Capital Commitments and Private Debt Lending in Crises

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Abstract

I study how capital commitments affect the resilience of private debt funds' lending during crises by comparing private and public Business Development Companies (BDCs) during the COVID-19 shock. Using borrower-level regressions with firm-quarter fixed effects, I find that, in comparison to public BDCs, private BDCs sustained lending, providing about 7%, or $1.2 million, more credit to the same firm. My findings show that pre-committed capital, rather than liquidity buffers, shields private BDCs from financing frictions and enables them to maintain their credit supply when market-based funding is impaired. During crises, private BDCs continue drawing down their commitments to finance investments.

Keywords: Private Debt, Business Development Companies, Crises, Capital Commitments
JEL Classification: G01, G23, G29

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1 Introduction

Over the last decade, the private debt market nearly quadrupled its assets under management (AUM), growing from roughly \$0.5 trillion in 2014 to \$1.8 trillion by the end of 2024. With this rapid expansion, private debt funds have become important financiers of firms underserved by traditional funding sources such as banks (Davydiuk et al., 2024). Especially in the United States, small and middle-market firms rely heavily on private debt for their funding. Given the scale and growing importance of the private debt market, it is important to understand its resilience during periods of economic stress.

Nonbank lenders active in the syndicated loan market have been found to be highly cyclical in their credit supply (Fleckenstein et al. (2025)). Unlike these nonbank lenders, private debt funds rely on a distinct funding structure. They are financed through capital commitments, which provide them with off-balance-sheet equity. What do capital commitments imply for the resilience of private debt lending during crises? Do capital commitments allow private credit funds to sustain lending when fundamentals deteriorate? While the academic literature on private debt is growing, the implications of this reliance on pre-committed capital for private debt funds' lending behavior during crises remain to be empirically investigated.

In this paper, I investigate these questions through the lens of Business Development Companies (BDCs). BDCs are SEC-regulated private debt funds that can be public or private funds. Public BDCs collect equity through public share offerings. Private BDCs rely on capital commitments. Comparing private and public BDCs allows me to isolate the effect of capital commitments on investment behavior and lending resilience during periods of stress. Moreover, since private BDCs function like private debt funds, this setting lets me causally identify effects applicable to the private debt market as a whole.

I implement a difference-in-differences design with firm-quarter fixed effects, comparing the investment behavior of private and public BDCs during the COVID-19 pandemic to the same firms. I use the COVID-19 pandemic as a shock because it induced stress in financial markets, which limited public BDCs' access to equity and made private BDCs' access to committed capital potentially valuable.

My analysis shows that private BDCs, unlike their public counterparts, stabilize the credit supply during economic downturns. I document that, during the COVID-19 pandemic, private BDCs grew their debt investment in a given firm, on average, by 7.2% more than public BDCs. These effects translate to a roughly $750-million-higher total capital allocation by private BDCs compared to public BDCs during the shock period, or $1.22 million per firm.

Investment dynamics are largely driven by investments on the intensive margin and the amendment of existing loans. In particular, term loans extended by private BDCs experienced significant growth in their loan amounts during the crisis. These effects correspond to an additional $0.68 million per term loan. Moreover, private BDCs were also more likely than public BDCs to initiate new firm relationships during the stress period. The results suggest that private BDCs were nearly 33% more likely to make investments in new firms compared to their public counterparts. Overall, however, the number of new entries is small such that the intensive margin effect dominates. Thus, during shock periods, private BDCs especially preserve relationship credit.

Next, I investigate the mechanism behind the investment resilience of private BDCs, testing whether private BDCs' access to pre-committed, undrawn capital enabled them to sustain lending during the stress period. For the test, I regress private BDCs' investment on the interaction between their undrawn capital with a shock-period indicator variable, using two different measures of undrawn capital. The results show that private BDCs with one standard deviation more in undrawn capital invested up to 5.9% more in a firm's debt portfolio during the shock period. Also, the effects are robust to controlling for BDCs' previous-quarter leverage levels.

To further assert the channel, I test whether private BDCs actively draw down their capital or deploy accumulated cash buffers during the crisis instead. Using a local projection, I show that private BDCs' amount of drawn capital continued to increase following the onset of the COVID-19 pandemic. In subsequent tests, I directly compare the effect of undrawn capital with the effect of pre-shock cash buffers on private BDCs' lending during the crisis. I show that private BDCs' access to capital and not their liquidity were the key driver of their investment during the shock period.

In sum, my results corroborate that private BDCs' access to committed but undrawn capital shields them from financial market frictions, unlike public BDCs, which are disadvantaged during market stress. I provide evidence that private BDCs actively deploy their capital, responding to firms' financing needs during crises. Also, my results highlight the value of capital versus liquidity. Capital enables private BDCs to sustain lending during crises, while liquidity does not.

To better understand who receives capital during periods of stress, I investigate the role of information and private equity (PE)-sponsorship. Consistent with Jang (2025), I find that private BDCs mainly lend to PE-backed firms during the shock period. Hence, having a pre-shock PE-backed relationship to a private BDC is particularly valuable to firms. Apart from extending loans, BDCs may also invest in the equity of firms. Equity investments should provide BDCs with additional information about a given firm. I do not find evidence that pre-shock equity investments benefit portfolio firms in obtaining funding during crises. This finding contrasts with Davydiuk et al. (2025), who report that BDCs with simultaneous debt and equity investments invest more in a given firm.

Do BDCs misallocate credit to badly performing firms during crises? Since BDCs mainly invest in private US companies for which no firm data is available, I focus on survival rates and examine the performance of new investments for the last two quarters of my sample period. Only 3.6% of all sample firms went out of business by 2025.

Moreover, my empirical tests show that investments made during the shock performed slightly better than investments made before the shock, without evidence for differential effects between public and private BDCs. Hence, my results do not suggest that BDCs misallocate credit during stress periods.

To assess robustness, I examine the impact of debt constraints on BDC investment during the crisis period. Using two different measures of debt constraints, I estimate triple difference-in-difference regressions. The results provide evidence that debt constraints were not the primary driver of the observed differences in the capital allocation of public and private BDCs during the stress period. Debt constraints apply symmetrically. Both public and private BDCs invest more as debt constraints ease. Furthermore, I do not find evidence that stress-induced asset markdowns drive the differences in investment dynamics between private and public BDCs during the shock, ruling out this alternative mechanism as a driver of BDCs' investment behavior, too.

Taken together, my findings contradict the conjecture that private credit funds exacerbate downturns by lending pro-cyclically. Capital commitments shield private debt funds from shocks and are the key driver of their lending resilience. During crises, when public BDCs' market-based funding is impaired, private BDCs deploy their off-balance-sheet capital. Since private debt funds, and as such BDCs, primarily lend to borrowers that are otherwise financing-constrained, the results highlight the benefits that private debt provides to these firms. Moreover, my results emphasize that, even within the nonbank sector, differences in equity structures shape funds' shock resilience and investment activity. Although private debt funds do not have access to central bank liquidity, their capital commitments can be considered functionally analogous to equity-funded backstops. These backstops enhance the resilience of private debt funds compared to other nonbank lenders.

Existing research on private debt focuses on establishing a general understanding of the market and its unparalleled growth (see, e.g., Aldasoro et al. (2025), Block et al. (2024), Chernenko et al. (2025), Davydiuk et al. (2024), Davydiuk et al. (2025), Haque et al. (2025b), Loumioti (2022), Munday et al. (2018), and Rintamäki and Steffen (2025)). Most of these empirical assessments of private debt rely on BDCs due to data availability. The first papers to emphasize differences in BDCs' organizational structures are Rintamäki (2024) and Haque et al. (2025a). To the best of my knowledge, my work is the first to empirically exploit the difference in public and private BDCs' capital structures and to examine the credit provision of private debt funds during crises, as well as the role of capital commitments therein.

Using public BDCs as the constrained counterfactual, I extend the analysis of Davydiuk et al. (2023), who document the effect of equity constraints on public BDCs. In using COVID-19 as a shock, I also relate to Jang (2025), who finds that direct lenders were more flexible than banks in supporting distressed firms during the COVID-19 pandemic. My analysis demonstrates how capital commitments shape the credit allocation of private debt funds during crises, enabling private BDCs to sustain lending when public BDCs are equity-constrained.

Jang and Rosen (2025) inquire whether private debt funds retrench during downturns but reach no conclusion due to limited empirical evidence. I fill this gap by providing direct evidence that capital commitments make private debt fund lending resilient to crises.

My work also relates to the literature on nonbank financial intermediation and its impact on financial stability (see, e.g., Buchak et al. (2018), Chernenko et al. (2022), Erel and Inozemtsev (2025), and Fleckenstein et al. (2025)). Irani et al. (2021) show that, in the syndicated loan market, nonbanks with fragile funding reduced lending more sharply during the 2008 financial crisis than those with stable funding. Beyond the stability of funding, my work emphasizes the value of capital backstops for the stability of the loan supply, particularly for firms that are typically financing-constrained.

Lastly, I relate to the literature analyzing the funding provision to firms during the COVID-19 pandemic. The literature highlights the role of contingent bank credit as a funding source for firms and assesses the adverse effects on bank health and the aggregate credit supply resulting from the correlated drawdowns of credit lines during the pandemic (see, e.g., Acharya et al. (2024a), Acharya et al. (2024b), Acharya and Steffen (2020), Chodorow-Reich et al. (2022), Greenwald et al. (2025), and Li et al. (2020)). My work emphasizes the resilience and reliability of private debt funds' funding provision during crises, especially to small and non-investment grade firms. Moreover, unlike banks' liquidity provision, I show that private credit fund lending primarily grew through term loans. Also, I show that access to capital, rather than liquidity, was the primary reason for private debt funds' ability to sustain lending during the crisis. This is distinct from the papers showing how the Federal Reserve Bank's liquidity injection stabilized bond markets during the COVID-19 pandemic (see, e.g, Falato et al. (2021), Haddad et al. (2021), and O'Hara and Zhou (2021)).

The remainder of this paper is structured as follows. Section two provides information on private and public BDCs. Section three outlines the empirical strategy and identification. Section four describes the data, sample, and descriptive statistics. Section five presents the main results and investigates the mechanism. Section six examines the properties of BDC investment during crises. Section seven addresses robustness. Section eight concludes.

2 Institutional setting - Private and public BDCs

The following outlines the distinction between public and private BDCs to motivate my empirical setting. I show that private BDCs are an economically meaningful proxy for private debt funds and, in comparison to public BDCs, provide an ideal laboratory to causally infer the effect of capital commitments on private debt lending during crises.

