Endogenous Matching in the Private Debt Market

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Abstract

I study how a firm's organizational structure impacts capital allocation within the booming private debt industry. Focusing on business development companies (BDCs), important nonbank lenders, I document that perpetual-life BDCs lend more bilaterally to smaller and riskier borrowers while finite-life BDCs participate in larger deals with multiple lenders. This two-sided endogenous matching can arise from a search-theoretic model, where the lender's perpetual life incentivizes both counterparties to engage more in bilateral lending. With perpetual-life lenders, the borrower trades off a lower loan rollover risk for a higher coupon rate. Empirically this effect is 37 basis points based on an instrumental variable estimate. Stronger lending relationships also provide borrowers more stable credit and support employment growth.

JEL classification: G11, G20, G23, G24.
Keywords: *private debt, private credit, business development companies, permanent capital, organizational structure, investment horizon, relationship lending, matching, search theory*

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1 Introduction

How does the organizational structure of a firm influence its allocation of capital? In financial intermediation, this question has been explored in two distinct strands of literature: one focusing on banks (Berger et al., 2005; Berger & Udell, 2002) and the other on investment funds operating in public securities markets (Fama & Jensen, 1983; Stein, 2005). In this paper, I examine the novel dimension of the operating horizon of different types of firms by focusing on nonbank corporate lending in private debt markets.

Investment fund-originated corporate lending, referred to as "private debt" or "private credit," has expanded significantly following widespread bank disintermediation and has become an economically important asset class. For example, a J.P. Morgan report from April 2024 estimated that invested assets in the private debt industry (excluding dry powder) reached $1.7 trillion in the U.S. and $2.6 trillion globally in 2024 (Wigglesworth, 2024).[1] However, most of the lenders are inherently opaque in their investment activities, which has hampered research in this area.

I overcome this problem by focusing on business development companies (BDCs), which are closed-end investment companies and direct lenders of private mid-sized firms.[2] BDCs are organized either as *finite life funds (FLFs*), which often liquidate about 5-10 years after starting and are not publicly listed, or as *perpetual life funds (PLFs)*, which operate without a set end date and are typically publicly listed. Although these fund structures have been used in private markets everywhere, the focus on BDCs provides the necessary transparency, data, and historical context to study them. Focusing on decentralized and primary markets of illiquid loans also raises several questions that are absent from prior studies that analyze fund structures. Do some borrowers prefer particular types of lenders, and if so, why? Do lenders with different fund structures target different types of borrowers? Finally, if such endogenous matching arises, how do these lending relationships influence loan pricing and credit provision?

To answer these questions, I combine theory and empirical evidence, and here is a quick overview of the results. A dynamic equilibrium search model of the loan market generates endogenous two-sided matching between the different types of lenders and borrowers. PLFs, which do not experience portfolio liquidation with the same intensity as FLFs, invest more in long-term bilateral lending relationships and attract more bor-

[1] For comparison, in the U.S. the private debt is now larger than the $1.4 trillion leveraged loan market (Morningstar, 2024) and the $1.6 trillion high-yield bond market (S&P Global, 2024) that concentrate on large borrowers.

[2] Similarly to the broader private debt industry, the size of the BDC sector has exploded from approximately $22 billion in 2010Q1 to $343 billion in 2024Q1 (LSTA, 2024).

rowers to search for and match with them. However, while a match with a PLF benefits the borrower in the form of a lower loan rollover risk, the borrower has to pay a higher interest rate as a trade-off. Consistent with the model's predictions, I show that BDCs specialize in different types of lending activities, based on their fund structure. PLFs primarily focus on lending to smaller borrowers either bilaterally or as the largest lender among multiple lenders, while FLFs are more likely to lend to larger and less opaque companies, with a less concentrated lender base. Moreover, PLFs can obtain higher interest rates, even for observably similar loans. To address endogeneity issues, I employ multiple identification approaches, including two instrumental variables. Finally, I show how stronger lending relationships support borrowers' access to credit and their employment growth, and present new facts about aggregate loan pricing in this market.

The focus on BDCs is useful for two reasons: First, unlike private debt funds, the other more opaque lenders in this market, all BDCs report detailed portfolio holdings data to the U.S. Securities and Exchange Commission (SEC). I conduct a major data gathering exercise by collecting this rich loan-level information from the regulatory filings and construct a type of credit-register of the BDC universe. These data offer a unique window to analyze nonbank lending and loan pricing in detail. Second, while the rise of both the private debt industry and perpetual-life fund structures within private markets are fairly recent phenomena, BDCs have existed for decades and operated both PLF and FLF structures for a long time.[3] This provides helpful context also when assessing these more recent trends.

Similarly, how a firm's organizational structure affects credit allocation is an open question that has not received much research attention, especially among private market intermediaries. This is despite the fact that there exist opposite views on how the traded PLF versus private FLF structure should affect investment behavior. Among practitioners, the claim that fund horizon may influence lending strategies is considered reasonable. One piece of evidence for this view is captured in the following annual report excerpt from a perpetual-life BDC, where the fund lists its sources of competitive strengths:

> *Our long-term investment horizon gives us great flexibility, which we believe allows us to maximize returns on our investments. Unlike most private equity and venture capital funds, as well as many private debt funds, we will not be required to return capital to our shareholders once we exit a portfolio investment. We believe that freedom from such capital return requirements, which allows us to invest using a longer-term focus, provides us with a better opportunity to increase total returns on invested cap-*

[3]PLFs have even been called the "holy-grail" of alternative investments. (Financial Times, 2015, CFA Institute, 2021)

ital, compared to other private company investment vehicles.[4]

This quote directly supports the idea that fund structures that better support long-term investing allow for flexibility and provide better access to attractive investment opportunities. However, the notion that a publicly traded PLF structure achieves this better than a private FLF structure is in stark contrast to the view that publicly listed firms are less suited to pursue long-term risky investments due to managerial short-termism (Stein, 1989). Fundamentally, determining which of these two forces dominates is an empirical question and one that my research can address.

The alternative lending strategies that I find different types of BDCs to engage in loosely resemble practices that have typically been referred to as "relationship lending" and "transactional lending" in the bank lending literature (Bolton et al., 2016; Boot, 2000). Now, if we use the term "relationship lending" to describe the lending done by the largest (or the only) BDC lender of a given borrower then the economic magnitude of the sorting pattern implies that the average share of the loan portfolio allocated to relationship loans is approximately 79% for the traded perpetual-life funds and 50% for private finite-life funds.[5] This sorting is evident in every quarter of the sample and is robust to the empirical approach used to identify it.[6]

However, this is an equilibrium outcome resulting from two-sided endogenous matching. Although lenders can choose which potential borrowers to target, the opposite also holds. Furthermore, in a decentralized and primary market search frictions play an important role. To explain this endogenous matching and generate testable predictions, I introduce a tractable continuous-time dynamic search model of the loan market.

On the lending side of the model, the fund managers can either search and match with borrowers to form long-term bilateral relationships or they can invest in liquid multi-lender deals with lower interest rates. While the bilateral lending relationships that arise from matching in the search markets have higher expected returns, searching is costly, and in the event of fund liquidation, these types of loans are hard to sell in secondary markets. Thus, lenders with high liquidation probability (that is FLFs) are less likely to exert effort in search while those that do not expect liquidation (that is PLFs) invest more in search.

[4]Blackstone Secured Lending Fund 10-K, 2021.

[5]I use the term "relationship lending" flexibly and only to put some labels on these lending activities. Even so, similar types of lender concentration measures have been used in the bank lending literature to refer to stronger lending relationships. See e.g. Berger, Klapper, and Udell (2001), Bharath et al. (2011, 2007), Harhoff and Körting (1998), Ongena and Smith (2000), and Schenone (2010).

[6]For example, the finding is not driven by observable fund characteristics like fund size, nor unobservable characteristics, like BDC adviser's reputation or risk aversion that can be controlled using different fixed effects.

The borrowing side of the bilateral search market can be viewed as consisting of small and opaque borrowers with poor outside options and potentially no access to the multi-lender market. These borrowers are incentivized to seek financing from the bilateral search markets instead, and although searching is costly, it is still preferable over the alternative of not obtaining financing. In contrast, larger and more established firms with good outside options do not search for bilateral lenders because they find it more attractive to rely on more competitive multi-lender deals.

The equilibrium credit allocation and loan pricing arise endogenously. FLFs that may be liquidated in the future, choose to lend less using bilateral relationship loans than PLFs and instead invest more in transactional multi-lender deals. Moreover, when a match occurs, PLFs, with better initial bargaining positions, can obtain a higher interest rate from the deal, which allows them to form more attractive bilateral lending relationships. Hence, when trading with a PLF, the bilateral relationship borrower trades off lower loan rollover risk for a higher interest rate and vice versa when borrowing from a FLF.

In the empirical part of the paper, I test the model's predictions. While my main purpose is to document the empirical patterns and confirm the model predictions, I show that the fund type also seems to have a causal effect on capital allocation and loan pricing. The identification problem is that fund managers are not randomly assigned to run different types of funds. I address this problem in multiple ways: i) using tight fixed effects that for example allow me to look at two funds with different structures launched by the same parent (technically "adviser"), ii) using two instrumental variables for fund structures—the first one uses the aggregate variation in the attractiveness of IPO fundraising conditions, and the second one uses the dominance of a given fund type in a particular geographic region as in Berger et al. (2005), iii) transition sample of funds that transform from a FLF to a PLF, iv) alternative economically motivated dependent variables and v) alternative deal-level dataset, propensity score matching and many other robustness tests. All the results support a causal interpretation between fund type and more concentrated or fully bilateral relationship lending.

Similarly, I also test the other model prediction that the perpetual-life fund structure increases the lender's reservation rate and the average coupon rate they can obtain. Again, I address the potential selection issue using an instrumental variable and estimate that having a traded perpetual-life fund type as the lender increases the coupon rate by 37 basis points (bps), which corresponds to roughly 5% of the average coupon spread in the sample.

Finally, I investigate how lending relationships influence credit provision across various credit conditions. I find that strong borrower-lender relationships, particularly with

perpetual-life funds (PLFs), enhance credit access and may help alleviate funding frictions for distressed borrowers.[7] I also show that these borrowers seem to benefit from stronger lending realtionships in the form of higher subsequent employment growth.

These private mid-sized borrowers that rely on BDC financing populate the U.S. middle market. Since the associated debt market remains relatively opaque, in the last part of the paper I document new facts about aggregate level and cyclicality of the yields spreads of these loans.

I begin by using data on BDC portfolios to back out the discount rates of these loans. Then using these yields-to-maturity (YTM), I construct an index that is representative of the average YTM, and the loan spread, that typical direct lending investments in the U.S. middle market have. Like many other yield spreads, the yield spread for average middle-market loans is countercyclical and time varying. During the sample period from 2005Q1 to 2022Q4, the yield spread for middle market loans averaged approximately 10%, reaching 16.6% during the Great Recession. For reference, this spread is, on average, 4.5% higher than the corresponding spread in either the high-yield corporate bond market or the liquid B-rated loans in the leveraged loan market. However, potentially because the valuation of many of the most illiquid loans is based on fair value assessments, the average spread tends to spike less in crisis periods compared to public bond and loan markets. To analyze this further, I introduce a simple model-free method using BDCs' stock prices and yield information to back out stock-market-implied discount rates for BDC loan portfolios. I show that the average stock-market-implied middle market yield spread has the same level, but is more volatile than the average spread based on fair value assessments.

In summary, to the best of my knowledge, this study is the first to examine how a fund's organizational structure affects its allocation of capital in the private debt market. Using a two-sided search and matching model and its testable predictions, I show that fund structure impacts the whole market structure of private debt market. My findings can inform debates about the costs and benefits of different organizational structures and suggest that how the popularity of different fund vehicles evolve is likely to be a key driver that shapes the loan markets going forward.

Related literature: My paper is related to the nascent strand of literature on private debt markets and BDCs, which can be broadly classified into four segments. The first set of studies investigates the rise of nonbank direct lending and generally finds that an

[7]These findings are also robust also to very granular Borrower $\times$ Time + Lender $\times$ Time fixed effects. Borrower $\times$ Time fixed effects control for borrower-time specific demand shocks in the spirit of Khwaja and Mian (2008), while Lender $\times$ Time fixed effects control the possibility that these results originate from lender-specific funding shocks.

increase in bank regulation was a major driving force behind this market shift (Bednarek et al., 2023; Davydiuk, Marchuk, & Rosen, 2024b; Fritsch et al., 2021; Irani et al., 2021; Loumioti, 2022). Compared with banks, Carey, Post, and Sharpe (1998), Chernenko, Erel, and Prilmeier (2022), Denis and Mihov (2003), and Haque, Mayer, and Stefanescu (2024) find that nonbanks generally lend to riskier companies using more junior loans. I contribute to this literature by showing new descriptive evidence of how the credit provision and pricing of these new types of lenders have varied across business cycles and in the cross-section.

The second set of studies investigates BDCs' frictions and investment practices through the lens of agency conflicts (Kallenos & Nishiotis, 2023), leverage limits (Balloch & Gonzalez-Uribe, 2021), market discipline (Davydiuk, Marchuk, & Rosen, 2024b), regulatory arbitrage (Chernenko, Ialenti, & Scharfstein, 2024) and dual-holdings of equity and debt (Davydiuk et al., 2024). I contribute by highlighting that equilibrium lending relationships arise from two-sided matching and that the organizational structure of BDCs is a key determinant in this process.

The third set of studies focuses on the links between debt providers and private equity (PE) sponsors and the differences between PE-backed (sponsored) and non-PE-backed (non-sponsored) borrowers. Such differences have been studied, at least through the lens of pricing (Buchner et al., 2023), monitoring (Haque, Mayer, & Wang, 2023), distress resolution (Hotchkiss, Smith, & Strömberg, 2021), debtor-equity holder conflicts (Buchner, Lopez-de Silanes, & Schwienbacher, 2022), and general management practices using survey evidence (Block et al., 2024). Jang (2023) also studies relationship lending by showing that direct lenders in general engage in relationship lending. While Jang (2023) focuses on whether and how they do so, my focus is on why they do it, who does it in particular, and the effects it has on loan pricing, credit provision, and portfolio firm employment.

The fourth set of studies investigates the performance of BDCs and private debt funds (Böni & Manigart, 2022; Erel, Flanagan, & Weisbach, 2024; Kallenos & Nishiotis, 2023; Munday et al., 2018; Nesbitt, 2017; Suhonen, 2023). All of these papers analyze *realized* returns, and I contribute to this literature by providing new facts about observable discount rates, which are proxies of *expected* returns.[8]

My paper also builds on several older strands of literature in economics and finance. First is the long strand of literature that analyzes why different organizational structures exist, especially in the context of investment funds (Cherkes, Sagi, & Stanton, 2009; Deli

[8]My exercise on measuring and analyzing the middle market loan spreads is also similar in spirit to Elkamhi, Li, and Nozawa (2024) and Fleckenstein and Longstaff (2023) who analyze the pricing of hard-to-measure assets: AAA-rated collateralized loan obligations (CLOs) and small business equity returns, respectively.

& Varma, 2002; Fama & Jensen, 1983, 1985; Stein, 2005), and how the choice of fund structure affects market functioning (Giannetti & Kahraman, 2018; Shleifer & Vishny, 1997). I mainly contibute to the latter but deviate from the previous work in two ways. First, given that all BDCs are technically closed-end funds I focus on the differences between PLFs and FLFs rather than open- versus closed-end funds. Second, I focus on direct lending in primary markets, while the previous literature focuses mostly on investing in publicly traded securities in the secondary markets. These markets differ significantly in not only how they operate, but also how the fund structure contributes to market functioning.[9]

Second, I build on the literature on relationship banking.[10] While, because of its large scale, I cannot do full justice to all the work done in this area, there are several extensive survey articles that specifically do this (Boot, 2000; Degryse & Ongena, 2008; Elyasiani & Goldberg, 2004; Kysucky & Norden, 2015). I differ from this strand of literature by studying nonbanks rather than banks and focusing on mid-sized firms rather than small business lending or the syndicated lending of large firms. Nonetheless, my paper can also speak to theories of what makes banks special. Although the focus has often been on banks' role in mitigating information asymmetries, I show that simply the going-concern operating model of banks and nonbank PLFs can support more exclusive relationship lending activity.

Third, I build on the literature on sorting and matching.[11] Related to my study, Sorensen (2007) analyzes matching in the venture capital industry while Schwert (2018) analyzes it among large firms and banks. However, both my research question and approach are very different. I also provide an explicit micro foundation for endogenous matching patterns using a search-theoretic model that builds on Diamond (1982), Mortensen (1986), and Pissarides (1985). My focus on primary markets also differs from most search-model applications in finance, which typically concentrate on secondary markets. In direct lending and primary markets, the emphasis is not on the gains from trading an asset with other investors but on establishing a mutually beneficial, long-term relationship between the lender and the borrower.

[9]Organizational structure has also been studied among banks in the context of bank size and soft information processing (Berger et al., 2005; Berger & Udell, 2002) but the fund structure dimension that I focus on is very different.

[10]For early theoretical work on see e.g. Leland and Pyle (1977), Diamond (1984, 1991), Sharpe (1990), Rajan (1992) and Boot and Thakor (2000), and for early empirical work see e.g. James (1987), Petersen and Rajan (1994, 1995), Berger and Udell (1995), Berlin and Mester (1999), Hubbard, Kuttner, and Palia (2002) and Degryse and Ongena (2005).

[11]For survey articles see, e.g. Chade, Eeckhout, and Smith (2017) and Rogerson, Shimer, and Wright (2005).

2 Institutional details

2.1 U.S. middle market

Direct lenders typically serve mid-sized firm that populate the middle market. The middle market in the U.S consists of about 200,000 private businesses, makes up roughly one-third of private sector GDP, and employs approximately 48 million people. The middle market companies are those firms with revenues between $10 million and $1 billion.[12] Carey, Post, and Sharpe (1998) and Denis and Mihov (2003) show that non-bank private debt, rather than bank debt or public debt, is mostly used by the borrowers with the riskiest credit profiles. Moreover, following the post-Global Financial Crisis (GFC) banking regulation, banks became even more reluctant to lend to the riskier companies creating an opening for many private lenders, such as BDCs, to step in and fill the gap created by banks (Chernenko, Erel, & Prilmeier, 2022; Davydiuk, Marchuk, & Rosen, 2024a).

In the investor presentations, the middle market is typically divided into two: the upper and the lower middle market. The upper-middle market has relatively few numbers of large firms that may have access to the broadly syndicated loan market or sometimes even the corporate bond market when raising debt financing. These players are often backed by private equity sponsors, and even in deals that only involve private debt lenders, the debt financing is provided by multiple lenders. While working with these borrowers is relatively simple due to their high level of transparency, PE-backing, and standardized deal terms, the downside is that the loan pricing is highly competitive. The lower middle market on the other hand consists of smaller borrowers with fewer outside options when seeking funding. These firms may also be too risky for banks which leaves BDCs and other nonbank direct lenders as their only option. These firms may also not have a PE-sponsor. These factors could imply that nonbank direct lenders may have considerable market power when negotiating deals with these companies, and evidence from prior literature suggests that there is a premium both when dealing with firms not sponsored by PE and/or lower middle market (Buchner et al., 2023; Cliffwater, 2023). The problem for lenders is that sourcing and deal origination are much more time-consuming and expensive compared to working in the upper middle market or with financial sponsors. For example, one estimate by a portfolio manager suggests that operating in a non-sponsored market takes 50-100% more working hours (Kindert, 2019).

[12] Source: National Center for the Middle Market (2024)

2.2 BDC primer

Business development companies are part of the expanding private debt industry that is populated by private debt funds and BDCs. Although BDCs are subject to differential regulation in comparison to private debt funds, they are considered to represent typical direct lenders in this space (Block et al., 2024).

A BDC is a closed-end investment fund that focuses on investing in and supporting the growth of small and medium-sized companies in their early stages of development. To qualify as a BDC, a company must comply with Section 54 of the Investment Company Act of 1940. The unique regulatory framework for BDCs was created by the U.S. Congress in 1980 with an intention to promote job growth and raise funds for emerging businesses in the United States. In fact, at least 70% of BDC's assets need to be invested in private U.S. companies, or thinly traded public companies with a market capitalization of less than $250 million. While BDCs can make equity or bond investments most of BDC investments are in the form of private loans.

When requested, BDCs need to provide "significant managerial assistance" to their portfolio companies in the form of guidance about management, operations, or business, and indeed many managers are actively involved in the operations of their portfolio companies, providing advice and offering their networks to use. Perhaps not coincidentally, BDC managers have high-powered incentives to perform well that resemble those in the private equity industry.[13]

BDCs can be managed internally or externally. The management of the externally managed funds is outsourced to an external fund management company (called "Adviser") and these BDCs are usually affiliated with some larger investment management company. On the other hand, internally managed funds do everything "in-house" and these BDCs do not necessarily have any affiliations to larger asset managers. The share of internally managed funds has declined rapidly in past decades and in 2022Q4 the large majority of BDCs were externally managed funds.

BDCs themselves also actively use leverage, but the maximum allowed leverage is regulated by the U.S. Securities and Exchange Commission (SEC). For leverage, BDCs typically use bank loans, but increasingly also bonds and other publicly traded debt.

2.3 BDC types

Business development companies can be broadly classified into two categories: traded and non-traded BDCs. While both types face the same regulatory treatment and reporting

[13] I describe the typical management fee contract of a typical BDC in Appendix H.

requirements and have the same tax advantages, the two biggest institutional differences between the fund types boils down to i) differences in their liquidity profile and ii) differences in their investment horizon.

First, the shares of traded BDCs trade in the stock market and thus provide continuous liquidity to their shareholders. In contrast, the stocks of non-traded BDCs are not listed on public exchanges, which means non-traded BDCs have to provide liquidity to their shareholders by other means. Generally, non-traded BDCs can be further classified as public non-traded and private non-traded BDCs, with the difference being that the shares of public non-traded BDCs can only be bought and sold through periodic share buybacks or on a secondary market, which can be illiquid[14], while private non-traded BDCs usually have a structure similar to private equity funds, where the fund raises capital in advance from the limited partners (LPs) and then general partners (GPs) gradually deploy this capital as investment opportunities arise. This capital call and drawdown structure makes many private BDCs even more illiquid than their public non-traded counterparts and indeed these vehicles are typically only available to institutional or accredited investors.

Second important difference between BDCs is whether the fund has a finite-life or a perpetual-life. This dimension is largely co-mingled with the first one since non-traded BDCs have usually a finite-life, while traded BDCs always have a perpetual-life. The finite life funds (FLFs) are also called "life-cycle funds" since these funds have distinct fund-raising, investment, and exit phases. Finite-life BDCs usually plan to liquidate the fund or exit via a "liquidity event" within 5-10 years from the fund's inception while while perpetual funds (PLFs) do not typically have an exit date.[15] This characteristic of the life-cycle-funds implies that they may need to start liquidating the fund's investments after reaching a certain age. This contrasts with traded BDCs that in principle could have an infinite investment horizon. From 2020 onwards, some non-traded BDCs have also started to form as perpetual-life non-traded BDCs; among them Blackstone Private Credit Fund (or "BCRED") the largest BDC with over $50 billion assets under management at the end of 2022. Although technically both traded PLFs and non-traded PLFs have long investment horizons, in the empirical analysis, I treat these as separate fund categories. This is because most non-traded PLFs typically start the investment operations by buying an existing (typically syndicated) loan portfolio from a bank, where the loan terms have

[14]The repurchases are offered up to redemption limits, where the company offers some percentage or dollar amount of the outstanding shares and offers to repurchase those shares. Non-traded BDC for example could offer to buy 5% of the shares back every quarter.

[15]In addition to liquidating the fund and returning the proceeds to shareholders other possible liquidity events are a merger with a traded BDC, or an IPO and thus becoming a perpetual-life BDC.

already been negotiated, while older-type traded PLFs typically gradually build up the portfolio by forming new lending relationships themselves. Unfortunately, due to the novelty of non-traded perpetual-life funds, I have loan-level data from only four of these types of funds which poses some issues when drawing statistical inferences relating to the behavior of non-traded PLFs.[16] Due to these reasons I am mainly interested in studying differences of traded PLFs and FLFs. Figure 1 illustrates these BDC categories.

[Figure 1 here]

The strand of literature that focus on fund structures that invest in public securities typically make a distinction between closed-end fund and open-end fund (Cherkes, Sagi, & Stanton, 2009; Giannetti & Kahraman, 2018; Stein, 2005). However, all BDCs are technically types of closed-end funds so a distinction to perpetual-life funds and finite-life is more suitable. That being said, out of the three, the nontraded perpetual-life funds are thought to be closest of the open-end fund structure.

3 Theoretical framework

In this section, I present a tractable search-theoretic model that produces predictions about how BDCs sort and match into different types of lending activities. I start by introducing a simple example of the lender's problem and then generalize it to an equilibrium model. The model is purposely stylized to allow for closed-form solutions, but this simplicity can accommodate richer economic insights.

3.1 A simple example

To fix ideas, I begin with a problem of a BDC manager searching for a lending relationship in a discrete time while for now treating the matching intensity as exogenous. She seeks to maximize the present value of her lifetime expected utility $E_t \sum_{\tau=0}^{\infty} \beta^\tau x_\tau$, where $\beta \in (0,1)$ is the discount factor, x_τ is income at τ, and E_t denotes the expectation at time t. Income is $x_\tau = C$, where C is constant net repayment (or coupon) and $x_\tau = R$ if she is

[16] The result that PLFs (as a whole) differ in their lending from FLFs stays virtually unchanged even if I drop the non-traded PLFs from the sample or pool them with the traded PLFs into a single category.

not in a relationship and instead has invested the funds in her liquid outside option that can be rolled over period-by-period.[17] [18]

The manager chooses a policy that describes whether to accept an investment offer or not. I begin with the case where the a manager without a project samples an i.i.d. offer for each period from a known distribution with cumulative distribution function (CDF) $F(C)$. If an offer is rejected, the manager invest the money to outside option for that period instead.[19]

Hence, $V_l^R(C) = \frac{C}{1-\beta}$ is the net present value to accepting an offer C and engaging in a relationship. Similarly, the value of not engaging in relationship lending at time t is $V_{l,t}^{NR} = R + \beta E_t[\max\{V_{l,t+1}^R(C'), V_{l,t+1}^{NR}\}]$, where the expectation is with respect to the next offer C'. In words, $V_{l,t}^{NR}$ is the payoff from rejecting an offer, earning R, waiting and sampling again.

Let the value of having an offer C in hand at time t be

$$O_t(C) = \max\{V_{l,t}^R(C), V_{l,t}^{NR}\} = \max\left\{\frac{C}{1-\beta}, R + \beta E_t[O_{t+1}(C')]\right\} \tag{1}$$

Since $V_{l,t}^R(C)$ is increasing, there is a unique C_R called the reservation coupon such that $V_{l,t}^R(C_R) = \frac{C_R}{1-\beta} = V_{l,t}^{NR}$, with the property that the agent should reject $C < C_R$ and accept $C > C_R$. At the threshold, the manager is indifferent between accepting or rejecting the offer, implying that $C_R = (1-\beta)R + \beta(1-\beta)E_t[O_{t+1}(C')]$, which expresses C_R in terms of the unknown function O_{t+1}. To eliminate O_{t+1}, insert $R + \beta E_t[O_{t+1}(C')] = \frac{C_R}{1-\beta}$ into equation (1) and integrate to obtain $E_t[O_{t+1}(C)] = E_t[\frac{\max\{C,C_R\}}{1-\beta}]$; then we have

$$C_R = (1-\beta)R + \beta \int_0^\infty \max\{C, C_R\} dF(C) \tag{2}$$

Further subtracting βC_R from both sides of Equation (2) gives

[17] For tractability, I assume that the money is lent gradually with period investments I. Then we can view C as the periodic net payoff. Formally $C = (1+c)I - I = cI$ where c is the periodic net return. Normalizing $I = 1$ we can also interpret C as the coupon rate for a one period investment. R is also a net expected payoff.

[18] Following Rogerson, Shimer, and Wright (2005) I formulate the problem as if the agent is interested in maximizing the expected discounted income. This is naturally the same as maximizing expected utility if the agent is risk neutral but also if she is risk-averse and markets are complete, since then she can maximize utility by first maximizing income and then smoothing consumption.

[19] Following the prior literature I assume each manager only samples one offer per period and that previously rejected offers cannot be called back, although this is not a restrictive assumption because the problem is stationary so an offer that is not accepted today would not be accepted tomorrow either.

$$C_R = R + \frac{\beta}{1-\beta}\int_{C_R}^{\infty}(C - C_R)dF(C) \tag{3}$$

It can be shown that the solution to this equation is unique.[20] Even without imposing any functional form on CDF F to solve C_R, we can analyze how different parameters impact C_R using the implicit function theorem. For example, it is easy to show that $\frac{dC_R}{d\beta} > 0$, which implies more patient lenders set higher reservation coupons.

In the next section, I present an equilibrium model where lenders have different risks of fund liquidation. Moreover, in the previous example, the offers come to lenders exogenously, and thus the more patient lenders choose the outside option over their relationship offer more often. However, in the following equilibrium model, this changes when we allow the lenders to endogenously choose their search intensity. In this equilibrium model, by searching more, they also match more and the two-sided optimization implies every match leads to a relationship.

3.2 The equilibrium model

3.2.1 Lender's problem

We now move to continuous-time analysis, which allows for more tractability and lets us endogenize the search intensity. Let $V_l^R(C_{bl})$ stand for the value of being in a relationship with periodic repayment rate C_{bl}, which equals the net present discounted value of the investment. I use subscripts with C_{bl} since this repayment rate will be negotiated in equilibrium between the lender l and the borrower b. The lender's value of not being in a relationship is V_l^{NR}. In such a case lender invests in the liquid multi-lender market that yields a periodic expected payoff of R.

Let us focus on a lender l and a borrower b but I show how this example applies to any arbitrary pair. Suppose borrower's default arrive according to a Poisson process with parameter λ_b.[21] Similarly, the lender may liquidate the fund she runs and permanently exit the market according to an independent Poisson process with parameter δ_l. In the

[20] Intuitively, since 1) the left-hand side (LHS) of the equation is increasing in C_R and the right-hand side (RHS) is decreasing in C_R, there can exist at most one intersection and 2) for $C_R = 0$, the RHS is positive while LHS is zero so an intersection must exist. Formally the RHS, denoted as $T(C_R)$ can be shown to be a contraction, meaning there is a unique solution to $C_R = T(C_R)$, and the sequence $C_{N+1} = T(C_N)$ converges to C_R as $N \to \infty$ starting from any initial value of C_0.

