Sophisticated Price Inflation in Private Credit Funds*

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August 2026

Abstract

We document a liquidity gradient in reported prices across private credit vehicles. During aggregate stress, including the COVID-19 and 2022 rate-hike episodes, closed-end BDCs reported higher loan prices than semi-liquid BDCs, which in turn reported higher loan prices than open-end mutual funds and ETFs. The same gradient appears before issuer-level distress events, including defaults and especially payment-in-kind conversions. Asset-side characteristics, especially loan opacity, explain a large fraction of the gradient. Yet significant price differences remain, suggesting a distinct disciplinary role for investor liquidity on the liability side. Using mutual fund and ETF prices as benchmarks, we estimate BDC-level NAV inflation, which implies a $2.74 billion transfer from new investors to incumbent investors of semi-liquid BDCs between 2019 and 2025. Overall, private credit funds inflate loan prices in a sophisticated manner, with price inflation amplified by asset opacity and constrained by investor redemption rights.

Keywords: private credit, valuation discretion, investor liquidity

*The authors do not have any relevant or material financial interests related to the research described in this paper.

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1 Introduction

Private credit has grown into a major part of the financial system, with global assets now estimated at more than $3 trillion (Alternative Investment Management Association, 2025). Recently, the sector has entered a period of substantial stress. On the asset side, investors and analysts have raised concerns about the quality of private credit assets, especially among software borrowers whose business models may become obsolete because of AI automation.[1] On the liability side, private credit vehicles with redemption features experienced large outflows, forcing funds to gate redemptions, raise liquidity, or sell loans.[2]

A central debate is whether private credit funds mark their loan holdings correctly when negative shocks arrive. This question matters because inflated loan prices can make funds appear healthier than they are, allow managers to be over-compensated, and distort investors' capital allocation decisions. It also matters for the fragility of the funds, because inflated NAVs can create incentives for investors to redeem before loan values are marked down, leaving losses to remaining investors and amplifying redemption pressure. Recently, the SEC has initiated investigations regarding alleged fraud in private credit funds' valuation practices[3], and there is growing evidence of price discrepancies across funds[4].

This paper provides a detailed analysis of loan prices reported by private credit funds. Our central finding is a liquidity gradient in reported prices. After negative shocks, open-end mutual funds and ETFs mark down loan prices the most, semi-liquid BDCs mark down prices less, and conventional closed-end BDCs report the smallest markdowns. We explain this gradient through differences in both assets and liabilities across private credit vehicle structures. On the asset side, less liquid vehicles hold more opaque loans, where external

[1] For example, Reuters reports that U.S. private-credit defaults reached a record level in 2025.

[2] Private credit funds experiencing large redemption requests in 2025 and 2026 include Blue Owl, Blackstone, BlackRock, Apollo, Ares, and Cliffwater.

[3] https://www.bloomberg.com/news/articles/2026-05-04/sec-investigating-alleged-fraud-in-private-credit-atkins-says

[4] https://www.ft.com/content/a8337bf7-7b9d-4b8e-8ac3-6a30a8d2e907?syn-25a6b1a6=1

benchmarks are weaker and valuation discretion is greater. On the liability side, investor liquidity disciplines price reporting because inflated NAVs are more costly when investors can redeem more easily at the NAV. Overall, our findings suggest that private credit funds inflate loan prices in a sophisticated manner: price inflation is concentrated where it is hardest to detect and constrained where investor redemption threats are strongest.

Several considerations shape how managers report fair values for the assets they hold. Higher marks increase assets under management, improve reported performance, and can raise fee compensation, but valuation discretion is constrained by external benchmarks, auditors, valuation agents, boards, and investors. We therefore expect price inflation to be larger for opaque loans, where valuation inputs are less observable, issuers are unrated or private, and few other holders provide external benchmarks. We also expect price inflation to be decreasing in investor liquidity. When investors can redeem or tender shares at NAV, inflated marks allow them to exit at overstated prices and impose losses on remaining investors, so stronger investor exit rights should discipline reported prices.

To test these hypotheses, we analyze loan-level holdings and reported fair values from Form N-PORT filings for open-end mutual funds and ETFs, and from Form 10-K and 10-Q filings for BDCs. We focus on senior secured first-lien term loans to compare instruments with similar contractual form and seniority. We classify BDCs into semi-liquid and conventional closed-end vehicles based on their disclosed share repurchase policies.

We begin by documenting significant differences in the assets held across different types of private credit vehicles. Loans held by mutual funds and ETFs are relatively transparent. For example, about 90% of their loans are classified as having a fair value determined using observable inputs (Level 2), 70% carry issuer credit ratings, 50% of their issuers are publicly traded, and 80% of their loans are held by 10 or more distinct fund families. In contrast, loans held by semi-liquid BDCs are substantially more opaque. About 85% of their loans do not have observable inputs (Level 3), 80% of their loans do not carry issuer credit ratings,

80% of their issuers are private, and 85% of their loans are held by single-digit number of distinct fund families, with about 20% held by a single fund family. Loans held by closed-end BDCs are even more opaque. This asset-composition pattern is important because we show that opacity provides more discretion to funds to inflate reported NAVs. Since the funds offering less liquidity hold more opaque loans, these funds will have more discretion to inflate their reported NAVs.

Our first set of tests examines aggregate stress periods, when loan values decline because of negative aggregate shocks. We focus on the COVID-19 crisis and the increase in interest rates during 2022. During the first quarter of 2020 and the second quarter of 2022, the Morningstar LSTA U.S. leveraged loan index fell roughly 10% and 5%, respectively, providing us with two periods of aggregate stress to examine reporting behavior. In normal times before aggregate stress arrives, reported loan prices are very close to par and remarkably similar across fund types. During stress periods, however, reported prices diverge sharply. Mutual funds and ETFs mark down loan prices the most, semi-liquid BDCs mark down prices less, and closed-end BDCs report the least markdowns. Regression estimates confirm that this gradient is robust to controlling for fund characteristics, loan characteristics, loan fixed effects, and issuer-industry-by-quarter fixed effects, providing confidence that the differences in fair value reporting do not reflect differences in loan fundamentals.

We then ask why this liquidity gradient arises. We first show that price inflation is concentrated among opaque loans with weak external benchmarks. Level 3 loans, loans issued by unrated borrowers, loans issued by non-public firms, and loans held by only one fund family have significantly higher reported prices during the stress periods. Controlling for these characteristics substantially reduces the cross-vehicle price differences, indicating that differences in asset composition explain an important part of the liquidity gradient. However, even after controlling for opacity and a wide range of fund and loan characteristics, significant vehicle-level differences remain. Moreover, for a small set of loans held by multi-

ple types of funds during the same stress periods, we still find that mutual funds and ETFs report lower prices than semi-liquid BDCs, which in turn report lower prices than closed-end BDCs. Therefore, asset opacity is an important determinant of reported price inflation, but does not fully explain the differences between fund types. The liquidity gradient remains economically significant, suggesting that investor liquidity itself plays a disciplinary role that limits funds' ability to report inflated prices.

We find a similar liquidity gradient in response to issuer-level distress. We define distress using either default or loan conversion to payment-in-kind (PIK). A default captures severe credit deterioration and a PIK conversion captures a softer form of distress in which the borrower stops paying interest in cash and instead capitalizes unpaid interest into principal. In response to both types of distress, mutual funds and ETFs begin marking down loans multiple quarters beforehand, consistent with prices being forward-looking. In contrast, semi-liquid BDCs and particularly closed-end BDCs mark down distressed loans much later and in much smaller magnitudes. The contrast is particularly stark for PIK conversions. Mutual funds and ETFs begin marking down prices several quarters before a PIK conversion, but both types of BDCs report very little decline even at the time of conversion. This pattern is consistent with an "amend-and-pretend" interpretation, in which BDCs accommodate borrower distress through PIK amendments while keeping reported loan values close to par.

We next compare the informativeness of reported prices. If BDCs report higher prices because they filter out transitory market noise, then their reported prices could be more informative about future fundamentals. If, instead, BDCs delay or mute markdowns, then their prices should be less informative about future distress. Using receiver operating characteristic (ROC) curves, we find that prices reported by all three vehicle types are informative about future defaults. However, prices reported by mutual funds and ETFs are substantially more informative about future PIK conversions than prices reported by BDCs. This result further supports the fact that BDC prices are less responsive to early signs of borrower

distress, especially when distress is resolved through PIK rather than formal default.

Finally, we quantify the economic consequences of price inflation. Using mutual fund and ETF prices as market-based benchmarks, we estimate BDC-level NAV inflation by comparing BDC-reported loan values to values implied from prices reported by mutual funds and ETFs. NAV inflation is close to zero in normal times but rises substantially during stress periods. For semi-liquid BDCs, inflated NAVs cause a value transfer between investors because investors purchase and redeem shares at the reported NAV. Following Zitzewitz (2003) and Choi et al. (2022), we estimate the dilution costs associated with net flows and NAV inflation. Because semi-liquid BDCs have consistently experienced large net inflows, including during the two periods of aggregate stress, inflated NAVs have generated gains for incumbent investors and large costs for entering investors. These value transfers could reverse as semi-liquid BDCs begin experiencing net outflows (Fang et al., 2026).

Overall, our findings show that private credit price inflation is sophisticated. It is concentrated in opaque assets and less present in vehicles with greater investor liquidity. The evidence does not imply that all high marks are fraudulent or that investor liquidity explains all valuation differences. Rather, the results show that asset opacity and vehicle structure jointly shape reported fair values. Less liquid vehicles hold more opaque loans, and weaker investor exit rights leave greater room for discretionary marks. Investor redemption threats therefore serve as a disciplinary device for fair value reporting in private credit.

1.1 Related literature

This paper contributes to the literature on valuation discretion and misreporting by investment funds. Prior work shows that assets that are difficult to value create scope for stale or discretionary marks. Cici et al. (2011) document dispersion in mutual funds' valuations of corporate bonds. Agarwal et al. (2023a), Kwon et al. (2020), and Atanasov et al. (2023)

study valuation discretion in mutual funds' private-firm and structured-product holdings. Related work on hedge funds shows that managers can smooth or manipulate reported returns when assets are illiquid or self-reported (Getmansky et al., 2004; Agarwal et al., 2011; Bollen and Pool, 2009, 2012; Cassar and Gerakos, 2011). A related literature studies stale NAVs, dilution, and predictable returns in mutual funds (Chalmers et al., 2001; Greene and Hodges, 2002; Zitzewitz, 2003; Choi et al., 2022). We extend this literature to private credit funds, where valuation discretion is especially important because loans are illiquid, privately negotiated, and often difficult to benchmark. Closest to our setting, Jang and Kim (2025) show that third-party appraisers and creditors can discipline the marks reported by private credit funds, while information asymmetry contributes to valuation dispersion. We contribute by studying how reported loan prices vary across investment vehicles and show that funds offering greater investor liquidity report less inflated prices during periods of stress.

This paper also contributes to the growing literature on private credit and direct lending. Existing work studies the rise of private debt funds, the organization of direct lending, the characteristics of middle-market borrowers, and the role of private credit in the broader financial system (Block et al., 2024; Chernenko et al., 2022; Davydiuk et al., 2024a,b; Ivashina, 2025). Recent papers examine the scale, lending technology, cyclicality, and financial-stability implications of private credit (Jang et al., 2025, 2026; Hinzen et al., 2026; Matvos et al., 2026; Chernenko et al., 2025; Chernenko and Scharfstein, 2025). In closely related work, Rintamaki and Steffen (2025) document the use of PIK amendments as a form of borrower forbearance or "shadow default". We add to this literature by studying fair-value reporting by private credit funds at the loan level. Our results highlight an interaction between asset opacity and vehicle design. Less liquid private credit vehicles hold more opaque loans and report higher prices on those loans after negative shocks.