BDCs are US-based investment funds that follow the same investment strategies as direct lending funds, the fastest-growing and largest sub-segment of the private debt market. Like direct lending funds, BDCs' AUM greatly expanded over the last years. Between 2019 and 2024, BDCs' AUM grew from $125 billion in 2019 to $440 billion by 2024. In 2024, BDCs managed assets roughly equal to 70% of the direct lending market.

BDCs can be public or private funds. Like direct lending funds, private BDCs rely on capital commitments. Public BDCs collect equity through public share offerings. I exploit this variation in BDCs' capital structures to identify the effect of capital commitments on private debt lending during crises, using private BDCs as proxy for direct lending funds and public BDCs as the counterfactual.

Like direct lending funds, private BDCs collect capital commitments from institutional investors to establish a fund. During the first three to four years of a BDC's life, the fund managers gradually call on the committed capital to finance their investments. With these capital calls, the managers successively build up the fund's portfolio. This is consistent with the investment period of direct lending funds. Any undrawn but committed capital remains off-balance sheet (dry powder). Private BDCs, like direct lending funds, are closed-end vehicles, and capital commitments are firm.

Conversely, public BDCs are established through an IPO of the fund. The cash collected through the IPO is directly invested, often in an already existing loan portfolio. The build-up of a public BDC's portfolio typically takes less than a year.[1] Public BDCs do not have off-balance-sheet dry powder. All the equity capital collected through the IPO is directly paid into the fund and on the balance sheet.

[1] In recent years, many new public BDCs were private BDCs that went public after allotting all their committed capital. IPO of private BDCs allow their initial investors to cash out.

To illustrate the difference between public and private BDCs, the following describes the growth path and capital structure of one representative private and public BDC. Figure 1 displays the development of the assets and capital stock of Runway Growth Finance Corp., set up as a private BDC, and Great Elm Capital Corp., set up as a public BDC. Both funds registered as BDCs in 2016: Great Elm Capital Corp. in September, and Runway Growth Finance Corp. in December. Great Elm Capital Corp. conducted its IPO in November 2016, while Runway Growth Finance Corp. only went public in October 2021.

In line with the gradual build-up of private debt funds accompanied by capital calls, Runway Growth Finance Corp. grew its capital stock and assets successively over time. Conversely, Great Elm Capital Corp.'s assets and capital stock experienced a strong increase following its IPO in 2016. Thereafter, the capital stock of Great Elm Capital Corp. remained relatively steady. Increases indicate the issuance of new shares.

For both BDCs, the gap between their capital and assets illustrates the use of leverage. The decline in both BDCs' assets in early 2020 illustrates the effect of asset devaluations due to the pandemic.

Before the pandemic, on December 31, 2019, Great Elm Capital Corp. had a leverage ratio of 41%, which was financed by three notes due in 2022, 2024, and 2025. Paid-in capital plus common stock equaled $193 million, or 66% of total assets. Runway Growth Finance Corp. had a leverage ratio of 12% based on its borrowings of $61 million under a $100 million (revolving) credit agreement.[2] Paid-in capital plus common stock totaled $385 million, or 74% of total assets. Because Runway Growth Finance Corp. was a private BDC on December 31, 2019, it also had access to $99.5 million in undrawn capital commitments, equal to 22% of its overall committed capital.[3]

[2] The liquidity was available until May 31, 2022, and matured on May 31, 2024.

[3] The leverage ratio is defined as the percentage share of total debt to total assets. Note that paid-in capital plus common stock is not equal to a BDC's net assets, which account for total distributable earnings/losses.

Per regulation, public and private BDCs must invest 70% of their portfolio in eligible assets. Eligible assets are the debt and equity of small- and medium-sized private or thinly capitalized US firms. Moreover, BDCs must adhere to an asset coverage ratio (ACR) of 200%.[4]

While these regulations are BDC-specific, BDCs and private debt funds have similar portfolios and leverage levels. Both BDCs and private debt funds mainly grant loans, but also invest smaller shares of their portfolios in firm equity or other credit products such as CLOs. Furthermore, the average leverage ratio of US private debt funds is 40% (Block et al. (2024)), and both private debt funds and BDCs utilize long-term, fund-level debt to leverage individual investments.

Thus, using BDCs as a laboratory, with private BDCs functioning like private debt funds and public BDCs serving as the counterfactual, allows me to study private debt funds' capital commitments and causally infer their effect on capital allocation during crises.

3 Empirical strategy

The next two sections describe the empirical setup and identification.

3.1 Empirical setup

The objective of my analysis is to compare the difference in private and public BDCs' investment during a stress period and assess the role of capital commitments therein. To causally identify the effect of crises on BDC lending, I employ a difference-in-difference estimation. I take advantage of the fact that private BDCs operate like private debt funds while public BDCs provide a natural counterfactual.

[4] Since 2018, BDCs may elect to decrease their ACR to 150%. This decision requires approval by the BDC board or shareholders/investors.

As a shock, I use the outbreak of the COVID-19 pandemic in early 2020. The COVID-19 pandemic was an adverse exogenous shock to the economic environment, disrupting economic activity and leading to a sharp increase in uncertainty and stress in financial markets. This stress in financial markets shocked BDCs' access to funding, which I expect to make private BDCs' access to off-balance sheet dry powder valuable.

For the assessment, I focus on BDCs' investment activity between 2019Q1 and 2021Q1. Based on the sequence of events, I consider the first three quarters of 2020 as shocked. The indicator variable $Shock_t$, which is one for 2020Q1, 2020Q2, and 2020Q3, and zero otherwise, captures the period of stress.

Public BDCs, my control group, cannot access pre-committed equity capital. When financial markets are stressed, their market-based funding capacity becomes constrained. Consequently, public BDCs can only reinvest the repayments of existing investments, their cash at hand, or their pre-committed debt in accordance with their leverage constraints.[5] Conversely, private BDCs, my treated group, have recourse to dry powder. Therefore, they should be less affected by the shock and any shock-imposed financial constraint. Their pre-committed capital should shield them from financing frictions and allow them to continue expanding their portfolio. Hence, private BDCs should invest more *in comparison* to public BDCs during the shock, whereby the effect should be a combination of public BDCs' investment being muted and private BDCs having the capacity to continue investing and investing more. Accordingly, I define the indicator variable $Private_b$ as one for private BDCs and zero for public BDCs.

To assess the effect of the COVID-19 shock on BDCs' investment activity, I estimate firm- and asset-level regressions with different measures of capital allocation as the dependent

[5] Public and private BDCs do not hold large sums of excess cash because they must distribute 90% of their taxable income to investors.

variable. At the firm level, the stylized regression is:

$$y_{f,b,t} = \beta Private_b \times Shock_t + \gamma \mathbf{B}_{b,t} + \sigma \mathbf{F}_{f,t} + \theta_f + \tau_b + \eta_t + +\epsilon_{f,b,t} \tag{1}$$

$y_{f,b,t}$ is the measure of capital allocation to firm f by BDC b in quarter t. The BDC-type indicator variable $Private_b$ is one for private BDCs and zero for public BDCs. The shock-period indicator variable $Shock_t$ is one for 2020Q1, 2020Q2, and 2020Q3 and zero otherwise. $\mathbf{B}_{b,t}$ is a vector of time-varying BDC controls for BDC b in quarter t. $\mathbf{F}_{f,t}$ is a vector of time-varying firm controls for firm f in quarter t. θ_f denote firm fixed effects for firm f. τ_b denote BDC fixed effects for BDC b. η_t denote time fixed effects for quarter t. For asset-level estimations, I further include $\mathbf{A}_{a,f,b,t}$, a vector of time-varying asset controls for asset a of firm f invested by BDC b in quarter t, and asset fixed effect for asset a, ζ_a.

At the firm level, the measure of capital allocation is the log portfolio amount of firm f invested by BDC b in quarter t. The portfolio amount is the sum over all assets a of firm f invested by BDC b in quarter t. Hence, $log(I_{f,b,t}) = log(\sum_{a \in A_{f,b,t}} x_{a,f,b,t})$.

3.2 Identification

The identifying assumptions for my empirical strategy are a) the shock is exogenous, and b) public and private BDCs follow parallel trends in the absence of treatment.

With regard to assumption a), COVID-19 was an unanticipated and externally imposed shock. Reversed causality, i.e., that BDCs changed their investment behavior in anticipation of the shock, is no concern in this setting. Also, the constraints imposed by the shock must be exogenous. They cannot derive from BDCs' portfolios or capital structure. This is true, too. COVID-19 led to turmoil in the stock market which shocked public BDCs' access to equity. Private BDCs' capital commitments were left unaffected.

Regarding assumption b), I verify the parallel trend assumption by re-estimating

Equation 1 as event study. For the event study, I use 2019Q4, the last quarter before the COVID-19 shock, as the baseline period. At the firm level, the stylized event study regression becomes:

$$\begin{aligned} y_{f,b,t} &= \sum_{q} \beta_q \left(\text{Private}_b \times 1_{\{t=q\}}\right) + \gamma \mathbf{B}_{b,t} + \sigma \mathbf{F}_{f,t} + \theta_f + \tau_b + \eta_t + \varepsilon_{f,b,t} \\ q &\in \{2019\text{Q1},\ 2019\text{Q2},\ 2019\text{Q3},\ 2020\text{Q1},\ 2020\text{Q2},\ 2020\text{Q3},\ 2020\text{Q4},\ 2021\text{Q1}\} \end{aligned} \tag{2}$$

For the parallel trend assumption to hold, interaction effects for 2019Q1, 2019Q2, and 2019Q3 should not be significantly different from zero. Further, because the stress period lasted only until 2020Q3, the interaction effects for 2020Q4 and 2021Q1 should level off.

To identify the source of the difference-in-difference effect, I decompose the event study from Equation 2 by BDC type, estimating the following stylized regression for public and private BDCs separately:

$$\begin{aligned} y_{f,b,t} &= \sum_{q} \beta_q 1_{\{t=q\}} + \gamma \mathbf{B}_{b,t} + \sigma \mathbf{F}_{f,t} + \theta_f + \tau_b + \eta_t + \varepsilon_{f,b,t} \\ q &\in \{2019\text{Q1},\ 2019\text{Q2},\ 2019\text{Q3},\ 2020\text{Q1},\ 2020\text{Q2},\ 2020\text{Q3},\ 2020\text{Q4},\ 2021\text{Q1}\} \end{aligned} \tag{3}$$

In Equations 2 and 3, all variables are defined as in Equation 1.