[21] As a side note, parameter λ_b can differ accross borrowers b and, although it is not my interest here, by setting the underlying distribution appropriately we can fit the model's resulting interest rates (Eq. (19)) to match the actual data.

event of fund liqudidation, the bilateral loan's principal I gets paid back but loan is not rolled over anymore. I also assume that with liquid multi-lender loans lender also obtains additional liquidation value L. This is a simple way to capture the enhanced liquidity of the multi-lender deals and L can be viewed as profits from being able to pass the loan to a new investor through a secondary market.[22] There are two types of lenders, FLFs and PLFs, the only difference between them being that FLFs liquidate the fund with a higher probability $\delta_{FLF} > \delta_{PLF}$. Since their optimization problem is otherwise similar, I solve the model using the subscript l (as a lender) to refer to both. Finally, the lenders and borrowers are matched according to an independent Poisson process with parameter α_{lb}.

The parameter α_{lb} is a product of two parts: α_l, which the lender l can choose by investing in costly search, and α_b which the borrower b can choose by investing in search. This implies that even if the lender invests in search by setting $\alpha_l > 0$ but the borrower does not search and sets $\alpha_b = 0$, then $\alpha_{lb} \equiv \alpha_b \alpha_l = 0$, and the probability of a match is zero regardless of how actively the lender searches. The (utility) cost of search has a quadratic form $\frac{1}{2}\alpha_l^2$.[23] Now consider the case where the period length is short and denoted by Δ. The discount factor is $\beta = \frac{1}{1+r\Delta}$, the probability of an offer is $\alpha_{lb}\Delta$, the probability of borrower b's default is $\lambda_b \Delta$, and the probability of lender l's liquidation is $\delta_l \Delta$ per period.[24]

Then Bellman's equations for the manager without and with relationships respectively are

$$V_l^{NR} = R\Delta - \frac{1}{2}\alpha_l^2\Delta + \frac{1-\delta_l\Delta}{1+r\Delta}\left[\alpha_{lb}\Delta\int_0^\infty \max\{V_l^R(C_{bl}), V_l^{NR}\}dF(C_{bl}) + (1-\alpha_{lb}\Delta)V_l^{NR}\right] + \frac{\delta_l\Delta}{1+r\Delta}L \tag{4}$$

$$V_l^R(C_{bl}) = C_{bl}\Delta + \frac{1-\delta_l\Delta}{1+r\Delta}\left[\lambda_b\Delta V_l^{NR} + (1-\lambda_b\Delta)V_l^R(C_{bl})\right] \tag{5}$$

Taking limits as $\Delta \to 0$ and using $\alpha_{lb} = \alpha_b\alpha_l$ gives

[22] The intuition why these additional profits should arise only from liquid loans is simple: Relationship loans with concentrated lender base are typically illiquid and very information-sensitive assets and thus not tradeable in the secondary markets. In contrast, transaction-based loans with multiple lenders are often liquid, less informationally sensitive, and thus tradeable. Relatedly, direct bilateral loans are typically so called Level 3 asset based on ASC 820 accounting standard while syndicated loans are Level 2 assets with more transparent valuation and better liquidity.

[23] It is natural to think there is a cost when trying to match more frequently with borrowers. Especially since it is typically the smaller and more opaque borrowers that get matched through these search markets. Indeed, as was pointed out in Section 2 some loans such as those to nonsponsored companies or to smaller less recognized companies often require considerably more work with deal-sourcing, due diligence, and managerial assistance compared to sponsored borrowers or larger firms.

[24] I implicitly ignore the chance of multiple events within a period, and assume that Δ is sufficiently short so that all these probabilities are less than 1.

$$\underbrace{(r+\delta_l)V_l^{NR}}_{\text{Required return}} = \underbrace{R}_{\text{Net payoff}} + \underbrace{\delta_l L}_{\text{Profit from liquidation}} - \underbrace{\frac{1}{2}\alpha_l^2}_{\text{Search cost}} + \underbrace{\alpha_l\alpha_b \int_0^\infty \max\{V_l^R(C_{bl}) - V_l^{NR}, 0\} dF(C_{bl})}_{\text{NPV increase of matching and switching to relationship state}}$$

$$\underbrace{(r+\delta_l)V_l^R(C_{bl})}_{\text{Required return}} = \underbrace{C_{bl}}_{\text{Net payoff}} + \underbrace{\lambda_b[V_l^{NR} - V_l^R(C_{bl})]}_{\text{NPV decrease of borrower defaulting}}$$

Left hand side of the equations can be interpreted as instantaneous required returns while the right-hand sides are the corresponding expected returns. Noting that $(r + \delta_l)V_l^{NR} = C_{R,bl}$, and using the similar steps as before we can combine these to get

$$C_{R,bl} = R + \delta_l L - \frac{1}{2}\alpha_l^2 + \frac{\alpha_l\alpha_b}{r+\delta_l+\lambda_b}\int_{C_{R,bl}}^\infty (C_{bl} - C_{R,bl}) dF(C_{bl}) \tag{6}$$

Managers without relationships choose α_l to maximize the value of the search so taking the first order condition (FOC) we get the optimal α_l, which is

$$\alpha_l = \frac{\alpha_b}{r+\delta_l+\lambda_b}\int_{C_{R,bl}}^\infty (C_{bl} - C_{R,bl}) dF(C_{bl}) \tag{7}$$

As one can see α_l is increasing α_b. This implies that lender's search effort is dependent on which borrower b she is targeting and how much that borrower searches.[25]

3.2.2 Borrower's problem

Now we can easily run the same analysis for the borrower. She seeks to maximize the present value of her lifetime expected profits. When receiving financing, the borrower can invest in a project that produces a flow output Y_b, while the flow repayment rate is C_{bl}. The flow profit that the borrower receives is their difference, $Y_b - C_{bl} = \pi_{bl}$.[26]

$$(r+\lambda_b)V_b^{NR} = -\frac{1}{2}\alpha_b^2 + \alpha_b\alpha_l \int_0^\infty \max\{V_b^R(\pi_{bl}) - V_b^{NR}, 0\} dF(\pi_{bl}) \tag{8}$$

$$(r+\lambda_b)V_b^R(\pi_{bl}) = \pi_{bl} + \delta_l[V_b^{NR} - V_b^R(\pi_{bl})] \tag{9}$$

[25] More accurate notation would be to explicitly denote $\alpha_l \equiv \alpha_{l(b)}$ to emphasize this dependence. I show below that as lenders can freely choose which borrower to target this dependence disappears. I refer to α_l and α_b for simplicity.

[26] For simplicity when borrower defaults her liquidation value is always normalized to zero.

Analogously to the lender case the reservation profit $\pi_{R,bl}$ satisfies $V_b^R(\pi_{R,bl}) = V_b^{NR}$, and the similar steps as before give

$$\pi_{R,bl} = -\frac{1}{2}\alpha_b^2 + \frac{\alpha_b \alpha_l}{r + \delta_l + \lambda_b} \int_{\pi_R}^{\infty} (\pi_{bl} - \pi_{R,bl}) dF(\pi_b) \tag{10}$$

A borrower wants to maximize the her value of not being in a relationship by optimally choosing α_b. So taking FOC from Equation (10) produces

$$\alpha_b = \frac{\alpha_l}{r + \delta_l + \lambda_b} \int_{\pi_{R,bl}}^{\infty} (\pi_{bl} - \pi_{b,R}) dF(\pi_{bl}) \tag{11}$$

To get a sense of what types of borrowers decide to search in the first place, consider two types of borrowers: small firms and big firms. Assume that small firms cannot raise funds using multi-lender market, and fix the outside option of not matching with the relationship lender to $\pi_{R,bl} = 0$, which is the profit of not obtaining financing. This implies $\pi_{bl} - \pi_{R,bl} = Y_b - C_{bl}$. So small firms always search relationships, $\alpha_b > 0$, unless the expected profits in Equation 11 are negative, $\int_0^{\infty} \pi_{bl} dF(\pi_{bl}) < 0$ or $\alpha_l = 0$. In contrast, big firms have access to a transactional lending market where they can raise debt with a periodic rate of R. This implies that for the big firms the flow profit over their reservation profit is $\pi_{bl} - \pi_{R,bl} = Y_b - C_{bl} - (Y_b - R) = R - C_{bl}$. This will always be nonpositive, because there is no C_{bl} that would be acceptable for both the lender and the large firm. If large firm were to match with any relationship lender through search, then no lender would accept an offer with $C_{bl} < C_{R,bl}$ because this type of rate would violate the lender's participation condition. On the other hand, the large firm itself would not accept any offer with $C_{bl} > R$, because this would imply that $\pi_{bl} - \pi_{R,bl} < 0$. Since the large firm knows this it will never try to look for a bilateral lender via search markets ($\alpha_b = 0$) and only borrows using the multi-lender market where it pays a periodic interest rate R. To summarize, only small borrowers match with (either type of) lenders in the search market, while large firms only use the multi-lender market and this type of borrower-side sorting also appears in the data. For the remaining part of this theoretical analysis we can focus on these small borrowers with $\pi_{R,bl} = 0$ that obtain credit via search markets.

3.2.3 Bargaining

When borrower and lender match they engage in Nash-bargaining regarding the repayment rate C_{bl}. This problem can be written as

$$\max_{C_{bl}} \quad [V_l^R(C_{bl}) - V_l^{NR}]^{\theta_l} [V_b^R(Y_b - C_{bl}) - V_b^{NR}]^{1-\theta_l} \tag{12}$$

where θ_l measures the bargaining power of the lender. I allocate the details to the Appendix B, but this Nash-bargaining problem has a following solution.

$$C_{bl} = C_{R,bl} + \theta_l(Y_b - C_{R,bl}) \tag{13}$$

So in the special case $\theta_l = 1$, the lender captures all the surplus which means $Y_b = C_{bl}$, whereas when $\theta_l = 0$, the borrower captures all the surplus and the coupon rate equals the reservation coupon rate of the lender, so $C_{R,bl} = C_{bl}$.

3.2.4 Search equilibrium

The randomness in match profitability is generated by the exogenous variation in the lender's bargaining power θ_l. I assume $\theta_l \in [0,1]$ is sampled from a uniform distribution $\theta_l \sim Unif[0,1]$.[27] This functional form provides an analytical solution for the model. So, to calculate the optimal α_l and α_b we need to know the distribution of C_{bl}. Since $C_{bl} = C_{R,bl} + \theta_l(Y_b - C_{R,bl})$ then also C_{bl} has uniform distribution $C_{bl} \sim Unif[C_{R,bl}, Y_b]$ since at the upper limit $\bar{C}_{bl} = Y_b$ and at the lower limit $\underline{C}_{bl} = C_{R,bl}$. This further implies that $f(C_{bl}) = \frac{1}{Y_b - C_{R,bl}}$ and $dC_{bl} = (Y_b - C_{R,bl})d\theta_l$. These facts allow us to write Equation (7) as

$$\begin{aligned}
\alpha_l &= \frac{\alpha_b}{r + \delta_l + \lambda_b} \int_{C_{R,bl}}^{Y_b} \theta_l(Y_b - C_{R,bl}) f(C_{bl}) dC_{bl} \\
&= \frac{\alpha_b}{r + \delta_l + \lambda_b} \int_0^1 \theta_l(Y_b - C_{R,bl}) d\theta_l \\
&= \frac{\alpha_b}{r + \delta_l + \lambda_b} (Y_b - C_{R,bl}) \Big|_0^1 \frac{\theta_l^2}{2} \\
&= \frac{\alpha_b (Y_b - C_{R,bl})}{r + \delta_l + \lambda_b} \frac{1}{2}
\end{aligned}$$

The second row changes the limits of integration using the fact that C_{bl} vary from $C_{R,bl}$ to Y_b as θ_l vary from 0 to 1. Let us then do the same for the borrower's FOC by writing Equation (11) as

[27] These limits imply that on average lender and borrower share the surplus equally. By changing the limits to vary, for example between $[0, \bar{\theta}]$, we would obtain an additional parameter $\bar{\theta}$ that would influence the equilibrium solution. All else being equal, a higher $\bar{\theta}$ would increase the lender's search effort relative to that of the borrowers.

$$
\begin{aligned}
\alpha_b &= \frac{\alpha_l}{r+\delta_l+\lambda_b}\int_0^{Y_b-C_{R,bl}}(1-\theta_l)(Y_b-C_{R,bl})f(\pi_{bl})d\pi_{bl} \\
&= \frac{\alpha_l}{r+\delta_l+\lambda_b}\int_0^{1}\theta_b(Y_b-C_{R,bl})d\theta_b \\
&= \frac{\alpha_l}{r+\delta_l+\lambda_b}(Y_b-C_{R,bl})\Big|_0^1\frac{\theta_b^2}{2} \\
&= \frac{\alpha_l(Y_b-C_{R,bl})}{r+\delta_l+\lambda_b}\frac{1}{2}
\end{aligned}
$$

In this case, the second row changes the limits of integration using the fact that π_{bl} vary from 0 to $Y_b - C_{R,bl}$ as $\theta_b \equiv 1 - \theta_l$ vary from 0 to 1. Comparing the result in the last row to the one we obtained for α_l, we immediately notice that when the expected bargaining power is balanced between the lender and the borrower, that is $E(\theta_l) = \frac{1}{2}$, then the optimal solutions for both parties are symmetric. We can solve the equilibrium reservation payoff for the $C_{R,bl}$ for the lender from these two results. Start by defining $\frac{\alpha_b}{\alpha_l}$ from both equations and then equate to get

$$(Y_b - C_{R,bl})^2 = 4(r+\delta_l+\lambda_b)^2$$

This is simply a second-order polynomial equation for $C_{R,bl}$, which is easy to solve. The two solutions are $C_{R,bl} = Y_b \pm 2(r+\delta_l+\lambda_b)$. However, since it has to be that $Y_b \geq C_{R,bl}$ for there to be something to bargain over, only one of the solutions can describe the equilibrium and it must be

$$C_{R,bl} = Y_b - 2(r+\delta_l+\lambda_b) \tag{14}$$

Plugging the right-hand side of Equation (14) back into Equation (7) and Equation (6), while using the fact that we just showed that $\int_{C_{R,bl}}^{\infty}(C_{bl}-C_{R,bl})dF(C_{bl}) = \frac{1}{2}(Y_b - C_{R,bl})$, we get the equilibrium solution for the optimal search efforts for the lender and the borrower

$$\alpha_b = \alpha_l = \sqrt{2(C_{R,bl}-R-\delta_l L)} = \sqrt{2(Y_b-R-\delta_l L)-4(r+\delta_l+\lambda_b)} \tag{15}$$

Lastly if we plug Equation (14) into Equation 13 we get the equilibrium coupon rate

$$C_{bl} = Y_b - 2(r+\delta_l+\lambda_b)(1-\theta_l) \tag{16}$$

Now if we are happy with the assumption that a lender l is exogenously allocated to

search a particular type of borrower b, then we would have our equilibrium solution.[28] However, instead the last thing I do is let the lenders to concentrate their search efforts where it is most profitable for them. I show in the Appendix B that as I endogenize this choice of the lender then it must hold that $Y_b = Y + 2\lambda_b$ where Y is the flow output of a relationship borrower that has no default risk—a useful benchmark. Since the Y_b now contains $2\lambda_b$ as the "default premium" then this implies that Equations (14), (15) and (16) transform into

$$C_{R,bl} = Y - 2(r + \delta_l) \tag{17}$$

$$\alpha_b = \alpha_l = \sqrt{2(Y - R - \delta_l L) - 4(r + \delta_l)} \tag{18}$$

$$C_{bl} = Y + 2\theta_l \lambda_b - 2(r + \delta_l)(1 - \theta_l) \tag{19}$$

From this equilibrium solution we can now draw important lessons. First, in this special case where $E(\theta_l) = \frac{1}{2}$ and lenders and borrowers on average divide the surplus equally, we have that $\alpha_b = \alpha_l$ meaning that lenders and borrowers exert equal amount of effort when searching. If the limits of distribution of θ_l are different then the relative barganing power of the counterparties further influences the result.

Second, in this equilibrium, every match leads to a lending relationship. This implies that per each unit of capital PLFs do not just search more $\alpha_{PLF} > \alpha_{FLF}$ but also match more, accept more offers and consequently lend more via the search markets relative to FLFs. Since $\alpha_{lb} = \alpha_b \alpha_l = 2(Y - R - \delta_l L) - 4(r + \delta_l)$, we see that matching frequency and correspondingly the relationship lending activity with lender l and a borrower b is decreasing in fund liquidation probability δ_l. Higher liquidation probability δ_l lowers the search effort through two channels: i) funds with high liquidation risk are particularly interested in holding liquid non-relationship asset that can be sold forward with profits L, ii) the high liquidation risk lowers the incentives to engage in costly search because the benefits of exerting effort are less likely to fully materialize due to shorter relationship. Search market activity is also decreasing in time discount rate r, and the attractiveness of outside option R and L, and increasing with the profitability of relationship lending overall Y.

To formalize the relationship between δ_l and search and market activity we get the following proposition.

PROPOSITION 1 (P1). *PLFs lend more using bilateral lending relationships than FLFs.*

[28] Indeed there may exist frictions that can give rise to such an assumption. For example, if managers have fixed mandates toward their investors or how the portfolio manager allocates task to each "product line" employee within the fund which can both restrict lender's search to particular types of borrowers.

Proof: The proof follows directly from simple observation that $\delta_{FLF} \geq \delta_{PLF}$ leads to $\alpha_{PLF,b} = 2(Y - R - \delta_{PLF}L) - 4(r + \delta_{PLF}) \geq 2(Y - R - \delta_{FLF}L) - 4(r + \delta_{FLF}) = \alpha_{FLF,b'}$ which clearly holds for any tuple of borrowers (b, b'), including the case where $b = b'$, since α_{lb} does not depend on the identity of the borrower. Q.E.D.

This proposition shows that irrespective of how lenders and borrowers pair up, a PLF without a relationship will always search, match and lend more than a FLF without a relationship. The second proposition relates to the equilibrium "coupon" or repayment rate.

PROPOSITION 2 (P2)**.** *A bilateral "relationship" loan negotiated by a PLF has on average a higher interest rate relative to a similar loan negotiated by a FLF.*

Proof: The proof follows directly from simple observation that conditional on borrower type b, the expected value of the coupon rate is higher for PLFs than for FLFs. Formally $E(C_{b,PLF}) = Y + \lambda_b - (r + \delta_{PLF}) > Y + \theta_l\lambda_b - (r + \delta_{FLF}) = E(C_{b,FLF})$ where I have used the fact that $E(\theta_l) = \frac{1}{2}$ and that $\delta_{FLF} > \delta_{PLF}$. Q.E.D.

It is worth highlighting that although PLFs do more relationship lending that is associated with higher coupon rates $C_{bl} > R$ than for transactional lending, this proposition implies that even for ex ante similar relationship loans, PLFs can, on expectation, get better loan terms than FLFs. It is easy to see that these propositions translate into direct predictions of the model, which are tested in the empirical section.

3.2.5 Additional discussion

Before moving to test these model predictions, here are a few clarifying comments about sorting on each side of the market. First, why would a borrower want to match with PLFs if they have to pay a higher interest rate on average with these types of lenders? As the model illustrates, on the one hand FLFs have lower reservation coupon than PLFs, which means that with FLFs there is more surplus for the borrower to bargain for but on the other hand having a PLF-lender is less risky. In fact, it is easy to show that borrower is completely indifferent between which lender to search and match with since the expected value of dealing with either lender is the same. Using the asset pricing analogue, when dealing with a FLF-lender borrower trades off higher expected dividends (lower interest rate) for higher discount rates (higher counterparty liquidation risk) and these two forces exactly cancel out. More discussion in Appendix B.

Second, given that the expected value of running a PLF exceeds that of running a FLF, why would any manager bother launching a FLF rather than a PLF in the first place? While there can be multiple reasons, the simplest is to think of fundraising costs. Even if *after* successful fundraising the market value of operating a PLF is higher than that of a FLF then if the probability of actually conducting a successful PLF-fundraising (typically an initial public offering, IPO) is lower than conducting a FLF-fundraising then (some) managers may ex-ante prefer launching a FLF over PLF. I show a simple example that formalizes this idea in Appendix B and thus endogenizes manager's choice of fund structure. This extension has no impact on the rest of the model or the propositions.

3.2.6 Regarding the assumptions

First, in this model when a relationship is formed, it is continued until perpetuity unless borrower defaults or lender liquidates. In reality, while the loan maturities in the data span just a few years and not to perpetuity, many relationships are renewed frequently when the borrower refinances her old loan so these relationships can be viewed as valuable assets that generate income streams for both parties through multiple refinancing cycles.

Second, while the assumption that a manager forms and maintains a single lending relationship at a time, may sound restrictive, it is a useful modeling tool and not at all restrictive. One could think of a BDC consisting of multiple "product lines" where each fund employee searches for potential borrowers and forms a relationship when a suitable match is found. For example, a BDC manager with 100 employees has the resources to form and maintain lending relationships with 100 borrowers when operating at "maximum capacity". Furthermore, while different product line employees may form relationships with borrowers at different times due to sampling variance, studying the product line of a single employee is fully representative of the fund behavior as a whole since the fund's environment and horizon impacts all employees similarly. Thus, from the analysis of a single employee, we can make inferences about the portfolio behavior of the fund as a whole.

4 Data

4.1 BDC holdings and fund characteristics

I collect a list of BDCs from SEC's Business Development Company Reports.[29] All BDCs have to report their portfolio holdings in quarterly 10-Q and 10-K filings under the section Schedules of Investments (SOI). In SOI, BDCs report for each loan (or security) held in their books the following security level details: Borrower company name, loan type (such as senior secured debt), fair value, par value, cost, coupon rate, and usually also the benchmark rate (such as LIBOR) and maturity date.[30] This information appears in the filings from loan origination until the loan is repaid, sold, restructured, or written off. I hand-collect these portfolio holdings from these filings that are reported in SEC EDGAR for the period 2005Q1 to 2022Q4.[31] For the pre-2005 period, the cross-section of BDCs is very narrow while the data quality deteriorates significantly. I merge the files and link portfolio companies based on company names.[32] To help track loan positions across time I use identifying information of the lender, borrower, and debt class. I allocate additional details about the data collection to Appendix D. The resulting data can be described as a rich credit registry of the BDC sector.

I also collect information on management fees from the annual reports that are reported in the section "Investment Advisory Agreement". By reading all historical reports I can track when shareholders have made changes to these fees in shareholders meetings. From 10-Ks I also collect standard information such as the legal status of the firm; Traded PLF, Non-Traded PLF, or FLF, when the BDC was established, whether the BDC is externally or internally managed, and if externally managed what entity is the fund's adviser.[33][34]

[29] https://www.sec.gov/open/datasets-bdc

[30] Fair values track changes in security value taking into account the probability and magnitude of losses of the loan given the borrower's current circumstances and riskiness, as well as broader market conditions. These values are determined by the lender or third-party valuation agents and formal guidance is given by the Financial Accounting Standards Board's ASC 820 accounting standard (previously, "FAS 157").

[31] There are some BDCs for which I do not find these reports from SEC EDGAR. However, it seems these are the less-important and mostly tiny BDCs anyway since they lack information also in other data sources.

[32] For a subset of BDCs for the post-2017Q2 period, I also obtain these holdings from Factset with security and portfolio company identifiers and with matching borrower names I utilize mapping files generated by the Pitchbook's matching algorithm while also checking matches by hand.

[33] In some results, I control the identity of the investment adviser using fixed effects. These fixed effects are based on these adviser-groupings, although some parent companies of BDCs operate multiple sub-investment advisers in which case I still group the subsidiary BDCs under the same parent company adviser. These results are naturally restricted only to externally managed funds, since internally managed funds operate as single entities.

[34] Since only the externally managed funds report their fee structure, I set the fee parameters for internally managed funds to zero because otherwise any regression with fee parameters as controls would drop all the

4.2 Financials

Based on the firm tickers or names of BDCs, I get market pricing from CRSP, balance sheet and income statement information from S&P Capital IQ, and Refinitiv (now LSEG) Workspace. When available I augment the portfolio company-specific information—such as the PE-backing status—using data from S&P Capital IQ, SNL Financial, Refinitiv Workspace, Preqin, and Pitchbook. Unfortunately, since most portfolio companies are private the financial information for most firms is scarcely available. Furthermore, I merge the data with aggregate interest rate and index series. LIBOR and LIBOR-swap rates are obtained from Refinitiv Workspace, while other rate series are from FRED. I obtain data on leveraged loan spread from the Fed Financial Stability Report from May 2023. The data shows a secondary-market discounted spread to maturity, which is a constant spread used to equate discounted loan cash flows to the current market price. The data for the Fed report is originally sourced from PitchBook Data, Leveraged Commentary & Data. For some tests, I use the borrower firm's employment level and growth as the dependent variable. Information about the number of employees for most of these private companies is not publicly available, thus following Davydiuk, Marchuk, and Rosen (2024a) I use the number of employees enrolled in the firm's pension plan as a proxy for this. Lastly, I got average equity closed-end fund discount data from Investment Company Institute (Duvall & Atamanchuck, 2023).

4.3 Definition of the key variables

The model distinguishes between one-to-one bilateral lending and lending with multiple lenders. So the strength of the lending relationship is a measure lending exclusivity. I use this idea when constructing the empirical measures while simultanously following the prior literature. For example, Bharath et al. (2011, 2007) define the lending relationship in the syndicated loan market based on the share of credit provided to borrower b by lender l out of all the credit provided to the borrower within the past five years by the syndicated lenders. While keeping the main idea the same my credit-registry type of data accommodates two improvements to their measure. First, as the authors acknowledge, in the case of multiple lenders their deal-level data often does not report the shares of each lender so they have to use aggregate deal values in allocating positions of different

missing observations associated with internally managed funds. However, by including in the regression specification an indicator variable that tracks the status of the fund being internally managed, ensures that this adjustment of missing observations does not mechanically bias the coefficients of the fee parameter controls. Appendix H gives more information about the typical fees and differences between externally and internally managed funds.

lenders to borrowers. My holdings data does not have this drawback since I do observe the lender shares. The second advantage is that I observe all the lending relationships formed with BDCs every quarter so I can track this measure of lender share period-by-period and do not have to rely on information about loan originations within the past five years.[35]

I follow Bharath et al. (2011, 2007) by defining two measures of relationship strength: First $Rel(Amount)_{blt}$ is the lender l's share of the borrower b's total observable credit outstanding in a given period t. Second, similarly to Bharath et al. (2011), my main variable is $Rel(Dummy)_{blt}$ which is an indicator variable that takes a value of one if the lender l's $Rel(Amount)_{blt}$ is the largest among all the lenders that lend to borrower b in that period t. Naturally when borrower b borrows just from a single lender $Rel(Amount)_{blt} = 100\%$ and thus $Rel(Dummy)_{blt}$ also takes a value of one. Although, the interpretation of the point estimates differs based on which measure I use, they both give very similar results with the same economic and statistical interpretations. Lastly we can aggregate loan level data to a portfolio level to analyze what fraction of the portfolio in value weighted terms is allocated to particular types of loans. In Appendix G I show that these measures strongly correlate with other proxies of relationship strength and discuss the fact that I do not observe non-BDC relationships in the main dataset. A detailed description of these and other variables used in the study is presented in Appendix A.

4.4 Descriptive statistics

Table 1 reports the descriptive statistics, which are divided into two panels based on the granularity of the dataset. Panel A shows the statistics from the BDC-level data. We see that from the panel 64% of Lender-YearQuarter observations originate from traded PLFs, 34% of the observations are from FLF and 2% are from non-traded PLFs. The median (mean) size of the fund is $600 million ($1.44 billion). Panel B shows the statistics from the loan position level data. I exclude any non-debt positions (e.g. cash, equity, preferred stocks) and positions that are classified as *Structured Product* such as CLOs from the sample since such positions are unsuitable for testing the model's predictions. We see

[35] Any relationship lending measure that relies on past data mechanically biases the results towards older funds even if they are at the observation date an insignificant lender for that borrower. Since PLFs are typically older than FLFs due to their long investment horizon, such a measure would further strengthen the observed sorting pattern between relationship lending and fund structure. The fact that repeated interactions are usually more likely for long-horizon-funds provides an additional reason why this fund structure supports relationship lending activity, by focusing on current relationship exclusiveness/strength I am defining these relationship measures conservatively while avoiding the influence of this mechanical duration bias.

from Panel B that the median (mean) loan position is about $8.3 million ($17.5 million). Also, it illustrates that 83% of the loan observations are considered to be senior and/or secured, while revolvers and subordinated debt comprise of 9% and 8% of the total number of observations, respectively. 65% of observations are categorized as relationship loans based on $Rel(Dummy)$. The median debt position share allocated to a given borrower is 1%.

[Table 1 here]

[Figure 2 here]

Figure 2 plots the aggregated assets under management (AUM) and a number of funds of each type of BDC. The figure gives a fairly representative overview of the total size of the BDC sector over the years.[36] As the figure dramatically illustrates the size of the BDC sector doubled in 2 years, from $140 billion in 2020Q4 to $284 billion in 2022Q4. Traded BDCs are the largest category but in past years non-traded BDCs have gained popularity. In terms of AUM, this has been to a large extent driven by a couple of very large nontraded perpetual-life BDCs but in terms of the number of funds, it has been largely driven by the emergence of many smaller finite-life funds.

Although BDCs are also considered to represent typical non-BDC direct lending funds in the private debt industry (Block et al., 2024; Nesbitt, 2019), the composition of different types of funds among BDCs seen in Figure 2 does not translate into similar shares between different types of private debt funds. This is because historically, both in terms of AUM and in terms of number of funds, the finite-life funds have dominated the private markets. Evidence of this is illustrated in Figure 3 that shows the share of perpetual-life funds among all newly launched funds, both in the global private equity and private debt industry, respectively. The figure confirms the statement that most new funds have traditionally been finite life funds.[37] However the figure also shows the recent dramatic

[36]The sample excludes those funds with business models that are not comparable to typical BDCs specialized in middle market direct lending, such as those that mainly invest in equities, operate as REITs, VC funds, or have otherwise atypical business models. Also, the sample omits funds for that do not have quarterly reports in SEC EDGAR.