Finally, our paper relates to work on liquidity transformation, fund fragility, and investor discipline. A large literature shows that open-end mutual funds investing in illiquid assets

are vulnerable to strategic redemptions, liquidity hoarding, fire sales, and run-like dynamics (Chen et al., 2010; Goldstein et al., 2017; Morris et al., 2017; Jiang et al., 2021; Falato et al., 2021; Haddad et al., 2021; Jin et al., 2022; Ma et al., 2022; Fang and Goldstein, 2026; Fang et al., 2026). Other work studies mechanisms that mitigate redemption externalities, including swing pricing, redemption fees, redemption in kind, and inter-fund liquidity management (Capponi et al., 2020; Agarwal et al., 2023b; Huang and Keister, 2024; Agarwal and Zhao, 2019; Ma et al., 2025). Our contribution is to uncover a countervailing benefit of investor liquidity: it disciplines reported valuations. Vehicles that offer stronger investor liquidity mark down loans more aggressively and report prices that are more informative about future distress, suggesting that redemption threats constrain valuation discretion.

2 Background and Data

2.1 Private credit vehicles

Traditionally, private credit and other illiquid risky assets, such as private equity, have been accessed through unregistered drawdown funds. These funds are typically organized as limited partnerships and are not registered as investment companies under the Investment Company Act of 1940. Institutional investors, such as pension funds and insurance companies, commit capital ex ante and contribute it over time through capital calls as the general partner identifies investment opportunities (Ye, 2025). Although unregistered funds represent the majority of the private credit industry, they are opaque by design and are therefore not included in our analysis due to the lack of observable data (Matvos et al., 2026).

Funds registered under the 1940 Act can be distributed more broadly through broker-dealers, RIAs, and wealth-management channels. Registered funds are required to provide detailed public reporting, providing an observable window into the broader private credit sector.

Within registered funds, business development companies (BDCs) are the main vehicle for private credit. To maintain BDC status, a fund must generally invest at least 70% of its assets in loans issued by private companies and other eligible assets. BDCs also receive more flexible leverage treatment than other registered funds. Whereas registered funds are generally subject to a 300% asset-coverage requirement for debt, BDCs are subject to a less stringent 200% asset-coverage requirement, which may be reduced to 150% if the required approvals and conditions are satisfied.

Conventional BDCs resemble traditional drawdown funds and investors cannot redeem shares directly from the fund at net asset value. Investors seeking liquidity must sell their shares to other investors, either on an exchange if the BDC is publicly listed, or through broker-dealers and other secondary-market channels if the BDC is not listed. In either case, exit occurs at a market-clearing price rather than through redemption at reported NAV. Some publicly traded BDCs also conduct discretionary share repurchases, but these repurchases are distinct from a standing investor right to exit at NAV.

In recent years, there has been rapid growth in so-called "semi-liquid" BDCs (Fang et al., 2026). These vehicles offer periodic share repurchase programs that allow investors to tender shares back to the fund at or near NAV. A typical semi-liquid BDC offers to repurchase up to 5% of shares outstanding each quarter, usually subject to board discretion and pro rata allocation if investor tender requests exceed the repurchase limit. Figure 7 shows examples of these semi-liquidity provisions. Semi-liquid BDCs therefore provide partial liquidity: investors cannot redeem freely, but they have a recurring mechanism to exit the vehicle at reported NAV.

This semi-liquidity is more limited than the liquidity provided by open-end mutual funds (MFs) and exchange-traded funds (ETFs). In MFs, investors can generally redeem shares daily at end-of-day NAV. ETFs provide intraday secondary-market liquidity, although transaction prices can deviate from NAV, especially during periods of market stress (Ma et al.,

2025).

These institutional differences imply a natural ordering of investor liquidity across the vehicles in our sample. Open-end MFs and ETFs provide the greatest liquidity, semi-liquid BDCs provide limited quarterly liquidity at NAV, and conventional closed-end BDCs provide the least investor liquidity. This ordering is central to our analysis because, as we will show, investor exit rights discipline reported fair values.

2.2 Private credit holdings

Figure 1 shows the aggregate size of loan MFs and ETFs, semi-liquid BDCs, and closed-end BDCs since 2019. The size of loan MFs and ETFs has remained relatively stable, hovering around $100 billion. Closed-end BDCs have grown steadily, from less than $100 billion in 2019 to nearly $250 billion in 2025. By contrast, semi-liquid BDCs have grown explosively, with total assets increasing from around $10 billion in 2019 to more than $300 billion in 2025.

Figure 2 describes the characteristics of different private credit vehicles' loan portfolios along several dimensions. Panel A focuses on fair value measurement. MFs and ETFs directly report fair value classification for each position in N-PORT, and for BDCs we can infer fair value classification from the overlapped holdings with other N-PORT filers. Almost no loan is classified as Level 1, which corresponds to directly observed market prices, since most of them are rarely traded. Most loans held by MFs and ETFs are classified as Level 2, meaning that their valuations are based on observable inputs, such as dealer quotes or matrix pricing. In contrast, more than 70% of semi-liquid BDC loan holdings and more than 80% of closed-end BDC loan holdings are either classified as Level 3, where valuations rely on unobservable inputs and managerial judgment, or are not held by any N-PORT filer and therefore cannot be inferred.

Panel B reports the composition of loan holdings by issuer credit rating, using ratings from S&P, Moody's, and Fitch. Close to 80% of loans held by MFs and ETFs are issued by rated borrowers, with most rated borrowers clustered around the B category. In contrast, only about 20% of loans held by semi-liquid BDCs and less than 15% of loans held by closed-end BDCs are issued by rated borrowers.

Panel C reports the composition of loan holdings by whether the issuer is publicly traded and therefore included in the Compustat database. Close to 50% of the loans held by MFs and ETFs are issued by public firms, whereas around 80% and 85% of the loans held by semi-liquid and closed-end BDCs are held by private firms.

Panel D reports the composition of loan holdings by number of distinct fund family holders. For MFs and ETFs, the loans they hold tend to have a very dispersed investor base. Specifically, for close to 80% of the loans they hold, there are 10 or more distinct fund family holders. In contrast, BDCs' loans have a much more concentrated investor base. More than 80% and close to 90% of the loans held by semi-liquid and closed-end BDCs have less than 10 distinct fund family holders. About 20% and 40% of the loans held by semi-liquid and closed-end BDCs have one single fund family holder, whereas this number is less than 2% for MFs and ETFs.

Taken together, the four panels of Figure 2 reveal a clear ordering in portfolio transparency. Loans held by MFs and ETFs are the most transparent, loans held by semi-liquid BDCs are less transparent, and loans held by closed-end BDCs are the least transparent. This ordering mirrors the liquidity ranking of the vehicles described in Section 2.1: the vehicles offering less investor liquidity also tend to hold loans with greater valuation discretion.

To better understand the overlapped loans between vehicle types, which is an important part of our analysis later, we calculate summary statistics for three subsets of the loan universe: loans only held by MFs and ETFs, loans held by both MFs and ETFs and BDCs, and

loans only held by BDCs. Table 1 shows the results. Consistent with Figure 2 above, loans held by MFs and ETFs are much more likely to have fair value level 1 or 2, be rated, be publicly traded, and have more number of distinct holders, compared to loans held by BDCs. Interestingly, the loans that are held by both MFs, ETFs and BDCs are very similar to – if not more transparent than – loans held by MFs only. For example, the overlapped loans have more distinct number of fund family holders. In other words, the overlapped loans tend to be the most transparent ones, rather than a simple average of the loans held by MFs and ETFs and the loans held by BDCs.

Table 1 also shows that default incidence is broadly similar across the holdings of different vehicles. In contrast, payment-in-kind (PIK) conversions are much more common among loans held by BDCs than among loans held by MFs and ETFs. This difference foreshadows our later results: while all vehicles eventually mark down loans approaching severe distress, BDC-reported prices are substantially less informative about future PIK conversions.

2.3 Hypotheses on fair value reporting

All vehicles in our sample report the fair value of each loan they hold. These loan-level fair values aggregate to fund-level total assets and net asset value (NAV), which in turn determine reported performance, management fees, incentive fees, leverage ratios, and investor subscription and redemption prices. Fair value reporting is therefore not merely an accounting exercise: it directly affects both fund managers and fund investors.

Fair value measurement is governed by FASB ASC Topic 820, which defines fair value as "the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date." ASC 820 also establishes a three-level hierarchy of valuation inputs. Level 1 inputs are quoted prices for identical assets in active markets. Level 2 inputs are observable inputs other than quoted prices, such as

dealer quotes or prices of comparable instruments. Level 3 inputs are unobservable inputs that rely more heavily on models and managerial judgment. This hierarchy is central to our setting because private credit loans are often illiquid, infrequently traded, and difficult to benchmark.

Managers have incentives to report higher fair values. Higher reported values increase assets under management, improve reported performance, and can raise both management and incentive fees. At the same time, fair value reporting is constrained by auditors, valuation agents, boards, investors, and the availability of external price signals. We therefore do not interpret high reported prices mechanically as fraud. Instead, we use price inflation to describe a relative phenomenon: reported loan values that remain high when market-based or otherwise comparable prices suggest that larger markdowns are warranted.

Private credit loans are especially useful for studying this discretion because their payoff structure is asymmetric. A typical term loan is issued near par, with the coupon spread set so that the initial value is close to principal. Unlike equity, a loan has limited exposure to upside cash-flow shocks because contractual repayments are fixed and excess firm value accrues primarily to equity holders. By contrast, loans are highly exposed to downside shocks: deteriorating borrower fundamentals, higher default risk, covenant amendments, payment-in-kind conversion, or default can all reduce expected cash flows. As a result, reported loan prices are typically anchored near par in normal times and move meaningfully when negative shocks arrive. These are precisely the periods when valuation discretion is most economically important: managers can inflate prices by delaying or muting markdowns in response to negative shocks.

We organize the empirical analysis around four hypotheses.

Hypothesis 1: Opacity. Price inflation should be larger for loans with less transparent valuation inputs. When a loan has observable market prices, dealer quotes, public issuer information, credit ratings, or many other holders, inflated marks are easier to detect and harder to justify. By contrast, when a loan is Level 3, unrated, issued by a private firm, or held by only a small number of lenders, outside benchmarks are weaker and fair value estimates rely more heavily on judgment. We therefore predict that reported prices will be higher, especially after negative shocks, for more opaque loans.

Hypothesis 2: Size of position. Price inflation should be larger for positions that are more important to the fund's portfolio. Inflating a small position has little effect on total assets, NAV, or reported performance. Inflating a large position has a much larger effect on fund-level outcomes and therefore provides stronger incentives for discretionary marking. We therefore predict that, after negative shocks, reported prices will be higher for loans that represent larger shares of a fund's portfolio.

Hypothesis 3: Leverage. Price inflation should be larger for more leveraged funds. Leverage amplifies the effect of asset markdowns on equity NAV. In addition, many private credit funds borrow against the value of their assets, so lower reported collateral values can reduce borrowing capacity, tighten asset coverage ratios, or otherwise constrain fund operations. These forces make downward marks more costly for levered funds. We therefore predict that, after negative shocks, more leveraged funds will report higher loan prices than otherwise similar less leveraged funds.

Hypothesis 4: Investor liquidity. Price inflation should be decreasing in investor liquidity. As discussed in Section 2.1, the vehicles in our sample differ sharply in the strength of investor exit rights. Loan mutual funds and ETFs provide the greatest liquidity, semi-liquid BDCs provide limited periodic liquidity at NAV, and conventional closed-end BDCs provide

the least direct investor liquidity. Stronger investor liquidity makes inflated NAVs more costly because investors can redeem or exit when reported prices are too high. We therefore predict a monotone liquidity gradient in reported prices: after negative shocks, loan MFs and ETFs should report the lowest prices, semi-liquid BDCs should report intermediate prices, and closed-end BDCs should report the highest prices.