The objective of my analysis is to identify BDC supply effects. Because the COVID-19 pandemic not only affected financial markets but also firms, it is important to control for firm-specific demand effects. To mitigate concerns that public and private BDCs select fundamentally different firms that would be differentially affected by COVID-19, I restrict my sample to firms with a public and private BDC relationship throughout the sample period. Moreover, I employ firm-quarter fixed effects following Khwaja and Mian (2008) to absorb all firm-specific variation per quarter, including quarterly firm-specific demand shocks. Firm-quarter fixed effects allow me to isolate supply differences resulting from the different access to capital by private and public BDCs during this stress period. Thus, my results for all estimations employing firm-quarter fixed effects show the difference in capital allocation between public and private BDCs for the *same* firm in the *same* quarter.

Employing firm-quarter fixed effects following Khwaja and Mian (2008) comes with several caveats. First, the approach restricts the sample to firms with multiple lending relationships. These tend to be larger and may not represent the universe of borrowers. Section 4.3 addresses this concern. Second, the design identifies relative supply shifts across BDCs within a firm and quarter. Thus, the results should not be interpreted as direct measures of aggregate credit supply. Third, because the identification relies on within-firm cross-BDC variation, it is important to ensure the appropriate clustering of standard errors and to address potential concerns about measurement error. I cluster my standard errors at the BDC-firm level to account for correlation at the BDC-firm level. With regard to measurement error, to prevent valuation effects from biasing my results, my analyses use investment positions at amortized cost, i.e., the historical cost adjusted for principal repayments and impairments.[6]

4 Data sources, sample, and descriptive statistics

The following sections describe my data sources, the BDC and firm sample, and summary statistics.

4.1 Data sources

I compile a comprehensive dataset containing quarterly fund and investment data. The main data source is BDCs' regulatory filings, primarily their annual and quarterly filings (10-K and 10-Q). They are available on the Securities and Exchange Commission's (SEC)

[6] Note that I also exclude any BDC-firm pair with at least one negative "at cost" item, as I cannot properly interpret the development of these investments.

Electronic Data Gathering, Analysis, and Retrieval (EDGAR) System.

BDCs' annual and quarterly filings contain information on BDCs' balance sheets, income, cash flow, debt financing, and, in the case of private BDCs, capital commitments. Most importantly, BDCs' annual and quarterly filings list their investment portfolios alongside some performance metrics, such as non-accrual rates. The information on the investment portfolio includes the firm name, a BDC-reported industry, and key investment characteristics, such as the fair value or amortized cost of a position, the maturity, spread, or shares invested. Various other regulatory filings provide me, for example, with information on when a BDC registered as such with the SEC.

I complement the information provided by BDCs' regulatory filings with data available on CapitalIQ and PitchBook, which allows me to add information on BDCs' portfolio firms and the BDCs themselves. For instance, Capital IQ provides me with information on BDCs' merger activity and offering history. I use both data sources to obtain information on the IPO and incorporation dates of the funds. Further, I map all BDC portfolio firms to a unique CapitalIQ and PitchBook firm ID. Through PitchBook, I obtain transaction data for BDCs' portfolio firms and a unified industry code.

4.2 BDC sample

My sample contains information for 58 BDCs, spanning the nine quarters between 2019Q1 and 2021Q1. Of these 58 BDCs, 42 are public and 16 are private funds. Total assets of my sample BDCs amount to $\frac{3}{4}$ of total BDC AUM by 2019Q4, or \$87.5 billion. The share of private BDC assets is 16%, which is on par with the actual share private BDCs had of total BDC AUM by 2019Q4.

To be included in my sample, BDCs had to be active throughout the entire sample period. By excluding BDCs that registered or de-registered during my sample period, I intend to prevent effects related to the setup and wind-down of BDCs from biasing my results. Also, I exclude BDCs that conducted an IPO during my sample period, i.e., changed their type. Again, this is to prevent any confounding effects. Finally, I exclude all non-traded BDCs. Non-traded BDCs are BDCs trading on sub-exchanges and with continuous offerings of their shares. Continuous offerings are distinct from capital commitments and traditional public issuances. Therefore, excluding non-traded BDCs ensures that I can clearly identify the effect of capital commitments on BDC lending during crises.

Regarding a potential survivorship bias stemming from the exclusion of BDCs that deregistered after 2019Q4, I review regulatory filings and news articles for these BDCs and find no evidence that any deregistration was caused by the COVID-19 pandemic. Survivorship bias from excluding these BDCs is therefore unlikely.

For all private BDCs, I verify their capital commitments and drawdowns. For all public BDCs, I have information on their IPO date and offering history.

4.3 Firm sample

Between 2019Q1 and 2021Q1, my 58 sample BDCs made 85,600 investments in 4,625 firms. To prevent that firm-specific demand and BDC selection effects drive the results, I constrain my sample to firms that had an investment relationship with at least one public and one private BDC throughout the sample period.

The final sample comprises 805 unique firms, 16.6% of all sample firms. These firms have 28,300 unique investment observations across the nine quarters of the sample period, or 33% of the aggregate sample. Based on the average investment size, the final sample is similar to the non-restricted sample.

In the final sample, 86% of all investments are debt investments and 14% are equity investments. Based on PitchBook's industry classification, most firms in the final sample provide business products or services (27.6%) or are IT firms (26.5%), followed by firms that provide consumer products and services (16.8%) and healthcare firms (16.7%).[7]

4.4 Descriptive statistics

Table 1 displays summary statistics for my public and private sample BDCs for December 31, 2019, and conducts difference in means tests. Panel A shows fund-level characteristics, Panel B provides information on BDCs' portfolios, and Panel C displays investment characteristics.

Public BDCs are substantially older than private BDCs. The mean age of public BDCs is 10.6 years, compared to 2.5 years for private BDCs. Also, private BDCs have, on average and at the median, slightly higher asset valuations. Size (total assets), leverage ratios, net investment income, and dividends paid are not statistically significantly different for public and private BDCs.

At the BDC portfolio level, public BDCs' portfolios at amortized cost are larger than private BDCs' portfolios, reflecting the valuation differences found in Panel A. The summary statistics in Panel B also reveal that the portfolios of public and private BDCs are somewhat differently composed. Private BDCs invest more than 90% in debt. Public BDCs invest, on average, only roughly 78% in debt, 12% in firm equity, and 7% CLO and fund investments, whereby the latter includes joint venture investments in sub-funds.

Portfolio betas for all investments, displayed in Appendix Table A2, indicate that public and private BDCs' portfolios move positively, although not strongly, with the market. The betas of their debt and equity portfolios are not statistically significantly different.

Panel C shows that public BDCs' investments are larger than the investments of private BDCs. The average investment of a public BDC is $9.66 million. The average investment of a private BDC is $6.19 million. On average, firms receive two tranches

[7] Further information on the sectoral composition of BDCs' portfolio can be found in Appendix Table A1.

from a BDC, independent of the BDC type. Aggregating investments at the firm level (undisplayed), the average portfolio size is roughly \$20 million for public and \$13 million for private BDCs. Generally, more than 80% of BDCs' debt investments are floating rate investments, and 4.3% have payment in kind (PIK) components.

Overall, public and private BDCs mainly differ in age, portfolio composition, and investment size. In the following estimations, BDC fixed effects absorb any age effects among BDCs. Also, fundamental differences in portfolio composition and investment size are absorbed by BDC fixed effects. The coefficients of the interaction term are therefore identified from the within-fund changes over time, rather than cross-sectional differences between funds.

5 Main results

As the first step in my analysis, I assess whether public and private BDCs indeed exhibited different investment behaviors during the COVID-19 crisis. The following sections establish the main result at the firm level and address intensive and extensive margin investments at the firm and asset level. As the second step, I investigate the mechanism, assessing how access to undrawn committed capital drove the lending of private BDCs during the crisis.

5.1 Aggregate portfolio developments

Figure 2 displays the growth of public and private BDCs' combined debt and equity portfolio. The solid line shows the aggregate public BDC portfolio scaled by its 2019Q4 value. The dashed line shows the aggregate private BDC portfolio scaled by its 2019Q4 value.

Until the onset of the COVID-19 pandemic, the portfolios of public and private BDCs expanded. The growth rate of public BDCs was substantially smaller than the growth rate of private BDCs, but much larger in absolute terms when considering the average size of public BDCs. With the onset of the pandemic, the growth of public BDCs' portfolios notably deteriorated and contracted as of 2020Q2. Conversely, private BDCs continue to expand their portfolio, although their growth rate also slightly flattened as of 2020Q2.

Next, I formally test whether private BDCs invested more than public BDCs during the COVID-19 crisis. I estimate BDC-firm-level regressions in line with Equation 1 but using BDC and firm-quarter fixed effects. The log portfolio amount of firm f invested by BDC b in quarter t is the dependent variable. Table 2 displays the results. In column (1), the firm portfolio aggregates debt and equity investments. In column (2), the firm portfolio only aggregates debt investments, and in column (3), the firm portfolio only aggregates equity investments.

To absorb firm-specific variation in a given quarter, the regressions include firm-quarter fixed effects. All regressions control for the number of assets invested by BDC b in firm f in the previous quarter $t-1$ to control for the intensity of the BDC-firm relationship. Also, the regressions account for whether a BDC acquired another BDC in a given quarter using the indicator variable $Acquisition_{b,t}$, which is one if a BDC acquired another BDC in a given quarter and zero otherwise.

The results provide evidence that private BDCs supplied more capital to the same firms during the COVID-19 shock than public BDCs, and that this capital was mainly supplied through debt investments. The coefficients in columns (1) and (2) indicate that private BDCs grew their investment, on average, by 7.2% more than public BDCs during the stress period. Both effects are statistically significant at the 1% level with similar test statistics. Also, the coefficients of column (1), for the aggregate portfolio, and column (2), for the debt portfolio, are equivalent. Conversely, the effect for firms' equity portfolio is only 1.4% and statistically insignificant. The effects are thus debt-driven. In economic terms, based on the average BDC-firm debt portfolio of \$16.9 million, the effects suggest that private BDCs supplied \$1.22 million more debt to the same firm than public BDCs during the shock.[8]

To assess the parallel trend assumption, Figure 3 Panel A presents event study plots based on estimations in line with Equation 2 but using BDC and firm-quarter fixed effects. The figure shows that for the aggregate and debt portfolio, the parallel trend assumption for public and private BDCs holds. Following the shock, the difference-in-difference coefficients increase in magnitude and become statistically different from zero. Consistent with the recovery of financial markets by the end of 2020Q3, the effects begin to taper off.