[37]This Preqin Pro data excludes most BDCs (which are in minority anyway) and the fund categories for private debt funds do not distinguish between PLFs and FLFs. However, given that most listed, evergreen, open- and semi-open-ended funds have perpetual life, these are likely to be fairly good estimates.

increase in the share of new funds that are (most likely) operated as perpetual life funds.[38]

[Figure 3 here]

[Table 2 here]

Returning to our focus of BDCs, Table 2 shows the average fund characteristics, the differences in these means between fund types, and the associated standard errors for the post-2011 period. During the pre-2011 period, the sample generally consists only of traded BDCs.[39] Results from these univariate tests provide preliminary support for the model's predictions. PLFs allocate a larger fraction of their loan portfolios to loans in which they are the only or the largest lenders for that borrower. The mean difference is statistically significant between traded PLFs and FLFs and the result is also robust to using complementary measures of relationship lending: the share of the loan portfolio allocated to firms in which the lender also has an equity (or preferred stock) stake, the share of the portfolio allocated to "Level 3 assets" that are described as the most illiquid and opaque by the ASC 820 accounting standard and the loans with high coupon spreads.[40] The loan portfolio yield spread and coupon spread over the benchmark LIBOR rate are also higher for traded PLF and these funds also seem to hold a marginally larger fraction

[38]Some potential explanations for the increase in PLF popularity include i) the increasing fundraising challenges associated with FLF-structure, ii) demand for liquidity from institutional end-investors iii) expansion to cater retail clients iv) having more stable long-term funding sources following tie-ups with insurance companies. In 2023Q1, the seven large US public PE firms held 37% of their aggregate AUM in PLFs. (Pitchbook, 2023)

[39]Funds that are non-traded but planning to conduct an IPO, say, within a year, are unlikely to view themselves as finite-life funds because they have plans to continue operating as PLF after the listing. It is thus likely that these funds thus start to operate as de-facto PLFs already before an IPO. To mitigate this concern I exclude the observations that appear within a year before any realized IPO. Indeed, the sample of FLFs for the pre-2011 period consists only of BDCs that were non-listed at inception but then almost immediately (within a few months) conducted an IPO, so excluding the problematic observations thus restricts the sample to the post-2010 period. Including these 46 fund-YearQtr observations, however, has almost no impact on any of the results.

[40]High share of loans with equity stakes can be thought to proxy of a more exclusive relationship since the more opaque or riskier borrowers typically grant the use of equity stakes to align the interest of shareholders and creditors, which results in a deeper relationship between the lender and borrower. By accounting standards, Level 3 assets are classified as the hardest to value and most illiquid assets. Thus Level 3 assets better align with the model's interpretation of a relationship loan since some of the typical transaction-driven loans—like those originated by the broadly syndicated loan market—are often traded in the secondary markets, and are classified as more liquid Level 2 assets. Appendix G presents additional tests based on these alternative measures with similar findings.

of their loan portfolio in non-sponsored loans. These early findings are consistent with Proposition 1 and 2.

However, these results do not extend to differences between non-traded PLFs and FLFs. This is unsurprising since i) the sample contains only a handful of recently launched non-traded PLFs with only a few quarters of observations and ii) unlike most of the other funds nontraded PLFs typically start the investment activity with an existing loan portfolio that is bought from a bank which implies that these relationships are not initially formed between the BDC and the portfolio company. This makes most of these loans ill-suited to test the theory's predictions.

There are also other differences between fund types. First, traded BDCs have on average higher base fees, performance fees, and hurdle rates relative to non-traded funds.[41] These fee differences, which are paid as expenses by the fund, also tend to have a direct mechanical impact on differences in profitability (measured in ROE) but such differences are not statically significant in the table. Finally, the PLFs are on average larger than the FLFs. Since it is clear that some of these fund characteristics correlate with fund type, I include them as control variables when analyzing the multivariate regression results below.

To see how persistent are the differences in relationship lending share, Level 3 asset share and portfolio's coupon rate, I plot the average value of those characteristics for each period for each fund type in Figure 4. Especially, the differences between traded PLFs and FLFs are highly persistent across time. The average values for the non-traded PLFs is accompanied with high confidence intervals due to the low number of funds in the sample most of which are launched in the late part of the sample.

[Figure 4 here]

5 Testing the model's predictions

Let us start by analyzing the main prediction from the model that on average PLFs engage more in typically bilateral relationship lending than FLFs (Proposition 1). Afterwards I present the main results using loan-level data and also test Proposition 2.

[41] Most BDC managers have very unique compensation structures, which is something I control in my analysis. Since the fee structure itself is not at the center of the analysis I will allocate a detailed description of these institutional details to Appendix H.

5.1 Testing Proposition 1

I start by running simple BDC-time-level panel regression where the par-weighted share of loan portfolio held in relationship borrowers for BDC-lender l in period t is regressed on indicator variables indicating whether the BDC is a traded PLF or non-traded PLF in that period. The coefficients on these indicator variables have the interpretation that they reveal how much each of these fund types allocates more to relationship lending relative to a finite-life fund lender, which is the benchmark fund type. I also test and confirm that these results largely arise from the positions where the lender l is the only BDC-lender for that borrower by using as the second dependent variable the par-weighted share of loan portfolio held in loans where the BDC is the only BDC-lender for that borrower.

While I include the indicator variable for non-traded PLFs as an explantory variable, my focus is mainly on traded PLFs. The main reason for this is that the non-traded PLFs typically start their operations by buying an existing loan portfolio from the bank and only then start to participate in search markets to find new relationships. Since these initial loans are typically broadly syndicated loans (with multiple lenders), they automatically shift the loan portfolio to non-relationship lending type of assets. The fact that all the non-traded PLFs in the sample are newly launched funds amplifies this issue. So overall, their business model does not translate well into testing the theory's predictions. The additional problem is that the emergence of nontraded PLF structure is so recent phenomenon that I have only a few observations of these funds in my sample.

The two types of regressions that I run are

$$Rel.\,lending\,share_{l,t} = \beta_1\, TradedPLF_{l,t} + Controls + FixedEffects + \varepsilon_{l,t} \tag{20}$$

$$Single\,lender\,share_{l,t} = \beta_1\, TradedPLF_{l,t} + Controls + FixedEffects + \varepsilon_{l,t} \tag{21}$$

Regardless which dependent variable we use, the Proposition 1 predicts that β_1 should be positive. Although the main purpose here is to test if there exists endogenous matching in the loan market, one could go further and argue that fund structure is the causal driver behind what type of lending activity the fund engages in. While I think there is a case to be made in favor of such an interpretation, fully overruling an alternative explanation is difficult.

The main threat to identification is that an asset manager that launches a PLF, rather than an FLF, would have engaged more heavily in relationship lending *regardless* of this decision (or would have been more attractive counterparty for relationship borrowers

regardless). Unfortunately, since fund managers are not randomly allocated to run funds with different structures, from the face of it we cannot assign a causal interpretation for the estimates of β_1. If the factors that influence the manager's decision about which type of fund to launch, also directly influence the manager's portfolio allocation decisions, then if left unconditioned, these factors could generate an omitted variable bias in the reported coefficients.

My empirical strategy aims to address this concern in several different ways. First, I discuss what I consider to be the most influential variables that could confound the results and then directly control for these in columns (2)-(7). Second, I use loan-level data and two instrumental variables for the fund structure. The more granular data also allows me to include *Borrower* $\times$ *Time* fixed effects that rule out the explanation that the observed equilibrium sorting by lending styles is *only* driven by funds engaging in deals with different population borrowers. Third, I restrict the sample to a transition sample of funds that previously operated as FLFs but then transition to PLFs through an IPO and analyze these transition dynamics. Fourth, I do propensity score matching, using Pitchbook's deal-leval data and using alternative measures of relationship lending but I allocate these robustness tests to the Appendix G for brevity. All tests support causal interpretation.

[Table 3 here]

Table 3 presents the portfolio-level OLS results. The control variables I use on the right-hand side of the regression are the indicator variable that the lender is a non-traded PLF, one period lagged log size of the fund, fund leverage, fund profitability (measured as return on equity, ROE), an indicator variable that takes a value of one when the fund is internally managed and zero otherwise, and finally three variables related to the fees and management incentives: base management fee, net investment income incentive fee, and the hurdle rate for this performance fee. Controlling for these fees related to management incentives is important since they directly influence end-investors' appetite for different fund types[42] but could also have a direct impact on the willingness of the fund to take risks.[43]

[42]FLFs that mostly serve accredited limited partner investors have historically had lower fees in exchange for the more illiquid shares while traded PLFs have had higher fees in exchange for being accessible to broader investors base and having more liquid share base.

[43]Note that many of these control variables could even be viewed as outcomes of fund type implying they might suffer from being "bad controls" (Angrist & Pischke, 2009) and should be excluded from the specification to begin with. However, if one is skeptical about the interpretation that fund type is the prim-

Even after controlling for observables, there may be characteristics like the lender's reputation, fundraising ability, investment policy, management's risk aversion, and corporate culture that are all specific to the fund's investment adviser (the entity that actually runs the fund) and may influence both the selection to fund types but also the BDC's portfolio choice directly. Indeed, one potential concern is that the differences in propensity to engage in relationship lending originate not from the differences between fund types but due to differences in fund advisers' characteristics. For example, if the investment approach of all Blackstone's funds significantly differs from the approach of KKR's funds, and Blackstone tends to operate mainly PLFs while KKR tends to operate mainly FLFs, then I could mistakenly assign the difference between relationship lending shares to be due to the fund type while, in reality, it is caused by differences in the fund adviser's investment approach.[44] By introducing Adviser fixed effects in column (3), or even $Adviser \times YearQtr$ fixed effects to account for changes in these strategies over time in column (4), I narrow the focus to externally managed funds and exclusively to advisers who have launched multiple funds, some PLFs and others FLFs, enabling us to analyze differences in relationship lending propensity within the adviser's portfolio of funds. As expected, these fixed effects absorb a lot of the variation from the data, evidenced by the high R^2 in columns (3) and (4), but the main results remain strongly economically and statistically significant. However the fact that coefficient shrink when adding *Adviser* fixed effect indicates that different advisers engage in different types of investment strategies to some extent and the fact that some advisers are more likely to run PLFs and others FLFs may explain part of the unconditional sorting patterns.

The purpose of the remaining columns (5)-(7) is to show that these results arise in large part from bilateral relationships and not only from positions in which the lender is the largest lender among multiple lenders. These results are similar to those in columns (1)-(4) and equally robust. Next, I move to the main results that are based on the loan-level data. Also, in the remaining part of the analysis, I focus only on relationship strength measures, $Rel(Dummy)$ and $Rel(Amount)$ variables introduced earlier, that capture both these intensive and extensive margins simultaneously.

itive manager decision, then these controls could be useful to include. To remain open to this interpretation I include these variables in the main regression. However, their inclusion changes the coefficients very little as shown when moving from column (1) to column (2), so in practice this problem seems to have a negligible impact on results.

[44] Blackstone and KKR are examples of investment companies that operate multiple BDCs.

5.2 Instrumental variable research design and loan level data

In this section, I use loan-level data to analyze if the relationship lending measures are associated with the fund structure. This granular loan-level data, observed at the level of lender l, borrower b, quarter t and debt class k, allows me to further locate how the sorting and endogenous matching arise. I run the following regression.

$$y_{l,b,k,t} = \beta_1 Traded\ PLF_{l,t} + Controls + FixedEffects + \varepsilon_{l,b,k,t} \tag{22}$$

where $y_{l,b,k,t} \in \{Rel(Dummy), Rel(Amount), \ln(\#of\ Employees)\}$. In addition to the relationship lending variables defined above, I add a third variable, the logarithm of the number of employees that the borrower firm has, which proxies for the size of the borrower. The motivation for using this dependent variable comes from a pre-established notion in the prior literature that the borrowers that rely on relationship lending tend to be smaller and more opaque. Thus using a proxy of the borrower size provides a complementary view of testing the influence of fund structure on relationship lending activity. Although the sample shrinks somewhat when using this variable, it is one of the few measures that I have about borrower companies that is still sufficiently broadly available in the sample without raising major concerns about selection bias.

Using $Rel(Dummy)$ as a dependent variable effectively transforms the model into a linear-probability model, implying that the coefficients can be broadly interpreted as how much a unit increase in that variable increases the probability that a loan is held by the largest —- or only—lender for that borrower. When using $Rel(Amount)$ as the dependent variable, the coefficients can be broadly interpreted as measuring how many percentage points a unit increase in that variable increases the lender's share of the borrower's total BDC-originated debt.

Using more granular controls and fixed effects allows me to analyze if the observable sorting pattern occurs primarily due to different BDCs engaging in lending with different types of borrowers or does the sorting pattern also occurs independently of borrower identity. For example, if results generally disappear when adding $Borrower \times YearQtr$ fixed effect, this would indicate that the major reason behind sorting is the differences between borrower base (single-lender borrowers versus multi-lender borrowers), while if the coefficients stay unchanged when adding such fixed effects would indicate that even when restricting the analysis to same firm borrowing from multiple different types of BDCs, the PLFs typically hold larger positions.

The loan-level panel has the additional benefit that it allows us to study the partial correlation of relationship lending measures with other borrower and loan variables.

Specifically, we would expect that observations with high value for $Rel(Dummy)$ and $Rel(Amount)$ also occur with loan terms and borrower characteristics that more naturally take the interpretation of typical borrowers using relationship loans. Thus, in addition to including previous lender-level variables, I also add observable loan and borrower characteristics that help to provide descriptive evidence that this is indeed the case. In these tests, I use conservative three-way clustered standard errors at $Borrower + Lender + YearQtr$ level, further adding the borrower dimension to the one used in portfolio-level regressions. Borrower-level clustering accounts for any residual autocorrelation in relationship measure for each borrower.

However, having controls may not be enough. As outlined above, the BDC manager's choice of which fund to launch is potentially endogenous. Perhaps a manager who chooses to launch PLF or conduct an initial public offering (IPO) and convert her FLF to a PLF would have engaged more in relationship lending regardless of her choice of fund type. To help address this endogeneity, I use an instrumental variable for the *Traded PLF* that leverages manager's propensity to react to the attractiveness of the IPO market. A good instrument needs to satisfy the relevance condition, that is the instrument needs to correlate with the instrumented variable, and exclusion restriction, that is the instrument affects the dependent variable only through the instrumented variable but not through other channels. The equity market sentiment is a potential candidate since it directly impacts the probability of conducting a successful IPO and thus the manager's willingness to launch (or convert to) a traded PLF. However, equity market sentiment in the stock market of large public companies is unlikely to influence BDC managers' investment behavior in the loan market of small and mid-sized private companies besides through the channel that operates through IPO fundraising. I use the average premium/discount of the existing equity closed-end funds in the market during the previous quarter as a measure of equity market sentiment because it is likely to be highly correlated with the IPO activity of BDCs. Furthermore, using closed-end fund discount as a measure of investor sentiment has a long history in the finance literature (Baker & Wurgler, 2007; Lee, Shleifer, & Thaler, 1991). Finally, when a BDC conducts an IPO and becomes a traded PLF, this instrumental variable is then censored to the level it was during the quarter before the IPO. This is due to the fact that among BDCs, the decision to go public typically operates in one direction only, which effectively makes the influence of stock market sentiment on fund structure irrelevant afterward.[45] Since funds time their fundraising activity differently we can also include time fixed effects that control for aggregate conditions. Below I also introduce an alternative instrument that focuses on the borrower's choice of lender

[45] I present some descriptive results to support the instrument in Appendix F.

type as in Berger et al. (2005). Having a second IV addresses any concerns about exclusion restriction of the first instrument.

[Table 4 here]

Table 4 presents the regression results. The results from columns (1) to (7) indicate that a loan is more likely to be associated with strong lending relationship if it is made to a non-PE-sponsored borrower, the loan type is a revolver or subordinated debt, the loan position is large, the loan maturity is short, or the loan is made either by a non-traded PLF or a traded PLF (relative to FLF). For example, the point estimates for *TradedPLF* variable in column (1) suggest that, all else equal, traded PLFs (rather than FLFs) are about 19% more likely to be the only or the largest BDC lender for that borrower in any given period. The corresponding figure for non-traded PLF is 22%. Interestingly, I do not find evidence that fund's leverage, fee structure, or internally versus externally managed status plays any role in determining the relationship loan status.

Whereas the *YearQtr* fixed effect specifications in columns (1) allow the variation to originate from all the lenders, columns (2) and (5) first extend the fixed effects to *Borrower*-level and then columns (3) and (6) to *Borrower* $\times$ *YearQtr* level, thus fully controlling the borrower identity and restricting the sample only to borrowers that have multiple loans outstanding to different lenders in a given period. While the point estimates for *Traded PLF* shrink, they remain statistically significant. Thus, columns (3) and (6) imply that results do not *only* originate from different fund types serving different types of borrowers but traded perpetual-life funds are also more likely to hold bigger positions among the borrowers that borrow from multiple different types of lenders. Lastly, columns (4) and (7) show the results from the second stage of the two-stage least square regression where I have instrumented for the fund structure using the *IPO Attractiveness* variable. The point estimates increase from those reported in columns (2) and (5), indicating that endogeneity may bias the OLS coefficients downward.

Column (8) provides support also for the idea that different fund types may target borrowers of different sizes. Using a subsample of firms of which I observe the employee count of each firm, we see that PE-sponsored firms are generally larger, longer time-to-maturity is associated with larger firms and the lender is less likley to have an equity stake in bigger companies. We see that the coefficient of *Traded PLF* is negative indicating that traded PLFs lend to smaller firms compared to FLFs. Lastly, in column (9) I interact *Traded PLF* (and *NonTr. PLF*) with *Rel*(*Dummy*). What we see is that traded PLFs are more likely to be lenders of smaller companies only for positions where they have a strong

or a bilateral relationship with that borrower. The negative point estimate of $Rel(Dummy)$ indicates that also when FLF is the lender a higher $Rel(Dummy)$ is associated with smaller borrowers but this correlation is less pronounced than with traded PLFs. Overall, all results support Proposition 1.

5.3 Other robustness tests

I augment the results above using multiple robustness tests presented in the Appendix G. First, I show that results are robust to using a propensity-score-matched fund sample on a list of covariates. This approach alleviates the possibility that PLFs and FLFs differ fundamentally in other aspects besides their fund structure. Second, I run the portfolio level regression using complementary measures of relationship lending: the share of Level 3 assets in the portfolio, loan portfolio spread and coupon rate, the share of loan portfolio held in firms where the BDC also holds an equity stake, leverage ratio and share of loan portfolio held in firms that have access to broadly syndicated loan market. Third, I test the robustness findings to inclusion of other non-BDC lenders with a deal-level data from Pitchbook. This alternative dataset lets me analyze the correlation between various relationship lending proxies and fund type at the time of deal origination.

5.4 Testing Proposition 2

We found support for Proposition 1. Now we test Proposition 2, which is that more exclusive or fully bilateral "relationship" loan negotiated by a PLF has on average a higher coupon interest rate relative to a similar loan negotiated by a FLF. However, this is potentially much more difficult since the Proposition 2 relies on the assumption that we can observe in the form of the loan's coupon rate how the surplus between lender and borrower is shared. However, while I referred the periodic payment as coupon rate in the model, this payment from borrower to lender could in principle incorporate many other non-observable components of loan terms that are not reflected in coupon pricing. This means that the coupon rate is potentially only a good proxy of how the surplus is being shared but not an all-inclusive measure of this. This caveat should be kept in mind.

I start by running the following loan-level regression that tests the prediction of Proposition 2.

$$CouponRate_{l,b,k,t} = \beta_1 Traded\,PLF_{l,t} + Controls + FixedEffects + \varepsilon_{l,b,k,t} \tag{23}$$

where the dependent variable is the coupon rate (denoted as %) of a debt position held

by lender l in borrower b in debt class k in time t. The main explanatory variables is $Traded\ PLF_{l,t}$ as before.

The main problem relates to identification. There is a selection issue that perhaps loans held by traded PLFs are observably different from those held by FLFs, and require a high interest rate not because of the lender's high reservation coupon rate and market power but simply due to risk. I address this issue with granular sets of fixed effects and instrumental variables. What also helps with the identification is that the model suggests that the benefit of *Traded PLF* should appear primarily among relationship loans. By interacting *Traded PLF* with $Rel(Dummy)$ we can test this to see if the coupon rate difference arises primarily from relationship loans ($Rel(Dummy) = 1$) or from non-relationship loans ($Rel(Dummy) = 0$). So, the alternative specification takes the form

$$\begin{aligned} CouponRate_{l,b,k,t} = \beta_1\, Traded\ PLF_{l,t} + \beta_2\, Traded\ PLF_{l,t} \times Rel(Dummy)_{l,b,t} \\ + Controls + FixedEffects + \varepsilon_{l,b,k,t} \end{aligned} \tag{24}$$

where we expect $\beta_2 > 0$, while the sign of β_1 could go either way.[46]

[Table 5 here]

Table 5 presents the results. Column (1) shows that when conditioning only with time-fixed-effects to control for the overall level of interest rates, the loans held by traded PLFs have higher coupon rates than those held by FLFs while non-traded PLFs have lower coupon rates than FLFs. However, this could be due to differences in underlying risk. When I add controls in column (2) we find that this coefficient shrinks but remains statistically significant. In column (3) I test equation 24. Consistent with the model's predictions I find that loans, with $Rel(Dummy) = 1$ that are more likely to be negotiated by lender and borrower bilaterally in search markets, are associated with a premium for traded PLFs, while there is no effect with $Rel(Dummy) = 0$. In column (4) I add borrower fixed effect to control any unobservable variation that relates to borrower identity. In column (5), I also instrument the fund type using similar IVs as in Table 4, however since we now have an interaction term I add another instrument where I interact $Rel(Dummy)$ with $IPO\ Attractiveness$. As before $IPO\ Attractiveness$ provides the plausible exogenous

[46] In the current formulation of the model the expected return that both PLFs and FLFs can obtain from the multi-lender market is set at R by an assumption. Again R is not the same as the coupon rate. Moreover, one could equally assume, and without loss of generality, that $R_{FLF} \neq R_{PLF}$. So the model has little insights regarding the β_1 term.

identifying variation. The total premium increases since both *Traded PLF* and the interaction term *Traded PLF* $\times$ $Rel(Dummy)$ increase. This implies that potential endogeneity seems to downward bias the OLS coefficients, and after correcting this the traded PLFs enjoy a premium of 95 bps—of which 58 bps originate from non-relationship loans while an additional 37 bps from relationship loans. To remain conservative I take only this interaction-term (β_2) estimate from column (5) as the takeaway estimate for the roll-over risk premium that the traded PLFs enjoy. Comparing this estimate to an average coupon spread in the sample we can infer that the relationship borrowers seem to be willing to accept roughly 5 percent increase in the average coupon spread when borrowing from a traded PLF. Overall, the results in Table 5 provide wide support for Proposition 2.

Relating to the signs of other coefficients, it is interesting that $Rel(Dummy)$ is positive before controlling for loan and borrower observables but not afterward. This suggests that relationship loans are typically associated with riskier borrowers but controlling for observable loan riskiness relationship borrowers may obtain lower coupon rates when using a relationship lender than otherwise.The finding that stronger relationships are associated with lower interest rates is also documented among larger firms in the broadly syndicated loan market (Bharath et al., 2011) and this result is often interpreted as stronger relationships alleviating asymmetric information issues between the lender and the borrower or with other lenders (Ivashina, 2009; Sufi, 2007).

I find these pricing and loan market matching results to be robust to the use of an alternative instrument for the fund type based on the geographical presence of a particular fund type within the home state of the borrower (Berger et al., 2005) but I allocate these results to Appendix G for brevity.

5.5 Transition sample

Both instruments introduced above may still be subject to criticism that exclusion restriction may not be satisfied. I show another robustness test that may further alleviate sample selection bias and endogeneity concerns. I focus on a restricted transition sample of the same BDCs that were private and subsequently conducted an IPO during the sample period. In this transition sample, the post-IPO observations can be considered the treatment group, with the data pre-IPO as the control group. I analyze how different variables that describe lending relationships evolve during the five years after the lender conducts an IPO. I also include a four-year pre-treatment period. This figure shows the effects of public listing status on different loan measures. Specifically, I run the following

regression model

$$y_{blkt} = \sum_{\tau=-15,\tau\notin-1}^{20} \beta_\tau D_{lt,IPO+\tau} + Controls + Fixed\,Effects + e_{blkt} \tag{25}$$

where D_{IPO+0} is an indicator variable that takes a value of one if the lender conducts an IPO in that period and zero otherwise; D_{IPO+1} takes a value of one if the lender conducts an IPO in the previous period, etc. I use four different dependent variables for y_{blkt}: an indicator variable that takes a value of one if the lender is the only lender for that borrower in that period and zero otherwise *Single lender*, the two relationship lending measures, $Rel(Dummy)$ and $Rel(Amount)$, and the loan's coupon rate. I also include the BDC- and loan- and borrower-level controls.[47] The regressions include *Borrower*, *YearQtr*, *DebtClass* fixed effects and I also include *BaseRate* $\times$ *YearQtr* fixed effects when the dependent variable is the coupon rate. I then collect the β_τ coefficients from these regressions and plot the estimates in the Figure 5.

[Figure 5 here]

Figure 5 provides additional support for the interpretation that traded PLF status has potentially also a causal link to more concentrated relationship lending activity and loan pricing. Although, the decision to conduct an IPO is still likely to be endogenous, when interpreting these patterns it is comforting to see that there are no stark observable pretrends before the IPO in the relationship lending measures. The exception is the bottom-right figure for *Coupon Rate* (%) where the estimates seem to be at a higher level about three years before the IPO and shrink close to zero about one year before the IPO. The preparation for the IPO may be associated with lenders window-dressing their loan portfolio, by removing the riskiest (high coupon rate) loans from the portfolio and moving back to riskier loans after the IPO, a practice that could potentially generate the V-shaped pattern in the bottom-right figure. What is also interesting is that the effect of traded status does not seem to be immediate but operates with about a six-quarter lag. However, once the effect of the fund's public status starts to take effect it shifts the portfolio allocation of these funds toward more exclusive lending relationships and higher coupon rates. These effects also seem persistent, with having positive effects lasting at least 20-quarters after the initial IPO date.

[47] In most BDCs' investment advisory agreements the parameters of the management compensation contract are adjusted upward in the event of a fund's IPO. Given that i) these fees are direct outcome of BDC's public status, and thus bad controls, and ii) the associated multicollinearity is particularly problematic in this restricted sample, I do not include these variables as controls.

5.6 Fund structure and credit provision

We may still be interested in knowing how the credit provision between these fund types differ based on borrower's situation. For this, I run the following regression

$$\ln Credit_{blk,t} = \beta_1 Traded\ PLF_{lt} \times Rel(M)_{blt} + \beta_2 Fair/Par_{blkt} \times Rel(M)_{blt} \quad (26)$$

$$+ \beta_3 Traded\ PLF_{lt} \times Fair/Par_{blkt} \times Rel(M)_{blt} + other\ terms + e_{bltk} \quad (27)$$

The idea is to test if PLFs lend more to more distressed borrowers, that is to borrowers with low loan values measured as level of $Fair/Par$. I also make a distinction between stronger and weaker lending relationships when testing this. The dependent variable is the natural logarithm of the credit outstanding for the borrower b from the lender l at time t in the debt class k. For brevity, in Equation (26) I have pooled all the other interaction terms and their coefficients and fixed effects to the *other terms* vector. As before, I use $Rel(Dummy)$ with $Rel(Amount)$ as my relationship measure of $Rel(M)$.

Table 6 presents the results. I find that $\beta_1 > 0$, and $\beta_2 > 0$ and $\beta_3 < 0$ and this result holds for both $Rel(Amount)$ and $Rel(Dummy)$. My main coefficient of interest is the interaction term $Traded\ PLF \times Fair/Par \times Rel(M)$ for both $Rel(Amount)$ and $Rel(Dummy)$ because it shows if traded PLFs hold bigger positions in their relationship loans even when the loan is not performing well. With $\beta_3 < 0$ interpretation is that all else equal traded PLFs lend more to firms with whom they have strong lending relationships and they lend more than FLFs also when loan value is low that is when $Fair/Par$ is low.

These results hold irrespective of specification—even in column (3) and (6) where I am controlling for granular $YearQtr \times Borrower + YearQtr \times Lender$ fixed effects. The results also hold with instrumental variables. In summary, the presence of the relationship lender seems to be beneficial for the borrower especially when it is having a low loan value, since relationship lenders are more likely to keep holding/refinancing their loans even in bad times. These results are consistent with previous studies of bank lending relationships, such as Petersen and Rajan (1994, 1995) showing that lenders with a vested interest in the continuation of a borrower tend to offer more favorable loan terms when the borrower is in trouble.

Also, consistent with what we found earlier, the coefficient on β_1 is positive, indicating the traded PLFs are asociated with more credit especially to firms to which they have a strong relationship. I also include the results for non-traded PLFs and find that all the analogous coefficients of β_1 and β_2 and β_3 have the same signs when using $NonTr.PLF$ instead of $Traded\ PLF$. These findings further support the important role of the invest-

ment horizon in the fund structure. In the Appendix G.9, I augment these results by showing that strong lending relationships support employment growth especially when the borrower is experiencing distress.

6 Aggregate pricing facts about the U.S. middle market

Since the middle market loan market is more opaque than most other debt markets, it is useful to describe the market by documenting how the discount rates for middle market loans have varied over time. I construct yield-to-maturity rates from the loan level data, where the Borrower-Lender-DebtClass tuple, identifies a loan position. I solve the yield-to-maturity (YTM) at time t, ytm_t, numerically from the formula

$$FairValue_t = \sum_{\tau=1}^{T} \frac{Coupon_{t+\tau}}{(1+ytm_t)^{\tau}} + \frac{ParValue_{t+T}}{(1+ytm_t)^{T}} \tag{28}$$

where T is the remaining years to maturity.

While the validity of these yield-to-maturity estimates relies on the accuracy of using the standard bond valuation formula for loans that may have different characteristics than traditional bonds, I run robustness tests where I adjust the standard formula to incorporate special loan characteristics and find that such adjustments have a small impact on baseline empirical results. I discuss these implicit assumptions and the robustness checks in Appendix E. Equation (28) shows that ytm is broadly influenced by three components: coupon rate, fair value-to-par value, and time to maturity.[48] Figure 6 shows the average ytm, coupon rate, time-to-maturity and fair-to-par ratio across all loans in a given period. The figure shows that the average level of ytm has exhibited a considerable amount of time series variation and the level has come down somewhat from the early years of the sample. This is broadly explained by the decline in the average coupon rate during the sample period caused by the declining trend in benchmark interest rates. The biggest spikes in ytm seem to be caused by changes in the fair-value-to-par-value ratio, which has fluctuated around 0.93 experiencing spikes downward during recessionary periods. Finally, the average maturity has declined. The approximation formula in Equation (29) suggests when the loan is trading at a discount, a decrease in time-to-maturity should

[48]To see how each component influenced the ytm one could analyze a textbook approximation formula that can be useful for back of the envelope calculations.

$$ytm_t \approx \frac{Coupon_t + \frac{ParValue_t - FairValue_t}{T}}{\frac{ParValue_t + FairValue_t}{2}} \tag{29}$$

have an increasing effect on ytm.

[Figure 6 here]

To understand the spread variation of middle market loans I first calculate yield spread for each loan as a difference between loan's yield-to-maturity and the yield-to-maturity of a corresponding maturity-and coupon-matched synthetic risk-free bond. Then I take the cross-sectional average each period spread to get the average middle market loans spread. This average spread is plotted in Figure 7 in blue. For comparison, I include the high-yield bond spread and single-B-rated leveraged loan spread in the figure. Finally, I include an alternative measure of the middle market spread that is implied by the stock market pricing of BDCs' loan portfolios. I will first concentrate on describing the first three series and explain the construction of the fourth, stock market implied series, later below.