These hypotheses are not mutually exclusive. In particular, portfolio opacity tends to be correlated with investor liquidity. Less liquid vehicles may endogenously hold more opaque loans, where valuation discretion is greater. Even conditional on loan opacity and other characteristics, however, differences in investor exit rights may continue to discipline reported fair values. Our empirical analysis therefore first examines whether reported prices differ across vehicles and then asks how much of this difference is explained by opacity, position materiality, leverage, and investor liquidity itself.

2.4 Data and sample

Data on open-end mutual funds and ETFs come from the SEC Form N-PORT Data Sets. Form N-PORT reports fund-level information, including total assets and other fund characteristics, as well as security-level portfolio holdings. For each loan position, the data include the issuer name, instrument type, principal amount, fair value, and other security characteristics. We focus on the MFs and ETFs whose average portfolio weight in loans exceeds 50%.

Data on BDCs come from the SEC BDC Data Sets and Form 10-K and 10-Q filings. The SEC BDC Data Sets provide the universe of BDC Central Index Keys (CIKs), which we use to retrieve all relevant 10-K and 10-Q filings directly from EDGAR. These filings contain fund-level financial statements and loan-level schedules of investments. For each portfolio position, BDCs report information such as issuer name, industry, instrument type, maturity

date, principal amount, cost, and fair value. We classify BDCs as either conventional closed-end BDCs or semi-liquid BDCs by examining textual descriptions of their share repurchase policies in 10-K and 10-Q filings, following Fang et al. (2026). Figure 7 provides examples of semi-liquid repurchase policies disclosed in BDC filings.

We restrict the sample to senior secured first-lien term loans. We exclude revolvers, second-lien loans, junior loans, unitranche loans, delayed-draw term loans. We also exclude notes, bonds, and other non-comparable instruments. This stringent restriction allows us to compare reported prices across vehicles for loans with similar contractual form and seniority.

A further challenge is that BDCs almost always report portfolio holdings at calendar quarter-ends, while many MFs and ETFs report holdings at non-quarter-end dates, such as February, May, August, and November. To make the timing of reported prices comparable across vehicles, we restrict the MF and ETF sample to observations with report dates in March, June, September, and December. These quarter-end observations account for roughly one-third of the loan MF and ETF universe.

For each loan position, we clean its textual description and match it to entities in Compustat, DealScan and Pitchbook using a fuzzy-matching algorithm. We define **a unique issuer** by a distinct Compustat identifier (GVKEY), DealScan identifier (borrower_id), or Pitchbook identifier (issuer_id), in that order. We define **a unique loan** by the combination of issuer and maturity date.[5]

Our main outcome variable is the reported loan price, defined as fair value divided by principal amount and expressed as a percentage of principal. This measure is directly observed for each loan position held by the vehicles in our sample. We exclude prices during the four quarters following an issuer default, when principal amounts are often written down and

[5]MFs and ETFs report "annualized rate" in Form N-PORT, rather than separately reporting the floating benchmark, spread, or spread over benchmark. This makes it difficult to use interest-rate terms as an additional dimension for identifying unique loans.

reported prices can mechanically reset toward par.

MFs and ETFs directly report the fair value hierarchy classification of each position in Form N-PORT. For BDC-held loans, loan-level fair value classifications are not available. We therefore infer fair value measurement for the subset of BDC-held loans that can be linked to loans reported by N-PORT filers.

Finally, issuer credit ratings from S&P, Moody's, and Fitch are obtained from the rating agencies' public rating-history files. SEC Rule 17g-7 requires nationally recognized statistical rating organizations (NRSROs) to make rating histories publicly available beginning in 2012Q4.

3 Stress Periods and Price Inflation

The section examines reported loan prices across private credit vehicles during stress periods, when there are negative shocks to aggregate cash flows. We focus on two stress episodes: the COVID-19 crisis from 2020Q1 to 2020Q2 and the rate-hike episode from 2022Q2 to 2022Q4. Figure 8 confirms that these periods coincide with large declines in the LSTA Leveraged Loan 100 Index.

Figure 3 plots the raw distributions of reported loan prices across vehicles around these two stress episodes. Each observation is a loan-vehicle-quarter, where holdings are aggregated across all MFs and ETFs, all semi-liquid BDCs, or all closed-end BDCs, and distributions are weighted by holding amounts. Before stress periods, reported prices are similar across vehicles, and MFs and ETFs if anything report slightly higher prices than BDCs. During stress periods, however, a clear monotone liquidity gradient emerges. Closed-end BDCs report the highest loan prices, semi-liquid BDCs report slightly lower prices, and loan MFs and ETFs report the lowest prices. In other words, MFs and ETFs mark down their loans

much more aggressively: by about 15% of par during COVID-19 and 5% of par during the 2022 rate-hike episode. Semi-liquid BDCs report smaller markdowns, around 5% and 2% of par, respectively. Closed-end BDCs report the smallest markdowns, around 3% and 1% of par. Thus, aggregate stress periods reveal not merely dispersion in reported prices, but a systematic gradient in which vehicles with weaker investor liquidity report higher loan values.

A natural concern is that different vehicles hold loans that are differentially exposed to aggregate shocks. For example, loans held by MFs and ETFs may be issued by firms in more cyclical industries whose cash flows revised more during stress periods. To formally test whether reported prices differ across vehicles during stress periods, we estimate the following regression:

$$ReportedPrice_{i,j,t} = \beta StressPeriod_t \times VehicleType_i + \gamma Controls + FE + \epsilon_{i,j,t}. \quad (1)$$

Each observation is fund i's holding of loan j in quarter t. *ReportedPrice* is reported fair value as a percentage of principal. *StressPeriod* is an indicator for whether quarter t falls in one of the two stress episodes. $VehicleType$ indicates whether the reporting vehicle is a loan MF or ETF, or a closed-end BDC, respectively; semi-liquid BDCs are the omitted category. Fund-level controls include returns over the past year, log total net assets, and debt-to-asset leverage. Loan-level controls include fair value level, issuer credit rating, whether the issuer's equity is publicly listed, the number of distinct fund family holders, years to maturity, and the size of the position relative to the fund's portfolio. The fixed effects include fund fixed effects, loan fixed effects, and issuer-industry-by-quarter fixed effects. Loan fixed effects absorb time-invariant loan characteristics, such as loan spreads, while issuer-industry-by-quarter fixed effects compare loans issued by firms in the same industry at the same time. Standard errors are three-way clustered by fund, issuer, and year-quarter.

Table 2 reports the results. In normal periods, reported prices are statistically similar across vehicles. During stress periods, however, reported prices separate sharply. The coefficient on the interaction between $StressPeriod$ and $MF\&ETF$ is highly significant at -3.411%, meaning that loan MFs and ETFs report prices about 3% of par lower than semi-liquid BDCs. The coefficient on the interaction between $StressPeriod$ and $Closed-EndBDC$ is highly significant at 0.862%, implying that closed-end BDCs report prices close to 1% of par higher than semi-liquid BDCs. Together, these coefficients imply a monotone liquidity ranking during stress: closed-end BDCs report the highest prices, semi-liquid BDCs report intermediate prices, and loan MFs and ETFs report the lowest prices. Columns 3 and 4 show that this pattern appears separately during COVID-19 and during the rate-hike episode. The magnitude is larger during COVID-19, although statistical power is weaker because there were much fewer semi-liquid BDCs in 2020.

What explains this liquidity gradient in reported prices? Section 2.3 suggests four potential channels: loan opacity, size of position, fund leverage, and investor liquidity. We examine these channels by augmenting Equation 1 with interactions between the stress-period indicator and additional explanatory variables:

$$\begin{aligned} ReportedPrice_{i,j,t} =& \beta_1 StressPeriod_t \times VehicleType_i \\ &+ \beta_2 StressPeriod_t \times X_{i,j,t} + \gamma Controls + FE + \epsilon_{i,j,t}. \end{aligned} \tag{2}$$

where $X_{i,j,t}$ includes the variables corresponding to the hypotheses in Section 2.3. The coefficient β_2 captures whether a given loan or fund characteristic is associated with higher reported prices during stress, while β_1 captures residual differences across vehicles after accounting for these characteristics.

Table 3 reports the results. We begin with opacity. We measure loan opacity using four variables: whether the loan is classified as Level 3, whether the issuer has no credit rating from S&P, Moody's, or Fitch, whether the issuer is private and therefore not publicly traded,

and whether the loan is held by only one fund family. Columns 2 through 5 show that the interactions between *StressPeriod* and these opacity measures are positive and statistically significant. During stress periods, opaque loans carry higher reported prices, or equivalently are marked down less. Moreover, adding these opacity interactions substantially reduces the cross-vehicle coefficients. This pattern is consistent with the evidence in Section 2.2: less liquid vehicles hold more opaque loans, and opaque loans provide greater scope for discretionary marking.

To assess whether the effect of opacity is similar across vehicle types, Table 4 estimates the opacity specifications separately for MFs and ETFs, semi-liquid BDCs, and closed-end BDCs. The interaction between *StressPeriod* and opacity is generally positive and of similar magnitude across vehicle types. For example, the coefficient on the interaction between *StressPeriod* and *Level*3 is 3.615 for MFs and ETFs, 3.437 for semi-liquid BDCs, and 2.474 for closed-end BDCs. Therefore, opacity is associated with higher reported prices not only among BDCs, but also among MFs and ETFs. This confirms that a key reason why MFs and ETFs exhibit less price inflation overall is that they hold fewer opaque loans.

Columns 6 and 7 of Table 3 examine position size and fund leverage. The interactions between *StressPeriod* and portfolio weight, and between *StressPeriod* and leverage, are not statistically significant. These results provide little evidence that larger positions or more leveraged funds report systematically higher prices during aggregate stress, contrary to Hypotheses 2 and 3.

Column 8 includes all interactions simultaneously. The opacity interactions, especially those based on fair value level, credit rating, and public listing status, remain statistically significant. The cross-vehicle coefficients shrink further, confirming that asset composition explains an important part of the liquidity gradient in reported prices. However, the vehicle coefficients remain statistically and economically significant. During stress periods, after controlling for opacity and other fund and loan characteristics, loan MFs and ETFs report

prices 0.793% of par lower than semi-liquid BDCs, while closed-end BDCs report prices 0.526% of par higher than semi-liquid BDCs.

Column 9 further includes loan-by-quarter fixed effects, comparing reported prices across vehicles for the same loan in the same quarter. This specification removes all loan-time variation by construction and therefore focuses only on loans held by multiple vehicle types. Because overlapping loans are relatively transparent, and because many MF/ETF loans do not overlap with BDC holdings, this is a stringent test. Even in this specification, significant differences remain: conditional on holding the same loan at the same time, loan MFs and ETFs report lower prices than semi-liquid BDCs, and semi-liquid BDCs report lower prices than closed-end BDCs. This evidence supports Hypothesis 4: the inherent difference in investor liquidity across vehicle types contributes to the difference in reported prices. Even after controlling for loan opacity and comparing overlapping holdings, vehicles with weaker investor liquidity report higher prices during aggregate stress, as these vehicles face fewer threats from investor redemptions that can exploit the mispricing.

4 Issuer Distress and Price Inflation

The previous section shows a liquidity gradient in reported prices around stress periods, when there are negative shocks to aggregate cash flows and default probability increases for all issuers. In this section, we examine realized distress events at the issuer level, including default and conversion to PIK. We continue to find the same liquidity gradient in reported prices around these realized distress events: closed-end BDCs report higher prices than semi-liquid BDCs, which in turn report higher prices than MFs and ETFs.