Panel B decomposes the effect for the debt portfolio by BDC type to understand the source of the effect, estimating a regressions as displayed in Equation 3 but using BDC and firm fixed effects. Again, the graph confirms parallel trends pre-shock. In line with public BDCs' being constrained by the shock, public BDCs' growth rates are smaller or similar to the 2019Q4 growth rate following the onset of the COVID-19 pandemic. Conversely, private BDCs increased their growth rates following the shock. Hence, a combination of more debt investments by private BDCs and slightly negative but mainly unchanged growth rates by public BDCs drive the positive difference-in-difference effect found in Table 2. The decomposition suggests that private BDCs actively took advantage of new investment opportunities, scaling up their portfolios during the shock.

5.2 Intensive and extensive margin lending

The following sections examine the extensive and intensive margin lending to understand who benefits from the capital supplied by private BDCs during the shock.

[8] Appendix Table A3 re-estimates column (2), including additional control variables. The result does not change.

5.2.1 Intensive margin lending

To analyze the intensive margin lending by public and private BDCs during the COVID-19 pandemic, I focus on the provision of capital to firms that were in BDCs' portfolios at least in the last quarter pre-shock (2019Q4) and the first shock quarter (2020Q1). I examine the development of BDC-firm portfolios and individual assets provided by a BDC to a firm in a given quarter. Table 3 Panel A displays the regression results. Column (1) displays the results for a regression with the log portfolio amount of firm f provided by BDC b in quarter t as the dependent variable. Columns (2) and (3) display the results of regressions with individual assets as the dependent variable. These regressions look at the growth of asset a in the portfolio of firm f provided by BDC b in quarter t. Since the results are debt-driven, the estimations focus on debt investments only.

One challenge with regard to asset-level estimation is that my dataset does not include asset-specific IDs. I can neither trace the development of the exact asset nor include asset fixed effects. Therefore, I scale asset-level investments by the BDC-firm-specific 2019Q4 portfolio such that the dependent variable is defined as follows:

$$I_{\text{Asset}_{a,f,b,t}} = \frac{I_{a,f,b,t}}{\sum_a I_{a,f,b,\text{2019Q4}}}$$

This definition anchors asset values to the benchmark of a BDC's pre-shock exposure to a firm, allowing me to assess the growth of the asset relative to the relationship baseline.

Moreover, as BDC assets are small, log transformations can overemphasize changes in the asset amount, inflating residual variance and reducing statistical power. Scaled values do not exhibit this problem. Figure A1 in the Appendix displays the distribution of logged and normalized values for public and private BDC assets, corroborating this presumption.[9]

As in previous regressions, all estimations in Table 3 control for the intensity of a

[9] For more information see Section 12.1 in the Appendix.

BDC-firm relationship by including the lagged number of assets per relationship in the previous quarter, and for acquisitions by including the indicator variable $Acquisition_{b,t}$. At the portfolio level, I further control for PIK loans in firms' portfolios in a given quarter as PIK components lead to a capitalization of interest rates. At the asset level, I control for asset characteristics. By using asset-specific indicator variables I account for whether an asset had a PIK component or was a floating rate instrument. In the asset-level regressions, I also include granular asset-type fixed effects.

The result in column (1) provides evidence for a strong intensive margin effect at the debt portfolio level. The coefficient suggests that, on average, private BDCs invested 7.4% more in their existing portfolio firms than public BDCs during the COVID-19 shock.

At the asset level, the estimate in column (2) suggests that private BDCs grew individual debt investments by 4.25 pp compared to public BDCs during the shock. The coefficient is statistically significant at the 1% level. For term loans, the effect increases to 5.36 pp, and the t-statistic increases too. These results suggest that private BDCs extended their intensive margin lending mainly through term loans. In dollar amounts, given the average term loan size of \$12.7 million, the results suggest that private BDCs allotted roughly \$680,000 more to an individual asset than public BDCs during the period of stress.

Did the intensive margin lending occur through the amendment of existing loans or the issuance of new loans? Table 3 Panel B shows the result of a Poisson regression investigating this question. The dependent variable is the number of debt investments, or debt assets, provided to firm f by BDC b in quarter t. The explanatory variables are equivalent the Panel A column (1).

The coefficient of the interaction term, although statistically significant at the 10% level, does not corroborate the presumption that private BDCs extended more new tranches to their borrowers than public BDCs during the shock. The coefficient of the interaction term $Private_b \times Shock_t$ is very small and negative, suggesting that the number of private BDC investments in a given firm declined by 0.012 during the shock period. The negative sign of the coefficient might be due to a small number of maturing investments.

Taken together with the results in Panel A, the Poisson regression indicates that private BDCs provided their funding by amending existing investments. Also, because portfolio-level coefficients exceed asset-level coefficients, it appears that some, but not all, firm-specific loans were amended.

5.2.2 Extensive margin lending

When assessing the formation of new BDC-firm relationships, I face a potential selection bias related to the timing of relationship formation. To address this potential bias, I restrict the sample to firms that a) had an existing BDC relationship before 2020Q1, and b) formed at least one new BDC relationship after 2019Q4. For these firms, I construct a BDC-firm-quarter panel with eight observations per BDC-firm pair, spanning 2019Q2 to 20201Q1. I exclude 2019Q1 from the panel because I cannot distinguish between new and existing relationships for this quarter.

The subsample panel allows me to assess who was more likely to enter a given firm during the shock period, a public or a private BDC. I define an indicator variable $Entry_{f,b,t}$, which is one for the quarter in which a new BDC-firm relationship was established, and zero for all other seven quarters. The unconditional probability of entry is thus 12.5%. The subsample contains 385 out of 805 sample firms.

Using the indicator variable $Entry_{f,b,t}$ as the dependent variable, I estimate a linear probability model at the BDC-firm level. Table 4 displays the results. Acquisitions of other BDCs mechanically generate new BDC-firm relationships that appear as new entries even though they do not reflect active investment decisions. To prevent confounding effects, in column (1), I control for acquisitions in a given quarter using the same indicator variable as in previous tests. Because the indicator variable might be limited in its ability to absorb acquisition-driven noise, I exclude acquiring BDCs in column (2). Again, firm-quarter fixed effects absorb any unobserved, time-varying firm characteristics that might affect BDCs' entry decision. Hence, the identification of the effect relies solely on cross-sectional variation in the entry behavior across fund types, conditional on a firm's specific state in a given quarter.

Column (1) indicates that private BDCs have a 2 pp higher probability of entering a new firm relationship during the stress period than public BDCs. Yet, the coefficient is statistically insignificant. When excluding acquiring BDCs in column (2), the effect size doubles to 4.1 pp and becomes statistically significant at 5% level. The stark change in the coefficient size and statistical significance suggests that the indicator variable $Acquisition_{b,t}$ is indeed unable to capture the effect of BDCs acquiring other BDCs in this specification.

Compared to the unconditional mean probability of entering a new firm relationship, the effect size in column (2) amounts to a near 33%-higher probability of private BDCs lending to a new firm compared to public BDCs during the shock.

5.3 Mechanism

In this section, I assess the mechanism behind the differences in private and public BDCs' investment dynamics during the COVID-19 crisis. Precisely, I first test the hypothesis that access to off-balance-sheet capital led private BDCs to invest more in their portfolio firms during the shock. Then, I assert the channel by analyzing whether private BDCs sustained lending through actively drawing down their capital or by deploying accumulated cash buffers.

5.3.1 Investment and access to dry powder

During the COVID-19 pandemic, public BDCs were constrained in their ability to issue new shares as market turmoil made share issuances infeasible or prohibitively expensive. For example, the net asset value of SLR Investment Corp. was $19.24 per share on March 31, 2020, but the BDC's stock only traded at $11.64 per share at market closing. Issuing shares would have implied a 40% discount. Conversely, private BDCs had access to committed off-balance-sheet dry powder. The average percentage share of undrawn committed capital to total committed capital was 36% as of December 31, 2019. Compared to their total assets, private BDCs even had an average of 47% of committed but undrawn capital outstanding.[10]

To test my hypothesis, I conduct subsample tests for all private BDCs. Table 5 displays the results. For the estimations, I use two continuous measures of BDC dry powder as of 2019Q4, and interact these measures with the shock- period indicator variable $Shock_t$. The first measure, $Undrawn_{b,2019Q4}$, is defined as the percentage share of undrawn committed capital to the total commitment amount on December 31, 2019. The second measure, $Undrawn_{b,2019Q4}/Assets_{b,2019Q4}$, is defined as the percentage of the undrawn commitment amount to total BDC assets as of December 31, 2019. Both measures are standardized to a mean of zero and a standard deviation of one.

Because the tests rely on private BDC observations only, firm-quarter fixed effects now provide estimates only for firms with at least two private BDC relationships per quarter. Hence, the interaction effect shows the difference in investment by private BDCs with more versus less available dry powder to the *same* firm. Because the objective of the analysis is to generally understand whether dry powder lets private BDCs invest more during crises, I use industry-quarter fixed effects in the estimations instead. Industry-quarter fixed effects absorb all industry-specific variation in a given quarter, controlling

[10] Appendix Table A4 provides summary statistics for private BDCs' undrawn committed capital on December 31, 2019.

for industry-specific firm demand. To control for time-invariant firm characteristics, I add firm fixed effects separately. In these estimations, the coefficient of the interaction term thus signifies the mechanism in general. It indicates how much a private BDC with one standard deviation more dry powder invested during the shock period compared to the average private BDC, controlling for industry-specific demand and time-invariant differences between firms. Columns (5) and (6) display the results for the most parsimonious estimations with firm-quarter fixed effects, examining investments in the *same* firm.

The estimations control again for the intensity of a BDC-firm relationship in the previous quarter. Also, to control for potential leverage effects, columns (3) to (6) control for a BDC's previous-quarter leverage. I do not need to control for acquisitions as private BDCs do not acquire other BDCs during my sample period. Again, I focus on the debt portfolio of firms.

Testing the mechanism in general, columns (1) to (4) provide evidence corroborating that private BDCs with more undrawn committed capital invest more during shocks. Precisely, the estimations suggest that private BDCs with a one standard deviation larger share of dry powder invested between 3.0% and 5.8% more in a firm's debt portfolio during the shock compared to the average private BDC. For both measures of undrawn capital, the coefficients are statistically significant at the 1% and 5% level. The effects and their statistical significance are smaller when controlling for firm fixed effects alongside industry-quarter fixed effects in columns (3) and (4). This suggests that time-invariant firm-specific variation absorbs important variation in private BDCs' investment during the crisis.