[Figure 7 here]

The figure illustrates that the middle market spread (solid blue line) is almost always above the high-yield bond spread (dotted black line) and liquid leveraged loan spread (dashed brown line). The average distance to both is on average 4.5%. However, a natural question is why is the middle market spread lower than these other fixed-income spreads during the Great Financial Crises (GFC), if we exclude the explanation that middle market loans are safer in crisis periods.[49] Since BDCs need to report the value of their holdings at each quarter-end based on what they would expect to receive for an asset in an *orderly* market transaction, then the yield estimates for the middle market loans may reflect the fundamental riskiness of the loan in markets that are not plagued by disorder in the market. Since in public markets, liquidity providers demand a yield premium for supplying that liquidity to the sellers, an outsized selling pressure may significantly impact prices during periods of market turmoil. Indeed there is considerable evidence that during crisis times many asset prices are exposed to these fire sales and markets exhibit seeming arbitrage opportunities.[50] This public market feature, not present in the private

[49]Default risk of these different assets is briefly discussed in Appendix F using data about historical default rates.

[50]For evidence of fire sales in corporate bond markets see e.g. Ellul, Jotikasthira, and Lundblad (2011), Ma, Xiao, and Zeng (2022), Feldhütter (2012).

markets, causes greater price volatility for high-yield bonds and liquid (secondary market traded) leveraged loans that may not reflect the fundamental riskiness of the asset.

Alternatively, a case can be made that even during market turmoil prices of actively traded assets fully and accurately reflect the fundamentals of the underlying assets and it is the loan values based on fair value assessments that are wrong. Taking this argument even further one could claim that the BDC managers try to *purposely* misreport the value of the portfolio for their benefit.

Regardless, of which view is closer to the truth, it is interesting to know what spread the stock market would assign to BDCs' loan portfolios if it were to decide. To get an estimate of this I use a model-free methodology that is detailed below and information about listed BDCs' stock market pricing relative to the fair value assessment of the BDC's underlying portfolio.

To start, let us denote the value of the investment portfolio according to the analyst's fair value assessment as $P_{t+1}^{FV} = f(y_{t+1}^{FV})$ and according to the market's assessment as $P_{t+1}^{Mkt} = f(y_{t+1}^{Mkt})$ where $f(.)$ is some differentiable function and $y_{t+1}^{(.)}$ is the log yield-to-maturity, $y_{t+1}^{(.)} = \ln(1 + ytm_{t+1}^{(.)})$, that imply a given value of the portfolio according to the fair-value assessment or the stock market's assessment. Using a first-order Taylor-series expansion for both $\ln(P_{t+1}^{(.)})$ around some long-run log-YTM $\bar{y}$, we can write log prices as linear functions of log-YTMs:

$$\ln(P(y_{t+1}^{FV})) = \ln(f(\bar{y})) + \frac{1}{f(\bar{y})}\frac{df}{dy}(y_{t+1}^{FV} - \bar{y}) \tag{30}$$

$$\ln(P(y_{t+1}^{Mkt})) = \ln(f(\bar{y})) + \frac{1}{f(\bar{y})}\frac{df}{dy}(y_{t+1}^{Mkt} - \bar{y}) \tag{31}$$

Then subtracting the second equation from the first, denoting $-\frac{1}{f(\bar{y})}\frac{df}{dy}$ as D, which happens to be the definition of a modified duration, and taking the exponent on both sides of the equation we have

$$\frac{P(y_{t+1}^{FV})}{P(y_{t+1}^{Mkt})} = \exp(-D(y_{t+1}^{FV} - y_{t+1}^{Mkt})) \tag{32}$$

Then using the definition of $y_{t+1}^{(.)}$ for terms on the right-hand side of the equation, we can write

$$\frac{P(y_{t+1}^{FV})}{P(y_{t+1}^{Mkt})} = \left(\frac{1 + ytm_{t+1}^{Mkt}}{1 + ytm_{t+1}^{FV}}\right)^{D} \tag{33}$$

Finally, by rearranging we have

$$ytm_{t+1}^{Mkt} = \left(\frac{P(y_{t+1}^{FV})}{P(y_{t+1}^{Mkt})}\right)^{1/D}(1 + ytm_{t+1}^{FV}) - 1 \tag{34}$$

Since in practice, we observe all the components on the right-hand side of the Equation (34) we can calculate the ytm_{t+1}^{Mkt}. First, ytm_{t+1}^{FV} is the fair-value-weighted average yield-to-maturity in a BDC's loan portfolio. $P(y_{t+1}^{FV})$ is the sum of net-asset-value (NAV) and net debt, while $P(y_{t+1}^{Mkt})$ is the sum of the market value of equity and net debt. This latter sum contains the implicit assumption that the reported book debt equals the stock market's estimate of the value of the debt. It is also important to subtract the cash holdings since we evaluate the market's pricing of investment portfolio net of cash holdings. The duration D is proxied by 0.8 times the average time-to-maturity of the BDC's portfolio and if the BDC does not report the time-to-maturities of its loans, I use the median time-to-maturity of other BDCs' portfolios that are trading in that quarter. Lower D will generally increase the volatility of the ytm_{t+1}^{Mkt} estimate and I show in the Appendix E.3 how the estimates change as we change the duration estimates.[51] Note that we observe only the stock market's estimate of the full BDC's portfolio, not the middle market loan component of it. Since many BDCs hold not just middle market loans, but also other instruments such as equity securities and structured products in their portfolios, which are priced differently from loans, the large changes in the market-implied value of BDC portfolio may over-or underestimate the market-implied spread of the loan portfolio. This is because the stock market pricing of a BDC reflects also the discount rates of these other components in a BDC's portfolio that may experience larger or smaller changes in discount rates relative to middle market loans. To the extent that these other components have a small weight in BDC's investment portfolio or that their pricing does not differ significantly from the loan portfolio, the approximation error is likely to be small.[52] The outcome of this exercise averaged across all BDCs is the dashed red line in Figure 7.

As one can see from the figure, the stock market implied middle market spread is much more volatile and at times much higher than the middle market spread based on fair value assessments. Especially, during GFC and COVID-crisis this measure exhibits large spikes that are much higher than spread estimates based on fair value assessments. However, the same dilemma on how to interpret these market turmoil periods when

[51] If the loans are mainly floating rate, they would have very low interest rate duration, however they do still contain meaningful spread duration.

[52] The sample excludes the BDCs, which mostly hold equity securities or otherwise operate with a business model that deviates from direct lending, which mitigates this issue.

valuing private assets remains: to what extent these spikes in spreads are due to middle market specific deterioration in loan conditions not captured in fair-value assessments, and to what extent they are due to panic selling of BDC stocks in the stock market. Even if the stock market were to agree with the fair value estimate of the loan portfolio, it may still discount the loan portfolio if it thinks the that BDC that holds it can "generate alpha" for the portfolio (thus making the portfolio value higher with BDC involvement) or is plagued by costly agency issues (thus making the portfolio value lower with BDC involvement). So fundamentally we cannot disentangle the stock market disagreeing with fair-value estimates of middle market loans from agency/alpha issues of the BDCs that hold them. This second problem is similar in spirit to the previously discussed and debatable differences in the prevalence of market frictions and the degree of market efficiency.

7 Conclusion

This paper analyzes how does the organizational structure of a firm affects its allocation of resources? I analyze capital allocation in the booming private debt industry and the U.S. middle market using unique loan-level data from business development companies (BDCs). I examine differences between the two organizational structures under which BDCs and many other nonbank financial intermediaries operate: traded perpetual-life and private finite-life. To capture the decentralized nature of the primary loan markets I build dynamic continuous-time equilibrium search and matching model where the perpetual-life of the lender incentives both the lender and the borrower to engage more in bilateral "relationship" lending. The perpetual-life increases the lender's reservation rate and forces the borrower to make a tradeoff between lower loan rollover risk, with having a counterparty that does not experience liquidation, and a higher interest rate.

When testing the model's predictions, I find that the organizational structure of the BDC-fund predicts what type of investment behavior it engages in and generates two-sided endogenous matching. Perpetual-life funds lend bilaterally to underserved and risky borrowers while finite-life funds participate in larger deals with multiple lenders. The increase in coupon rate is estimated to be about 37 bps using an instrumental variable. I also show that perpetual-life credit is targeted more towards relationship borrowers that have worse credit conditions. Finally, I provide new stylized facts about loan pricing in the U.S. middle market more broadly.

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Figures and Tables

Figure 1. BDC types

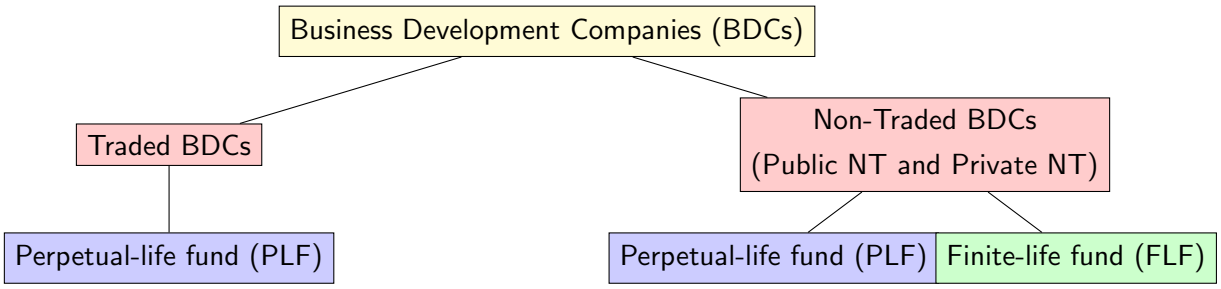


Figure 2. Total asset under management (AUM) and number of BDCs by types

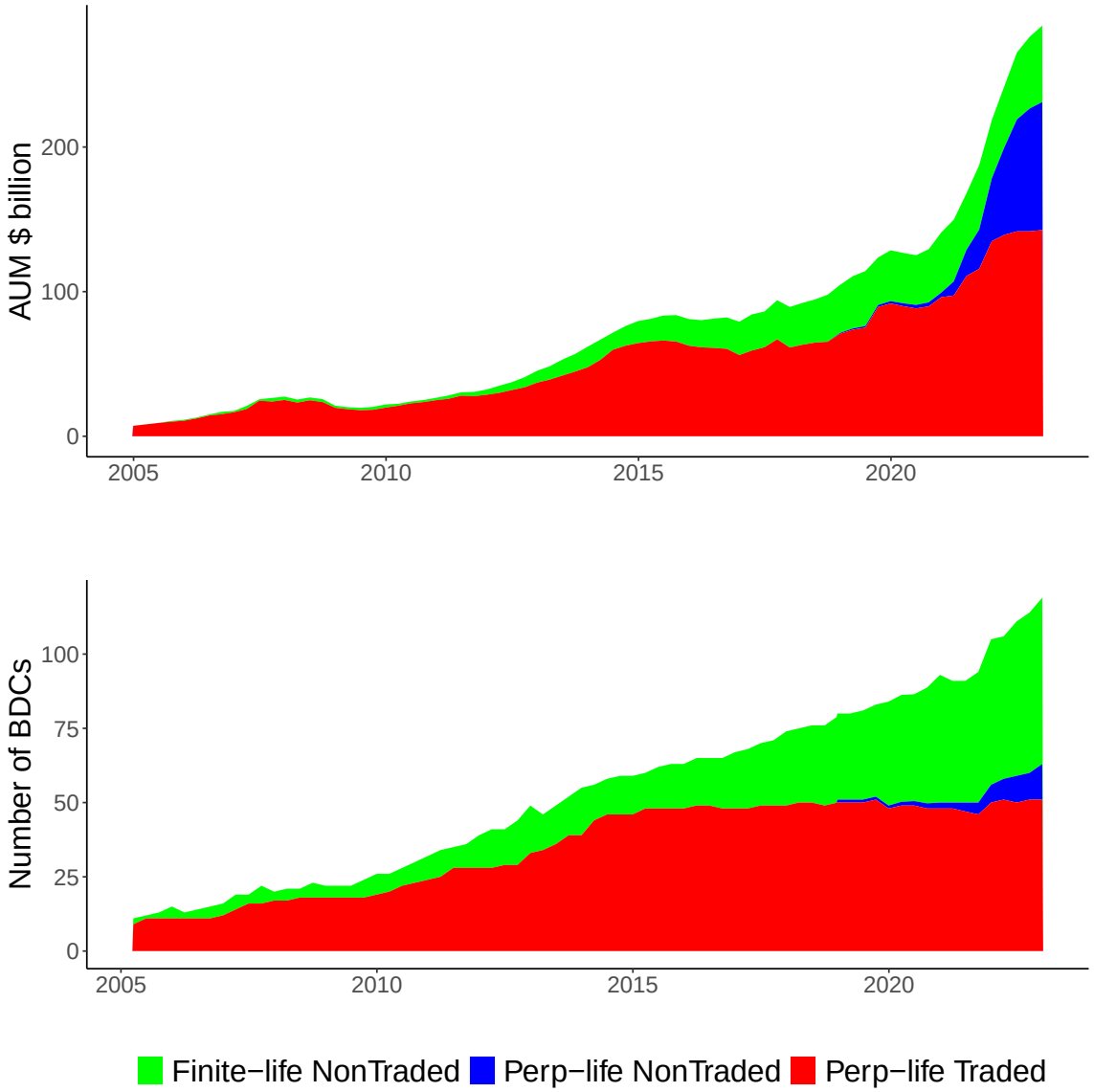


Figure 3. Share of newly launched funds in a given year that are likely to operate as perpetual-life funds

The figure illustrates the share of new private equity funds (left) and private debt funds (right) that are launched each year and are likely to operate with a perpetual-life structure. Data spans years between 2001 and 2023 and includes all newly launched funds worldwide in the Preqin Pro database. Data was downloaded on September 9th, 2024. Funds are categorized as likely operate with a perpetual-life structure if Preqin assigns them one of the following statuses: ″Evergreen″, ″Listed″, ″Open Ended″ or ″Semi-Open Ended″, which are typically structured as perpetual-life funds. Many of the BDCs do not appear in this sample.

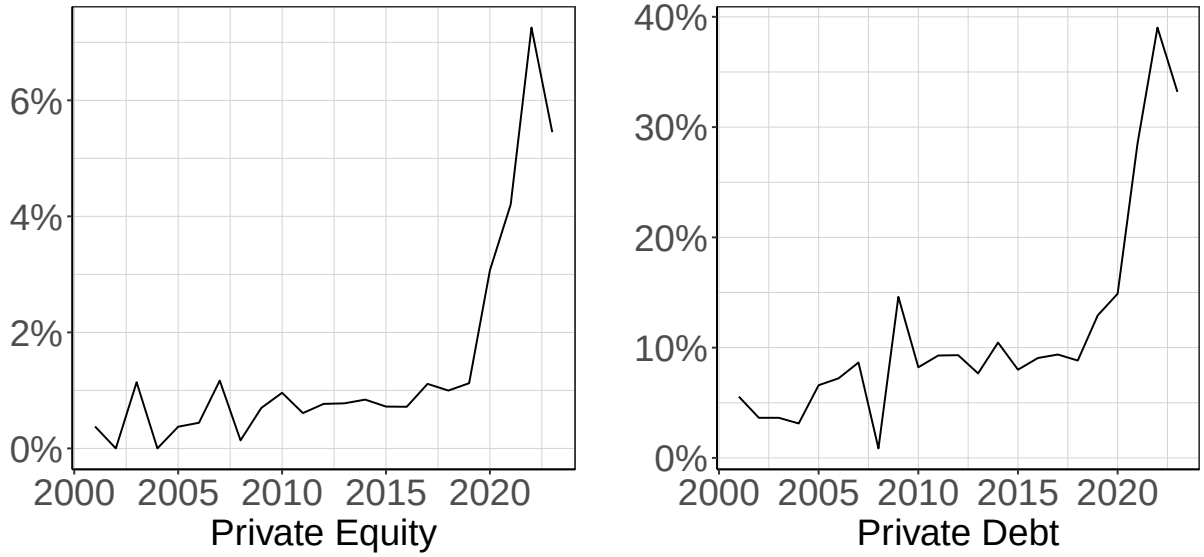


Figure 4. Portfolio differences by fund types

This figure shows the average portfolio characteristics within each type of BDC fund category. The top panel shows the average share of the loan portfolio allocated to loans classified as relationship lending. The share of relationship lending in the loan portfolio for each lender is the par value-weighted share of the loan portfolio allocated to borrowers with whom the lender has a strong relationship, that is positions with $Rel(Dummy) = 1$. The middle panel shows the share of assets allocated to the most opaque and illiquid Level 3 asset category of the ASC 820 accounting standard. The bottom panel shows the average coupon rate of the loan portfolio. The whiskers denote 95% bootstrapping confidence intervals.

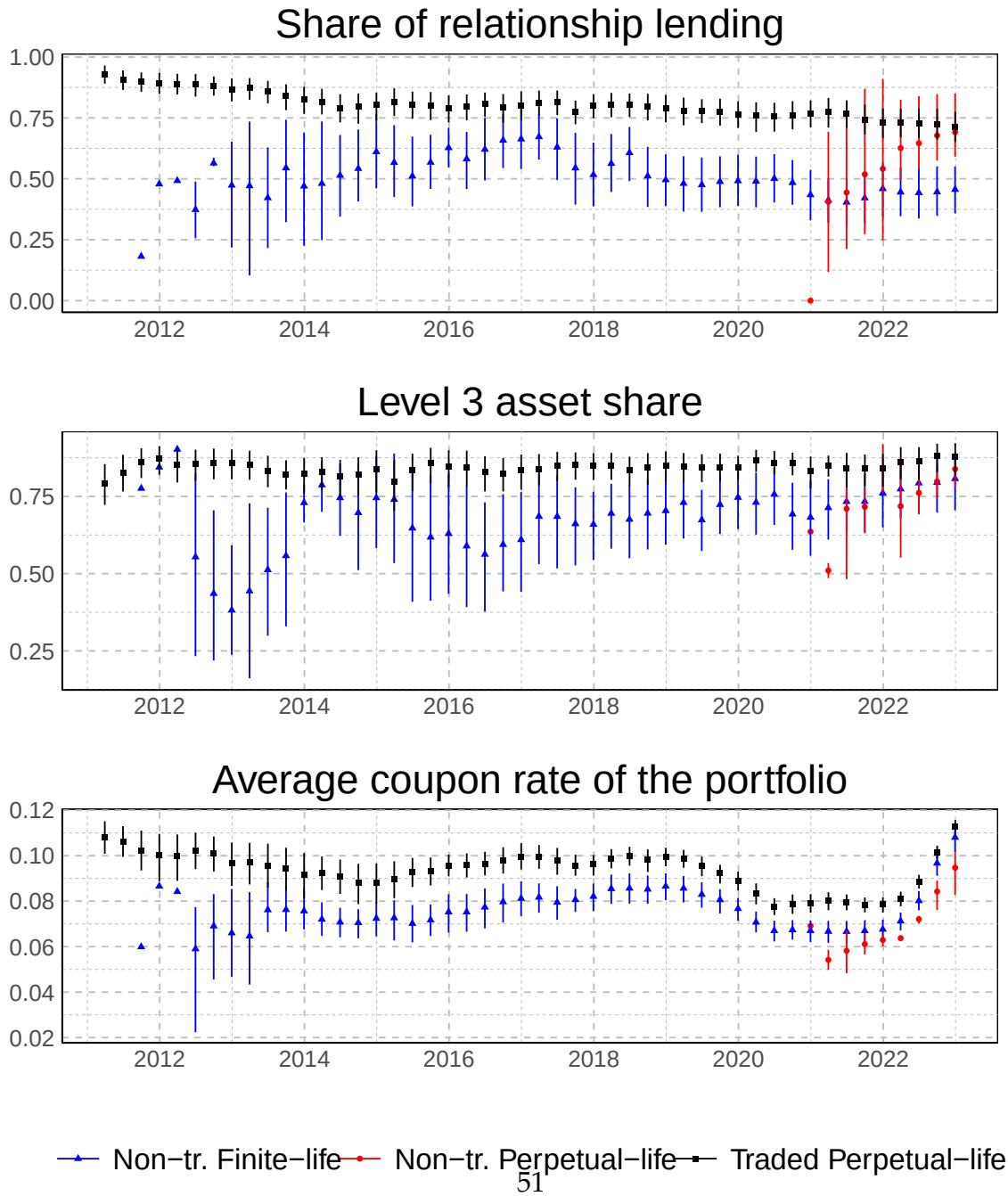


Figure 5. Robustness: The effects of transitioning to a traded BDC around the IPO date

This figure shows the effects of public listing status on different loan measures. The sample includes all loan observations for the BDCs that conduct an IPO at some point in the sample within nine years around the IPO date. I collect the β_τ coefficients from the following regression and plot the estimates in the figure. The regression model is

$$y_{blkt} = \sum_{\tau=-15,\tau\notin-1}^{20} \beta_\tau D_{lt,IPO+\tau} + Controls + Fixed\,Effects + e_{blkt}$$

where $D_{lt,IPO+0}$ is an indicator variable that takes a value of one if the lender conducts an IPO in that period and zero otherwise; $D_{lt,IPO+1}$ takes a value of one if the lender conducts an IPO in the previous period, etc. The dependent variables y_{blkt} are an indicator variable that takes a value of one if the lender is the only lender for that borrower in that period and zero otherwise, the two relationship lending measures and the loan's coupon rate. BDC-level controls include lagged size, lagged leverage, lagged profitability (ROE), and an indicator variable for an internally managed fund. Loan and borrower-level controls include an indicator variable if the loan is associated with a lender's equity stake, log par value of the loan, the fair-to-par value of the loan, position share of the loan in the lender's loan portfolio, and the loan's coupon rate (except when the coupon rate is itself used as a dependent variable). The regressions include the following fixed effects: *Borrower*, *YearQtr*, *DebtClass*. I also include $BaseRate \times YearQtr$ fixed effects when the dependent variable is the coupon rate. All the variable definitions are found in Appendix A

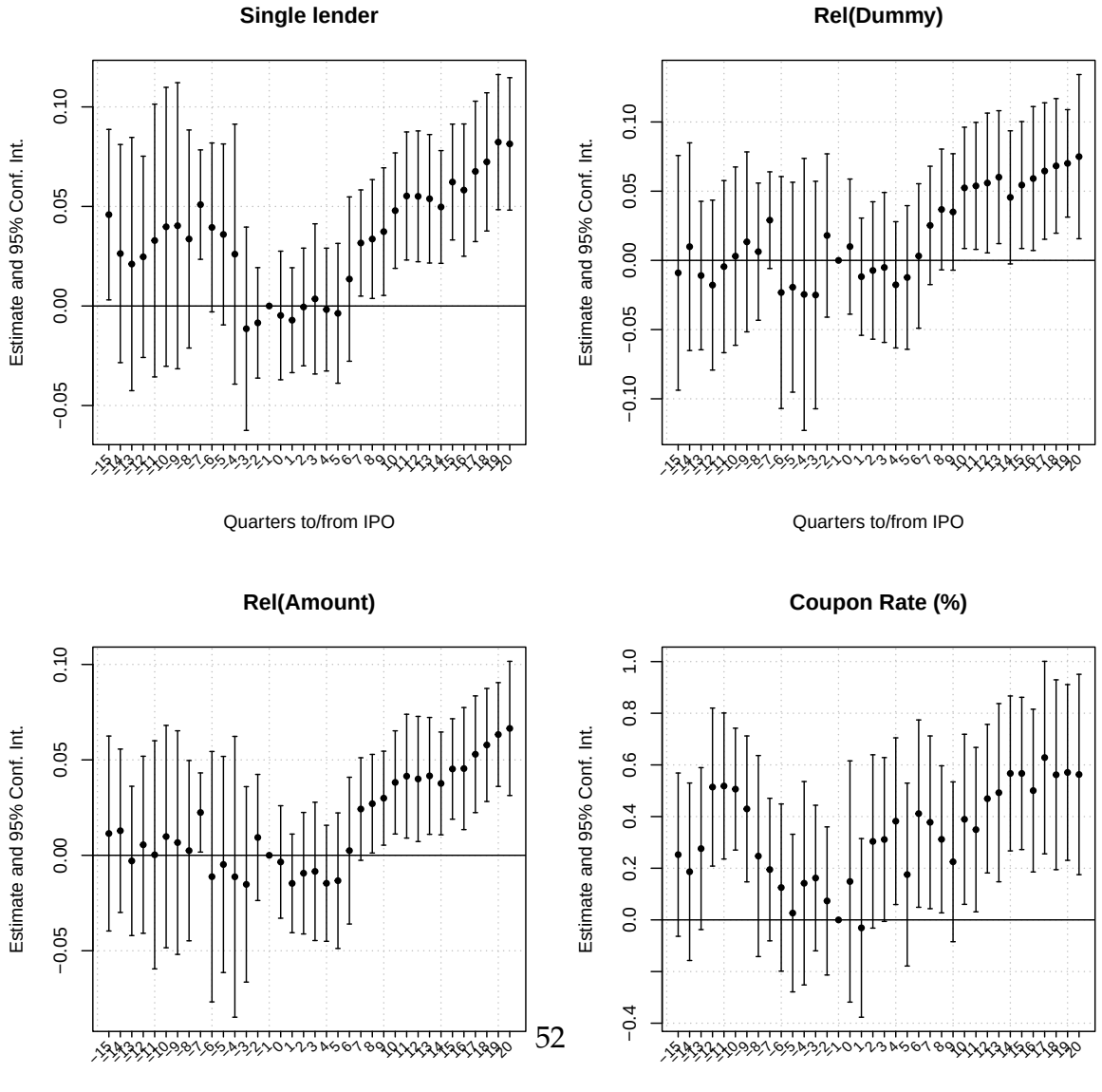


Figure 6. Loan properties for an average U.S. middle market loan

The figure shows different loan properties in each time period based on cross-sectional average of all the loans in BDCs' portfolios excluding structured products like CLOs, cash, and other non-loan categories. Fair Value / Par Value is a measure of the price of the loan: when it is below (above) one the average loan trades at a discount (premium).

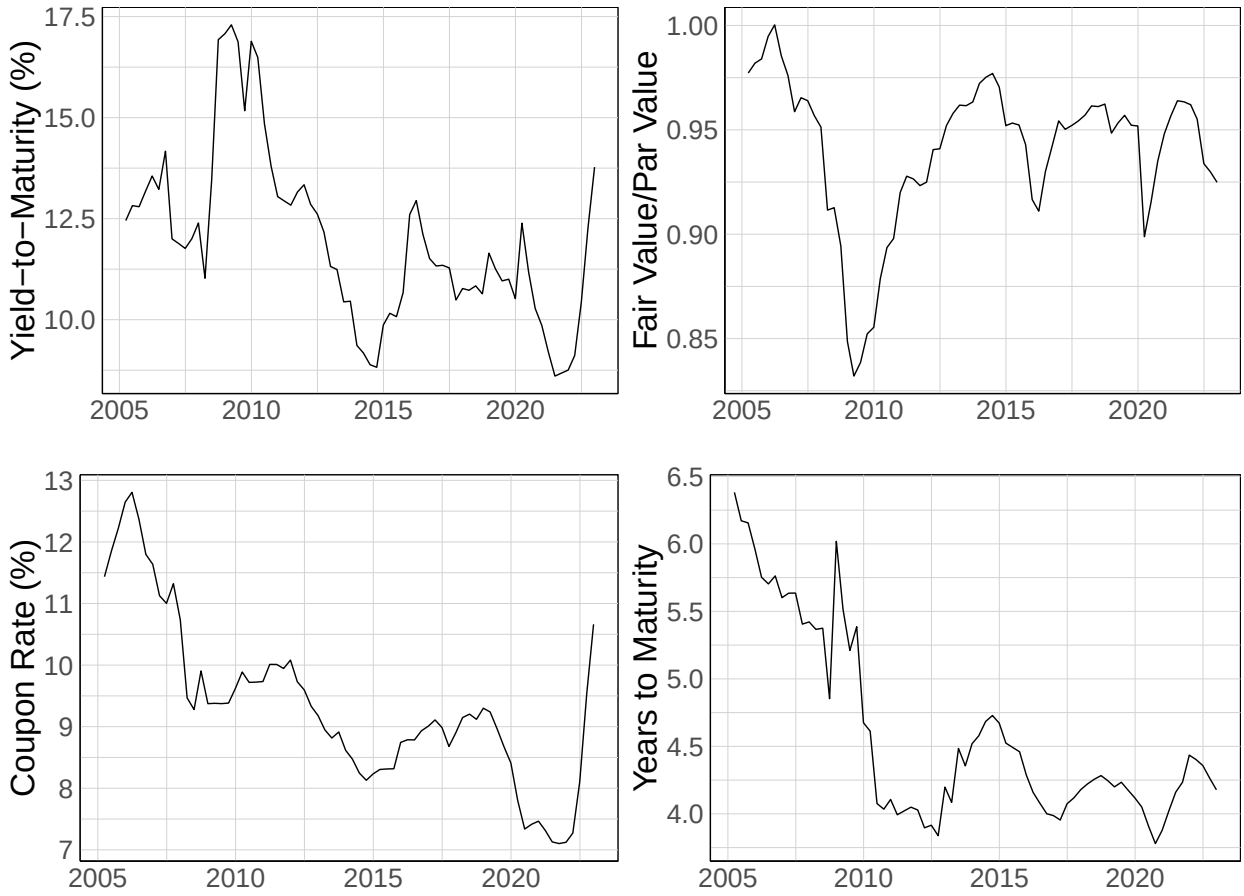


Figure 7. Loan spreads in different U.S. corporate debt markets

Middle Market loan spread is the average loan spread across all direct loans in BDCs' portfolios. These loans are mainly offered to middle-market companies. The loan spread for any given middle-market loan is calculated based on the difference between the loan's actual yield to maturity and the yield to maturity of coupon and maturity-matched synthetic risk-free loan. Middle Market (Market Implied) spread is the stock market implied discount rate of the loan portfolio of an average BDC implied relative to the 3-month US LIBOR rate. The construction of this variable is explained in Section 6 in detail. High-yield bond spread is the ICE BofA US High Yield Index option-adjusted spread, while the Leveraged loan spread is the average spread of single-B-rated secondary-market leveraged loans. The sample runs from 2005Q1-2022Q4.