We define an issuer to be **in default** if it satisfies any of three criteria. First, the issuer is in default if its issuer credit rating from S&P, Moody's, or Fitch is "CC" (equivalently "Ca"),

"C", "D", "RD", or "SD". Second, the issuer is in default if any of its loans are flagged in Form N-PORT under Item C.9.c, 'Currently in default? [Y/N]," or under Item C.9.d, 'Are there any interest payments in arrears or have any coupon payments been legally deferred by the issuer? [Y/N]."[6] Third, the issuer is in default if any of its loans are reported as non-accrual in BDC 10-K or 10-Q filings, meaning that the loan is no longer accruing interest income.

PIK conversion captures a milder but economically important form of borrower distress. When a borrower cannot or does not make interest payments in cash, lenders may allow interest to be paid in kind, so that unpaid interest is capitalized into principal. As Rintamaki and Steffen (2025) emphasize, PIK can function as a form of "shadow default" and is associated with elevated future default risk. We define an issuer to be **in PIK** if any of its loans are flagged in Form N-PORT under Item C.9.e, 'Is any portion of the interest paid in kind? [Y/N]," or if any of its loans reported in BDC 10-K or 10-Q filings carry a nonzero PIK interest rate. We exclude loans that are in PIK throughout our sample period, since some loans are structured with PIK features at issuance rather than converted to PIK in response to distress.

Figure 4 plots raw distribution of reported prices around distress events. We restrict the sample to loans whose issuers eventually enter default or PIK, align observations by the event quarter $t = 0$, and plot reported prices from eight quarters before distress through the event quarter. Panel A focuses on defaults. Loan MFs and ETFs begin marking down distressed loans several quarters before default, consistent with prices incorporating rising risk of default before its final realization. Semi-liquid BDCs also mark down these loans, but much later and by less. Closed-end BDCs report the smallest markdowns and appear to adjust prices meaningfully only shortly before default. The price jumps in the event quarter correspond to restructurings where loan principals (the denominator) are impaired, so we

[6] Our results are robust to excluding Item C.9.d.

exclude the event quarter in the following regression analyses.

Panel B shows that the contrast is even sharper around PIK conversions. Loan MFs and ETFs begin marking down loans several quarters before PIK conversion, indicating that these events are preceded by observable deterioration in borrower fundamentals. By contrast, both semi-liquid and closed-end BDCs report little decline in prices before or even at the time of PIK conversion. This pattern suggests that BDCs treat PIK conversion differently from default: rather than immediately recognizing the cash-flow impairment through lower marks, they often leave reported loan values largely unchanged.

To estimate these patterns more formally, we adapt Equation 2 to issuer-level distress:

$$\begin{aligned} ReportedPrice_{i,j,t} =& \beta_1 IssuerDistress_{j,t,t+4} \times VehicleType_i \\ &+ \beta_2 IssuerDistress_{j,t,t+4} \times X_{i,j,t} + \gamma Controls + FE + \epsilon_{i,j,t}. \end{aligned} \tag{3}$$

Each observation is fund i's holding of loan j in quarter t. *ReportedPrice* is reported fair value as a percentage of principal. $IssuerDistress_{j,t,t+4}$ is an indicator equal to one if the issuer of loan j enters default or PIK conversion within the next four quarters. We estimate the specification separately for defaults and PIK conversions. Defining distress over the next four quarters captures the forward-looking nature of loan prices: if distress is predictable, reported prices should adjust before the event occurs. As before, we include fund-level and loan-level controls, as well as fund fixed effects, loan fixed effects, and industry-by-quarter fixed effects. Standard errors are three-way clustered by fund, issuer, and year-quarter.

Table 5 reports the default results. The coefficient on the default indicator is strongly negative, indicating that loans approaching default trade at substantially lower reported prices on average. More importantly, the interaction terms reveal a liquidity gradient in the extent of markdowns. Relative to semi-liquid BDCs, open-end MFs and ETFs report significantly lower prices before default, while closed-end BDCs report significantly higher

prices. In Column 1, MFs and ETFs report prices 5.654% of par lower than semi-liquid BDCs, whereas closed-end BDCs report prices 1.175% of par higher than semi-liquid BDCs. Thus, as default approaches, reported prices are lowest for the most liquid vehicles and highest for the least liquid vehicles.

We then examine whether this gradient is explained by the hypotheses in Section 2.3. Columns 2 through 5 interact the default indicator with measures of loan opacity. Loans that are Level 3, unrated, issued by private firms, or held by a single fund family have economically higher reported prices before default, although these estimates are not statistically significant. Adding these opacity interactions modestly reduces the vehicle coefficients, consistent with the interpretation that part of the cross-vehicle difference comes from differences in amount of opaque loans held. Column 6 shows that larger portfolio positions are reported at higher prices before default, consistent with Hypothesis 2: managers have stronger incentives to avoid markdowns on positions that have larger effects on fund-level NAV. Column 7 shows that more levered funds reported lower prices on defaulted loans, contrary to Hypothesis 3.

Column 8 includes all interactions simultaneously. Even after controlling for opacity, position size, leverage, and other fund and loan characteristics, closed-end BDCs report significantly higher prices than semi-liquid BDCs, which in turn report significantly lower prices than open-end MFs and ETFs. The liquidity gradient is the same as in the aggregate-stress analysis and aligns closely with the ordering of investor liquidity: vehicles with stronger investor exit rights mark down more before default, while vehicles with weaker exit rights report higher prices. This evidence supports Hypothesis 4, that redemption threats inherent in vehicle structure discipline reported prices.

Column 9 includes loan-by-quarter fixed effects, which compare different vehicles' reported prices for the same loan in the same quarter. This specification necessarily restricts the sample to loans held by multiple vehicle types. Within this selected set of commonly held

loans, differences across vehicles are much smaller and statistically insignificant. This result is informative for two reasons. First, it suggests that much of the default-related price gradient occurs among loans that do not overlap across vehicles, where external benchmarking is more limited. Second, it is consistent with the evidence in Section 2.2: overlapping loans are the most transparent, so they leave less room for valuation discretion.

Table 6 reports the results for PIK conversions. The coefficient on the PIK indicator is negative, indicating that loans approaching PIK conversion have lower reported prices on average. However, the cross-vehicle differences are much larger than for defaults. The interaction between PIK and the MF/ETF indicator is strongly negative, confirming the raw pattern in Figure 4: MFs and ETFs report substantially lower prices before PIK conversion, whereas BDC prices respond very little.

Columns 2 through 8 progressively add interactions between PIK and the explanatory variables from Section 2.3. These controls do not explain the large difference between MF/ETF prices and BDC prices. In Column 9, we add loan-by-quarter fixed effects and restrict attention to commonly held loans. The MF/ETF–BDC price gap becomes smaller, but remains statistically significant and economically meaningful. These results suggest that BDCs are particularly slow to recognize PIK-related deterioration in their reported prices.

The evidence around PIK conversions is consistent with an "amend-and-pretend" interpretation. Rather than forcing a borrower into default and marking down the loan, lenders may amend the loan to allow interest to be paid in kind and keep the reported value close to par. This behavior is especially relevant for BDCs, whose loans are substantially more likely to experience PIK conversion, as shown in Table 1. Together, the default and PIK results show that the liquidity gradient in reported prices is not limited to aggregate stress periods. It also appears around realized issuer distress, especially when distress can be accommodated through loan amendments rather than recognized through default.

5 Informativeness of Reported Prices

Our analyses so far establish that, in response to either aggregate shocks or individual distress events, MFs and ETFs mark down loan prices more than semi-liquid BDCs, which in turn mark down loan prices more than closed-end BDCs. Which reported prices are more informative of future distress events such as default and PIK conversion? After all, markets are not always fully efficient and known to exhibit excess volatility, and BDCs can in theory filter out sentiment and other uninformative noises, insulating loan prices from excess volatility (Chodorow-Reich et al., 2021; Coppola, 2025). Therefore, it is not obvious which reported prices would have better predictive power of real distress events in the future.

To answer this question, we construct a panel dataset where each observation corresponds to an issuer in a given quarter. For each issuer in a given quarter, we calculate the weighted average loan price reported by MFs and ETFs, semi-liquid BDCs, or closed-end BDCs. We ask: how well do average loan prices reported by a given vehicle type predict default or PIK conversion eight quarters ahead?

Since default and PIK conversion are both rare events, conventional mean-squared-error-based approach can be dominated by non-event observations and therefore provide a misleading assessment. Instead, we calculate receiver operating characteristic (ROC) associated with each price measure. Specifically, given a classification rule – for example, if average loan prices reported by MFs and ETFs fall below \$80, we predict 8-quarter-ahead default to be true, and otherwise we predict no default – we calculate the associated true positive rate and false positive rate. We repeat this calculation across all possible price thresholds, separately for prices reported by MFs and ETFs, semi-liquid BDCs and closed-end BDCs. In general, higher true positive rate is associated with higher false positive rate. A better prediction manifests as having a bigger ratio between true positive rate and false positive rate – the prediction can correctly identify the true positives without triggering as many

false positives.

Figure 5 shows the ROC curves for the three vehicle types, where each dot on the curve corresponds to a classification threshold. In Panel A, for predicting future default, all three price measures are informative, and their differences are small. For example, all three price measures can attain a 60% true positive rate with only about 10% false positive rate.

However, the three prices have obvious differences in predicting future PIK conversions. Conditional on the same false positive rate, prices reported by MFs and ETFs clearly attain higher true positive rate than prices reported by semi-liquid and closed-end BDCs. For example, conditional on the same false positive rate at 20%, prices reported by MFs and ETFs have a true positive rate of 50%, whereas prices reported by semi-liquid and closed-end BDCs only have a true positive rate of 39% and 36%, respectively.

Together with our earlier analyses, these informativeness measures provide a full view of the picture. When severe distress such as default is approaching, all three vehicles mark down loan prices, and – although they mark down prices to different degrees – these markdowns provide informative signals of whether defaults will occur eight quarters later. However, with milder distress approaches, MFs and ETFs still mark down loan prices commensurably, whereas BDCs simply "amend and pretend" by granting PIK conversion and keeping the loan values unchanged. As a result, BDC prices have much less predictive power of future PIK conversion.

6 BDC-Level NAV Inflation

Assuming that loan prices reported by MFs and ETFs align with market prices, we can use them to approximate the true values of loans held by BDCs and in turn the true net asset values at the BDC level.

The loans held by BDCs have a small overlap with loans held by MFs and ETFs. To make meaningful inference at the BDC level, we assume that the portfolio of loans held by BDCs in any issuer industry is similar to the portfolio of loans held by MFs and ETFs, in a given quarter. Specifically, in each quarter, we pool together the loans held by a BDC in a particular issuer industry, and we assign it the average price reported by MFs and ETFs on their loans in the same industry. We repeat this for all industries for each BDC. By aggregating the differences between self-reported values and values implied by MF and ETF prices over all loans, we can derive a measure of NAV inflation at the BDC level:

$$NAVInflation_{i,t} = \frac{\sum_k Principal_{i,k,t}(Price_{i,k,t} - Price^{MF}_{i,k,t})}{TotalNetAssets_{i,t}}, \tag{4}$$

where the numerator is the sum of differences in self-reported versus implied loan values over all k industries, and the denominator is reported total net assets.

Panel A of Figure 6 shows the distribution of NAV inflation over time. NAV inflation is normally centered around zero, but significantly increases during stress periods, consistent with our analyses in Section 3.

Using this BDC-level NAV inflation measure, we can calculate the amount of dilution costs experienced by each semi-liquid fund in each period, following Zitzewitz (2003); Choi et al. (2022):

$$Dilution_{i,t} = 0 - NetFlow_{i,t} \times NAVInflation_{i,t} \tag{5}$$

Intuitively, incumbent investors incur a dilution cost if new investors can buy new shares at a too-low NAV or if exiting investors can sell shares at a too-high NAV.