Columns (5) and (6) examine the investment of private BDCs with more versus less undrawn committed capital to the *same* firm during the shock. The effect in column (5) indicates that private BDCs with a one standard deviation larger undrawn share of total commitments invested 4.3% more during the shock than the average private BDC. The effect in column (6) indicates that private BDCs with a one standard deviation larger undrawn share of committed capital to total assets invested 5.9% more during the shock than the average private BDC. Yet, only the effect for the second measure is statistically significant (column (6)).

The first measure in column (5), the undrawn share of total commitments, only indicates the remaining fraction of capital to be drawn. The second measure in column (6), the undrawn share of committed capital to total assets, benchmarks the remaining undrawn capital to a private BDC's total assets, implicitly measuring the economic potential of the undrawn capital. Hence, the absence of statistical significance for the first measure, the undrawn share of total committed capital, suggests that when it comes to which of two private BDCs lends to a given firm, the economic potential of the undrawn capital matters.

For all estimations, lagged leverage has no statistically significant effect on private BDC lending, suggesting that the effect of undrawn committed capital on private BDC lending is robust to leverage effects.

Taken together, the results in Table 5 provide evidence that undrawn committed equity enabled private BDCs to sustain lending during the COVID-19 shock.

5.3.2 Capital versus liquidity

The previous tests showed that private BDCs with more undrawn capital invested more during the crisis. To assess through which channel this undrawn capital enables private BDCs to sustain lending, I test whether private BDCs actively draw down their capital or deploy accumulated cash buffers made possible by these commitments.

First, I examine the development of drawdowns in the quarters following the shock using a local projections framework along the lines of Jordà (2005). I estimate the following local projection to assess the evolution of the drawn capital in comparison to the baseline quarter of 2019Q4:

$$Drawn\ Amount_{b,h} = \beta_h\ Drawn\ Amount_{b,2019Q4}\ +\ \mathbf{X_{b,2019Q4}} + \epsilon_{b,h} \tag{4}$$

$Drawn\ Amount_{b,h}$ is the amount of drawn committed capital by BDC b in a given quarter with $h \in \{2020Q1, 2020Q2, 2020Q3, 2020Q4, 2021Q1\}$. $Drawn\ Amount_{b,2019Q4}$ is the amount of drawn committed capital by BDC b in 2019Q4. $\mathbf{X_{b,2019Q4}}$ is a vector of BDC control variables for BDC b in 2019Q4. The vector of BDC control variables includes the founding year, the level of leverage, the cash share, the log amount of total assets, the portfolios' Herfindahl-Index, and the number of portfolio firms.

The coefficient β_h captures the persistence of one dollar of drawn committed capital in 2019Q4 for the h quarters thereafter. $\beta_h > 1$ implies that capital drawdowns are not only persistent but that private BDCs increase their drawn committed capital relative to the 2019Q4 level. Coefficients that are larger than one would be consistent with additional capital calls during the shock. Table 6 displays the results.

Each quarter's β is larger than one, and the coefficients increase as time progresses. The results of the local projection thus corroborate that private BDCs continue to draw down their committed capital following the onset of the COVID-19 pandemic.

Second, to show that undrawn committed capital and not cash allowed private BDCs to invest during the crisis, I re-estimate the equations from Table 5 using the measure $Undrawn_{b,2019Q4}/Assets_{b,2019Q4}$ and additionally include cash measures. Table 7 shows the results. Columns (1) and (2) control for the lagged cash share. Columns (3) and (4) include the interaction of the shock-period indicator variable $Shock_t$ with the pre-shock cash share of a private BDC. The pre-shock cash share is defined as a BDC's cash share on December 31, 2019. The estimations in columns (3) and (4) thus directly compare the effect of BDCs' access to undrawn capital and the effect of BDCs' cash buffers on their investment during the crisis. Because I am interested in the general channel, I focus on the estimations including firm and industry-quarter fixed effects. Again, all continuous variables are standardized to a mean of zero and a standard deviation of one.

The effect of private BDCs' access to undrawn committed capital on their investment during the shock appears to be robust to BDCs' cash holdings. When controlling for the lagged level of cash, in columns (1) and (2), the coefficients of the interaction term $Shock_t \times Undrawn/Assets_{b,2019Q4}$ barely change. In the direct comparison of the effect of BDCs' access to undrawn capital and the effect of BDCs' cash buffers, the estimations in columns (3) and (4) show that undrawn committed capital and not cash buffers let private BDCs sustain their debt investments during the crisis. The coefficients of the interaction term $Shock_t \times Undrawn/Assets_{b,2019Q4}$ increase slightly in magnitude and retain their statistical significance. One additional standard deviation of undrawn committed capital increases private BDCs' debt investments between 3.5% and 6.3% during the crisis. Conversely, the interaction term $Shock_t \times Pre\text{-}shock\, cash_{b,2019Q4}$ is not only statistical insignificance and also very small.

Taken together, my estimations corroborate that private BDCs invested more during the crisis due to their access to undrawn committed capital rather than cash buffers accumulated pre-shock. These results also highlight the value of capital versus liquidity. Capital enables private BDCs to scale up their portfolio, even during crises. Liquidity does not have the same effect. Hence, capital is the channel through which private BDCs stabilize the credit supply in crises, not liquidity.[11]

[11] Appendix Table A5 extends the estimations to test for the effect of debt liquidity versus cash liquidity versus undrawn committed capital. The results provide further evidence that neither liquidity from cash holdings nor liquidity from credit lines enables private BDCs to lend during the crisis, supporting that access to capital is the main driver of the results.

6 Properties of BDCs' credit allocation during crises

The following two sections examine the properties of BDC investments made during the COVID-19 shock. First, I study which firms BDCs invest in during crises. Second, I assess investment performance to understand if BDCs misallocate credit during shocks.

6.1 Who receives capital?

Which borrowers benefit from private BDCs' investment during the crisis? This section investigates which intensive-margin borrowers received additional debt. Table 8 displays the results.

One possibility is that BDCs allocate more capital to firms where they have an informational advantage. I measure the informativeness of a BDC-firm relationship by whether a BDC had an equity investment in a firm on December 31, 2019. Equity stakes make BDCs owners of firms and should provide them with additional information, allowing them to make more informed investment decisions. To test this hypothesis, Table 8 Panel A shows the results of a triple difference-in-difference estimation interacting $Private_b$, $Shock_t$, and the indicator variable $Equity_{b,f,t}$. $Equity_{b,f,2019Q4}$ is one if BDC b had an equity investment in firm f in 2019Q4. BDCs have simultaneous debt and equity investments in roughly 20% of all sample firms.

Contrary to the idea that equity investments provide private BDCs with an information advantage, leading them to invest more during the shock period, the estimation in column (1) does not provide evidence supporting this conjecture. The coefficient of the interaction term $Private_b \times Shock_t \times Equity_{b,f,2019Q4}$ is small, statistically insignificant, and negative. Also, the interaction term $Shock_t \times Equity_{b,f,2019Q4}$, although not small, is statistically insignificant.

To better understand the coefficient of the triple interaction term, I split the sample into BDC-firm pairs with equity investments and without (columns (2) and (3)) and estimate a difference-in-difference regression. For the BDC-firm pairs without an equity investment (column (3)), the difference-in-difference coefficient is similar to the main effect found in Table 2. This suggests that, in the absence of additional information, private BDCs generally invest. Conversely, for BDC-firm pairs with an equity investment (column (2)), the coefficient is smaller (4.3%) and statistically insignificant. This result can be considered as BDCs making more informed investment decisions during crises when additional information is available to them, investing in some cases but not in others.

Overall, the results suggest that equity investments do not provide firms with an advantage in securing capital during periods of stress. This is inconsistent Davydiuk et al. (2025), who find that BDC-firm pairs with debt and equity investments ("dual holders") benefit from more debt, especially from their dual-holder BDCs.

Another possibility is that the backing by private equity (PE) firms is important for whether firms receive additional funds during crises. Jang (2025) showed, for instance, that PE-sponsorship positively predicted a higher credit supply by private debt funds when borrowers are distressed during the COVID-19 pandemic. Table 8 Panel B displays the results of a triple difference-in-difference regression, testing whether private BDCs mainly invest in PE-backed firms during crises. Here, the third indicator variable is the indicator variable $PE\text{-}Backed_{f,2019Q4}$ which is one if a firm experienced a buyout or PE growth transaction within five years before the outbreak of the COVID-19 pandemic and zero otherwise. Roughly 75% of all sample firms were backed by PE funds before the onset of the pandemic.

In column (1), the baseline effect of $Private_b \times Shock_t$ becomes nearly zero and is statistically insignificant. The effect is now absorbed by the coefficient of the triple interaction term, which is large in size (9.4%) but its t-statistic is just below the critical threshold for statistical significance. To assess the absorbed variation, I split the sample by PE- and non-PE-backed firms and re-estimate the model as a difference-in-difference specification. Columns (2) and (3) show the results. The estimations corroborate that, consistent with Jang (2025), private BDCs provided more funding to PE-backed firms than public BDCs during the stress period (column (2)). For non-PE-backed firms, there is no evidence for a differential effect during the shock period. The coefficient in column (3) is statistically insignificant and small. In sum, these results underline the importance of PE-backing in receiving private BDC capital during crises.

6.2 Investment performance

Do BDCs invest in poorly performing firms during stress periods? Like private equity funds, private debt funds, and as such BDCs, mainly invest in private US companies for which no firm data is available. To overcome this problem, I first examine the survival rate of BDCs' portfolio firms using PitchBook data. Thereafter, I assess the performance of all new BDC-firm relationships made during the sample period.

Regarding firm survivorship, I obtain PitchBook transaction data for the period from 2021 to mid-2025. Transaction information is available for 80% of all sample firms. The data suggests that only 3.6% of all portfolio firms went out of business until mid-2025. Hence, there is no strong evidence that BDCs financed poorly performing firms.

Next, I assess the performance of new BDC-firm relationships toward the end of my sample period empirically. As dependent variable, I use the fair value-to-cost ratios ($\frac{I_{FV}}{I_C}$) of firms' debt portfolios in 2020Q4 and 2021Q1. Fair value-to-cost ratios measure the mark-ups or discounts on a portfolio's value relative to its cost. Higher ratios indicate stronger performance. For symmetry in the value changes, I log-transform the ratios. The test regresses the performance measure on an issuance-period indicator variable interacted with a BDC-type indicator variable. The issuance-period indicator variable,

$Issued\, Shock_{f,b,t}$, is one if a BDC-firm relationship was established during the shock with $t \in \{2020Q1,\ 2020Q2,\ 2020Q3\}$, and zero if the relationship was established before. New relationships in 2020Q4 and 2021Q1 are omitted from the estimations. The estimations further control for the entry valuation of a new BDC-firm relationship. Table 9 displays the results.