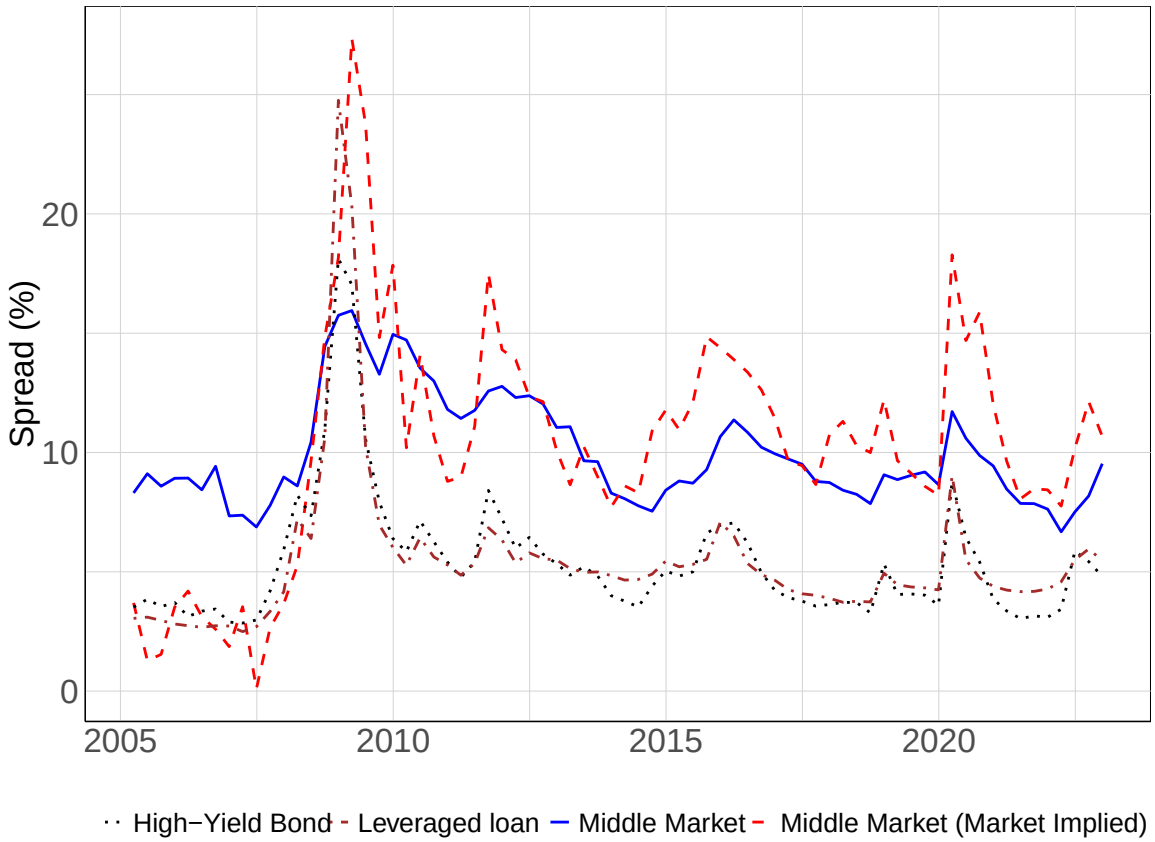


Table 1 Descriptive statistics

Panel A: BDC-level panel data						
Statistic	N	Mean	St. Dev.	Q1	Median	Q3
Traded PLF	3,387	0.64	0.48	0	1	1
Non-traded PLF	3,387	0.02	0.12	0	0	0
Finite Life Fund (FLF)	3,387	0.34	0.48	0	0	1
Fund Size ($ billion)	3,387	1.44	2.83	0.28	0.60	1.52
Leverage	3,225	0.41	0.16	0.35	0.44	0.51
Relationship lending share	2,788	0.72	0.26	0.59	0.79	0.93
PE sponsored lending share	2,788	0.63	0.16	0.56	0.64	0.72
Level 3 asset share	2,886	0.80	0.21	0.75	0.88	0.94
Internally managed	3,329	0.10	0.30	0	0	0
Age (in years)	3,387	6.11	4.91	2.25	5.00	8.75
ROE	3,120	0.07	0.21	0.02	0.08	0.13
Net Inv. Inc. Incentive Fee	3,305	0.17	0.06	0.17	0.20	0.20
Base Management Fee	3,329	0.01	0.01	0.01	0.01	0.02
Hurdle Rate	3,288	0.06	0.02	0.06	0.07	0.08

Panel B: Loan position-level panel data						
Statistic	N	Mean	St. Dev.	Q1	Median	Q3
Coupon rate (%)	204,001	8.47	2.65	6.63	8.27	10.17
YTM (%)	176,507	10.74	8.64	7.16	9.01	11.36
Yield Spread (%)	176,507	9.01	8.66	5.51	7.17	9.51
PE Sponsored	208,867	0.64	0.48	0	1	1
Rel(Dummy)	208,867	0.65	0.48	0	1	1
Rel(Amount)	208,867	0.64	0.38	0.25	0.79	1.00
Number of lenders	208,867	2.59	2.48	1	2	3
Position share	208,867	0.02	0.03	0.004	0.01	0.02
Par value ($ million)	208,867	17.46	36.03	3.06	8.27	18.92
Fair value to par value	208,867	0.94	0.15	0.96	0.99	1.00
Time to maturity (Years)	183,774	4.27	1.96	3.01	4.34	5.51
Revolver	208,867	0.09	0.28	0	0	0
Subordinated Debt	208,867	0.08	0.28	0	0	0
Senior or Secured Debt	208,867	0.83	0.38	1	1	1

This table gives the descriptive statistics of the variables used in the regressions. Variable definitions are given in Appendix A. The sample period is from 2005Q1 to 2022Q4.

Table 2 Differences in fund characteristics between BDC types

	FLF(1)	NT.PLF(2)	Tr.PLF(3)	(2)-(1)	S.E.	(3)-(1)	S.E.
Rel. lending share (%)	49.7	56.7	79.4	7.1	12.1	29.7	4.5
Level 3 assets share (%)	70.9	68.7	84.3	-2.1	5.7	13.4	3.3
Loans with equity stakes (%)	15.3	7.4	37.6	-7.8	3.6	22.4	4.3
Sponsored share (%)	64.9	64.3	62.9	-0.6	2.2	-1.9	2.3
Portfolio yield spread (%)	7.8	6.2	9.3	-1.6	0.4	1.5	0.4
Portfolio coupon spread (%)	6.4	5.4	8.2	-1	0.3	1.8	0.3
Ln Fund size	5.7	6.9	6.7	1.4	0.6	1.03	0.2
Leverage (%)	35.2	48.9	44.3	12.6	3.6	9.1	2.4
ROE (%)	5.9	10.6	6.0	4.7	6.6	0.1	1.1
Base management fee (%)	1.4	1.0	1.7	-0.4	0.1	0.3	0.1
Hurdle rate (%)	6.2	5.5	7.2	-0.8	0.5	1	0.3
NII incentive fee (%)	16.6	12.3	19.5	-4.3	0.8	2.9	0.8

This table presents the average values for different fund level characteristics by BDC types and the mean differences between the traded and non-traded perpetual-life funds (denoted as Tr.PLF and NT.PLF respectively) and finite-life funds (denoted as FLF). Rel. lending share (%), Sponsored share (%), and Loans with equity stakes (%) are the par-weighted share of the loan portfolio held in relationship loans, in loans to firms that have VC/PE-backing, and in loans to firms in which the lender also holds an equity or preferred stock stake. Level 3 assets share (%) is the share of the portfolio held in assets classified as most illiquid/opaque by the ASC 820 accounting standard. Portfolio yield spread (%) is the difference between the fair-value-weighted yield-to-maturity of the (loan) portfolio and the 3-month LIBOR rate. Portfolio coupon spread (%) is the difference between the par-value-weighted coupon rate of the (loan) portfolio and the 3-month LIBOR rate. Ln Fund Size is the natural logarithm of assets under the fund's management. Leverage (%) is the debt-to-assets ratio. ROE (%) is the return on equity. Base management fee (%), Hurdle rate (%), and Net investment income (NII) incentive fee (%) are the corresponding fee parameters in the fund's Investment Advisory Agreement. The sample is based on the 2011Q1-2022Q4 period. The associated standard errors (S.E.) are based on univariate regression results with two-way clustering by BDC and year-quarter level. The internally managed funds are removed when calculating the fee parameters, since these funds do not report similar management compensation and fee data.

Table 3 Relationship lending and fund type

Dependent Variables:	Relationship lending share				Single-lender share		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Traded PLF	0.27***	0.26***	0.19***	0.15***	0.30***	0.18***	0.11***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.03)	(0.02)
NonTr. PLF	0.11	0.16*	0.20***	0.33***	0.02	-0.02	0.11***
	(0.12)	(0.09)	(0.07)	(0.06)	(0.07)	(0.09)	(0.03)
ln Fund Size		0.04***	0.10***	0.13***	-0.04**	0.03***	0.05***
		(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Fund Leverage		-0.10	0.01	0.12	-0.15	0.02	0.03
		(0.10)	(0.08)	(0.08)	(0.12)	(0.08)	(0.09)
Base Management Fee		4.97	11.88***	9.49***	5.72	6.21*	1.04
		(5.73)	(3.22)	(3.02)	(5.71)	(3.32)	(3.09)
Hurdle Rate		3.39**	-0.36	-0.99	2.98	1.69	0.69
		(1.65)	(1.32)	(1.34)	(1.92)	(1.32)	(0.92)
Internally managed		0.24**	0.19**	0.08	0.22	0.24***	0.09
		(0.11)	(0.08)	(0.10)	(0.13)	(0.08)	(0.06)
Net Inv. Inc. Incentive fee		-0.39	0.22	0.12	-0.59	-0.16	0.12
		(0.39)	(0.40)	(0.41)	(0.48)	(0.32)	(0.26)
Fund ROE		0.02	0.04**	0.01	0.04	0.03	-0.06
		(0.03)	(0.02)	(0.06)	(0.04)	(0.02)	(0.05)
Fixed-effects							
YearQtr	Yes	Yes	Yes		Yes	Yes	
Adviser			Yes			Yes	
YearQtr-Adviser				Yes			Yes
Fit statistics							
Observations	2,886	2,584	2,584	2,584	2,584	2,584	2,584
Adjusted R^2	0.35	0.47	0.76	0.61	0.45	0.81	0.88

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

This table presents results from BDC-time level panel regression, where either the share of loan portfolio held in relationship loans (*Relationship lending share*) or the share of loan portfolio held in loans where the lender is the only lender (*Single lender share*) is regressed on various BDC characteristics. *NonTr. PLF*, *Traded PLF* are indicator variables that take a value of one if the BDC is operated as a non-traded or traded perpetual-life fund respectively in that period, and zero otherwise. Columns (2)-(6) control for lagged size, lagged leverage, lagged profitability (ROE), an indicator variable for a fund being internally managed, and three parameters that describe the BDC management compensation package: hurdle rate of the net investment income incentive fee, share of management's incentive fee, and the base management fee. Fixed effects: Investment *Adviser* refers to the identity of the parent organization of the BDC. *YearQtr* refers to the calendar quarter.

Table 4 OLS+IV: Determinants of relationship lending measures

Dependent Variables:	Rel(Dummy)				Rel(Amount)			ln# Empl.	
Model:	OLS (1)	OLS (2)	OLS (3)	IV (4)	OLS (5)	OLS (6)	IV (7)	OLS (8)	OLS (9)
Variables									
Traded PLF	0.19***	0.11***	0.08**	0.19***	0.05***	0.02**	0.10***	-0.19**	-0.008
	(0.05)	(0.03)	(0.03)	(0.06)	(0.02)	(0.01)	(0.03)	(0.08)	(0.09)
Traded PLF × Rel(Dummy)									-0.28***
									(0.08)
NonTr. PLF	0.22**	0.13**	0.10**	0.18**	0.07***	0.04*	0.09**	0.08	0.06
	(0.08)	(0.05)	(0.05)	(0.07)	(0.02)	(0.02)	(0.04)	(0.12)	(0.13)
NonTr. PLF × Rel(Dummy)									0.07
									(0.08)
PE Sponsored	-0.07***	-0.06***		-0.07***	-0.05***		-0.06***	-0.04	-0.08
	(0.01)	(0.02)		(0.02)	(0.02)		(0.02)	(0.09)	(0.08)
Subordinated Debt	0.09***	0.04*	0.06	0.04*	0.03**	0.04*	0.03**	0.18	0.21*
	(0.02)	(0.02)	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.12)	(0.12)
Revolver	0.12***	0.29***	0.44***	0.28***	0.19***	0.29***	0.19***	-0.31***	-0.26***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.01)	(0.09)	(0.09)
ln Time to maturity	-0.07***	-0.007	-0.02	-0.008	-0.01**	-0.02	-0.01**	0.24***	0.21***
	(0.008)	(0.007)	(0.02)	(0.008)	(0.005)	(0.01)	(0.006)	(0.04)	(0.04)
ln Par value	0.06***	0.13***	0.19***	0.13***	0.09***	0.13***	0.09***	-0.01	0.01
	(0.007)	(0.009)	(0.01)	(0.009)	(0.006)	(0.008)	(0.006)	(0.02)	(0.02)
Fair-to-Par value	0.04	0.02	0.02	0.02	0.010	0.01	0.008	-0.07	-0.04
	(0.03)	(0.01)	(0.03)	(0.01)	(0.01)	(0.02)	(0.01)	(0.14)	(0.14)
Lender has equity stake	0.10***	0.07***	0.08***	0.07***	0.05***	0.04***	0.05***	-0.47***	-0.42***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)	(0.01)	(0.01)	(0.06)	(0.06)
ln Fund Size	0.010	0.07***	0.09***	0.06***	0.05***	0.06***	0.04***	0.09***	0.09***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.006)	(0.009)	(0.008)	(0.03)	(0.03)
Fund Leverage	0.01	-0.005	-0.16*	-0.09	0.05	-0.04	0.007	-0.30	-0.34
	(0.15)	(0.06)	(0.09)	(0.07)	(0.04)	(0.04)	(0.04)	(0.28)	(0.27)
Internally managed	0.07	0.08	0.10*	0.02	0.008	0.01	-0.02	-0.92***	-0.92***
	(0.10)	(0.06)	(0.05)	(0.06)	(0.03)	(0.02)	(0.04)	(0.20)	(0.19)
Fund ROE	0.0006	0.02***	0.04	0.01*	0.01*	0.01	0.007	-0.55*	-0.52*
	(0.03)	(0.008)	(0.02)	(0.007)	(0.007)	(0.008)	(0.006)	(0.27)	(0.28)
Net Inv. Inc. Incentive fee	-0.28	-1.0**	-0.77*	-1.0**	-0.55**	-0.23	-0.50*	-1.8	-1.7
	(0.66)	(0.43)	(0.45)	(0.46)	(0.21)	(0.18)	(0.27)	(1.5)	(1.4)
Base Management Fee	3.8	2.7	0.88	1.3	1.5	0.23	0.77	8.0	6.7
	(5.2)	(2.6)	(2.8)	(2.9)	(1.6)	(1.2)	(1.8)	(10.9)	(10.4)
Hurdle Rate	0.43	1.5	1.3	1.5	0.60	0.05	0.45	-5.1*	-5.0**
	(1.4)	(1.1)	(0.99)	(1.1)	(0.60)	(0.43)	(0.68)	(2.5)	(2.3)
Rel(Dummy)									-0.14*
									(0.07)
Fixed-effects									
YearQtr	Yes	Yes		Yes	Yes		Yes	Yes	Yes
Borrower		Yes		Yes	Yes		Yes		
Rel. Start Date		Yes	Yes	Yes	Yes	Yes	Yes		
Adviser		Yes	Yes	Yes	Yes	Yes	Yes		
YearQtr-Borrower			Yes			Yes			
Fit statistics									
Observations	169,626	169,626	169,647	165,713	169,626	169,647	165,713	19,901	19,901
Adjusted R^2	0.18	0.54	0.31	0.54	0.74	0.82	0.74	0.09	0.11

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

The dependent variable in Columns (1)-(7) is either of the two relationship lending measures while in Columns (8)-(9) the dependent variable is the natural logarithm of the number of employees in the borrowing company. In Columns (8)-(9) the sample is based on only the fourth quarter of each year, since the employment numbers are available only annually. $Rel(Dummy)$ and $Rel(Amount)$ are measures of the strength of the lending relationship at time t. $NonTr.PLF$ and $Traded\,PLF$ are indicator variables that take a value of one if the BDC is operated as a non-traded or a traded perpetual-life fund, respectively, in that period, and zero otherwise. Columns (4) and (7) show the second-stage results based on the two-stage least square regressions. The instrumental variable is the *IPO Attractiveness*. All the variable definitions are found in Appendix A. Fixed effects: *Borrower* refers to the identity of the borrowing company. *Rel. Start Date* is the year-quarter where the borrower-lender pair enters the data for the first time. *YearQtr* refers to the calendar quarter. Investment *Adviser* refers to the identity of the parent organization of the BDC.

Table 5 OLS+IV: Determinants of coupon rate

Dependent Variable:	Coupon Rate (%)					
Model:	OLS (1)	OLS (2)	OLS (3)	OLS (4)	OLS (5)	IV (6)
Traded PLF	0.65***	0.57***	0.30**	0.06	0.02	0.58***
	(0.21)	(0.20)	(0.12)	(0.12)	(0.07)	(0.19)
Traded PLF× Rel(Dummy)				0.52***	0.28***	0.37**
				(0.12)	(0.09)	(0.15)
NonTr. PLF	-0.98***	-1.06***	-0.41	-0.38	-0.35**	-0.01
	(0.27)	(0.29)	(0.26)	(0.26)	(0.13)	(0.21)
Rel(Dummy)		0.32***	-0.11**	-0.44***	-0.29***	-0.37***
		(0.09)	(0.05)	(0.08)	(0.06)	(0.10)
ln Time to maturity			-0.18*	-0.17*	0.15	0.15*
			(0.09)	(0.09)	(0.09)	(0.09)
ln Par value			0.14***	0.13***	0.09***	0.10***
			(0.04)	(0.04)	(0.03)	(0.03)
Lender has equity stake			0.57***	0.56***	0.44***	0.46***
			(0.11)	(0.10)	(0.08)	(0.08)
Position share			2.60*	2.53*	1.22	1.30
			(1.47)	(1.45)	(1.21)	(1.24)
PE Sponsored			-0.02	-0.02	-0.12	-0.13
			(0.05)	(0.05)	(0.13)	(0.13)
BDC controls			Yes	Yes	Yes	Yes
Fixed-effects						
BaseRate-YearQtr	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr			Yes	Yes	Yes	Yes
Adviser			Yes	Yes	Yes	Yes
Rel. Start Date			Yes	Yes	Yes	Yes
DebtClass-YearQtr			Yes	Yes	Yes	Yes
Borrower					Yes	Yes
Fit statistics						
Observations	203,874	203,874	166,971	166,971	166,971	165,665
Adjusted R^2	0.26	0.27	0.46	0.46	0.72	0.72

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

This table presents results that regress the coupon rate on various loan and deal characteristics. *NonTr. PLF*, *Traded PLF* are indicator variables that take a value of one if the BDC is operated as a non-traded or traded perpetual-life fund, respectively in that period, and zero otherwise. $Rel(Dummy)$ is a measure of the strength of the lending relationship at time t. BDC controls include the following BDC-fund characteristics: lagged log fund size, lagged leverage, lagged profitability (ROE), an indicator variable for a fund being internally managed, and three parameters that describe the BDC management compensation package. The sample excludes structured product positions like loans to CLOs. The last column shows the second-stage results based on the two-stage least square regression. The instrumental variables are the *IPO Attractiveness*, and its interaction with $Rel(Dummy)$. All the variable definitions are found in Appendix A. Fixed effects: *Borrower* refers to the identity of the borrowing company. *BaseRate* refers to loan base rate. *Rel. Start Date* is the YearQtr where the borrower-lender pair enter the data for the first time. *YearQtr* refers to the calendar quarter. *DebtClass* refers to the type and seniority of a loan. Investment *Adviser* refers to the identity of the parent organization of the BDC.

Table 6 OLS+IV: Credit provision, lending relationships and fund structure

Dependent Variable:	ln Credit Outstanding$_t$							
Model:	OLS (1)	OLS (2)	OLS (3)	IV (4)	OLS (5)	OLS (6)	OLS (7)	IV (8)
Variables								
Rel(Dummy)$_t$	-0.57*	0.82***	0.49***	0.46				
	(0.30)	(0.18)	(0.14)	(0.28)				
Traded PLF$_t$	0.68***	0.67***			0.16	0.34*		
	(0.19)	(0.19)			(0.22)	(0.20)		
Fair/Par$_t$	1.0***	0.92***	1.8***	1.5***	0.71**	0.95***	1.6***	1.5***
	(0.27)	(0.28)	(0.27)	(0.26)	(0.29)	(0.30)	(0.30)	(0.21)
Traded PLF$_t$ × Rel(Dummy)$_t$	1.7***	0.65***	0.67***	0.87**				
	(0.41)	(0.23)	(0.21)	(0.41)				
Rel(Dummy)$_t$ × Fair/Par$_t$	1.1***	0.25	0.50***	0.52*				
	(0.28)	(0.18)	(0.15)	(0.29)				
Traded PLF$_t$ × Fair/Par$_t$	-0.36*	-0.37*	-0.61***		0.19	-0.06	-0.08	
	(0.20)	(0.21)	(0.18)		(0.23)	(0.21)	(0.22)	
Traded PLF$_t$ × Rel(Dummy)$_t$ × Fair/Par$_t$	-1.7***	-0.71***	-0.75***	-0.94**				
	(0.39)	(0.23)	(0.22)	(0.42)				
Rel(Amount)$_t$					-1.0***	1.6***	2.4***	2.4***
					(0.37)	(0.27)	(0.25)	(0.50)
Traded PLF$_t$ × Rel(Amount)$_t$					2.5***	1.1***	1.2***	1.3
					(0.51)	(0.32)	(0.39)	(0.79)
Rel(Amount)$_t$ × Fair/Par$_t$					1.5***	0.29	1.1***	1.1*
					(0.35)	(0.25)	(0.23)	(0.55)
Traded PLF$_t$ × Rel(Amount)$_t$ × Fair/Par$_t$					-2.4***	-1.2***	-2.0***	-2.0**
					(0.48)	(0.32)	(0.40)	(0.83)
NonTr. PLF$_t$	-0.46	-0.68			-1.3	-0.83		
	(0.84)	(0.71)			(0.94)	(0.77)		
NonTr. PLF$_t$ × Rel(Dummy)$_t$	2.1***	1.2*	1.6**	1.8**				
	(0.80)	(0.63)	(0.65)	(0.70)				
NonTr. PLF$_t$ × Fair/Par$_t$	1.0	1.2	2.0***	2.2***	1.9*	1.2	1.9***	1.9***
	(0.86)	(0.73)	(0.66)	(0.60)	(0.97)	(0.78)	(0.67)	(0.62)
NonTr. PLF$_t$ × Rel(Dummy)$_t$ × Fair/Par$_t$	-1.7**	-0.82	-1.3*	-1.5**				
	(0.82)	(0.65)	(0.68)	(0.73)				
NonTr. PLF$_t$ × Rel(Amount)$_t$					3.6***	1.8	1.3*	1.8**
					(1.0)	(1.1)	(0.76)	(0.81)
NonTr. PLF$_t$ × Rel(Amount)$_t$ × Fair/Par$_t$					-3.1***	-1.2	-1.7**	-2.2**
					(1.0)	(0.97)	(0.82)	(0.90)
Fixed-effects								
YearQtr	Yes	Yes			Yes	Yes		
Borrower		Yes				Yes		
YearQtr-Borrower			Yes	Yes			Yes	Yes
Lender-YearQtr			Yes	Yes			Yes	Yes
Fit statistics								
Observations	212,527	212,527	212,527	207,541	212,527	212,527	212,527	207,541
Adjusted R^2	0.08	0.51	0.40	0.40	0.07	0.52	0.49	0.48

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

The dependent variable *ln Credit Outstanding*$_t$ is the log of credit outstanding for a particular loan position at the end of quarter t. *NonTr. PLF* and *Traded PLF* are indicator variables that take a value of one if the BDC is operated as a non-traded or traded perpetual-life fund, respectively, in that period, and zero otherwise. *Fair/Par*$_t$ refers to the loan's fair value to par value ratio at time t. *Rel(Dummy)*$_t$ and *Rel(Amount)*$_t$ are measures of the intensity of relationship status at time t. The columns (4) and (8) show the second-stage results based on the two-stage least square regressions. The instrumental variables are the *IPO Attractiveness* and its interactions with either of the two relationship lending measures and *Fair/Par* ratio. All the variable definitions are found in Appendix A. Fixed effects: *Borrower* refers to the identity of the borrowing company. *YearQtr* refers to the calendar quarter. *Lender* refers to the BDC holding the loan.

Online Appendix to Endogenous Matching in the Private Debt Market

This Online Appendix contains the following sections

1. Appendix A contains the variable definitions
2. Appendix B contains additional details relating to the model and its extensions
3. Appendix C provides an illustrative snapshot of the list of BDCs and associated identifying information from the end of 2022
4. Appendix D gives additional details relating to the data construction
5. Appendix E discuss the details relating to yield construction and robustness
6. Appendix F contains additional descriptive statistics
7. Appendix G provides additional empirical results and robustness results
8. Appendix H contains information relating to BDC manager compensation contracts

Appendix A Variable definitions

Variable	Description	Level
Yield Spread	The yield spread is calculated based on the differences in yields-to-maturity between the loan and maturity and coupon-matched synthetic risk-free loan. For more details, see Section E.2	Lender-borrower-loan-level
Coupon Rate	The coupon rate of the loan position	Lender-borrower-loan-level
ln Time to maturity	Natural logarithm of the remaining time to maturity of a loan. Time to maturity is measured in fraction of years.	Lender-borrower-loan-level
Fair/Par	Fair value to par value ratio of a loan.	Lender-borrower-loan-level
ln Credit Outstanding	Total credit outstanding through the loan position to borrower b from the lender l. The outstanding par value of the loan denotes the outstanding credit committed.	Lender-borrower-loan-level
Single lender	An indicator variable that takes a value of one if the lender l is the only BDC-lender for a borrower b at time t and zero otherwise.	Lender-borrower-level
Rel(Amount)	Ratio between the amount of loans outstanding to lender l from borrower b and the amount of loans outstanding to all lenders from borrower b at time t.	Lender-borrower-level
Rel(Dummy)	An indicator variable that takes a value of one if the $Rel(Amount)$ of the pair lender l and borrower b is the largest for that borrower b among all the lenders of b at time t.	Lender-borrower-level
Position share	Ratio between the value of loans held by lender l with borrower b and the value of lender l's total loan portfolio.	Lender-borrower-level
Lender has equity stake	An indicator variable that takes a value of one when the loan position at time t is coupled with an equity position to the lender and zero otherwise.	Lender-borrower-level
PE Sponsored	An indicator variable that takes a value of one if the borrower b is backed by a PE or VC sponsor borrower at time t.	Borrower-level
Has received syndicated loan	An indicator variable that takes a value of one if the borrower b has received syndicated loan within past 5-years.	Borrower-level
ln # of Empl.	Natural logarithm of the number of employees in the borrowing company at time t. For more details on constructing the variable see Appendix D.	Borrower-level
$\Delta \ln Empl_{t,t+1}$	Four-quarter log change in employment for borrower b. Note that this will be based on an annual (not quarterly) panel. The growth rate is winsorized at 1% and 99% level.	Borrower-level
Mean(Traded PLF)	The equal-weighted average of *Traded PLF* indicator variable in each year- quarter among all BDCs that had any outstanding debt or equity position with any borrower in that state in that period	Borrower-level
Avg. position share	Average *Position share* of the lender that borrower at the end of that period.	Borrower-level
Avg. Fair/Par	Average $Fair/Par$ of all the outstaind loans for that borrower at the end of that period.	Borrower-level
Traded PLF	An indicator variable that takes a value of one if the lender is traded perpetual-life fund at time t and zero otherwise.	Lender-level
NonTr. PLF	An indicator variable that takes a value of one if the lender is a non-traded perpetual-life fund at time t and zero otherwise.	Lender-level
Finite Life Fund (FLF)	An indicator variable that takes a value of one if the lender is a finite-life fund at time t and zero otherwise.	Lender-level
Rel. lending share	Par-weighted share of the loan portfolio allocated to firms with $Rel(Dummy)$ equal one.	Lender-level
Single lender share	Par-weighted share of the loan portfolio are allocated to firms that have only a single lender in that period.	Lender-level
PE sponsored lending share	Par-weighted share of the loan portfolio allocated to firms with PE/VC backing.	Lender-level

Loans with equity stake	Par-weighted share of the loan portfolio allocated to firms where the lender also holds an equity or preferred stock stake.	Lender-level
Level 3 asset share	The share of the portfolio allocated to assets that are classified as the most illiquid Level 3 assets based on AS 820 accounting standard.	Lender-level
Fund Size	BDC's total assets (millions USD)	Lender-level
Leverage	Total liabilities/Total Assets	Lender-level
Age	Age of the fund in years is calculated from the date of BDC inception. If this date is not available the age of the BDC is defined as the maximum of the following: time since IPO, time since BDC financials first appear in the data.	Lender-level
Net investment income incentive fee %	The share of net investment income (NII) that the manager obtains conditional on reaching the hurdle rate	Lender-level
Hurdle Rate %	The minimum yield threshold of net investment income over net assets that the manager needs to reach before the incentive fee starts to be paid.	Lender-level
Base Management Fee %	Management fee tied to the fund's gross assets under management. When the base fee is paid on net assets instead, I scale the base fee of these observations by the net-assets-to-gross-assets ratio to make the quantities comparable.	Lender-level
Loan portfolio coupon spread %	The difference between the par value weighted coupon rate of the loan portfolio and the 3-month LIBOR rate. Structured products, like CLOs, are excluded from the calculation.	Lender-level
Loan portfolio yield spread %	The difference between the fair-value-weighted yield-to-maturity of the loan portfolio and the 3-month LIBOR rate. Structured products, like CLOs, are excluded from the calculation.	Lender-level
ROE	Return on equity defined as net income divided by one quarter lagged book equity	Lender-level
IPO Attractiveness	*IPO Attractiveness* is the average equity closed-end fund discount in the market in the previous quarter. (The closed-end fund discount is calculated as $\frac{Price-NAV}{NAV}$ where *Price* is the traded stock price of the fund and NAV is the net asset value per share.) Following an IPO this variable is censored to the level it was at the quarter before this IPO.	Lender-level

Appendix B Model Appendix

B.1 Bargaining

When borrower and lender match they engage in Nash-Bargaining regarding the repayment rate C_{bl}. The total surplus from forming the relationship is defined as $S_{bl} = V_b^R(Y_b - C_{bl}) - V_b^{NR} + V_l^R(C_{bl}) - V_l^{NR}$. As previously V_l^R and V_l^{NR} are defined as the value to the lender l from lending or not-lending respectively while the $V_b^R(Y_b - C_{bl})$ denotes the net present value to the borrower b of having a relationship with manager l while V_b^{NR} denotes the value of not having a relationship. The parties bargain over flow repayment rate C_{bl} so that the Nash-Bargaining problem can be defined as

$$\max_{C_{bl}} \quad [V_l^R(C_{bl}) - V_l^{NR}]^{\theta_l}[V_b^R(Y_b - C_{bl}) - V_b^{NR}]^{1-\theta_l} \tag{A1}$$

The first-order condition gives

$$\theta_l[V_b^{NR}(Y_b - C_{bl}) - V_b^{NR}]V_l^{R\prime}(C_{bl}) = (1-\theta_l)[V_l^R(C_{bl}) - V_l^{NR}]V_b^{R\prime}(Y_b - C_{bl}) \tag{A2}$$

which can be solved for C_{bl}. Now the value functions for the lender and borrower respectively were defined above and are rewritten here for convenience

$$(r+\delta_l)V_l^R(C_{bl}) = C_{bl} + \lambda_b[V_l^{NR} - V_l^R(C_{bl})] \tag{A3}$$

$$(r+\lambda_b)V_b^R(\pi_{bl}) = \pi_{bl} + \delta_l[V_b^{NR} - V_b^R(\pi_{bl})] \tag{A4}$$

In each case, the agent moves to the state without a lending relationship if her counterparty defaults. Taking the FOCs with respect to C_{bl}, the two equations imply that $V_l^{R\prime}(C_{bl}) = \frac{1}{r+\lambda_b+\delta_l}$ and $-V_b^{R\prime}(\pi_{bl}) = \frac{1}{r+\lambda_b+\delta_l}$ and then it is easy to show that $V_l^R(C_{bl}) - V_l^{NR} = \frac{C_{bl}-C_{R,l}}{r+\lambda_b+\delta_l}$ and $V_b^R(\pi_{bl}) - V_b^{NR} = \frac{\pi_{bl}-\pi_{R,bl}}{r+\lambda_b+\delta_l}$ where $\pi_{R,bl}$ denotes the reservation profit for the borrower from not borrowing from a lender l. Using these expressions we can reduce the Nash-Bargaining problem to

$$C_{bl} = \arg\max[C_{bl} - C_{R,bl}]^{\theta_l}[\pi_{bl} - \pi_{R,bl}]^{1-\theta_l} \tag{A5}$$

and since $\pi_{bl} = Y_b - C_{R,bl}$, and $\pi_{R,bl} = 0$ this has a solution

$$C_{bl} = C_{R,bl} + \theta_l(Y_b - C_{R,bl}) \tag{A6}$$

B.2 Borrowers choosing lenders

The model assumes that borrowers can only choose to search one type of lender. Now in equilibrium some borrowers choose to concentrate their search on FLFs and others on PLFs. Why? It turns out that borrowers are indifferent between when choosing between lenders, so the search activity of the each type of lender will then determine the search (and match) activity of borrowers with that particular lender through the equilibrium result of $\alpha_l = \alpha_b$.