Panel B of Figure 6 shows aggregate dilution costs for all semi-liquid BDCs. The dilution costs have been largely *negative*, because of consistent and large net inflows to semi-liquid BDCs and the fact that their NAVs tend to be inflated especially around stress periods. The sum of dilution costs over time is -$2.74 billion. In other words, incumbent investors of semi-

liquid BDCs have so far *benefited* tremendously from inflated NAVs, as new investors pay a market-up for new shares. Such dynamics are poised to change direction, as semi-liquid BDCs start to experience significant aggregate outflows for the first time.

7 Conclusion

Private credit funds hold illiquid loans whose fair values are difficult to verify, yet those fair values determine reported performance, fees, leverage ratios, and the NAVs at which investors enter and exit semi-liquid vehicles. This paper studies whether private credit funds mark these loans in a timely manner when negative shocks arrive. Using loan-level prices reported by open-end mutual funds and ETFs, semi-liquid BDCs, and closed-end BDCs, we document a systematic liquidity gradient in reported prices. During aggregate stress periods and before issuer-level distress events, closed-end BDCs report the highest loan prices, semi-liquid BDCs report intermediate prices, and open-end mutual funds and ETFs report the lowest prices.

We show that this gradient reflects both asset composition and valuation discipline. Less liquid vehicles hold more opaque loans, where external benchmarks are weaker and fair-value discretion is greater. These asset-side differences explain an important part of the cross-vehicle price gap. However, they do not explain it all. Even after controlling for opacity and other loan characteristics, and even when comparing overlapping loans held by different vehicle types in the same quarter, significant differences remain. This residual gradient is consistent with investor liquidity disciplining reported prices: vehicles with stronger exit rights face greater costs from inflated NAVs and therefore mark down loans more aggressively.

The price differences are economically meaningful. Prices reported by mutual funds and ETFs are more informative about future PIK conversions than prices reported by BDCs,

suggesting that BDC marks are less responsive to early signs of borrower distress. Using mutual fund and ETF prices as benchmarks, we estimate BDC-level NAV inflation and show that inflated NAVs generate transfers across investors in semi-liquid BDCs. During periods of net inflows, inflated NAVs benefit incumbent investors at the expense of new investors; during periods of outflows, the same mechanism can reverse and amplify fragility.

Overall, our findings suggest that price inflation in private credit is sophisticated rather than uniform. It appears when negative information arrives, concentrates in opaque loans where it is harder to detect, and varies systematically with vehicle liquidity. These results highlight a central tradeoff in private credit vehicle design. Restricting investor liquidity may reduce run risk, but it can also weaken the market discipline that constrains discretionary valuation. Conversely, stronger investor liquidity can create redemption pressure, but it also forces reported prices to respond more quickly to deteriorating fundamentals.

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Figures and Tables

Figure 1: **Assets under Management by Different Private Credit Vehicles**. This figure shows aggregate total assets for loan MFs and ETFs (blue), semi-liquid BDCs (red), and closed-end BDCs (green).

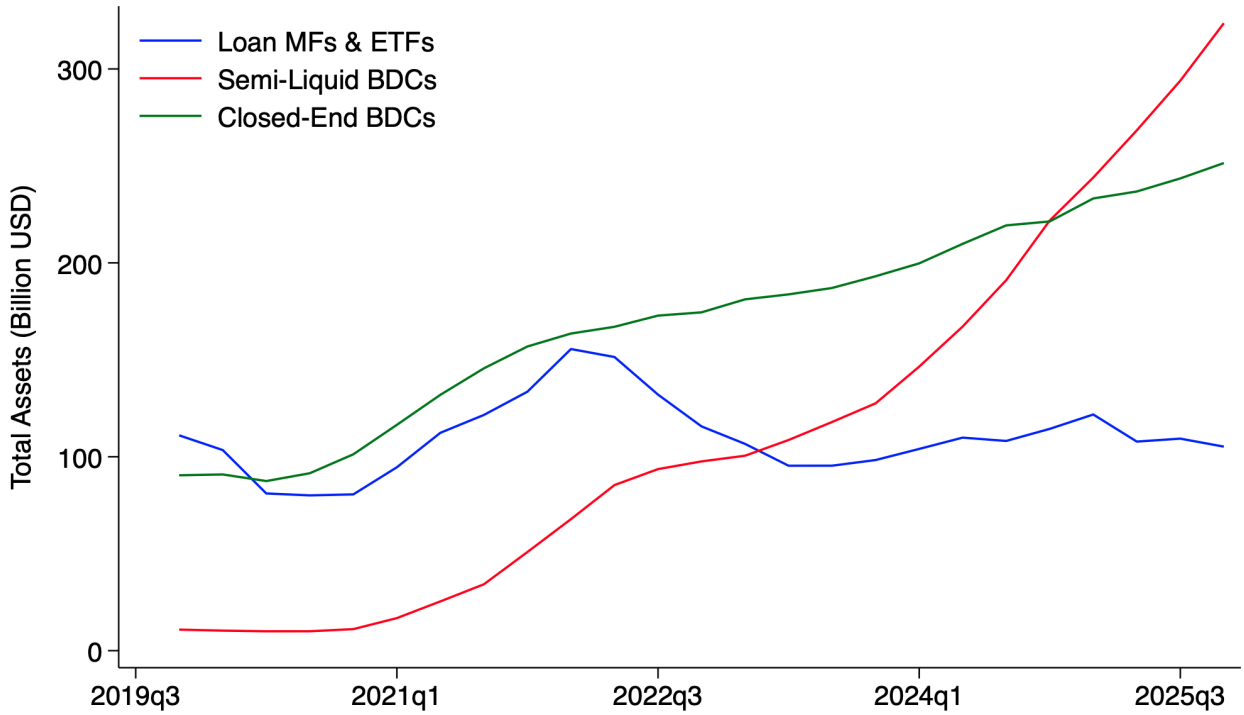
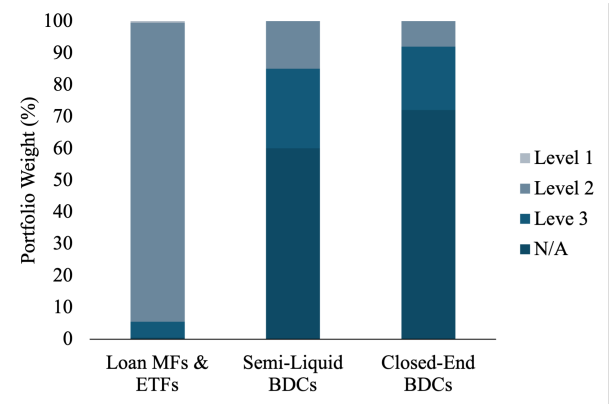
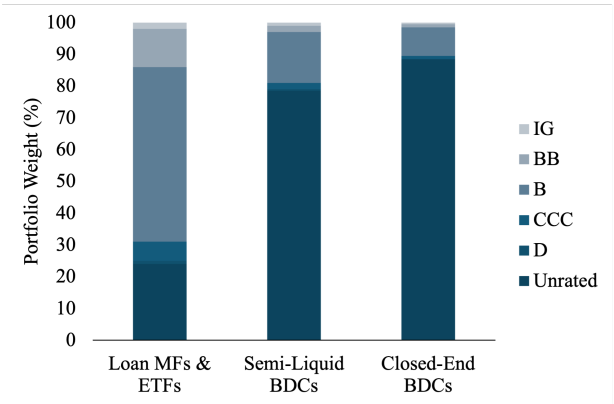


Figure 2: **Characteristics of Loans under Management by Different Private Credit Vehicles**. These figures show the composition of loans under management for different private credit vehicles, averaged over time. Panel A shows loan holdings by fair value level, Panel B by issuer credit rating, Panel C by whether the issuer's equities are listed on exchanges, Panel D by number of distinct fund family holders. The sample includes holdings of U.S. dollar-denominated loans and excludes notes and bonds.

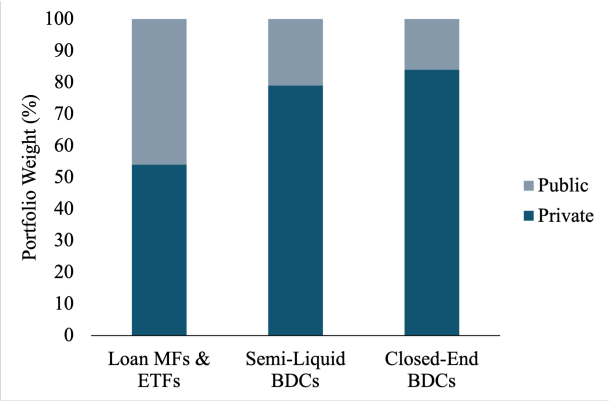
Panel A: By Fair Value Level



Panel B: By Issuer Credit Rating



Panel C: By Public Status



Panel D: By Number of Lenders

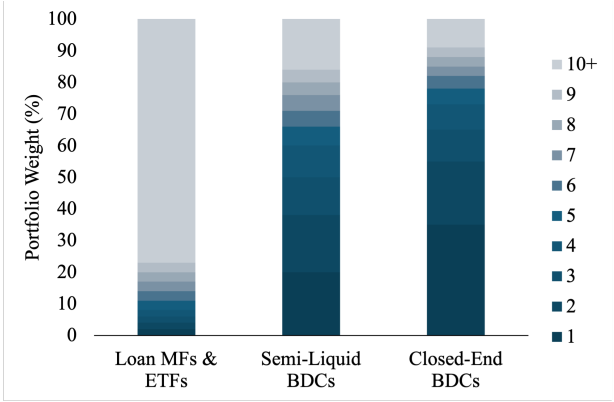
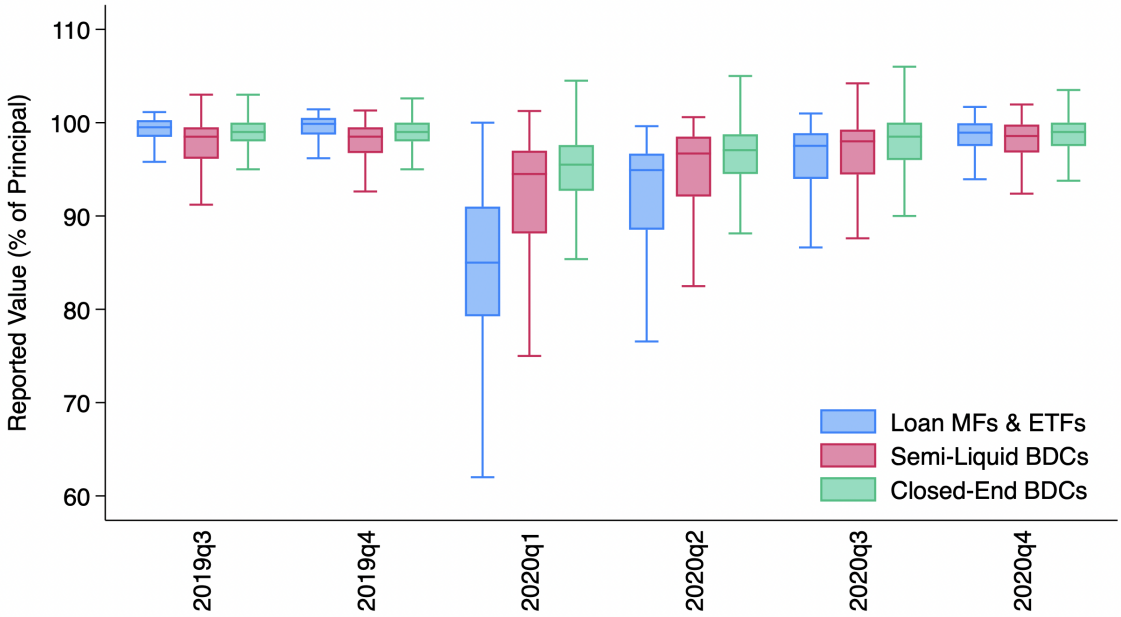


Figure 3: **Stress Periods and Reported Loan Prices across Private Credit Vehicles**. These figures plot the distributions of loan prices reported by different private credit vehicles during the COVID-19 crisis (Panel A) and the 2022 rate-hike episode (Panel B). We restrict to senior secured first lien term loans and exclude second-lien, unitranche, revolvers, and delayed draw loans. Restructured loans are also excluded.