The estimations do not provide evidence that BDCs invested in worse-performing firms during the shock compared to before. The coefficient of the interaction term is not statistically significant and very small. Rather, based on the coefficient of the indicator variable $Issued\, Shock_{f,b,t}$ in column (1), the results suggest that investments made by public and private BDCs during the stress period generally performed better than investments made before the crisis. The effect size of the indicator variable $Issued\, Shock_{f,b,t}$ is large, at 5.4%, and highly statistically significant.

Lastly, Section 6.1 indirectly shed light on the question of credit misallocation. The results in Table 8 Panel A are contrary to the intuition that private BDCs invest to preserve their equity stake, potentially misallocating credit.

Overall, my findings suggest that there is no evidence to support the notion that BDCs misallocate credit to poorly performing firms during crises.

7 Robustness

The following sections assess the robustness of my results to debt constraints and portfolio devaluations.

7.1 Debt constraints

By regulation, public and private BDCs are constrained in their ability to use leverage by an ACR. By default, BDCs have a 200% ACR, or a 50% leverage ratio.[12] ACRs decline with the fair value of BDCs' assets, increasing BDC leverage. Hence, asset devaluations due to COVID-19 constrained BDCs in their ability to use leverage without incurring additional debt.

To assess the effect of debt constraints on BDCs' investment during the shock period, I construct two measures of debt constraints. The first measure builds on BDCs' ACRs. Using the regulatory and actual ACR of a BDC on December 31, 2019, $Distance\,ACR_{b,2019Q4}$ is defined as the distance between a BDC's regulatory and actual ACR in pp:

$$Distance\,ACR_{b,2019Q4} = ACR_{b,2019Q4} - Limit_{b,2019Q4}$$

whereby $Limit_{b,2019Q4} \in \{150, 200\}$. As $Distance\,ACR_{b,2019Q4}$ increases (decreases), BDCs become less (more) debt-constrained.

As a second measure, I focus on the actual usable liquidity of BDCs going into the shock period. For the measure, I first calculate the maximum debt amount a BDC can incur as of December 31, 2019, based on BDCs' regulatory and actual ACRs ($Possible\,debt_{b,2019Q4}$). Then, I divide the maximum debt amount by the amount of undrawn credit lines as of 2019Q4 ($Undrawn_{b,2019Q4}$). The resulting measure is defined as follows:

$$Usable\,liquidity_{b,2019Q4} = \frac{Possible\,debt_{b,2019Q4}}{Undrawn_{b,2019Q4}}$$

As $Usable\,liquidity_{b,2019Q4}$ increases (decreases), BDCs become less (more) debt-constrained.[13]

[12] BDCs may elect to lower their ACR to 150%, or increase their leverage ratio to 67%. Lowering the ACR is subject to either board approval with a waiting period of 12 months, or BDCs can seek shareholder approval, upon which the change takes effect immediately. Increases in BDCs' debt capacities during the shock period would have an attenuating bias on my estimates, working against my hypothesis.

[13] Note that some BDCs do not use debt or only rely on SBA debentures, which are exempt from the

For the empirical tests, I interact each measure with the BDC-type and shock-period indicator variable for triple difference-in-difference estimations.

As of December 31, 2019, the average distance to a BDC's ACR was 163.56 pp, and the average usable liquidity of a BDC was 131.59%. Difference in means tests displayed in Appendix Table A6 do not provide evidence for statistically significant differences in public and private BDCs' averages for both measures. This suggests that public and private BDCs entered the pandemic with similar debt constraints.

Both BDC types should be, on average, equally debt-constrained by the COVID-19 shock. The interaction effect of $Shock_t$ and the constraint measure should be positive and statistically significant, capturing the general effect of less stringent debt constraints on public and private BDCs' investment during the shock period. As there should be no differential effect for private BDCs, the triple interaction term should be economically small and statistically insignificant. Because the difference in public and private BDCs' investment during the shock should not be driven by debt constraints, the magnitude and statistical significance of $Private_b \times Shock_t$ should neither drop in its economic size nor in its statistical significance.

Table 10 displays the results. The estimations provide evidence that the difference in public and private BDC investment during the shock period is robust to and not driven by debt constraints. For both measures, the economic magnitude of $Private_b \times Shock_t$ increases to 9.3% and 10%, respectively. The coefficients remain statistically significant at the 1% level. As conjectured, the triple interaction effects are comparably small and statistically insignificant. The interaction terms of the shock-period indicator variable and the measures of debt constraints are positive and statistically significant at the 1% and 5% level. These results corroborate that debt constraints affect public and private BDCs equally. Both BDC types invest more as these constraints ease. Precisely,

ACR. Ergo, these BDCs do not have an ACR and would be excluded from certain ACR-based tests.

one standard deviation more usable liquidity increases BDCs' investment by 4% during the shock period. Finally, the effects of debt constraints are smaller than the effect of $Private_b \times Shock_t$. This supports that debt constraints are not the key driver of the differences in BDCs' lending during the COVID-19 stress period.

7.2 Devaluations of portfolio assets

Apart from lowering BDCs' ACRs, the devaluation of BDCs' portfolio assets during the COVID-19 crisis might have stressed BDCs' balance sheets, preventing them from investing. If public BDCs were more affected than private BDCs, this might be an alternative mechanism driving the results. I assess this concern in Table 11.

To study the effect of asset devaluations on BDCs' investment, I construct two different triple difference-in-difference regressions. In column (1), I add a devaluation indicator variable to the interaction term of $Private_b \times Shock_t$. The indicator variable is one if a BDC's 2020Q1 portfolio devaluation is in the top quartile within its type, and zero otherwise. Distributions are computed separately by BDC type to capture more variation. In column (2), I use BDCs' portfolio devaluations in 2020Q1 as a continuous measure. The measure is standardized to a mean of zero and a standard deviation of one. Because my measures of devaluation rely on 2020Q1 data, I adapt the shock-period indicator variable to be one only for 2020Q2 and 2020Q3, and zero otherwise ($Shock2_t$).[14]

If devaluations were to drive the results, the triple interaction effect should be large and statistically significant.

Both estimations provide evidence that the effect of $Private_b \times Shock2_t$ is robust to portfolio devaluations. The baseline effect of $Private_b \times Shock2_t$ increases to 8.4% and 10%, respectively. Conversely, both coefficients for the triple interaction effect are small, around -1%, and statistically insignificant.[15] The same is true for the interaction term of

[14] For both devaluation measures, the calculations use BDCs' portfolio at fair value.

[15] A negative sign would be expected. Strong devaluations should decrease BDCs' investments.

the shock-period indicator variable and the respective devaluation measure.

Taken together, the tests do not provide evidence for the assumption that portfolio devaluations are the key reason for the differences in public and private BDCs' capital allocation during the shock period.

8 Conclusion

I examine the resilience of private debt funds' lending during crises and the role of capital commitments therein. Due to access to undrawn committed capital, I find that private debt funds can sustain lending when market-based funding is impaired, thereby stabilizing the credit supply.

To causally identify private debt funds' lending during crises and the effect of capital commitments, I compare the investments of public and private BDCs during the COVID-19 pandemic. Using borrower-level regressions with firm-quarter fixed effects, I show that private BDCs invest approximately 7% more in the same firms than public BDCs. The effects are economically large. Compared to public BDCs during the shock, private BDCs invest roughly \$1.22 million more in a given firm. Examining extensive and intensive margin lending, my tests show that private BDCs allocated most funding toward borrowers with existing relationships. The establishment of new lending relationships is less pronounced. Investments are debt-driven and made through the amendment and extension of existing loans.

Using different measures of private BDCs' committed but undrawn capital, the results corroborate that access to off-balance sheet capital shields private BDCs from financing frictions and enables them to sustain lending. Tests show that continued drawdowns of committed capital, rather than pre-shock accumulated cash buffers, are the key driver of private BDCs' lending during crises. Moreover, my regressions provide evidence that private BDCs actively deploy their capital, responding to firms' financing needs during crises.

Tests to understand the properties of private BDCs' investment show that especially firms backed by PE funds benefit from private BDC lending during crises. Further, investigating investment performance, I do not find evidence that private BDCs misallocate capital by investing in worse-performing firms.

An important concern is whether my results arise due to debt constraints or asset devaluations rather than private BDCs' access to undrawn committed capital. For robustness tests, I construct different measures of BDCs' debt constraints and portfolio devaluations. The results of my tests show that neither BDCs' debt constraints nor their portfolio devaluations drive the difference in investment dynamics between public and private BDCs during the COVID-19 crisis, ruling out both alternative mechanisms.

My findings show that, unlike other nonbank lenders, private debt funds do not pull back from lending during crises. Their undrawn capital shields them from market frictions, enabling them to provide a stable supply of credit to firms. Provided that private debt funds have become a major funding source of small and mid-sized firms, which are often constrained in their access to financing, my results highlight the benefit of receiving credit from private debt funds to these firms. Furthermore, my results emphasize that capital commitments are functionally analogous to equity-funded backstops. They enhance the resilience of private debt funds compared to other nonbank lenders during crises.

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10 Figures

Figure 1: BDC build-up by type

The figure displays the quarterly development of total assets and total capital, defined as common stock plus paid-in capital, in million USD for two BDCs. Runway Growth Finance Corp. is a private BDC, and Great Elm Capital Corp. is a public BDC. The short-dashed vertical lines indicate the BDCs' SEC-registration dates. The vertical short-dashed-dotted lines indicate the BDCs' initial public offering (IPO) dates.