To understand why borrowers are indifferent between lenders, first compare the value of being in a relationship with either PLF, $V^R_{b,PLF}$, or FLF, $V^R_{b,FLF}$. In equilibrium, the value of both relationships is

$$V^R_{b,PLF} = \frac{\pi_{b,PLF}}{r + \delta_{PLF} + \lambda_b} = \frac{(1-\theta_l)(Y_b - C_{R,PLF})}{r + \delta_{PLF} + \lambda_b} = 2(1-\theta_l)$$
$$V^R_{b,FLF} = \frac{\pi_{b,FLF}}{r + \delta_{FLF} + \lambda_b} = \frac{(1-\theta_l)(Y_b - C_{R,FLF})}{r + \delta_{FLF} + \lambda_b} = 2(1-\theta_l)$$

where I have used the fact that $C_{R,FLF} = Y_b - 2(r + \delta_{FLF} + \lambda_b)$ and $C_{R,PLF} = Y_b - 2(r + \delta_{PLF} + \lambda_b)$. So intuitively we can see that while the denominator of $V^R_{b,FLF}$ is higher since $\delta_{FLF} > \delta_{PLF}$ so is the numerator since $C_{R,FLF} < C_{R,PLF}$. In asset pricing-lingo the borrower trades off higher dividends for a higher discount rate. Note that θ_l is a random variable, so before bargaining, the expected value of both is $E(2(1-\theta_l)) = 1$.

Let us then compare value of not being in a relationship and instead searching for either PLF, $V^{NR}_{b,PLF}$ or FLF, $V^{NR}_{b,FLF}$. Since, the value of non-relationship with either activity is just the discounted value of the reservation profit of not getting funding, then these must be equal by the fact that the reservation profit of not obtaining lending is the same: zero.[53] More formally, we can use Equations (8) and (9) to write the value of non-relationships as

$$V^{NR}_{b,PLF} = \frac{\pi_{R,b}}{r + \lambda_b} = V^{NR}_{b,FLF} = \frac{\pi_{R,b}}{r + \lambda_b} = 0.$$

B.3 Lenders choosing borrowers

We could similarly analyze how lenders choose which type of borrowers to search if there are multiple types of relationships borrowers with different default rates λ_b. What

[53] This can for example be motivated by a free entry to either type of activity (Rogerson, Shimer, & Wright, 2005). But the main implication would also hold with an alternative $\pi_{R,b}$.

is the value for the lender l of not being in a relationship with borrower b? It is

$$V_{l,b}^{NR} = \frac{C_{R,bl}}{r+\delta_l} = \frac{Y_b - 2\lambda_b}{r+\delta_l} - 2$$

where I have again used the fact that $C_{R,bl} = Y_b - 2(r + \delta_l + \lambda_b)$. This implies that to make lender indifferent between searching for borrower b relatively to any other borrower b', we must have

$$V_{l,b}^{NR} = V_{l,b'}^{NR} \Leftrightarrow Y_b - 2\lambda_b = Y_{b'} - 2\lambda_{b'} \qquad \forall\ b \text{ and } b'$$

In words, any high risk borrower that wants to attract search from lenders need to have higher return project Y_b to compensate for the high default proabability λ_b. A useful benchmark is to assume there exist a borrower that poses no default risk ($\lambda = 0$) and denote the flow output from this project as Y. Then for any borrower it must hold that $Y_b = Y + 2\lambda_b$. I discuss how this impacts the equilibrium in the main text.

B.4 Lenders choosing fund types

The situation in the fundraising market is an important determinant of how managers select the fund structure. This idea can be formalized as follows. Assume a manager l without a fund wants to raise a fund at time t. The manager can conduct an IPO that will be successful with a probability p_{lt} after which she gets a value of V_{PLF}^{NR} but if the IPO fails, which happens with probability $1 - p_{lt}$, the manager gets zero. IPO's success probability p_{lt} may depend on the ability of the manager l, but primarily it is useful to think that it depends on the current situation in the stock market at time t. However, the manager does not have to do an IPO. She can also raise funds using private markets and get V_{FLF}^{NR} with certainty. Since the manager maximizes her expected utility, she will choose a fundraising policy that involves an IPO if and only if $p_{lt} V_{PLF}^{NR} \geq V_{FLF}^{NR}$ and raise private funding otherwise. Since we can easily show using the model solution that $V_{PLF}^{NR} > V_{FLF}^{NR}$, then the manager will only choose to do an IPO if $p_t > \underline{p} = \frac{V_{FLF}^{NR}}{V_{PLF}^{NR}}$. Translating this simple example into our empirical exercise and the use of instrumental variables, we can think of the sentiment of the stock market, like the average discount of closed-end equity funds, as one of the driving factors of $p_{lt} = f(sentiment_t)$.

Appendix C List of BDCs with lending data

Table A2 Snapshot of the BDCs with lending data available in 2022Q4

CompanyName	Adviser	Fund Type	Fund Size (mn$)	Rel. lending share	Single lender share
BLACKSTONE PRIVATE CREDIT FUND	BLACKSTONE	Non-tr. PLF	52692.90	0.93	0.11
ARES CAPITAL CORP	ARES	Traded PLF	22398.00	0.85	0.48
FS KKR CAPITAL CORP	FSKKR	Traded PLF	16124.00	0.89	0.57
OWL ROCK CAPITAL CORP	BLUE OWL	Traded PLF	13584.85	0.66	0.00
OWL ROCK CORE INCOME CORP	BLUE OWL	Non-tr. PLF	11036.36	0.59	0.04
BLACKSTONE SECURED LENDING FUND	BLACKSTONE	Traded PLF	9909.00	0.31	0.05
PROSPECT CAPITAL CORP	PROSPECT CAPITAL	Traded PLF	7890.41	0.94	0.68
OWL ROCK TECHNOLOGY FINANCE CORP	BLUE OWL	FLF	6663.37	0.66	0.01
HPS CORPORATE LENDING FUND	HPS	Non-tr. PLF	5873.03	0.65	0.30
GOLUB CAPITAL B D C INC	GC	Traded PLF	5665.75	0.71	0.13
MAIN STREET CAPITAL CORP	MAIN	Traded PLF	4241.89	0.81	0.13
GOLDMAN SACHS B D C INC	GOLDMAN SACHS	Traded PLF	3591.31	0.66	0.02
OWL ROCK CAPITAL CORP III	BLUE OWL	FLF	3552.74	0.13	0.00
NEW MOUNTAIN FINANCE CORP	NEW MOUNTAIN CAPITAL	Traded PLF	3354.93	0.49	0.10
HERCULES CAPITAL INC	HERCULESCAPITAL	Traded PLF	3028.86	0.95	0.88
MORGAN STANLEY DIRECT LENDING FUND	MORGAN STANLEY	FLF	2986.12	0.50	0.05
FRANKLIN BSP LENDING CORP	BENEFIT STREET PARTNERS	Traded	2979.88	0.62	0.30
GOLDMAN SACHS PRIVATE MIDDLE MARKET CREDIT II	GOLDMAN SACHS	FLF	2850.01	0.13	0.00
SIXTH ST SPECIALTY LENDING INC	SIXTHSTREET	Traded PLF	2836.95	0.89	0.61
OAKTREE SPECIALTY LENDING CORPORATION	OAKTREE	Traded PLF	2767.26	0.67	0.51
BARINGS B D C INC	BARINGS	Traded PLF	2709.96	0.53	0.12
BAIN CAPITAL SPECIALTY FIN INC	BAIN CAPITAL	Traded PLF	2592.43	0.82	0.56
S L R INVESTMENT CORP	SOLARCAPITAL	Traded PLF	2537.70	0.71	0.28
GOLUB CAPITAL BDC 3	GC	FLF	2505.32	0.46	0.05
OWLROCK CAPITAL CORP II	BLUE OWL	FLF	2326.45	0.01	0.00
BARINGS PRIVATE CREDIT CORP	BARINGS	Non-tr. PLF	2291.91	0.60	0.08
CARLYLE CREDIT SOLUTIONS	CARLYLE	FLF	2198.16	0.61	0.02
NEW MOUNTAIN GUARDIAN III BDC	NEW MOUNTAIN CAPITAL	FLF	2095.20	0.25	0.03
CARLYLE SECURED LENDING INC	CARLYLE	Traded PLF	2041.70	0.39	0.14
C I O N INVESTMENT CORP	CION	Traded PLF	1872.41	0.81	0.38
BLACKROCK T C P CAPITAL CORP	BLACKROCK	Traded PLF	1719.35	0.58	0.14
MONROE CAPITAL INCOME PLUS CORP	MONROE	FLF	1544.64	0.75	0.30
BARINGS CAPITAL INVESTMENT CORP	BARINGS	FLF	1319.27	0.20	0.01
CRESCENT CAPITAL B D C INC	CRESCENT	Traded PLF	1302.88	0.59	0.42
NUVEEN CHURCHILL DIRECT LENDING CORP	CHURCHILL	FLF	1253.96	0.70	0.53
PENNANTPARK INVESTMENT CORP	PENNANTPARK	Traded PLF	1236.01	0.64	0.21
PENNANTPARK FLOATING RT CAP LTD	PENNANTPARK	Traded PLF	1226.68	0.67	0.35
CAPITAL SOUTHWEST CORP	CAPITALSOUTHWEST	Traded PLF	1202.16	0.78	0.54
NMF SLF I	NEW MOUNTAIN CAPITAL	FLF	1196.57	0.13	0.04
KAYNE ANDERSON BDC	KAYNE ANDERSON	FLF	1194.39	0.69	0.57
AB PRIVATE CREDIT INVESTORS CORP	ABPRIVATECREDIT	FLF	1191.73	0.66	0.52
TCW DIRECT LENDING VII	TCW	FLF	1162.91	0.89	0.75
RUNWAY GROWTH FINANCE CORP	RUNWAYGROWTH	Traded PLF	1141.77	1.00	0.85
SLINVESTMENTCORP	MORGAN STANLEY	FLF	1135.86	0.10	0.06
TRINITY CAPITAL INC	TRINITY	Traded PLF	1126.44	0.94	0.79
MSC INCOME FUND	MAIN	FLF	1107.16	0.13	0.01
TCW DIRECT LENDING	TCW	FLF	1085.34	1.00	0.44
PALMER SQUARE CAPITAL BDC	PALMERSQUARE	FLF	1057.45	0.45	0.27
SARATOGA INVESTMENT CORP	SARATOGA	Traded PLF	1038.97	1.00	0.92
TRIPLEPOINT VENTURE GR BDC CORP	TRIPLEPOINT	Traded PLF	1014.53	0.99	0.28
MSDINVESTMENT	MSD	FLF	982.25	0.71	0.37
FIDUS INVESTMENT CORP	FIDUS	Traded PLF	935.96	0.96	0.81
STELLUS CAPITAL INVESTMENT CORP	STELLUS	Traded PLF	898.18	0.84	0.70
FRANKLIN BSP CAPITAL CORP	BENEFIT STREET PARTNERS	FLF	816.18	0.15	0.08
WHITEHORSE FINANCE INC	WHITEHORSE	Traded PLF	796.47	0.87	0.69
GLADSTONE INVESTMENT CORP	GLADSTONE	Traded PLF	771.56	0.99	0.99
HORIZON TECHNOLOGY FINANCE CORP	HORIZONTECHNOLOGY	Traded PLF	766.83	0.91	0.83
GLADSTONE CAPITAL CORP	GLADSTONE	Traded PLF	639.60	0.98	0.92
PORTMAN RIDGE FINANCE CORPORATION	BC PARTNERS	Traded PLF	619.49	0.54	0.19
GOLDMAN SACHS PRIVATE MIDDLE MARKET CREDIT	GOLDMAN SACHS	FLF	602.57	0.01	0.01
BLACKROCK CAPITAL INVT CORP	BLACKROCK	Traded PLF	589.06	0.14	0.01
MONROE CAPITAL CORP	MONROE	Traded PLF	565.00	0.46	0.32
SCP PRIVATE CREDIT INCOME	SOLARCAPITAL	FLF	553.26	0.25	0.03
O F S CAPITAL CORP	OFS	Traded PLF	520.72	0.59	0.33
TRIPLEPOINT PRIVATE VENTURE CREDIT	TRIPLEPOINT	FLF	480.58	0.50	0.42
TCW DIRECT LENDING VIII	TCW	FLF	464.15	0.89	0.68
AUDAX CREDIT BDC	AUDAX	FLF	443.65	0.46	0.41
COMMONWEALTH CREDIT PARTNERS BDC I	COMVEST	FLF	366.22	0.96	0.89
OXFORD SQUARE CAPITAL CORP	OXFORDSQUARE	Traded PLF	327.99	0.64	0.40
GREAT ELM CAPITAL CORP	GREATELM	Traded PLF	310.11	0.73	0.65
INVESTCORP CREDIT MANAGEMENT BDC	CM	Traded PLF	239.36	0.35	0.16
LOGAN RIDGE FINANCE CORPORATION	BC PARTNERS	Traded PLF	214.71	0.54	0.28
PHENIXFIN CORPORATION	MEDLEYCAPITAL	Traded PLF	205.38	0.51	0.44
AG TWIN BROOK BDC	ANGELO GORDON	FLF	203.07	0.79	0.74
MUZINICH BDC	MUZNICH	FLF	153.73	0.81	0.27
STEELE CREEK CAPITAL CORP	MOELIS	FLF	151.17	0.53	0.50
BC PARTNERS LENDING CORP	BC PARTNERS	FLF	109.47	0.10	0.06
GUGGENHEIM CREDIT INCOME FUND	GUGGENHEIM	FLF	62.15	0.65	0.51
NEXPOINT CAPITAL	NEXPOINT	FLF	55.25	0.59	0.59
HANCOCK PARK CORPORATE INCOME	OFS	FLF	53.64	0.06	0.03
PROSPECT FLOATING RATE ALTERNATIVE INCOME FUND	PROSPECT CAPITAL	FLF	33.81	0.07	0.14

Appendix D Details on data construction

D.1 Data cleaning for porfolio holding data

Data cleaning involves a multi-step process. I start by gathering the "Schedules of Investments" (SOI) filings for each BDC and quarter from SEC Edgar. Due to the diversity in reporting formats among firms and evolving levels of detail over time, I employ multiple subroutines and checks to standardize the data output across BDCs and periods. Drawing inspiration from Elkamhi, Li, and Nozawa (2024), these subroutines are tailored to address various tasks such as cleansing special characters, eliminating duplicate titles/headers, aligning distorted columns and rows, restoring negative values within parentheses, recoding N/A entries, removing subtotal rows, merging fragmented cells, creating new variables from subtitles, and restructuring tables, among other tasks. This process yields a panel dataset where raw information is reorganized so that each row represents an investment record complete with all its attributes. Additionally, I extract crucial information from lengthy descriptive text columns. For instance, if details such as loan type, maturity date, par value, or interest rate are bundled within a single column labeled "investment details," I employ regular expressions to extract and generate new variables for these particulars. For some of the early years in the sample, the BDCs do not report even the basic loan information like the coupon rates. When the data quality is bad in the sense that the reporting entity does not report the central information such as the interest rate or the principal of the loan, I exclude those year-quarters from the sample. I begin the sample from 2005Q1 onwards since pre-2005 the data quality is generally quite bad and the width of the cross-section is very narrow with only a handful of BDCs operating as direct lenders.

I use two-panel datasets with different levels of granularity in the analysis. First, at a more granular level, I use loan/position-level data. I construct the panel so that I can use fixed loan position characteristics like $Debt/AssetClass$, $YearQtr$, $BorrowerId$, $LenderId$ combo to identify a position.[54] For the majority of cases, these fixed position characteristics identify a single loan thus allowing me to track that loan through time. When the lender has outstanding two or more loans (or equity positions) with the same loan seniority (or debt class), to the same borrower, within the same quarter, this combo mentioned above does not identify a single position. Such loans could be hard to distinguish from one another between different time points. When this is the case I aggre-

[54] On the other hand, I cannot use variables such as $FairValue$, $ParValue$, $CouponRate$, $MaturityDate$ for tracking a loan position since these change through time as a function of market conditions and repayment/refinancing/renegotiation activity of the borrower and lender.

gate the principal and fair values and calculate the value-weighted average coupon rate and time-to-maturity of the loans effectively treating the positions as one. Fortunately, these cases are very rare so in practice, one can consider a debt position identified by the *Debt/AssetClass*, *BorrowerId*, *LenderId*-combo to identify a single loan position. Second, I use a BDC-time-level data to analyze BDC portfolio choice. This dataset is effectively just an aggregated version of the position-level data.

Since my interest in this paper is direct lending to standard businesses, I exclude all the investment to investment funds, cash and cash-like items, or structured products such as CLOs from the loan position data. Similarly, I also exclude option, warrant, equity and preferred stock positions that do not count as debt investments. Thus middle market lending is considered to consist of positions whose *Debt Class* is categorized as *Senior and/or Secured debt*, *Revolver*, or *Subordinated debt*.

D.2 Private equity sponsored firms

I use an indicator variable as a control variable that identifies if the portfolio firm is backed by a PE or VC sponsor in that particular quarter. To assign portfolio firms to those that are PE/VC-backed and those that are not, I employ a robust two-tiered matching strategy that utilizes different PE data sources to obtain the best possible coverage. First, I collect all the US-based VC and Buyout investments and exits from Refinitiv and Preqin made between 1997Q1 and 2022Q4. Using these transactions, I create a panel that allows me to track the ownership change of each VC/PE-backed firm in the US, Canada, and Europe. If at any given quarter the most recent transaction for that firm is not an exit of the VC/PE fund, usually in the form of acquisition by a non-PE backed firm, IPO or writedown, I classify the firm as being PE-backed.[55] I then merge this dataset to the BDC investment data using company names. For non-identical firm names, I use fuzzy matching and matching by hand while checking the validity of the matches using information about companies via Google searches. Second, I match my main dataset to the Pitchbook database using the platform's mapping algorithm. I then download all the deals these firms have conducted from Pitchbook which allows me to similarly track the ownership changes for that borrower. Combining the coverage from both sources allows me to correctly classify a firm as PE or VC backed with a very high probability. If the firm is not found in either sample I assign it as a non-PE backed firm with the exception that I exclude the positions where the "DebtClass" is classified as "Structured products"

[55]Since the PE-funds are in majority relative to VC owners in the US middle market I use the term PE-backer or PE-sponsor to refer to both PE and VC backers.

or "Cash" since these are mostly CLOs, money market funds and other investment vehicles, which do not fit this sponsored or non-sponsored categorization. The resulting data suggest that during the sample on average 60% of all investments are held in PE-backed firms. [56]

D.3 Employment data from DOL Form 5500

For companies funded by BDCs, I follow Davydiuk, Marchuk, and Rosen (2024b) and collect detailed employment information at the firm level. These data is extracted from the Annual Returns/Reports of Employee Benefit Plans submitted to the Department of Labor (DOL) through Form 5500. The DOL compiles data related to the headcount of employees participating in pension plans, including both defined benefit and contribution plans, as well as various health benefit plans. The obligation to submit Form 5500, mandated by the Employee Retirement Income Security Act of 1974, is applicable to a wide range of employers, encompassing even very small ones. Although these filings provide comprehensive coverage of pension offerings overall, it is important to note that the reported figures only offer an estimate of firm-level employment. This is because participation rates in pension plans tend to be higher among full-time and higher paid employees (see the discussion in Davydiuk, Marchuk, and Rosen (2024b) and the references therein). For each plan, I calculate the total active participant count by company name, employer identification number (EIN) and year. To link these employment data with my list of BDC portfolio firms, I first match all DOL-based companies with Pitchbook using the platform's matching algorithm and then use the Pitchbook identifiers to merge the resulting matches with my broader dataset.[57]

[56] Jang (2023) finds that the fraction of senior loans held by BDCs used for buyouts was 63% as of September 2022. While they consider only senior loans the level matches that of mine.

[57] When merging the annual DOL data with the main dataset, the merge based on Year-BorrowerId allocates the yearly employment level to each quarter within that year. However, these duplicated employment level observations do not bias the interpretation of the results in column (6) in Table 4, which is the only result in the paper where this merged quarterly sample is used. This is mainly because the standard errors in Table 4 are clustered are also at the Borrower level so the perfect (within year-borrower) residual autocorrelation is captured by these standard errors. This can be checked by dropping the duplicated employment results by subsetting this quarterly sample by including only one observation per year for each borrower (an action that lowers the sample size by a factor of four). However, when running the same regression with this subsetted sample, the coefficient values for *Traded PLF* and *NonTraded PLF* as well as the associated standard errors are very similar to a full sample results.

D.4 Discretionary choices in data cleaning

There are a few discretionary choices that I make during the data collection process that do not match the standard way of documenting numbers. For example, since the management fee parameters may slightly differ between companies if the "Investment Advisory Agreement" accommodates exceptions to the standard rule, then to map these to the standard rule I have to make some approximations. None of these changes have any meaningful impact on any of the results but I document the most significant changes here to stay transparent.

- Oxford Square Capital Corp, OXSQ, sets hurdle rate as h=min(UST + 500bps, 10%). I approximate this with a constant value of 6%. The annual hurdle rates for OXSQ for 2022, 2021 and 2020 calendar years were 6.26%, 5.36%, and 6.69%, respectively.
- Gladstone Capital Corporation, GLAD, sets base management fee as 2% and 0.5% on syndicated loans. I use their mean (1.25%) as a compromise.
- The financial year of Saratoga Investment Corp, SAR, ends at the end of February. I lag all quarters by one to match the end of Q4 as close to the end of December. For example, I refer to the financial quarter occurring between Dec-Feb as Q1.
- Capital Southwest, CSWC, one of the oldest BDCs, completely restructured its organization using a spinoff in Septemeber 2015. Before this CSWC had barely held any debt investments and the entity that came of the spinoff rose to be a very different company than what it was before.[58] Due to this restructuring, using the age of the fund gives a very misleading picture about CSWC's actual age or experience as a middle market lender. Instead, the date of the spin-off is a better measure since after that new CSWC started to actually engage in its modern direct lending business. Thus I set the CSWC start date to 2015Q1 and calculate the age based on this date instead. While this correction does not influence the main results the old CSWC's age being an outlier would add unnecessary noise to the point estimates.

Debt classification: While a majority of the debt and equity positions classified by the BDCs are reported in such a way that immediately makes clear how to categorize the debt, BDCs still can use discretion in how accurately they report the debt class or the security category of each position in their quarterly reports. This creates the problem that observably quite similar loans or equity positions are reported with different names. For example, effectively an equity position may be reported as "membership interest", or "Class A Units". Also, BDCs occasionally change how they report their loan portfolios for example by changing the information on loans from "term loan" to "first lien senior

[58] https://www.capitalsouthwest.com/media/CSWC-Company-Overview-9.30.23.pdf

secured debt".[59] To ensure that I am categorizing debt classes with a sufficient level of detail while also ensuring that I match the same loans with different periods or similar loans among different filers similarly, I create nine categories denoted as senior/secured debt, subordinated debt, revolver, preferred stock, warrant, structured product, equity, cash, and other. Secured/Senior debt is the broadest category that contains loans that are reported as senior and/or secured, as well as unitranche debt. The senior secured debt can be first lien or second lien and higher while the unitranche debt lies between senior debt and subordinated debt in the seniority of capital structure. [60] Subordinated debt contains subordinated debt as they are reported in SOI filings or one-stop-loans, royalty agreements, and deferrable debt. Revolvers contain all revolving credit like credit lines.[61] Structured products, that contain collateralized debt obligations, and mortgage passthrough instruments. Cash includes cash and cash equivalents, money market assets, and Treasury securities. Equity includes all equity securities, except preferred stocks. I pool all derivative securities like warrants and swaptions into single category.

Appendix E Details on yield construction and robustness results

E.1 Implicit assumptions on yield construction

Using the bond valuation formula for extracting the discount rates naturally contains implicit assumptions. First, since the coupon rate for many of these loans is based on a floating benchmark interest rate, expectations about the future level of the base rate impact the expected future coupons. The standard bond valuation formula assumes the coupon rate remains fixed during the remaining life of the bond. This means that using the coupon rate based on the prevailing base rate could introduce measurement errors in some future cash flows. To address such concerns, I solve the yield-to-maturity for each loan by adjusting the coupon rates to changes in the expected base rate that can be

[59] Finally, the way loan type is reported in its SEC filing versus in Factset subsample sometimes differs. For example, unitranche loans are often reported by Factset as simply senior secured debt.

[60] For some debt categories, the names of the loans do not immediately reveal the seniority, in these cases, I allocate the debt to senior and/or secured if collateral is known to be used with these loans. One example is bridge loans.

[61] Some loans are denoted as "Senior Secured Revolving Credit Facility" or something similar that reveals the loan's revolving nature. I categorize these loans as "Revolvers", effectively ruling that loans that have credit line type attributes are called revolvers regardless of whether they are also senior and/or secured. However, if the loan is a senior secured delayed drawdown term loan I classify it has senior secured—again to optimize the matching of the same loans with different naming conventions between periods.

proxied with forward rates of corresponding maturity, a methodology that is explained below in more detail.

Second, loans may have amortization schedules where repayment occurs earlier than for bullet loans. Although, Ricciardelli and Clements (2024) say that the vast majority of corporate direct lending is written with bullet repayment profiles, survey evidence by Block et al. (2024) suggests that only 30% of the loans originated by private debt funds in the US have a bullet schedule while the amortization with and without initial grace period collectively accounts for about 55% of loans all loans. Regardless, this ambiguity still raises concerns about whether assuming the bullet schedule when extracting the yield-to-maturity is reasonable. Using some amortization repayment schedule instead of a bullet repayment schedule, while fixing the price, coupon, and maturity date, effectively moves the cash flows closer to the present moment which means the yield must be higher to rationalize the same present value. Thus to the extent that I underestimate the use of a faster amortization schedule, my yield-to-maturity estimates will also underestimate the true yield-to-maturities. Unfortunately, since I do not observe the loan amortization schedules nor can I reliably extract them from par value estimates, I cannot fully address this concern. However, testing the magnitude of such downward biased measurement error with examples that assume a realistic amortization schedule indicates that the bias is likely to be quantitatively small.

Third, the current bond valuation formula assumes annual interest payments, if BDC loans use some different interest payment schedule, which they often do, this may introduce a small measurement error. I also examine the magnitude of such measurement error and find it to be quantitatively tiny.

Fourth, some loans may have payment-in-kind (PIK) optionality, but the current valuation approach does not incorporate this optionality.[62] While I do not examine the magnitude of such measurement error, based on the use of the word "PIK" in SOI filings this optionality impacts a tiny fraction of loans which indicates that any PIK-originated measurement error is not likely to change the interpretation of the level of yields on aggregate level. [63]

[62]The payment-in-kind have different meanings depending on the context but perhaps one used most often in loan context is that the borrower has the option to withhold from making the interest payment to preserve cash and instead the withholded interest payment is added to the principal to accumulate interest.

[63]The share of PIK income as a share of total income has averaged about 5% based on similar sample in the Cliffwater Index https://cliffwater.com/files/cdli/docs/Cliffwater_Report_on_US_DirectLending.pdf

E.2 Calculating the spread using maturity matched risk free rates

Calculating the spread of a floating rate loan is easy but not completely trivial. Here I introduce how I calculate the spread of an individual loan that I use in the analysis, and in the next section I add some additional considerations that I exclude from the baseline methodology for simplicity but that do not end up having a significant impact on the loan pricing results.

First, for each loan in each date, I calculate the price of a synthetic risk free bond with same coupon and maturity characteristics, using the spot rates, $rf_{t,t+\tau}$ of corresponding maturity zero coupon bonds using the data from Gürkaynak, Sack, and Wright (2007).[64] Since a coupon bearing bond is just a sum of different maturity zero-coupon bonds we can calculate the price of this synthetic bonds using following formula.

$$Price_t^{rf} = \sum_{\tau=1}^{T} \frac{Coupon_{t+\tau}}{(1+rf_{t,t+\tau})^{\tau}} + \frac{ParValue_{t+T}}{(1+rf_{t,T})^{T}} \tag{A7}$$

Then using the just calculated price we can back out the ytm_t^{rf} of this synthetic bond from the formula

$$Price_t^{rf} = \sum_{\tau=1}^{T} \frac{Coupon_{t+\tau}}{(1+ytm_t^{rf})^{\tau}} + \frac{ParValue_{t+T}}{(1+ytm_t^{rf})^{T}} \tag{A8}$$

Finally, we calculate the spread of this loan as $spread_t = ytm_t - ytm_t^{rf}$.