Panel A: COVID-19 Crisis



Panel B: 2022 Rate Hike

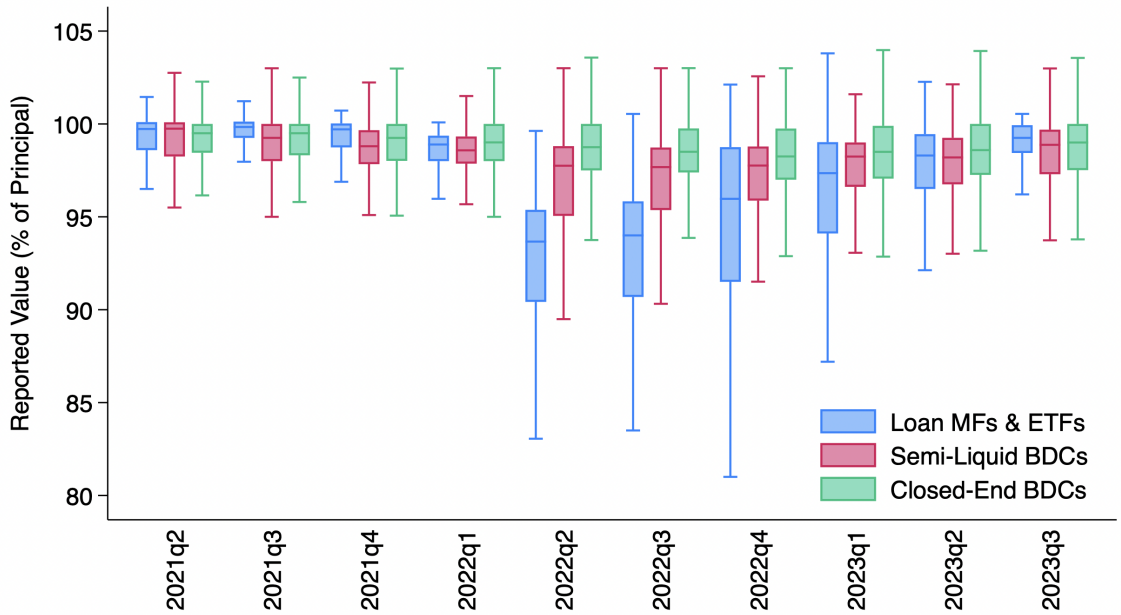
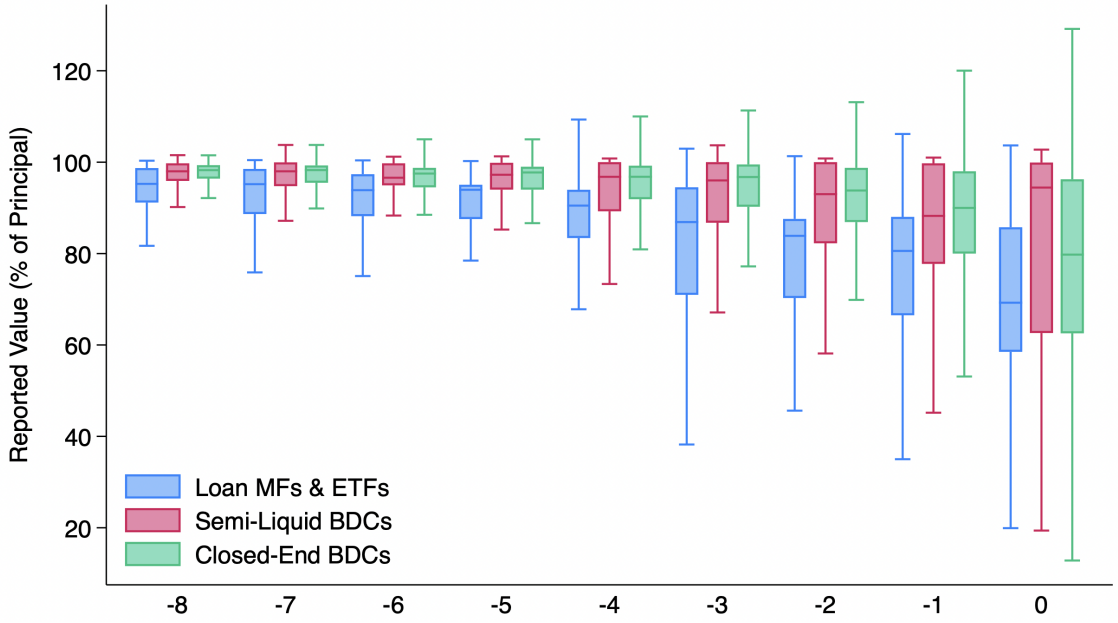


Figure 4: **Issuer Distress and Reported Loan Prices across Private Credit Vehicles**. These figures plot the distributions of prices reported by different private credit vehicles on loans that are approaching default (Panel A) or PIK conversion (Panel B). $t = 0$ corresponds to quarter of default or PIK conversion. We restrict to senior secured first lien term loans and exclude second-lien, unitranche, revolvers, and delayed draw loans. Restructured loans are also excluded.

Panel A: Reported Prices before Default



Panel B: Reported Prices before PIK Conversion

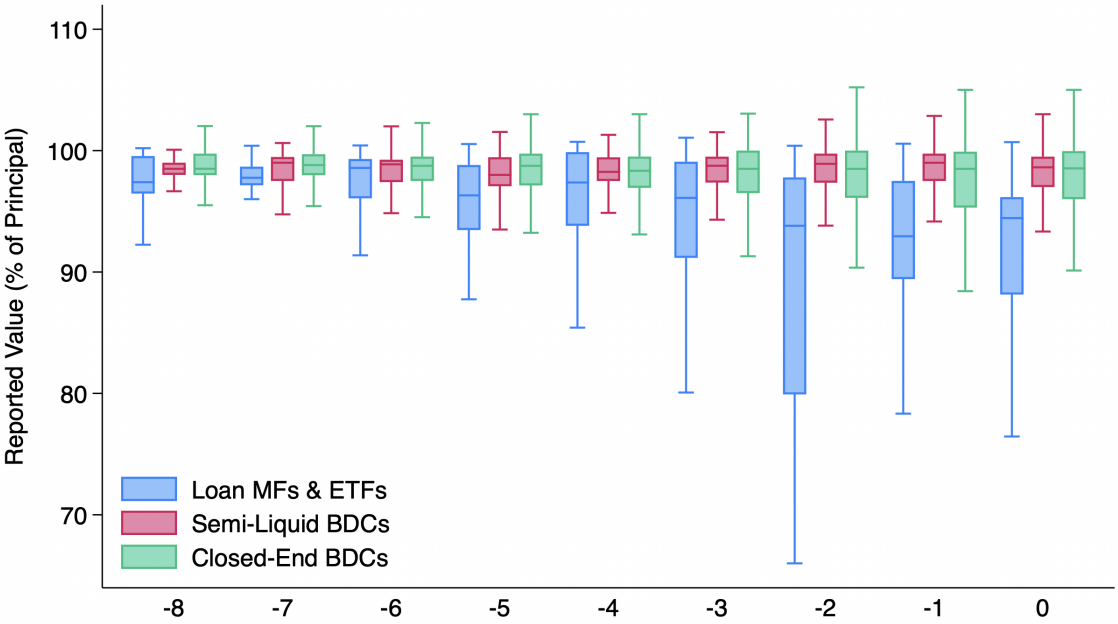
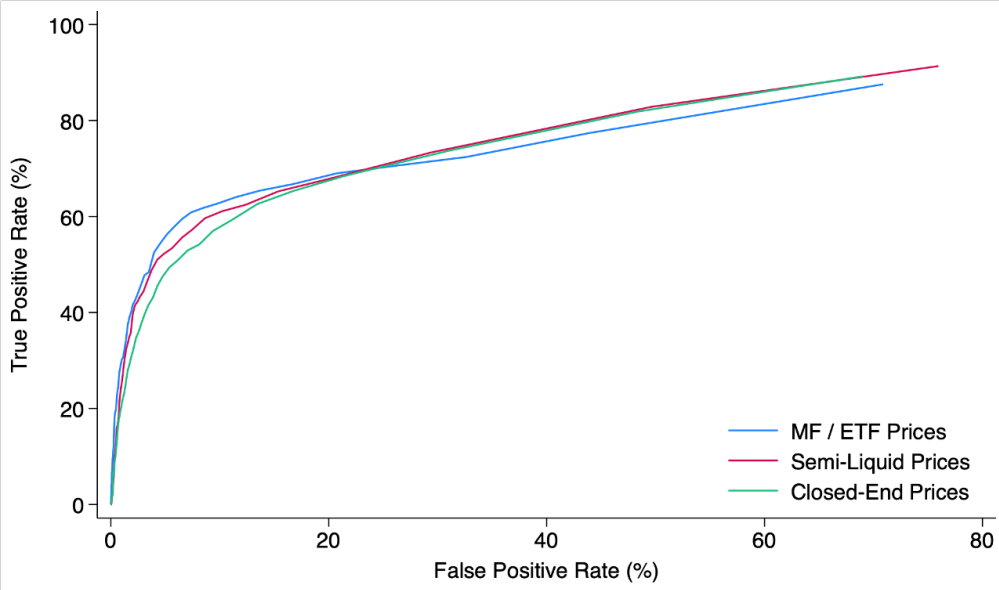


Figure 5: **Informativeness of Prices Reported by Different Private Credit Vehicles**. These figures plot the ROC curves comparing the informativeness of prices reported by different private credit vehicles for predicting future distress. The curves represent the predictive power of average prices reported by loan MFs and ETFs (blue), semi-liquid BDCs (red), and closed-end BDCs (green) for future default (Panel A) and future PIK conversion (Panel B). Each point on a curve corresponds to a different price-based prediction rule—e.g., predict future default when the reported value is below 80% of principal. The vertical axis reports the true positive rate, meaning the fraction of future default or PIK events correctly predicted. The horizontal axis reports the false positive rate, meaning the fraction of non-event observations incorrectly predicted as future default or PIK events. Curves closer to the upper-left corner indicate more informativeness and stronger predictive power.