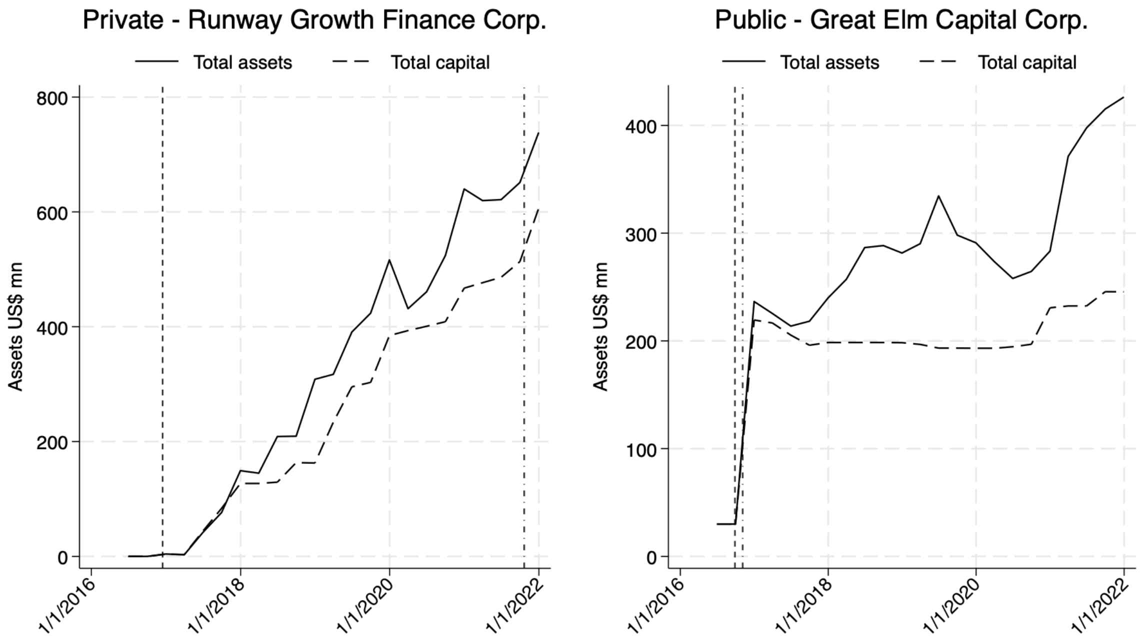


Figure 2: Growth of public and private BDCs' portfolios

The figure displays the aggregate portfolio of public and private BDCs by quarter. Aggregate values are defined as the sum of all debt and equity assets at cost by BDC type. Each quarterly aggregate value is scaled by the corresponding value as of December 31, 2019. The solid line shows the aggregate portfolio for public BDCs. The dashed-dotted line displays the aggregate portfolio of private BDCs.

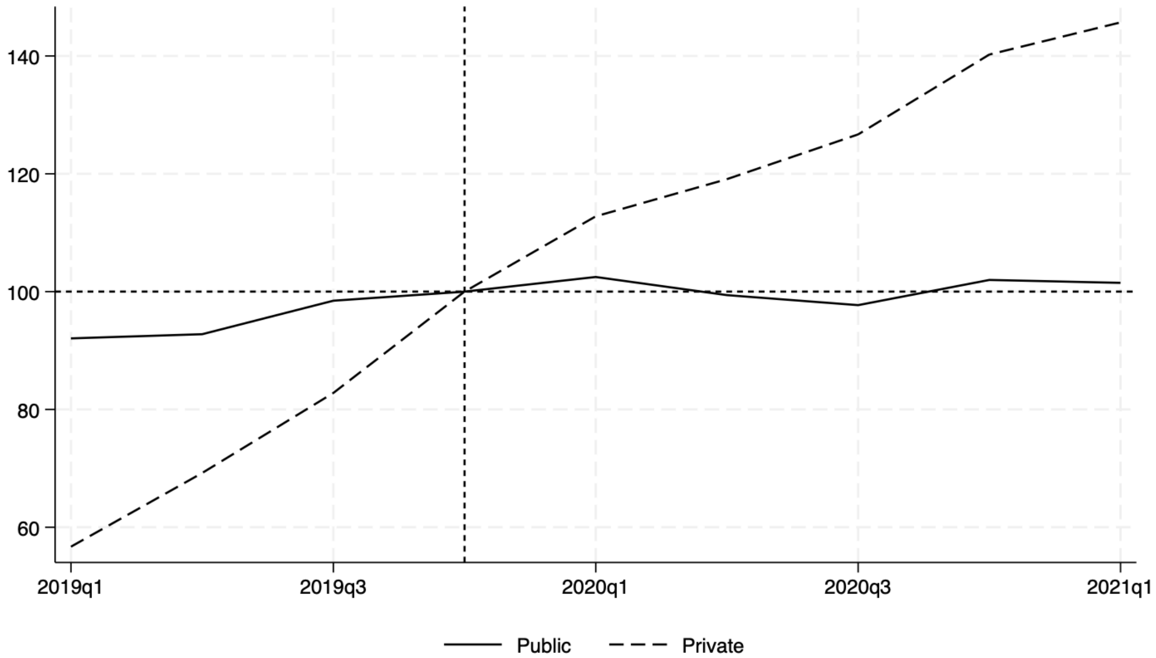
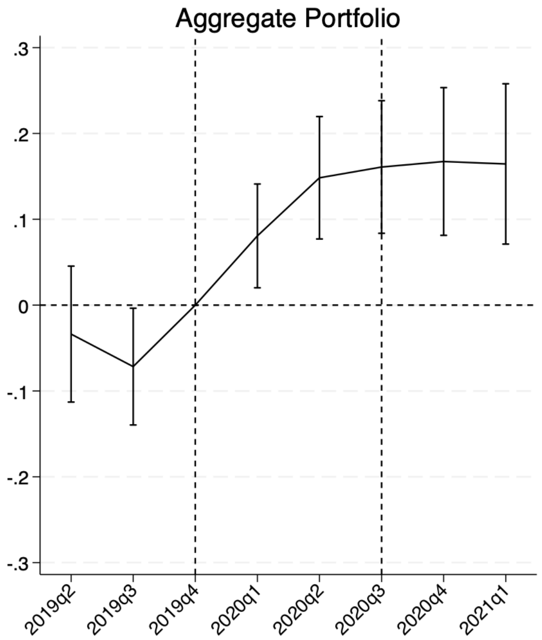
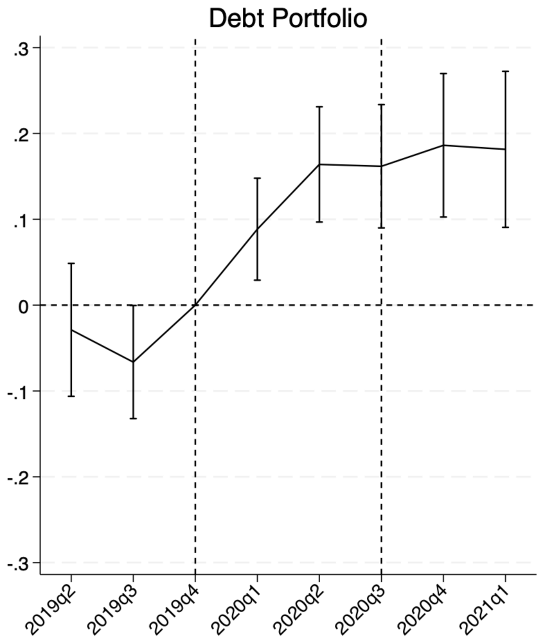


Figure 3: Event study - Firm-level estimation of public and private BDCs' portfolio growth

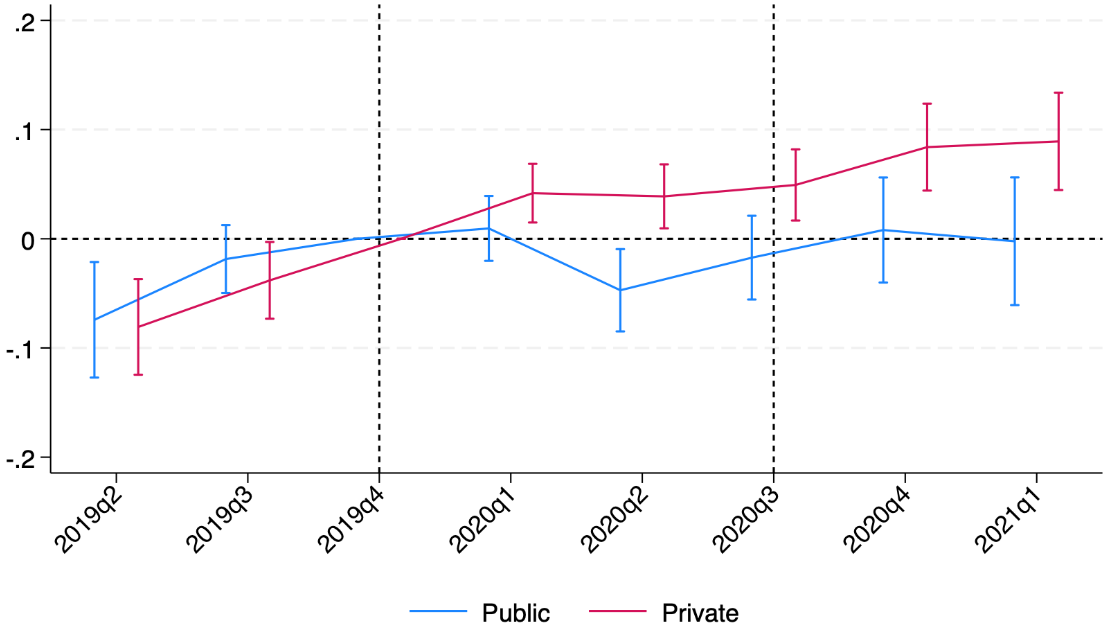
Panel A displays the coefficients of the interaction term of quarter indicator variables with a BDC-type indicator variable from an ordinary least squares (OLS) regression with the log portfolio amount of firm f invested by BDC b in quarter t as the dependent variable. The estimations are analogous to the estimations in Table 2 columns (1) and (2). Panel B displays the coefficients of quarter indicator variables from an OLS regression with the log debt portfolio amount of firm f invested by BDC b in quarter t as the dependent variable, estimated on the subsample of portfolio holdings by public (blue line) and private (red line) BDCs, respectively. The estimations are analogous to the estimation in Table 2 column (2), but only include BDC and firm fixed effects instead. In both panels, the reference period for the quarter indicator variables is set to zero for 2019Q4. The aggregate portfolio comprises all debt and equity investments in firm f by BDC b in quarter t. The debt portfolio aggregates all debt investments in firm f by BDC b in quarter t. The bars denote 95% confidence intervals. The data is winsorized at the 1% and 99% level.

