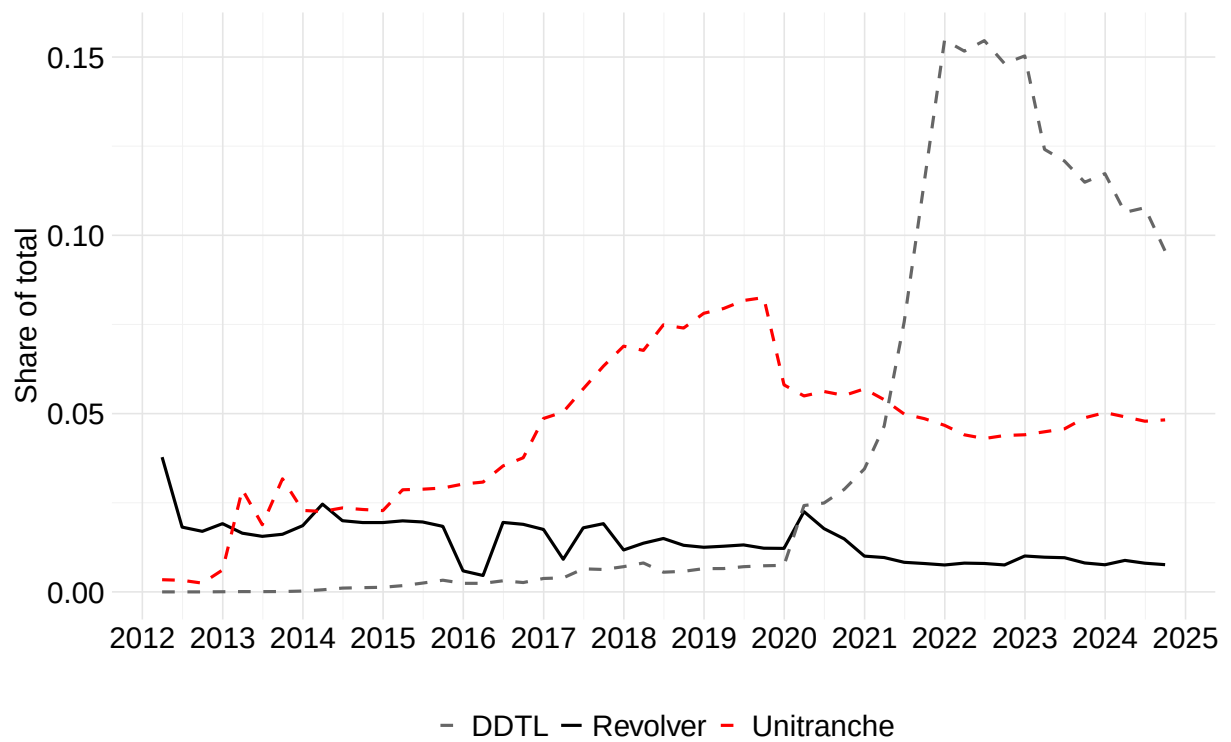


Figure A6: Loan Type composition for non-standard term loans

Table A5: Determinants of Revolvers and DDTLs loans

Dependent Variable: Model:	(1)	1(Revolver/DDTL) (2)
<i>Variables</i>		
NonAccrual _t	-0.21*** (0.04)	-0.37*** (0.05)
Fair/Par _t	-0.40*** (0.09)	-1.07*** (0.09)
Loan Size _t	-0.07*** (0.01)	-0.09*** (0.01)
Base rate _t	2.35*** (0.58)	8.48*** (1.57)
Fixed rate loan	-0.06** (0.02)	0.09*** (0.03)
Maturity _t	-0.01 (0.01)	-0.24*** (0.03)
Dual holding _t	0.01 (0.02)	0.05*** (0.02)
All-in-yield	0.54* (0.29)	-0.48 (0.34)
PIK Note	0.01 (0.02)	-0.11** (0.04)
PIK Toggle	0.00 (0.01)	-0.17*** (0.03)
PE Sponsored _t	0.08*** (0.02)	
Has bank financing _t	-0.05*** (0.01)	
<i>Fixed-effects</i>		
YearQtr	Yes	
Seniority	Yes	
YearQtr-Borrower-Seniority		Yes
<i>Fit statistics</i>		
Observations	232,107	322,129
Adjusted R ²	0.19	0.22

Clustered (YearQtr & BDC & Borrower) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results are based on loan-quarter level panel data. *NonAccrual_t* is an indicator variable that takes a value of one if the loan is reported as non-accrual for period *t*. *Maturity_t* is the natural logarithm of the remaining time to maturity. *Fair/Par_t* is the current valuation of the loan position. *LoanSize_t* is the natural logarithm of the cost value of the loan amount. *Fixedrate loan* is an indicator variable that takes the value of one if the loan has a fixed interest rate. *Base rate_t* is the loan's base rate at time *t* and zero if there is no base rate. *Dual holding_t* is an indicator variable that takes the value of one if the BDC also has an equity stake in the borrowing firm. We exclude the intercept term from the results whenever the model has one. We include several fixed effects: *BDC* refers to the identity of the BDC (Lender). *YearQtr* refers to the calendar quarter e.g. 2022Q4. *Borrower* refers to the identity of the borrower. *Seniority* refers to loan seniority. *LoanType* refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, year-quarter, borrower level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

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