Panel A: Price Informativeness of Future Default



Panel B: Price Informativeness of Future PIK Conversion

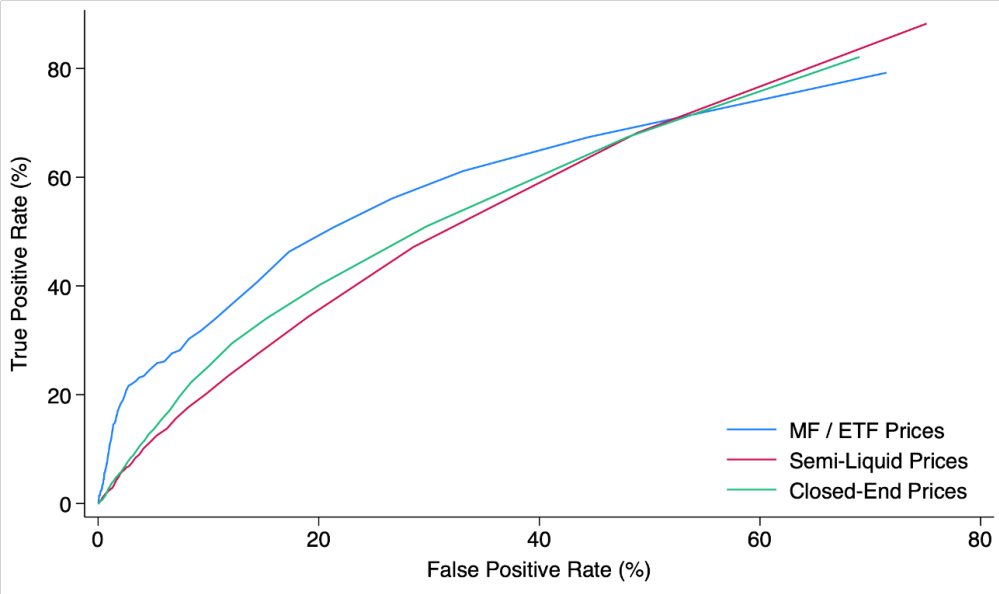
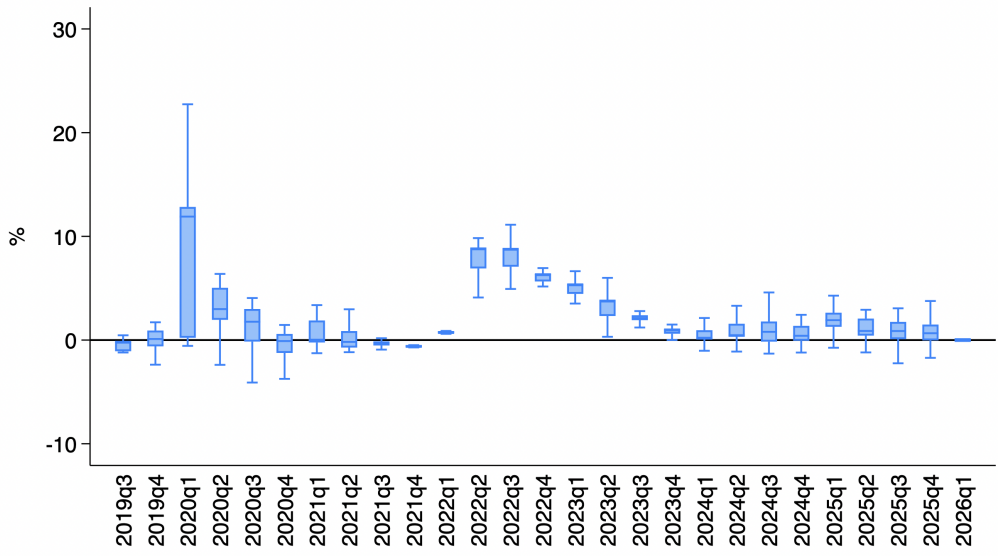


Figure 6: **BDC-Level NAV Inflation**. These figures demonstrate the magnitude of NAV inflation at the BDC level according to Equation 4. Panel A shows the distribution of NAV inflation across all BDCs over time. Panel B shows aggregate dilution costs (gains) for incumbent investors of semi-liquid BDCs, according to Equation 5.

Panel A: Distribution of NAV Inflation



Panel B: Aggregate Dilution Costs (Gains)

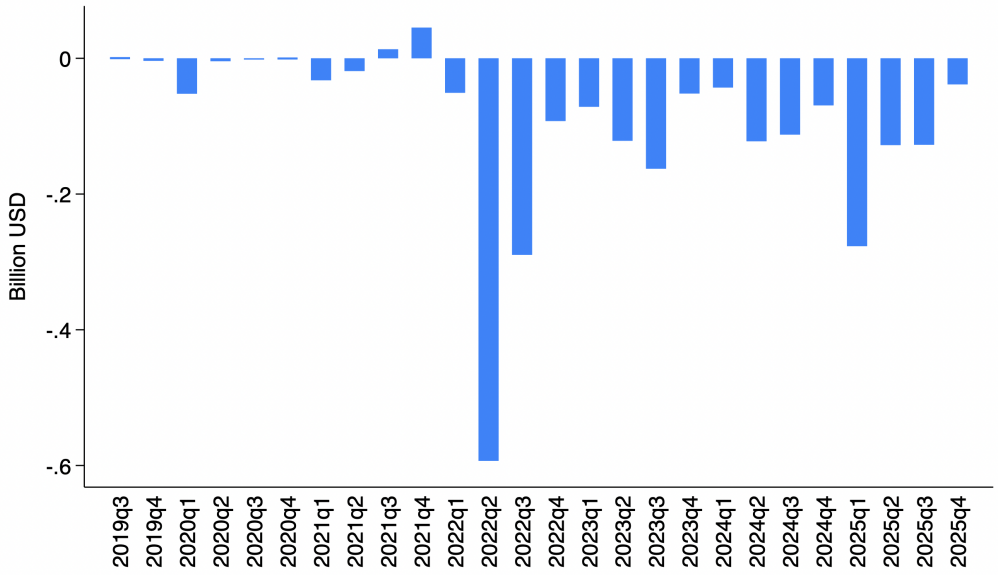


Table 1: **Characteristics of Loans by Different Holders**. These tables show summary statistics of three separate loan-quarter samples. Panel A focus on loans that are only held by loan MFs & ETFs. Panel B focus on loans that are held by both loan MFs & ETFs and BDCs. Panel C focus on loans that are only held by BDCs. Statistics are calculated using total holdings by all funds and BDCs as weights.

Panel A: Loans Only Held by Loan MFs & ETFs

	N	Mean	SD	P10	P50	P90
1[Fair Value Level 1 or 2]	19248	0.99	0.09	1.00	1.00	1.00
1[Rated]	19248	0.85	0.36	0.00	1.00	1.00
Rating (AAA = 1, D = 20)	14519	14.42	1.89	12.00	15.00	16.00
1[Publicly Traded]	19248	0.57	0.50	0.00	1.00	1.00
Number of Distinct Holders	19048	12.46	8.19	3.00	11.00	24.00
Average Years to Maturity	19248	4.71	1.49	2.75	4.75	6.50
1[Default]	19248	0.02	0.15	0.00	0.00	0.00
1[PIK]	19248	0.01	0.12	0.00	0.00	0.00

Panel B: Loans Held by Both Loan MFs & ETFs and BDCs

	N	Mean	SD	P10	P50	P90
1[Fair Value Level 1 or 2]	13484	0.99	0.11	1.00	1.00	1.00
1[Rated]	13484	0.87	0.33	0.00	1.00	1.00
Rating (AAA = 1, D = 20)	10746	15.09	1.36	13.50	15.00	16.00
1[Publicly Traded]	13484	0.42	0.49	0.00	0.00	1.00
Number of Distinct Holders	13419	19.06	12.09	5.00	17.00	37.00
Average Years to Maturity	13484	4.92	1.41	3.04	5.00	6.74
1[Default]	13484	0.03	0.17	0.00	0.00	0.00
1[PIK]	13484	0.03	0.16	0.00	0.00	0.00

Panel C: Loans Only Held by BDCs

	N	Mean	SD	P10	P50	P90
1[Fair Value Level 1 or 2]	110522	0.02	0.15	0.00	0.00	0.00
1[Rated]	110522	0.06	0.24	0.00	0.00	0.00
Rating (AAA = 1, D = 20)	7797	12.80	4.00	7.00	15.00	16.50
1[Publicly Traded]	110522	0.14	0.35	0.00	0.00	1.00
Number of Distinct Holders	110172	3.59	3.64	1.00	2.00	9.00
Average Years to Maturity	109459	4.35	1.87	2.00	4.50	6.50
1[Default]	110522	0.02	0.14	0.00	0.00	0.00
1[PIK]	110522	0.12	0.32	0.00	0.00	1.00

Table 2: **Stress Periods and Reported Loan Prices across Private Credit Vehicles**. This table examines differences in reported loan prices across private credit fund types during stress periods through Regression 1:

$$ReportedPrice_{i,j,t} = \beta StressPeriod_t \times VehicleType_i + \gamma Controls + FE + \epsilon_{i,j,t}.$$

Each observation corresponds to a fund i's holding of loan j in quarter t. $StressPeriod$ is an indicator of whether quarter t belongs to 2020Q1-Q2 or 2022Q2-Q4. $FundType$ is an indicator of whether fund i is loan MF / ETF, semi-liquid BDC (base case), or closed-end BDC. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Dependent Variable:	Reported Value (% of Par Amount)			
	(1)	(2)	(3)	(4)
1[MF & ETF]	0.682		0.682	
	(1.334)		(1.330)	
1[Closed-End BDC]	0.025		0.028	
	(0.128)		(0.140)	
1[Stress Period] × 1[MF & ETF]	-3.411***	-2.968***		
	(-4.666)	(-3.423)		
1[Stress Period] × 1[Closed-End BDC]	0.862***	0.877***		
	(5.265)	(4.521)		
1[COVID-19] × 1[MF & ETF]			-4.074**	-3.291*
			(-2.072)	(-1.907)
1[COVID-19] × 1[Closed-End BDC]			1.440**	1.989**
			(2.352)	(2.101)
1[2022 Rate Hike] × 1[MF & ETF]			-3.345***	-2.874***
			(-4.179)	(-3.040)
1[2022 Rate Hike] × 1[Closed-End BDC]			0.926***	0.929***
			(3.811)	(3.648)
Fund Controls	past performance, log TNA, leverage			
Loan Controls	fair value level, credit rating, publicly traded, number of holders, maturity, portfolio weight			
Fund FE		Y		Y
Loan FE	Y	Y	Y	Y
Issuer Industry FE × Year-Quarter FE	Y	Y	Y	Y
Standard Errors	three-way clustered by fund, by issuer, by time			
Observations	242923	242923	242923	242923
R2	0.406	0.419	0.406	0.419

Table 3: **Dissecting Differences in Reported Loan Prices During Stress Periods**. This table provides a dissection of the differences in reported loan prices across private credit fund types through Regression 2:

$$ReportedPrice_{i,j,t} = \beta_1 StressPeriod_t \times VehicleType_i + \beta_2 StressPeriod_t \times X_{i,j,t} + \gamma Controls + FE + \epsilon_{i,j,t}$$

Each observation corresponds to a fund i's holding of loan j in quarter t. $StressPeriod$ is an indicator of whether quarter t belongs to 2020Q1-Q2 or 2022Q2-Q4. $FundType$ is an indicator of whether fund i is loan MF & ETF, semi-liquid BDC (base case) or closed-end BDC. Price opacity is measured by whether the loan is level 3 or unrated by S&P, Moody's and Fitch. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Dependent Variable:	Reported Value (% of Par Amount)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1[Stress Period] × 1[MF & ETF]	-2.968***	-1.404**	-2.251**	-2.775***	-2.798***	-2.978***	-3.079***	-0.793**	-0.564*
	(-3.423)	(-2.566)	(-2.339)	(-3.091)	(-2.922)	(-3.432)	(-3.137)	(-2.256)	(-1.995)
1[Stress Period] × 1[Closed-End BDC]	0.877***	0.525***	0.636***	0.825***	0.817***	0.888***	0.885***	0.526***	0.448**
	(4.521)	(3.455)	(4.016)	(4.613)	(4.532)	(4.123)	(4.525)	(3.109)	(2.439)
1[Stress Period] × 1[Level 3 or NA]		3.128***						2.268***	
		(6.334)						(5.897)	
1[Stress Period] × 1[Unrated]			2.527***					1.129***	
			(5.133)					(3.806)	
1[Stress Period] × 1[Private]				0.910***				0.403**	
				(4.231)				(2.142)	
1[Stress Period] × 1[Solo-Lender]					0.530*			0.167	
					(2.039)			(0.906)	
1[Stress Period] × Portfolio Weight						-0.024		-0.082	
						(-0.198)		(-0.682)	
1[Stress Period] × Fund Leverage							-0.003	-0.004	
							(-0.291)	(-0.520)	
Fund Controls	past performance, log TNA, leverage								
Loan Controls	fair value level, credit rating, publicly traded, number of holders, maturity, portfolio weight								
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y	
Issuer Industry FE × Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	
Loan FE × Year-Quarter FE									Y
Standard Errors	three-way clustered by fund, by issuer, by time								
Observations	242923	242923	242923	242923	242923	242923	242923	242923	140762
R2	0.419	0.421	0.421	0.419	0.419	0.419	0.419	0.421	0.494