E.3 Duration sensitivity of stock market implied middle market risk premium

Figure A1 illustrate how the ytm_{t+1}^{Mkt} will vary if we change D. When duration grows the volatility of ytm_{t+1}^{Mkt} grows.

Appendix F Additional descriptive statistics

F.1 Composition of aggregate BDC portfolios

The BDC portfolios have experienced an evolution from subordinated debt toward senior and or secured debt; a trend which is illustrated in Figure A2. The share of equity as a percentage of total BDC AUM has remained fairly constant around 15%.

[64] https://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html

Figure A1. Stock market implied yield-to-maturity for average BDC portfolio

This figure shows the yield-to-maturity for an average BDC portfolio while changing duration (D) estimates. The formula for calculating the stock market implies yield-to-maturity is outlined in Equation (34). TMT in the legend refers to the average time to maturity loan portfolio.

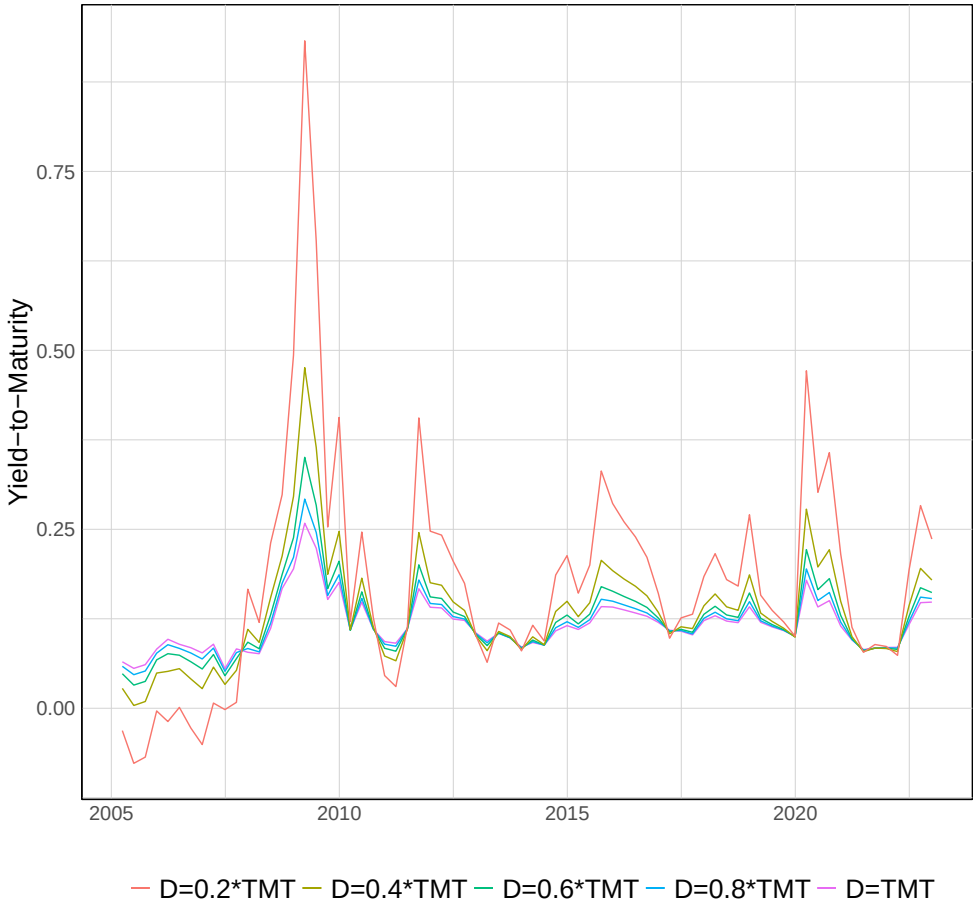
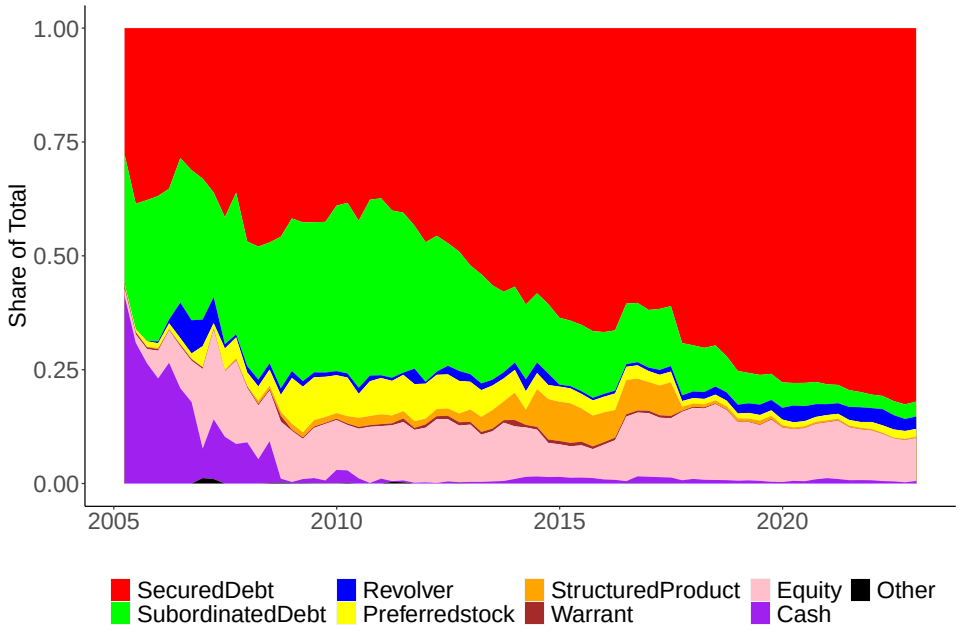


Figure A2. Share of debt class of total

This figure shows the aggregate share of each asset or debt class in BDC portfolios. The details of assigning the loans to different categories are discussed in this Appendix.



F.2 Realized losses in different debt markets

Figure A3 provides some aggregate level evidence about realized credit losses in the direct lending business of the US middle market relative to those in other similar fixed-income asset classes. Broadly it seems that the credit losses have not been any higher in middle market direct lending relative to other similar asset classes and bank lending.

F.3 Cyclicality of BDC lending

In this section, I analyze the aggregate lending patterns in the U.S. middle market. To give some idea of how the loan prices correlate with lending volumes, in Figure A4 I plot the average fair-value-to-par-value -ratio and the contemporaneous lending growth all debt positions averaged across four quarters to smooth out transitory and seasonal variation. The remarkably strong connection between loan values and lending indicates that a decline in borrowers' creditworthiness (correspondingly increase in risk) is generally associated with less lending.

Figure A3. Realized credit losses

Sources: The data is from Cliffwater 2023 Q2 Report on U.S. Direct Lending. The credit losses for BDC lending are based on CDLI realized net losses. (The CDLI sample is also based on BDC reports and is likely to be very similar to the sample used in this paper.) For bank lending, losses are based on the charge-off rate on business loans (FRED: CORBLACBS). For HY-bonds and leveraged loans, losses are based on their respective default ratios and recovery ratios from JPMorgan Markets, Bloomberg US High Yield Bond Index, and Morningstar LSTA US Leveraged Loan 100 Index.

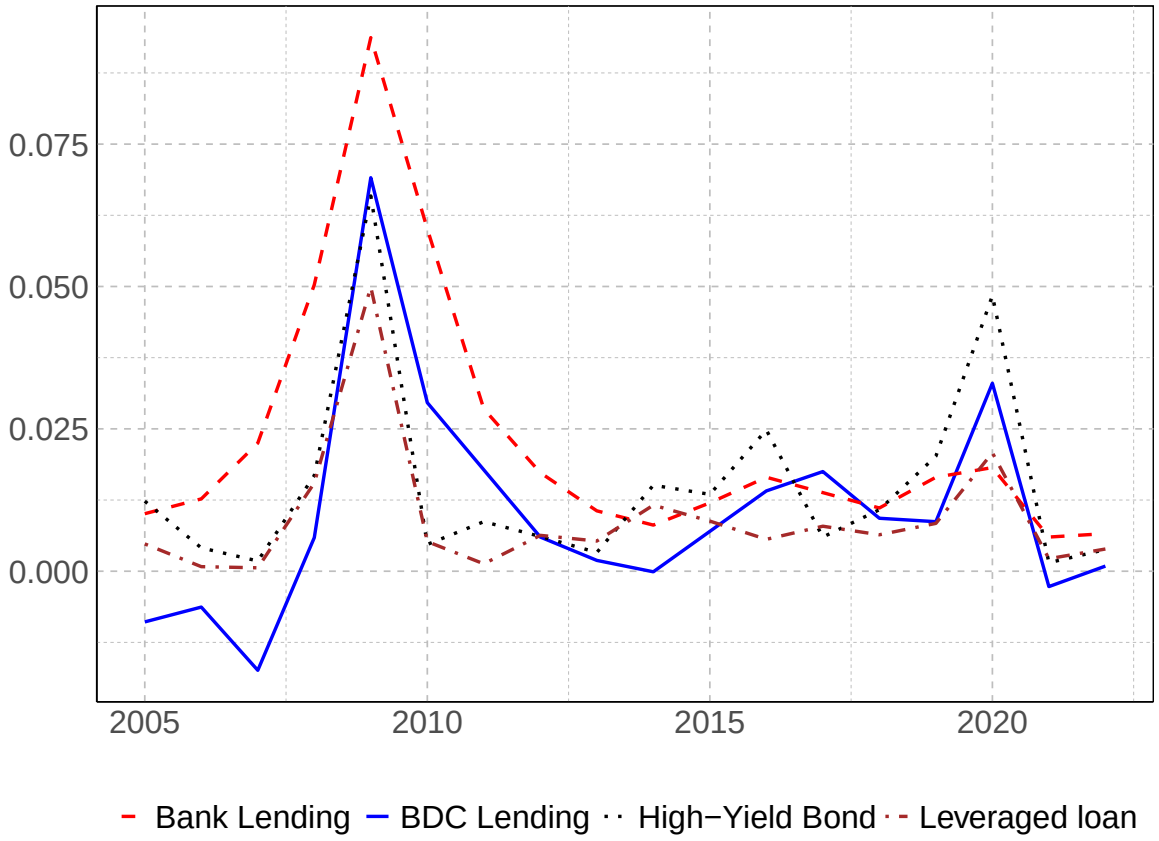
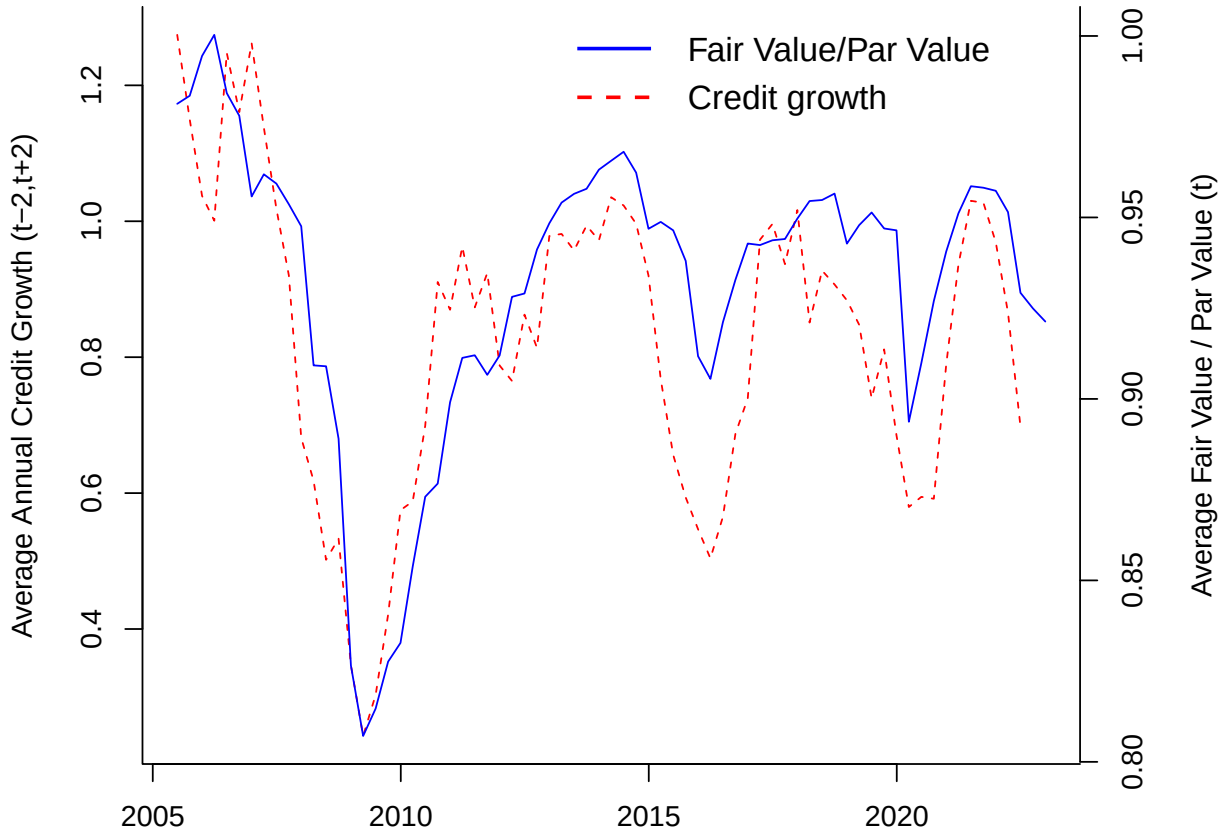


Figure A4. Price and volume of lending

This figure shows the fair-value-to-par-value -ratio and the annual lending growth of all loan positions (averaged across four quarters to smooth out transitory and seasonal variation). To include the change in loan balances coming from both new loans and existing loans, the growth rate of each loan position is defined as $Credit\ growth_{t,t+h} = 2 \times \frac{Credit_{t+h} - Credit_t}{Credit_{t+h} + Credit_t}$ using the standard Davis and Haltiwanger (1992) adjustment.



Appendix G Additional empirical results and robustness

G.1 Fund types and other portfolio measures

In this section, I present the results of the portfolio-level regression using other portfolio measures that are complementary to the baseline variable *Rel. lending share*. I use five variables: The first is the share of the portfolio held in level 3 assets of the ASC 820 accounting standard. These are the most illiquid and opaque assets which are hardest to value. Based on the view that relationship lending is often used with most opaque borrowers, then the share of Level 3 assets can be viewed as a reasonable proxy of the relationship lending activity by the lender. Second and third, I use the loan portfolio coupon rate or the yield spread as the dependent variable. Fourth I use the (par-weighted) share of the loan portfolio allocated to companies in which the lender also holds an equity stake. Fifth, I use the leverage ratio. Sixth, I use the par-weighted share of the loan portfolio held in loans where the borrower has issued a broadly syndicated loan within the past five years. All specifications control for the standard lender attributes like size, leverage, etc. Table A3 presents the results. Consistent with the view that PLFs engage more in relationship lending I find that traded PLFs allocate a bigger share of their portfolio to the most illiquid Level 3 assets and to loans of firms in which they also have equity stakes and less of companies that have recently accessed broadly syndicated loan market. Furthermore, traded PLFs hold loans with higher coupon rates and loan spreads. They also rely more on leverage. The results for the non-traded PLF do not seem to differ from those of FLFs.

G.2 Instrumental variable motivation

Figure A5 shows the correlation between the average equity closed-end funds' premium/discount and the total BDC IPO activity. In periods of high stock-market sentiment (measured as the average equity closed-end fund premium/discount), there is generally more BDC-IPO activity and vice versa. In time series regression higher sentiment in quarter t is associated with a higher number of BDC IPOs in quarter $t + 1$.

Ideally we could sharpen the identificaiton by restricting the sample to BDCs that start an IPO process but then change it as the market conditions change (Bernstein, 2015). Unfortunately, there are only a handful of BDCs in the sample that announce and later terminate an IPO process so control group would be negligible and thus data limits such exercise.

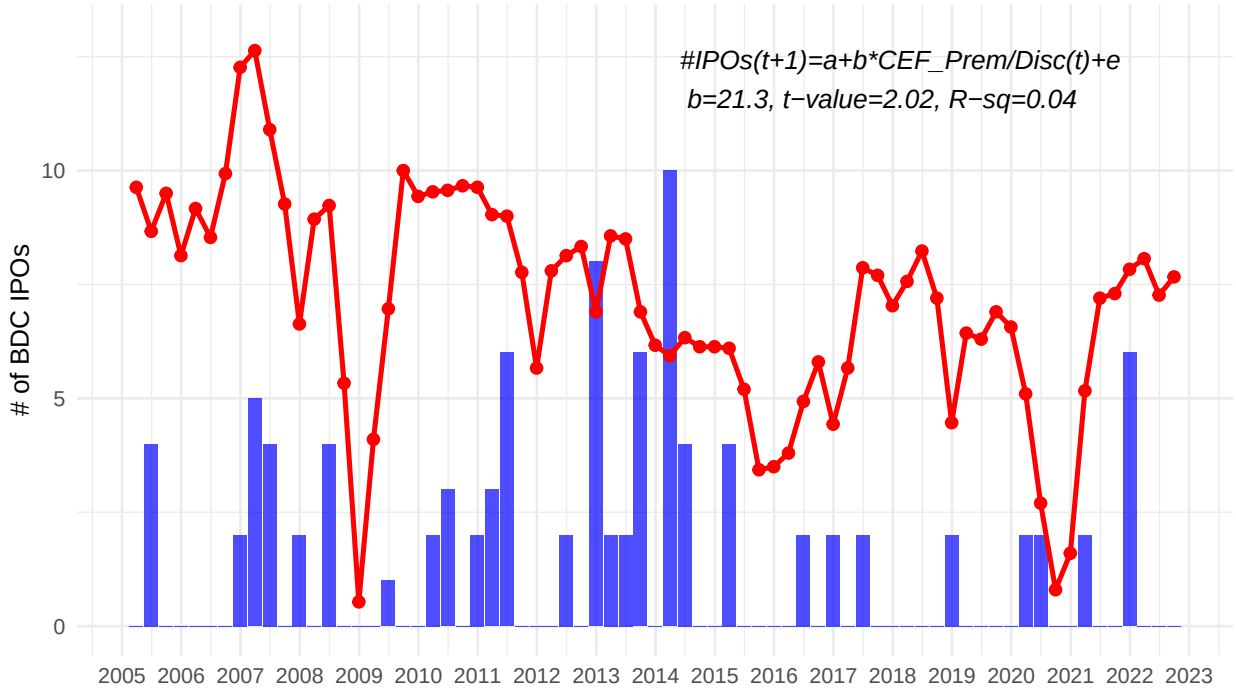
Table A3 Alternative portfolio measures and proxies of relationship lending activity

Dep. Variables:	Level 3	Coupon Rate	Spread	Equity stake	Leverage	Syndicated
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Traded PLF	0.10**	0.01***	0.01***	0.19***	0.09***	-0.11***
	(0.04)	(0.00)	(0.00)	(0.05)	(0.03)	(0.02)
NonTr. PLF	-0.09	-0.00	-0.00	-0.06	0.00	0.03
	(0.07)	(0.00)	(0.01)	(0.06)	(0.03)	(0.05)
BDC controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,798	2,669	2,178	2,584	3,160	2,584
Adjusted R^2	0.16	0.30	0.25	0.19	0.26	0.20

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

This table presents results from BDC-time level panel regression. *Level* 3 is the share of the portfolio held in most illiquid Level 3 assets (accounting standard ASC 820). *Coupon Rate* is the average coupon rate of loan portfolio. *Spread* is the yield to maturity of the loan portfolio over LIBOR 3M rate. *Equity stake* is the par weighted share of loan portfolio held in firms in which the lender also holds an equity or preferred stock stake. It is not the share of the portfolio held in equities or preferred stock. *Leverage* is the fund leverage ratio. *Syndicated* is the par-weighted share of loan portfolio held in companies that have accessed the broadly syndicated loan market within past 5-years. *NonTr. PLF*, *Traded PLF* are indicator variables that take a value of one if the BDC is operated as a non-traded or traded perpetual-life fund respectively in that period, and zero otherwise. All specifications control for lagged size, lagged leverage, lagged profitability (ROE), an indicator variable for a fund being internally managed, and three parameters that describe the BDC management compensation package: hurdle rate of the net investment income incentive fee, share of management's incentive fee, and base management fee. Exception is Column (5) that excludes lagged leveage from controls. The fixed effects: *YearQtr* refers to the calendar quarter.

Figure A5. Average equity closed-end-fund Premium/Discount and BDC IPO activity



G.3 Listed firms and broadly syndicated loans

One potential concern to the research methodology is that given that I am only using data from BDC filings, these filings might capture only a fraction of the total borrowing for any given borrower and the existence of other non-BDC lenders could then influence the construction of our relationship lending measures, if they were observed. For example, consider the case that BDC l is the only BDC-lender for a firm b implying that $Rel(Dummy) = 1$ and thus loans between the pair b and l are considered as "relationship loans". However, assume further that other *non*-BDC lenders are much more invested with that company and thus the BDC l is simply a side investor. In this case, it may not be reasonable to interpret the lender l as the relationship lender of the borrower b. This problem, arising from the fact that we do not typically observe all the lending transactions that occur in the private markets, is also present in prior work that similarly relies on data reported by the lenders or deals; e.g. Bharath et al. (2011, 2007). However, while I do not observe all the loans borrowers have outstanding to directly control for this possibility, there are practical reasons that should alleviate these concerns.

First, anecdotal evidence suggests direct lending is either made by a single lender or

by a club of few lenders (Nesbitt, 2019; Ricciardelli & Clements, 2024).[65] So if we observe there to be a firm with a single-BDC lender and a firm with multiple BDC-lenders then, if there exist other lenders for either of these firms, it is more likely they also are lending to the firm with already multiple-BDC lenders than those without. Since most loans with multiple-lender firms are already classified as transactional lending, then the bias that the other non-BDC lenders bring to the analysis is less likely to be a significant issue.

Second, I show empirical evidence consistent with this idea. Namely, I collect information on Pitchbook whether the borrowing company has received a syndicated loan market within past 5 years from that observation and similarly if the company's stock is listed in the stock market.[66][67] The idea is that these firms may be more likely to have good outside options or other lenders and are thus less likely to fit the traditional interpretation of relationship lending.

In Table A4 I show the updated regression results of column (1) originally in Table 3, while controlling for the listed status of the borrower with an indicator variable *Publicly Listed Borrower* and the indicator variable if the firm has received a syndicated loan within past 5 years from that observation date, *Has Received Syndicated Loan*. We see that syndicated status has a negative coefficient indicating that if the borrower has been borrowing from the syndicated loan market it is less likely that the loan is classified as a relationship loan. This is as we would expect since syndicated loan transactions are exactly the sort of loans that are considered to best illustrate transactional lending. On the other hand, the fact that the borrower's stock is listed in the public markets suggests that the loan is more likely to be treated as a relationship loan. Since the publicly traded companies often have other outside options at their disposal it is possible that in the case of these particular loans our measure $Rel(Dummy)$ may not represent relationship lending status. That being said, since Table A4 show that the loans to listed firms represent only about 1.4% of the total loan sample, any potential measurement error on $Rel(Dummy)$ due to will likely have marginal impact on any of the main results. Table

[65] Evidence from Pitchbook LCD 2023 shows that between 2020Q1-2023Q3 private credit deals with a single lender has averaged about 70% while loans that involve three or more lenders has averaged about 10%.

[66] BDCs are allowed to hold some publicly listed firms in their portfolios under special circumstances that is when the borrowing company satisfies the requirements of an "eligible portfolio company". For details see e.g. https://bdcreporter.com/bdc-primer/. However, as is evident from the results below, the number of such companies is minimal.

[67] I obtain the information about the "listed-stock" status of the portfolio firm using mapping files between Compustat-Pitchbook identifiers and between Factset-CRSP identifiers. Since I observe for almost all the firms either Pitchbook or Factset identifiers, an absence of match is a strong indicator of private status. For most companies, I also observe all its deal events in Pitchbook including IPOs or mergers, which allows me to track private vs public status across time.

Table A4 Robustness: Determinants of relationship lending measures

Dependent Variables:	Rel(Dummy)			Rel(D)(i)	Rel(D)(ii)	Rel(D)(iii)
	All	Excl. Listed	Excl. Synd.	Adjust dependent variable		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Traded PLF	0.18***	0.18***	0.22***	0.18***	0.20***	0.20***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)
Non-traded PLF	0.20**	0.20**	0.19**	0.22***	0.11*	0.12*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)
PE Sponsored	-0.05***	-0.05***	-0.04**	-0.05***	-0.11***	-0.09***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Subordinated Debt	0.06***	0.06***	0.06***	0.07***	0.08***	0.06**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Revolver	0.11***	0.11***	0.11***	0.13***	0.19***	0.19***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
ln Time to maturity	-0.07***	-0.07***	-0.06***	-0.07***	-0.11***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ln Par value	0.06***	0.06***	0.06***	0.06***	0.06***	0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Lender Has Equity Stake	0.09***	0.10***	0.10***	0.10***	0.16***	0.16***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Has Received Syndicated Loan	-0.09***	-0.09***				
	(0.02)	(0.02)				
Publicly Listed Borrower	0.07***		0.08***			
	(0.03)		(0.03)			
BDC controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	143,190	140,257	113,953	174,375	143,190	143,190
Adjusted R^2	0.18	0.18	0.18	0.16	0.19	0.18

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

This table shows what lender characteristics and loan characteristics are associated with measures of relationship lending. In this robustness test, I use two new indicator variables: *Publicly Listed Borrower* indicates that the borrower's stock is publicly listed. *Has Received Syndicated Loan* indicates that the borrower has obtained a syndicated loan within past 5 years. Columns (1) show the baseline results with these controls. Column (2) drops the listed firms from sample. Column (3) drops the firms that have borrowed from the syndicated loan market. Columns (4)-(6) adjust the definition of Rel(Dummy) by i) reclassifying loans that have Rel(Dummy)=1 and are publicly listed as Rel(Dummy)=0 and denote the resulting new variable as Rel(D)(i) ii) reclassifying loans that have Rel(Dummy)=1 and have borrowed from the syndicated loan market as Rel(Dummy)=0 and denote the resulting new variable as Rel(D)(ii) ,iii) reclassifying loans that have Rel(Dummy)=1 and are publicly listed or have borrowed from the syndicated loan market as Rel(Dummy)=0 and denote the resulting new variable as Rel(D)(iii). All columns include the following BDC level attributes as controls: lagged size, lagged leverage, lagged profitability (ROE), an indicator variable for a fund being internally managed, and three parameters that describe the BDC management compensation package; hurdle rate of the net investment income incentive fee, share of management's incentive fee, and base management fee. The remaining variable definitions are found in Appendix A. Fixed effects: *Borrower* refers to the identity of the borrowing company. *YearQtr* refers to the calendar quarter e.g. 2022Q4.

A4 also presents evidence of this. In columns (2) and (3) I rerun the regression while excluding the companies that are listed, or have received a syndicated loan within the past five years, respectively. In columns (4)-(6) I start from the (extreme) premise that if a firm has borrowed from the syndicated loan market or is listed, then the loans it has outstanding to BDCs cannot be considered to be relationship loans. In other words, under this premise, if $Rel(Dummy)$ is assigned a value of one, for such loans, it needs to be reclassified as zero. Thus I use new dependent variable, which is defined as $Rel(Dummy)(i) \equiv Rel(Dummy) \times (1 - Publicly\ Listed\ Borrower)$, $Rel(Dummy)(ii) \equiv Rel(Dummy) \times (1 - Has\ Received\ Syndicated\ Loan)$ and $Rel(Dummy)(iii) \equiv Rel(Dummy)(i) \times Rel(Dummy)(ii)$, where $Rel(Dummy)$ is the original dependent variable. These variables reclassify loans that are listed, have borrowed from the syndicated loan market in the past five years, or both, as having $Rel(Dummy) = 0$.

With each of these operations shown in columns (1)-(6) the positive coefficient on $Non - traded\ PLF$ and $Traded\ PLF$, which I documented in the main body of the paper stays almost unchanged. This result supports the interpretation that it is unlikely that not observing all the lenders for a given borrower would have a significant impact on the baseline results.

G.4 Fund type and maturity

Table A5 shows the results of regressing loan maturity or relationship length on fund type. The OLS regressions suggest that controlling for borrower identity, other observable loan terms, and other lender characteristics there is generally no difference in maturity of the outstanding loans between traded PLFs and FLFs. Instead, I do see that PLFs have longer relationships and these longer relationship seem to especially originate from the more exclusive relationship loans. Columns (7) and (8) show the results of borrowers that have loans outstanding with multiple lenders at a given period. Among these loans traded PLFs have longer relationships with the firm but this does not depend on whether they are now the largest lender for that borrower.