Table 4: **Stress Periods and Reported Loan Prices for Each Vehicle Type**. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Panel A: Prices Reported by Loan MFs & ETFs

Dependent Variable:	Reported Value (% of Par Amount)				
	(1)	(2)	(3)	(4)	(5)
1[Stress Period] × 1[Level 3 or NA]	3.615*				2.831
	(1.817)				(1.573)
1[Stress Period] × 1[Unrated]		-0.704			-1.248
		(-1.252)			(-1.300)
1[Stress Period] × 1[Private]			2.846**		2.975**
			(2.191)		(2.173)
1[Stress Period] × 1[Solo-Lender]				1.311	1.219*
				(1.573)	(1.728)
Fund Controls	past performance, log TNA, leverage				
Loan Controls	fair value level, credit rating, publicly traded, number of holders, maturity, portfolio weight				
Fixed Effects	Fund FE, Loan FE, Issuer Industry FE × Year-Quarter FE				
Standard Errors	three-way clustered by fund, by issuer, by time				
Observations	12243	12243	12243	12243	12243
R2	0.741	0.741	0.745	0.741	0.747

Panel B: Prices Reported by Semi-Liquid BDCs

Dependent Variable:	Reported Value (% of Par Amount)				
	(1)	(2)	(3)	(4)	(5)
1[Stress Period] × 1[Level 3 or NA]	3.437***				2.182***
	(5.658)				(4.278)
1[Stress Period] × 1[Unrated]		3.107***			1.228***
		(4.545)			(2.799)
1[Stress Period] × 1[Private]			1.609***		0.839***
			(5.809)		(3.398)
1[Stress Period] × 1[Solo-Lender]				1.131***	0.518
				(2.795)	(1.685)
Fund Controls	past performance, log TNA, leverage				
Loan Controls	fair value level, credit rating, publicly traded, number of holders, maturity, portfolio weight				
Fixed Effects	Fund FE, Loan FE, Issuer Industry FE × Year-Quarter FE				
Standard Errors	three-way clustered by fund, by issuer, by time				
Observations	93731	93731	93731	93731	93731
R2	0.462	0.462	0.460	0.460	0.463

Panel C: Prices Reported by Closed-End BDCs

Dependent Variable:	Reported Value (% of Par Amount)				
	(1)	(2)	(3)	(4)	(5)
1[Stress Period] × 1[Level 3 or NA]	2.474***				1.901***
	(3.989)				(3.894)
1[Stress Period] × 1[Unrated]		1.735***			0.901***
		(3.624)			(3.136)
1[Stress Period] × 1[Private]			0.426*		0.177
			(1.948)		(1.011)
1[Stress Period] × 1[Solo-Lender]				0.103	-0.069
				(0.660)	(-0.544)
Fund Controls	past performance, log TNA, leverage				
Loan Controls	fair value level, credit rating, publicly traded, number of holders, maturity, portfolio weight				
Fixed Effects	Fund FE, Loan FE, Issuer Industry FE × Year-Quarter FE				
Standard Errors	three-way clustered by fund, by issuer, by time				
Observations	135690	135690	135690	135690	135690
R2	0.426	0.426	0.426	0.426	0.427

Table 5: **Defaults and Reported Loan Prices across Private Credit Vehicles**. These tables examine differences in reported loan prices in response to loan defaults across private credit fund types through Regression 3:

$$ReportedPrice_{i,j,t} = \beta_1 Default_{j,t,t+4} \times VehicleType_i + \beta_2 Default_{j,t,t+4} \times X_{i,j,t} + \gamma Controls + FE + \epsilon_{i,j,t}$$

$Default$ is an indicator of the four quarters prior to default. Restructured loans are excluded from the sample. t-statistics are shown in parentheses. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Dependent Variable:	Reported Value (% of Par Amount)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1[Default]	-7.003***	-7.796***	-7.835***	-6.947***	-7.223***	-7.364***	-3.557*	-4.486**	
	(-6.274)	(-5.441)	(-5.380)	(-10.931)	(-8.376)	(-6.605)	(-2.000)	(-2.576)	
1[Default] × 1[MF & ETF]	-5.654*	-4.723	-4.974*	-5.670*	-5.665*	-5.522*	-8.418**	-7.163*	-0.712
	(-1.872)	(-1.590)	(-1.711)	(-1.892)	(-1.867)	(-1.843)	(-2.200)	(-1.892)	(-0.858)
1[Default] × 1[Closed-End BDC]	1.175***	1.146***	1.159***	1.160***	1.205***	0.918***	1.859***	1.529**	0.360
	(3.945)	(3.642)	(3.667)	(4.208)	(3.247)	(3.253)	(2.797)	(2.392)	(1.544)
1[Default] × 1[Level 3 or N/A]		1.437						1.275	
		(0.993)						(0.941)	
1[Default] × 1[Unrated]			1.089					-0.041	
			(0.645)					(-0.024)	
1[Default] × 1[Private]				-0.148				-0.379	
				(-0.056)				(-0.150)	
1[Default] × 1[Solo-Lender]					0.271			0.582	
					(0.191)			(0.477)	
1[Default] × Portfolio Weight						0.447*		0.407*	
						(1.816)		(1.711)	
1[Default] × Fund Leverage							-0.078*	-0.067*	
							(-1.890)	(-1.966)	
Fund Controls	past performance, log TNA, leverage								
Loan Controls	fair value level, credit rating, publicly traded, number of holders, maturity, portfolio weight								
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y	
Issuer Industry FE × Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	
Loan FE × Year-Quarter FE									Y
Standard Errors	three-way clustered by fund, by issuer, by time								
Observations	242923	242923	242923	242923	242923	242923	242923	242923	145714
R2	0.425	0.425	0.425	0.425	0.425	0.425	0.425	0.425	0.442

Table 6: **PIK Conversions and Reported Loan Prices across Private Credit Funds**. This table examines differences in reported loan prices in response to PIK conversions across private credit fund types through Regression 3:

$$ReportedPrice_{i,j,t} = \beta_1 PIKConversion_{j,t,t+4} \times VehicleType_i + \beta_2 PIKConversion_{j,t,t+4} \times X_{i,j,t} + \gamma Controls + FE + \epsilon_{i,j,t}$$

t-statistics are shown in parentheses. Restructured loans are excluded from the sample. *, **, and *** denote p-values less than 0.10, 0.05, and 0.01, respectively.

Dependent Variable:	Reported Value (% of Par Amount)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1[PIK]	-1.419***	-1.379***	-1.401***	-1.385***	-1.449**	-1.454***	-0.688	-1.007*	
	(-4.715)	(-4.476)	(-4.447)	(-3.904)	(-2.672)	(-4.732)	(-1.259)	(-1.896)	
1[PIK] × 1[MF & ETF]	-9.918*	-9.476*	-9.782*	-9.909*	-9.918*	-9.905*	-10.504**	-10.091**	-4.755*
	(-1.950)	(-1.880)	(-1.925)	(-1.944)	(-1.953)	(-1.948)	(-2.080)	(-2.010)	(-1.759)
1[PIK] × 1[Closed-End BDC]	0.093	0.082	0.089	0.087	0.096	0.083	0.191	0.169	0.271*
	(0.592)	(0.512)	(0.546)	(0.529)	(0.585)	(0.491)	(0.939)	(0.695)	(1.817)
1[PIK] × 1[Level 3 or N/A]		0.632						0.705	
		(1.054)						(1.179)	
1[PIK] × 1[Unrated]			0.199					0.160	
			(0.386)					(0.349)	
1[PIK] × 1[Private]				0.148				-0.152	
				(0.253)				(-0.271)	
1[PIK] × 1[Solo-Lender]					0.044			0.074	
					(0.093)			(0.158)	
1[PIK] × Portfolio Weight						0.033		0.020	
						(0.306)		(0.183)	
1[PIK] × Fund Leverage							-0.016	-0.016	
							(-1.216)	(-1.219)	
Fund Controls	past performance, log TNA, leverage								
Loan Controls	fair value level, credit rating, publicly traded, number of holders, maturity, portfolio weight								
Fund FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Loan FE	Y	Y	Y	Y	Y	Y	Y	Y	
Issuer Industry FE × Year-Quarter FE	Y	Y	Y	Y	Y	Y	Y	Y	
Loan FE × Year-Quarter FE									Y
Standard Errors	three-way clustered by fund, by issuer, by time								
Observations	242923	242923	242923	242923	242923	242923	242923	242923	145714
R2	0.419	0.419	0.419	0.419	0.419	0.419	0.419	0.419	0.442

Internet Appendix

Additional Figures and Tables

Figure 7: **Examples of Semi-Liquid BDCs.**

Blue Owl Capital Corp II, 2025Q3 10-Q

Share Repurchases

In the third quarter of 2017, we began offering, and on a quarterly basis, intend to continue offering, to repurchase shares of our common stock on such terms as may be determined by our Board in its complete discretion. The Board has complete discretion to determine whether we will engage in any share repurchase, and if so, the terms of such repurchase. At the discretion of our Board, we may use cash on hand, cash available from borrowings, and cash from the sale of our investments as of the end of the applicable period to repurchase shares.

All shares purchased by us pursuant to the terms of each offer to repurchase will be retired and thereafter will be authorized and unissued shares.

Any periodic repurchase offers are subject in part to our available cash and compliance with the BDC and RIC qualification and diversification rules promulgated under the 1940 Act and the Code, respectively. While we intend to continue to conduct quarterly tender offers as described above, we are not required to do so and may suspend or terminate the share repurchase program at any time.

Offer Date	Tender Offer Expiration	Tender Offer	Purchase Price per Share	Shares Repurchased
($ in thousands, except share and per share amounts)				
February 28, 2023	March 27, 2023	$ 23,099	$8.90	2,595,339
May 26, 2023	June 26, 2023	$ 36,020	$8.96	4,020,194
August 28, 2023	September 25, 2023	$ 28,144	$9.08	3,099,549
November 27, 2023	December 22, 2023	$ 16,397	$9.03	1,815,787
February 27, 2024	March 25, 2024	$ 60,509	$9.01	6,715,753
May 24, 2024	June 24, 2024	$ 31,358	$9.00	3,484,167
August 26, 2024	September 23, 2024	$ 33,505	$8.85	3,785,909
November 25, 2024	December 23, 2024	$ 38,391	$8.80	4,362,658
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

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Share Repurchases

The Board has complete discretion to determine whether the Company will engage in any share repurchase, and if so, the terms of such repurchase. At the discretion of our Board, the Company may use cash on hand, cash available from borrowings, and cash from the sale of our investments as of the end of the applicable period to repurchase shares. The Company has commenced a share repurchase program pursuant to which the Company intends to conduct quarterly repurchase offers to allow its shareholders to tender their shares at a price equal to the net offering price per share for the applicable class of shares on each date of repurchase. All shares purchased by the Company pursuant to the terms of each offer to repurchase will be retired and thereafter will be authorized and unissued shares.

The Company intends to limit the number of shares to be repurchased in each quarter to no more than 5.00% of its outstanding shares of common stock. Any periodic repurchase offers are subject in part to the Company's available cash and compliance with the BDC and RIC qualification and diversification rules promulgated under the 1940 Act and the Code, respectively. While the Company intends to continue to conduct quarterly tender offers as described above, the Company is not required to do so and may suspend or terminate the share repurchase program at any time.

Figure 8: **LSTA Leveraged Loan 100 Index**.