G.5 Deal-level analysis with Pitchbook data

For the same reason as stated in the beginning of the previous section, I investigate the presence of additional lenders and their impact on BDCs' lender shares using deal-level data sourced from Pitchbook. I source all the deals made by BDCs and all the deals classified by Pitchbook as "Private Credit" in the US from 2005Q1 to 2023Q4. Then I extend the deal-level data to a lender-deal-debt class-level. The advantage of this Pitchbook data

Table A5 OLS+IV: Maturity, relationship length and fund structure

Dependent Variables:	ln Time to maturity				ln Relationship length			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Traded PLF	0.0004	0.008	0.008	0.03	0.15***	0.06	0.06*	0.22***
	(0.01)	(0.01)	(0.006)	(0.02)	(0.05)	(0.04)	(0.03)	(0.07)
NonTr. PLF	0.03	0.03*	-0.003	0.001	-0.61***	-0.59***	-0.41***	-0.33***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.12)	(0.12)	(0.08)	(0.09)
ln Par value	0.01***	0.02***	0.005	0.006	0.009	-0.005	0.01**	0.02***
	(0.006)	(0.005)	(0.004)	(0.004)	(0.008)	(0.008)	(0.006)	(0.005)
Position share	-0.06	-0.06	-0.39	-0.39	0.09	-0.14	1.4*	1.4*
	(0.32)	(0.32)	(0.35)	(0.35)	(0.51)	(0.55)	(0.84)	(0.85)
Lender Has Equity Stake	-0.02	-0.02	-0.007	-0.01	0.35***	0.34***	0.29***	0.29***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.05)	(0.04)	(0.04)	(0.04)
Coupon rate	0.03***	0.03***	0.04***	0.04***	0.02***	0.02***	0.02***	0.02***
	(0.008)	(0.008)	(0.01)	(0.01)	(0.005)	(0.005)	(0.004)	(0.005)
Rel(Dummy)		0.01	-0.03*	-0.03**		-0.008	0.05**	0.09*
		(0.02)	(0.01)	(0.01)		(0.03)	(0.02)	(0.05)
Traded PLF × Rel(Dummy)		-0.02	0.02	0.02		0.19***	-0.02	-0.09
		(0.02)	(0.01)	(0.02)		(0.04)	(0.04)	(0.07)
NonTr. PLF × Rel(Dummy)		-0.01	0.03**	0.04***		0.01	0.06	0.06
		(0.02)	(0.01)	(0.01)		(0.09)	(0.07)	(0.08)
BDC controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
YearQtr-DebtClass	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-BaseRate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower	Yes	Yes			Yes	Yes		
YearQtr-Borrower			Yes	Yes			Yes	Yes
Fit statistics								
Observations	17,486	17,486	17,486	17,221	172,663	172,663	172,663	168,987
Adjusted R^2	0.55	0.55	0.82	0.83	0.51	0.52	0.70	0.69

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

The regression results are based on loan-level quarterly panel data. The dependent variable is the log time-to-maturity and log relationship length for a particular loan position in a given period. Columns (1)-(4) are based on a subset of the data that focus on the observations when the borrower-lender pair first appears in the data. *NonTr. PLF*, *Traded PLF* are indicator variables that take a value of one if the BDC is operated as a non-traded or traded perpetual-life fund, respectively in that period, and zero otherwise. $Rel(Dummy)$ is a measure of the strength of the lending relationship at time t. BDC controls include the following BDC-fund characteristics: lagged fund size, lagged leverage, lagged profitability (ROE), an indicator variable for a fund being internally managed, and three parameters that describe the BDC management compensation package. The columns (4) and (8) show the second-stage results based on the two-stage least square regression. The instrumental variables are the *IPO Attractiveness*, and its interaction with $Rel(Dummy)$. All the variable definitions are found in Appendix A. Fixed effects: *Borrower* refers to the identity of the borrowing company. *BaseRate* refers to the loan base rate. *YearQtr* refers to the calendar quarter. *DebtClass* refers to the type and seniority of a loan.

is that it lets us observe all the lenders involved in a particular deal where also a BDC is involved. Observing also the non-BDC lenders mitigates the issue that the borrowing company might have a large commitment to a non-BDC lender which could influence our interpretation of treating the largest BDC lender as the relationship lender of that firm. While Pitchbook does not exactly report how the lenders in a deal share the debt burden—only which lenders were involved in which facility of the total deal package, we can approximate the share of each lender's commitment by allocating each loan facility in a deal equally among the participants and then summing the positions of each lender among all the loan facilities that the lender is involved in.[68] Based on these figures I calculate that if a BDC is involved in a deal, the median (mean) share of all the BDCs of the total debt in the deal is 87.8% (67.5%). Now, if the latest debt deal involves all the lenders that the borrower has after the deal is made then this suggests that the assumption of focusing only on BDC lenders in the main body of the paper is reasonable since in these deals the BDCs collectively typically own most of the debt that a firm has outstanding.[69]

Independent of the calculations above, I also provide supportive evidence to the Proposition 1 and results presented in the main body of the paper using this deal-level data. As explained earlier, relationship lending deals are typically those made to smaller firms with fewer lenders involved. Again I investigate the correlation of *Traded PLF* and with some of these borrower characteristics at the time of the deal which can be considered to be proxies of relationship lending. Since I also have non-BDCs lenders in the sample I add indicator variables $Non-BDC\,lender$ to the regression.

Table A6 shows the correlation between BDC type and various deal variables that describe the borrowing company. Consistent with the interpretation that the lender horizon is a significant predictor of relationship lending I find that deals that Traded PLFs and Non-traded PLFs are less likely to be participants in deals with multiple lenders (columns(1)-(3)). Traded PLFs are also more likely to be lenders in deals that are made to companies with shorter deal histories (columns (4)-(6), new debt raised is smaller (columns (7)-(9)), and the employee count of the borrowing firm is smaller (columns (10)-(11)). Results are similar to non-traded PLFs except they seem to participate more in deals where the borrowing firm has a longer deal history—see the positive $Non-traded\,PLF$-

[68] For example, say a deal, financed by two lenders X and Y, involves a revolving credit worth \$10M to the borrower and a term loan worth \$50M. Assume that both lenders are assigned by the Pitchbook as the lenders of the term loan but only lender X is assigned as a lender of the revolving credit. In this setup, the assumption of the equally allocated shares would suggest that the position of lender X is \$10M+0.5 x \$50=\$35M, which is 58.3% of the total \$60M, while lender Y's position is the \$25M.

[69] The assumption that the lender base in the latest deals represents the lender base of the company at that point in time can be considered reasonable since often with LBOs or debt refinancing it is typical that all of the existing debt is paid back with new lenders replacing the existing lender base.

coefficient in columns (4)-(5). Overall these results provide independent support to those presented in the main body of the paper.

Table A6 Determinants of lender type and proxies of relationship lending at deal-level

Dependent Variables:	Num. of lenders			Deal No.			New Debt Amt.			Num.of Empl.	
	All	Only BDCs		All	Only BDCs		All	Only BDCs		All	Only BDCs
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Variables											
Traded PLF	-0.22***	-0.19***	-0.11***	-0.09***	-0.10***	-0.02***	-0.21**	-0.48***	-0.31***	-0.32***	-0.43***
	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)	(0.10)	(0.09)	(0.07)	(0.12)	(0.15)
Non-traded PLF	-0.22**	-0.22**	-0.23***	0.21***	0.07	-0.01	-0.36	-0.65**	-0.62***	0.16	0.02
	(0.10)	(0.10)	(0.07)	(0.06)	(0.06)	(0.01)	(0.25)	(0.29)	(0.18)	(0.10)	(0.20)
Non-BDC lender	0.15***			0.22***			1.27***			0.25*	
	(0.05)			(0.03)			(0.11)			(0.15)	
BDC controls		Yes	Yes		Yes	Yes		Yes	Yes		Yes
Fixed-effects											
DealYearQtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DebtClass	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower			Yes			Yes			Yes		
Fit statistics											
Observations	161,062	12,601	12,601	164,109	12,601	12,601	141,520	11,440	11,440	13,994	1,161
Adjusted R^2	0.22	0.11	0.48	0.22	0.11	0.94	0.21	0.13	0.49	0.18	0.15

Clustered (Deal ID & DealYearQtr) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table uses Pitchbook lender-deal level data to show how the lender's fund structure is associated with different deal measures and the characteristic of the borrower firm. The dependent variables used in Columns (1)-(11) are the number of lenders in the deal, the number of deals that the borrower has made so far (including the deal in place), the amount of new debt raised, the number of employees with all measured in logs. BDC attributes that are in control are (log) fund size, leverage, and profitability (ROE), an indicator variable for a fund being internally managed, and three parameters that describe the BDC management compensation package: hurdle rate of the net investment income incentive fee, share of management's incentive fee, and base management fee. Fixed effects: *DebtClass* refers to a type of loan the lender has committed. *DealYearQtr* refers to the calendar quarter when the deal is completed.

G.6 Propensity score matching

In this section, I apply matching to better control for the fundamental differences between perpetual-life funds and finite-life funds and thus alleviate some endogeneity concerns. I exclude the nontraded PLFs due to their different business model and just compare traded PLFs and FLFs.[70]

The matching has the following steps: First, I regress the *Traded PLF* on various BDC characteristics and Year-Quarter dummies using a logistic regression. To include the most important covariates to balance, while keeping the list from becoming unreasonable long and thus diminishing the space of reasonable matches, I include (one-quarter-lagged) log-fund size, fund leverage, and fund profitability (measured as ROE) to the list of covariates to balance. Then, I calculate propensity scores. That is for each fund, I calculate what is the predicted probability of receiving the treatment given their covariates. Finally, I match each treated unit with one or more control units that have similar propensity scores using optimal full-matching (Hansen, 2004). The goal is to create a matched sample in which the distribution of covariates is similar between the treated and control groups.[71] The key statistics used to evaluate the success of the match are presented in Table A7.

Table A7 Propensity score matching: covariate balance in the matched sample

	Mean PLF	Mean Non-PLF	Std.Mean.Diff.	Var.Ratio	eCDF Mean	eCDF Max
Distance	0.75	0.75	0.01	1.02	0.00	0.05
Ln Size	6.59	6.66	-0.06	0.46	0.10	0.20
Leverage	0.42	0.42	-0.00	1.20	0.05	0.13
ROE	0.06	0.05	0.05	0.68	0.02	0.05

The statistics used to analyze covariate balance are standardized mean differences (Std. Mean Diff.), variance ratios (Var. Ratio), and empirical cumulative distribution function (eCDF) statistics. Table excludes the *YearQtr* dummies from the list of covariates to keep it concise.

The results indicate a reasonably successful match as measured by the standardized mean differences (Std. Mean Diff.), variance ratios (Var. Ratio), and empirical cumulative distribution function (eCDF) statistics. Values of standardized mean differences and eCDF statistics close to zero which indicate good balance.[72]

After obtaining a good balance between the PLF and Non-PLF groups after matching, I proceed to the next step to analyze the difference in outcome between the two groups. I then rerun my baseline OLS regressions using the matched sample with weights from the first stage. I include the covariates used in the matching to this second stage since they

[70] The results would be similar even if we included them and pooled all PLFs into one category.

[71] I test different matching methods and find full-matching to perform best in this task.

[72] I exclude the results for the *YearQtr* dummies to keep the list short but the match statistics for them are good also.

can provide additional robustness to slight imbalances remaining after matching and can improve precision. I also include additional covariates as well as a batch of fixed effects.

Table A8 illustrates that the point estimates shown in Table 3 shrink slightly but remain strongly economically and statistically significant. Thus we can conclude that the unequal covariate balance is not behind the main results.

G.7 Determinants of Rel(Dummy) with other measures of relationship strength

While $Rel(Dummy)$ is an established measure of relationship lending used by prior literature, we can check that our measure also correlates with other proxies of relationship lending used in the literature, namely the relationship duration and the use of equity (or preferred stock) stakes in the lending relationship. Table A9 shows that $Rel(Dummy)$ is a strong predictor of relationship length. The higher the share of the lender in the total outstanding debt of the borrower to BDCs, the more likely the relationship between the lender and the borrower will last a long time.

These other measures of the relationship strength— *Relationship length* in particular— have some issues that make their use unfeasible as dependent variables. First, with *Relationship length*, for some lenders I do not have accurate information for all the loans about what the actual relationship duration is. There are many funds the SOI-filings become available only after they have existed and built their portfolio for some time. Since I do have data on when the portfolio companies first appeared in the BDC filings I cannot assign an accurate duration metric for these loans, and the variable definition for relationship length is downward biased for these lenders.

Second, portfolio companies occasionally change names, creating a measurement error that is particularly problematic with duration measures. This is because the new name could make it difficult to track the relationship across time when going unnoticed. Note that with $Rel(Dummy)$, this is less of a problem since $Rel(Dummy)$ is defined *within* a period and thus the new name change does not bias how $Rel(Dummy)$ is defined.

G.8 Results with the second instrument based on lender's geographical presence

As a robustness test for these results, I also try an alternative instrument for the fund type based on the geographical presence of a particular fund type within the home state of the borrower (Berger et al., 2005). The first instrument was concerned with endogenous

Table A8 Relationship lending and fund type: Propensity score matched data

Dependent Variables:	Relationship lending share				Single-lender share		
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Traded PLF	0.20***	0.19***	0.19***	0.24***	0.29***	0.14***	0.11***
	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)	(0.02)
BDC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects							
YearQtr		Yes	Yes		Yes	Yes	
Adviser			Yes			Yes	
YearQtr-Adviser				Yes			Yes
Fit statistics							
Observations	2,563	2,563	2,563	2,563	2,563	2,563	2,563
Adjusted R^2	0.33	0.33	0.60	0.32	0.45	0.80	0.90

Clustered (Subclass) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

This table presents results from BDC-time level panel regression using propensity-score matching. Traded PLF is an indicator variable that takes a value of one if the BDC is operated as a traded perpetual-life fund in that period, and zero otherwise. Non-traded PLFs are excluded from this sample. The first stage of the propensity score matching uses lagged size, lagged leverage, lagged profitability (ROE), and indicator variables for each *YearQtr* as covariates to balance. The second stage includes these controls as well as an indicator variable for a fund being internally managed, and three parameters that describe the BDC management compensation package: hurdle rate of the net investment income incentive fee, share of management's incentive fee, and base management fee. Fixed effects: *YearQtr* refers to the calendar quarter. Investment *Adviser* refers to the identity of the parent organization of the BDC. Standard errors are clustered by sublass, which is based on the first stage of propensity score mathing where treatment and control units are placed into subclasses based on quantiles of the propensity score in the treated group, in the control group depending on the desired estimand. Using two-way (or one-way) clustered Lender+YearQtr (or Lender) clustered standard errors produce results similar to those in Table III.

Table A9 Correlation between relationship strength measures

Dependent Variables:	ln Relationship length			Loan with equity stake		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Rel(Dummy)	0.090***	0.087***	0.032***	0.155***	0.036***	0.029***
	(0.008)	(0.007)	(0.006)	(0.009)	(0.005)	(0.005)
PE Sponsored	0.042***	-0.103***	-0.545	0.042***	-0.008	1.02
	(0.009)	(0.023)	(7.44)	(0.008)	(0.013)	(56.2)
ln Par value	0.020***	0.016***	0.020***	0.008***	0.015***	0.013***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Fixed-effects						
YearQtr	Yes	Yes		Yes	Yes	
Lender		Yes			Yes	
Borrower		Yes			Yes	
DebtClass		Yes	Yes		Yes	Yes
YearQtr-Lender			Yes			Yes
Borrower-YearQtr			Yes			Yes
Fit statistics						
Observations	191,649	191,649	191,649	216,466	216,466	216,466
Adjusted R^2	0.04	0.61	0.74	0.05	0.81	0.75

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

This table shows the correlation between alternative measures of relationship lending and $Rel(Dummy)$. ln *Relationship length* is the log of the one plus the borrower-lender relationship length measured in years. *Loan with equity stake* is an indicator variable that takes a value of one if the loan position is associated with lender having an equity stake in the borrowing firm and zero otherwise. All the variable definitions are found in Appendix A. Fixed effects: *YearQtr* refers to the calendar quarter. *DebtClass* refers to type and seniority of a loan. *Borrower* refers to the identity of the borrowing company. *Lender* refers to the BDC holding the loan.

selection of investment managers to launch alternative fund structures. In contrast, a complementary way of analyzing the effect of fund structure is to find an instrument for the fund structure that is independent of borrower's preference for a lender.[73]

To restate, the identification problem would be that some lender characteristics that are unrelated to the fund horizon make these lenders more attractive counterparties in the eyes of the borrowers. To address this problem we need an instrument that directly influences the borrower's propensity to choose a particular type of lender as a counterparty but is unrelated to these alternative lender characteristics that might influence borrower's choice.

Specifically, I instrument the lender's fund type using the average lender fund type in the market where the borrower is located. The idea is that if a firm borrows from a traded PLF because it is located in a market where there are only traded PLFs available, this does not reflect an endogenous choice on the part of the borrower, but rather an exogenous, geographically imposed limitation. The instrument, $Mean(Traded\ PLF)$, is simply the equal-weighted average of *Traded PLF* indicator in each year-quarter among all BDCs that had any outstanding debt or equity position outstanding with any borrower in that state in that period.

[73]Translating these into the model's language, the first instrument viewed the lending relationship from the lender's perspective and was interested in seeing how δ_l impacts α_l. However, the second instrument is more interested in the borrower's perspective and seeing how δ_l impacts α_b.

Table A10 Robustness: Determinants of relationship measure and coupon rate using geography-based instrument

Dependent Variables:	Rel(Dummy)		Rel(Amount)		Coupon Rate (%)			
Model:	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)	OLS (7)	IV (8)
Variables								
Traded PLF	0.16***	0.56**	0.12***	0.74**	0.18	2.65***	-0.04	-0.21
	(0.03)	(0.27)	(0.02)	(0.29)	(0.11)	(0.99)	(0.12)	(0.90)
Traded PLF × Rel(Dummy)							0.48***	2.71**
							(0.13)	(1.07)
NonTr. PLF	0.20***	0.43**	0.13***	0.49**	-0.58*	0.75	-0.32	-0.57
	(0.06)	(0.19)	(0.05)	(0.21)	(0.32)	(0.68)	(0.35)	(0.55)
NonTr. PLF × Rel(Dummy)							-0.46*	1.02
							(0.24)	(0.72)
Rel(Dummy)					-0.11**	-0.25***	-0.40***	-1.91***
					(0.05)	(0.09)	(0.09)	(0.72)
BDC controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan+Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
YearQtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adviser	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rel. Start Date	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DebtClass-YearQtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BaseRate-YearQtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	82,273	82,273	82,273	82,273	81,662	81,662	81,662	81,662
Adjusted R^2	0.27	0.23	0.34	0.16	0.47	0.41	0.48	0.44

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

This table presents results on regression models where the relationship lending measures or the coupon rate is regressed on various loan and deal characteristics using a subset of data where the borrower's location information is available. *NonTr. PLF*, *Traded PLF* are indicator variables that take a value of one if the BDC is operated as a non-traded or traded perpetual-life fund, respectively in that period, and zero otherwise. $Rel(Dummy)$ and $Rel(Amount)$ are measure of the strength of the lending relationship at time t. BDC controls include the following BDC-fund characteristics: lagged log fund size, lagged leverage, lagged profitability (ROE), an indicator variable for a fund being internally managed and three parameters that describe the BDC management compensation package. Loan+Borrower controls include log loan size, time to maturity, lender's position share, indicator variable if lender holds an equity stake, borrower's sponsor status, loan's fair-to-par ratio. The sample excludes structured product positions like loans to CLOs. The instrumental variable is the $Mean(Traded\ PLF)$, which is the probability that the lender is a traded PLF out of all the lenders that operate within the borrower's home state. All the variable definitions are found in Appendix A. Fixed effects: *BaseRate* refers to loan base rate. *Rel. Start Date* is the YearQtr where the borrower-lender pair enter the data for the first time. *YearQtr* refers to the calendar quarter. *DebtClass* refers to type and seniority of a loan. Investment *Adviser* refers to the identity of the parent organization of the BDC.

Table A10 shows the results.[74] These results are consistent with earlier results but imply an even larger effect of the lender's fund structure on relationship lending and coupon rate. For example, these results indicate that having a traded PLF as the lender increases the equilibrium coupon rate by 2.4%.

G.9 Relationship lending and employment growth

To provide some descriptive evidence of the influence of relationship lending on borrower's employment growth I construct a borrower-level panel with annual frequency. The loan-level panel data is now averaged to a borrower-level panel with no lender dimension. In particular, $Avg.\,Position\,share_{b,t}$ and $Avg.\,Fair/Par_{b,t}$ are the average of *Position share* and *Fair/Par* variables respectively across all lenders of a given borrower b at the end-of-year t. *Position share* measures how large the fraction of loans from the borrower b represents the portfolio of the lender l. The idea is that if the borrower accounts for a large fraction of the lender's total portfolio, then making the relationship more important for the lender.[75] The regression specification is as follows

$$\begin{aligned}\Delta \ln Employment_{b,t,t+1} = {} & \beta_1\, Avg.\,Fair/Par_{b,t} + \beta_2\, Avg.\,Position\,share_{b,t} \\ & + \beta_3\, Avg.\,Fair/Par_{b,t} \times Avg.\,Position\,share_{b,t} \\ & + Controls + FixedEffects + \varepsilon_{b,t,t+1}\end{aligned} \tag{A9}$$

where $\Delta \ln Employment_{b,t,t+1}$ is the change between end of year t and end of year $t+1$ in log number of employees for borrower b. The interpretation of coefficients is analogous to the case with credit growth as a dependent variable.

Table A11 presents the results. First, we see that coefficients on $Avg.\,Fair/Par$ and $Avg.\,Pos.\,share \times Avg.\,Fair/Par$ are positive and negative, respectively, and both are statistically significant. This implies that on average high (low) loan value predicts high (low) subsequent employment growth while the fact that the borrower is important to the lender dampens this relationship. So being an important part of the average lender's portfolio translates into higher employment growth for the borrower than what otherwise would be possible, and this effect operates more strongly in times when the borrower's

[74] Note that the sample is smaller in these regressions since the borrower location information is not available for the full sample. Also, since borrower fixed effects are almost perfectly colinear with their home state I cannot add borrower fixed effect since they would otherwise absorb the instrument.

[75] I do not include the values $Rel(Dummy)$ and $Rel(Amount)$ averaged across all lenders of borrower b since these variables do not have an interpretation that translates easily to the borrower-level panel. To still account for this lender-base concentration I include to the list of control variables an indicator variable that takes a value of one if the borrower has multiple lenders at time t and zero otherwise.

Table A11 Annual panel: Average loan values, relationships, and subsequent employment growth

Dependent Variable:	$\Delta \log Employment_{t,t+1}$		
Model:	(1)	(2)	(3)
Variables			
Avg. Fair/Par$_t$	0.30***	0.32***	0.33***
	(0.05)	(0.05)	(0.06)
Avg. position share$_t$	3.18**	3.84***	5.51***
	(1.38)	(1.39)	(1.89)
Avg. Fair/Par$_t$ $\times$ Avg. position share$_t$	-3.41**	-4.09***	-5.76***
	(1.42)	(1.44)	(1.97)
Controls		Yes	Yes
Fixed-effects			
Year	Yes	Yes	
Year-Industry			Yes
Fit statistics			
Observations	10,983	10,983	7,995
Adjusted R^2	0.01	0.02	0.03

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

This table shows how the strength of the average lender-borrower relationship and loan valuation impacts the borrower's subsequent employment growth. The dependent variable is the borrower firm's employment growth, which is defined as the log (annual) change in employment from end-of-year t to end-of-year $t+1$. In the loan level data, $Fair/Par_t$ refers to the fair value to par value ratio of the loan and $Position\ share_t$ is the borrower b's share in lender l's loan portfolio, both measured at time t. $Avg.Fair/Par_t$ and $Avg.Position\ share_t$ are the values of each of these variables averaged across all lenders of a given borrower b at the end-of-year t. The list of controls includes the sponsored status and lagged log employment level of the borrower, the log portfolio size of the average lender for that borrower, and an indicator variable if the borrower has multiple lenders all measured at time t. All the variable definitions are found in Appendix A. Fixed effects: *Year* refers to the calendar year. *Industry* refers to the borrower's primary industry.

loan values are low. The estimate of β_2 suggests that a 1% increase in the average position share of the lender translates into 0.03-0.05 log points higher employment growth next year, but this effect only arises when the borrower's average loan values are low. If the average loan is trading at par, that is $Avg.Fair/Par = 1$, then β_3 fully counteracts the effect of β_2.

Appendix H Details about the BDC management compensation

This Appendix gives some additional details about the BDC management compensation. BDCs can be categorized as internally or externally managed. The main difference between internally and externally managed BDCs is that internally managed companies hire their staff; analysts, managers, and executives to manage the company's assets, while externally managed BDCs outsource that task to a third party, the adviser of the BDC. The management compensation paid to external managers is based on management and performance fees, while internally managed funds pay their operating expenses, including salaries and bonuses to the investment professionals and do not report detailed management compensation data. The share of internally managed BDCs has gradually declined over the years and more than 90% of BDCs operating today are externally managed.[76]

While the compensation of employees and managers of internally managed BDCs is usually not reported in BDCs' annual reports, the fee structure of externally managed BDCs is similar across firms and almost always consists of two components: First, there is a fixed "Base management fee" that is usually somewhere between 1-2% firm's gross assets. Second, the performance fee usually has a two-part incentive fee which consists of two option contracts tied to the portfolio performance.

The first component of the incentive fee is called the "net investment income (NII) incentive fee", which is a performance fee that is some percentage (such as 20%) of the investment income generated within a quarter net of operating expenses (including the base management fee) and interest expenses, for the income that exceeds some minimum hurdle rate. This implies the value of this claim can be considered as the price of a call option on investment income.[77] The second component of the incentive fee is called a

[76] https://www.publiclytradedprivateequity.com/Structures/About-BDCs

[77] The end of quarter NII is compared to a hurdle rate which is usually 1.5-2% of preceding quarter's net assets and there is almost always a *catch-up clause* incorporated to the contract that allows management to take home, usually, a 100% of the return on NII exceeding the hurdle rate, up to the point that they have "catched-up" the other investors and accumulated back their 20% share of the NII. So, the true payoff func-

"capital gain incentive fee", and it gives the management some percentage point, usually the same as the NII incentive fee, of the cumulative aggregate, realized capital gains minus the sum of cumulative aggregate realized capital losses and aggregate unrealized capital depreciation. This component is also fundamentally just a call option with a state-dependent strike price. In the paper, I generally include only the net investment income incentive fee share in the regressions since the capital gain incentive fee is almost always set at the same level as that of net investment income incentive fee share, and thus the multicollinearity of the two regressors implies that one of them would get dropped from the model anyways.

There is usually a catch-up clause in most contracts that ensures management to get 100% of all income that exceeds the hurdle rate up until they have "catched-up" the missing part of the after they have. The presence of a catch-up clause also means that interest income incentive compensation could be approximated by a linear function instead of a non-linear piecewise function. Here is a typical explanation of the NII incentive fee with a catch-up clause taken from one firm's 10-K report:

Pre-Incentive Fee net investment income, expressed as a rate of return on the value of the Corporation's net assets (defined as total assets less indebtedness) at the end of the immediately preceding calendar quarter, will be compared to a "hurdle rate" of 1.75% per quarter (7% annualized). The Corporation will pay the Adviser an Incentive Fee with respect to the Corporation's Pre-Incentive Fee net investment income in each calendar quarter as follows: (A) no Incentive Fee in any calendar quarter in which the Corporation's Pre-Incentive Fee net investment income does not exceed the hurdle rate; (B) 100% of the Corporation's Pre-Incentive Fee net investment income with respect to that portion of such Pre-Incentive Fee net investment income, if any, that exceeds the hurdle rate but is less than 2.1875% in any calendar quarter (8.75% annualized); and (C) 20% of the amount of the Corporation's Pre-Incentive Fee net investment income, if any, that exceeds 2.1875% in any calendar quarter (8.75% annualized).

Figure A6 illustrates what the payoff of such an NII Incentive fee looks like as a function of NII yield. It is easy to show that this payoff can be replicated with two call options with different position sizes and different strike prices.

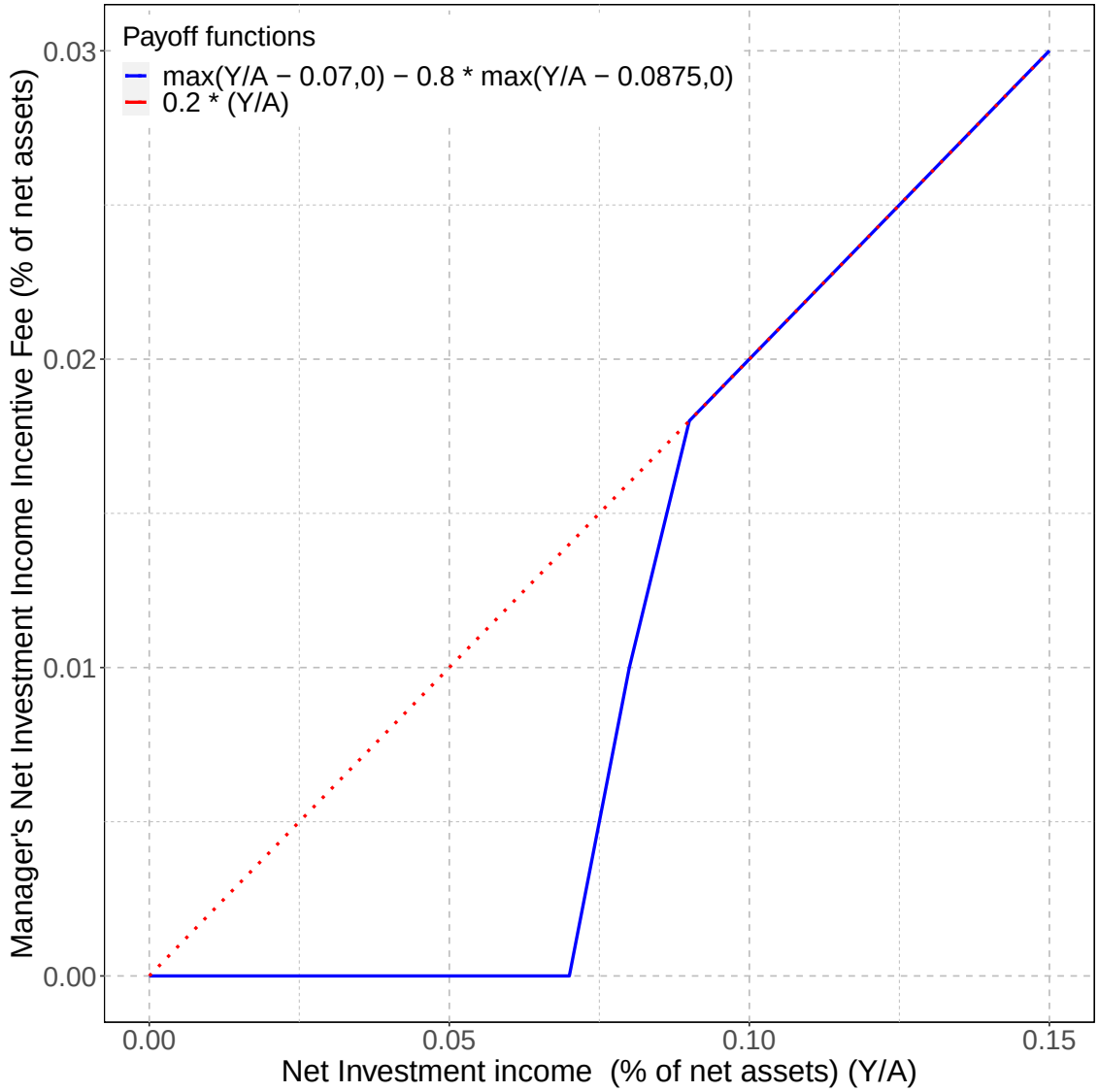
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tion of the NII component of the compensation can be modeled as one long and one short position in call options with different strike prices and different allocation sizes. Leaving aside these initial discontinuities that occur with small positive levels of NII, the payoff function of this incentive fee scales linearly with NII with a slope of 20% for values of NII above zero.

Figure A6. Example of a typical Net Investment Income Incentive Fee with a "catch-up" clause

The figure shows the payoff of a typical BDC manager's net investment income incentive fee as a function of the fund's net investment income as a percent of net assets. The hurdle rate is 7% annually while full catch-up is reached at 8.75%. When net investment income exceeds 8.75% of net assets, the incentive fee is 20% of total net investment income.



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