Panel A: Difference-in-difference estimation





Panel B: Estimation by BDC type



11 Tables

Table 1: Descriptive statistics by BDC type as of 2019Q4

The table shows mean and median values for the sample of public and private BDCs, and conducts difference in means tests. Panel A displays summary statistics for the sample of 42 public and 16 private BDCs at the BDC level as of December 31, 2019. The variables are defined as follows: Age is the time elapsed between a BDC's registration with the SEC and 2019Q4 in years. Assets are total BDC assets in million USD. $\frac{I_{fv}}{I_c}$ refers to the ratio of a BDC's portfolio at fair value in million USD divided by its portfolio at cost in million USD, expressed as a percentage share. Leverage is defined as total debt divided by total assets, expressed as a percentage share. Net investment income and dividends are expressed as a percentage share of total assets. Panel B displays summary statistics on the portfolio of all 42 public and 16 private BDCs at the BDC level as of 2019Q4. The variables are defined as follows: The number of firms is the number of portfolio firms. The number of tranches refers to the total number of individual investments, or assets (a), invested by a BDC in all its portfolio firms. The portfolio at its fair value and at cost is in million USD. The debt, equity, CLO, and money market fund share refers to the value-weighted percentage share of the respective asset class in the overall portfolio. Panel C displays summary statistics for individual investments as of 2019Q4 at the asset level. The summary statistics provide averages and medians for the aggregate sample (debt plus equity), for debt investments only, and for equity investments only. The number of observations varies accordingly. $Amount\,at\,fair\,value$ and $Amount\,at\,cost$ refer to the asset amount at fair value and at cost in million USD. $\#\,Traches\,per\,firm$ is the total number of investments, or assets (a), invested by a BDC in a portfolio firm. In all panels, ***, **, and * indicate the statistical significance for the difference in means test at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

Panel A: BDC characteristics

	Public		**Private**		**T-Test**
	Mean	Median	Mean	Median	Difference
Observations	42		16		
Age	10.61	8.88	2.53	2.12	8.08***
Assets (mn)	1754.51	729.11	861.81	453.04	892.70
$\frac{I_{fv}}{I_c}$ (%)	95.88	97.59	99.22	99.68	-3.34*
Leverage (%)	45.74	47.78	39.33	45.03	6.41
Net investment income / A (%)	0.89	0.92	0.92	0.99	-0.02
Dividends / A (%)	0.94	0.97	1.57	0.74	-0.63

Panel B: BDC portfolio characteristics

	Public		**Private**		**T-Test**
	Mean	Median	Mean	Median	Difference
Observations	42		16		
# Firms	92.74	75.50	71.06	59.00	21.68
# Tranches	182.12	131.00	126.94	80.00	55.18
Portfolio at fair value (mn)	1690.28	701.49	813.82	419.97	876.47
Portfolio at cost (mn)	1744.83	682.59	819.63	428.02	925.20*
Debt share (%)	77.77	83.41	93.60	98.22	-15.84***
Equity share (%)	11.59	7.66	1.13	0.63	10.46***
CLO/Fund share (%)	6.89	3.27	1.48	0.00	5.41**
Money market fund share (%)	3.55	0.00	3.78	0.00	-0.24

Panel C: Investment characteristics

	Public		**Private**		**T-Test**
	Mean	Median	Mean	Median	Difference
Aggregate					
Observations	7,649		2,031		
Amount at cost (mn)	9.66	3.98	6.19	1.06	3.46***
Amount at fair value (mn)	9.74	4.20	6.34	1.17	3.40***
# Tranches per firm	1.94	1.00	1.78	1.00	0.16***
Debt					
Observations	5,329		1,821		
Amount at cost (mn)	11.39	6.06	6.52	1.27	4.87***
# Tranches per firm	1.72	1.00	1.63	1.00	0.09*
Equity					
Observations	2,029		198		
Amount at cost (mn)	3.15	0.66	0.91	0.22	2.24***
# Tranches per firm	1.39	1.00	1.26	1.00	0.13

Table 2: Growth of BDC portfolios

The table displays the results of an OLS regression of the log portfolio amount invested in firm f by BDC b in quarter t on a BDC-type indicator variable interacted with a shock-period indicator variable for different portfolios. The portfolios refer to: *Aggregate* aggregates all debt and equity investments in firm f by BDC b in quarter t. *Debt* aggregates all debt investments in firm f by BDC b in quarter t. *Equity* aggregates all equity investments in firm f by BDC b in quarter t. The estimations control for BDC acquisitions using the indicator variable $Acquired_{b,t}$, and the number of investments made in firm f by BDC b in the previous quarter $t-1$. The indicator variable $Acquired_{b,t}$ is one if BDC b acquired another BDC in quarter t, and zero otherwise. The indicator variable $Private_b$ is one for private and zero for public BDCs. The indicator variable $Shock_t$ is one for 2020Q1, 2020Q2, and 2020Q3, and zero otherwise. All estimations include BDC and firm-quarter fixed effects. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1% , 5% , and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) log(I)	(2) log(I)	(3) log(I)
Private (0/1) × Shock (0/1)	0.072***	0.072***	0.014
	(2.921)	(2.982)	(0.331)
BDC FE	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adj. R^2	0.645	0.652	0.878
N	9,781	9,327	1,681
SE clustering	BDC-Firm	BDC-Firm	BDC-Firm
Sample	Aggregate	Debt	Equity

Table 3: Intensive margin growth

In Panel A, column (1) displays the results of an OLS regression of the log debt portfolio amount of firm f invested by BDC b in quarter t on a BDC-type indicator variable interacted with a shock-period indicator variable. Columns (2) and (3) display the results of OLS regressions of the scaled investment amount of investment a in firm f invested by BDC b in quarter t on a BDC-type indicator variable interacted with a shock-period indicator variable. Column (2) uses debt investment in general as the dependent variable, while column (3) only considers the term loans. All estimations employ the same controls as the estimations in Table 2. Additionally, the estimation in column (1) controls for whether a portfolio contained a payment in kind (PIK) investment using the indicator variable $PIK - PF_{f,b,t}$, which is one if a portfolio contained a PIK investment and zero otherwise. The estimations in columns (2) and (3) control for whether an investment was floating rate or with a PIK component. The variable $Floating_{a,f,b,t}$ is one if a loan was floating rate and zero otherwise. The variable $PIK - AT_{a,f,b,t}$ is one if an investment had a PIK component and zero otherwise. Column (2) also includes asset-type fixed effects. Panel B displays the results of a Poisson regression of the total number of debt investments of firm f invested by BDC b in quarter t on a BDC-type indicator variable interacted with a shock-period indicator variable. Controls are equivalent to Panel A column (1). Both panels only consider observations for borrowers that were in BDCs' portfolios throughout 2019Q4 and 2020Q1 (intensive-margin borrowers). The indicator variables $Private_b$ and $Shock_t$ are defined as in Table 2. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

Panel A: Portfolio and asset dynamics

	(1) log(I)	(2) I_{Asset} (%)	(3) I_{Asset} (%)
Private (0/1) × Shock (0/1)	0.074***	4.245***	5.356***
	(3.566)	(3.044)	(3.703)
BDC FE	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes
Asset type FE	No	Yes	No
Controls	Yes	Yes	Yes
Level	Portfolio	Asset	Asset
Adj. R^2	0.662	0.462	0.456
N	8,040	8,346	7,460
SE clustering	BDC-Firm	BDC-Firm	BDC-Firm
Sample	Debt	Debt All	Debt Term Loan

Panel B: Number of investments

	(1) # Investments
Private (0/1) × Shock (0/1)	-0.012*
	(-1.870)
BDC FE	Yes
Firm-Quarter FE	Yes
Controls	Yes
Pseudo R^2	0.234
N	8,128
SE clustering	BDC-Firm
Sample	Debt

Table 4: Extensive margin growth

The table displays the results from a linear probability model (LPM) regression of the indicator variable $Entry_{f,b,t}$ on a BDC-type indicator variable interacted with a shock-period indicator variable. The indicator variable $Entry_{f,b,t}$ is one if firm f and BDC b formed a new investment relationship in quarter t and zero otherwise. The specifications control for BDC and firm-quarter fixed effects. Column (1) controls for whether a BDC acquired another BDC in a given quarter using the indicator variable $Acquired_{b,t}$. Column (2) excludes all BDCs that acquired another BDC throughout the sample period. The indicator variables $Private_b$, $Shock_t$, and $Acquired_{b,t}$ are defined as in Table 2. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) Entry (0/1)	(2) Entry (0/1)
Private (0/1) × Shock (0/1)	0.020	0.041**
	(1.525)	(2.371)
Acquisition (0/1)	0.034	
	(1.061)	
BDC FE	Yes	Yes
Firm-Quarter FE	Yes	Yes
Adj. R^2	0.571	0.564
N	5,528	3,520
SE clustering	BDC-Firm	BDC-Firm
Sample	All	No Acquisitions

Table 5: Effect of capital commitments on private BDC investment during the shock

The table displays the results of OLS estimations of the log debt portfolio amount of firm f invested by BDC b in quarter t on a shock period indicator variable interacted with a continuous measure of private BDCs' committed but undrawn capital. The estimations are for the subsample of private BDC investments only. The continuous measure of a private BDC's undrawn capital, $Undrawn_{b,2019Q4}$, is defined as the percentage share of a BDC's undrawn capital to its overall committed capital on December 31, 2019. The continuous measure of a private BDC's undrawn capital, $Undrawn_{b,2019Q4}/Assets_{b,2019Q4}$, is defined as the percentage share of a BDC's undrawn capital to its total assets on December 31, 2019. Both continuous measures of undrawn committed capital are standardized to a mean of zero and a standard deviation of one. The indicator variable $Shock_t$ is defined as in Table 2. The control variables are equivalent to Table 2. All estimations additionally control for a BDC's leverage level, defined as the percentage share of total debt to total assets, in the previous quarter ($L1.Leverage$). Lagged leverage is standardized to a mean of zero and a standard deviation of one. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) log(I)	(2) log(I)	(3) log(I)	(4) log(I)	(5) log(I)	(6) log(I)
Shock (0/1) × Undrawn	0.058***		0.031**		0.047	
	(3.595)		(2.455)		(1.465)	
Shock (0/1) × Undrawn/Assets		0.054***		0.030**		0.059*
		(3.412)		(2.348)		(1.780)
L1.Leverage	0.051	0.049	0.006	0.005	-0.127	-0.125
	(1.133)	(1.096)	(0.164)	(0.142)	(-1.232)	(-1.224)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No
Industry-Quarter FE	Yes	Yes	Yes	Yes	No	No
Firm-Quarter FE	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.645	0.645	0.916	0.916	0.713	0.713
N	4,326	4,326	4,249	4,249	1,161	1,161
SE clustering	BDC-Firm	BDC-Firm	BDC-Firm	BDC-Firm	BDC-Firm	BDC-Firm
Sample	Debt	Debt	Debt	Debt	Debt	Debt
BDC type	Private	Private	Private	Private	Private	Private

Table 6: Local projection

The table displays the result of a local projection in line with Equation 4, regressing the quarterly values of private BDCs' drawn amount of committed capital for the quarter indicated in the column header (h) on the 2019Q4 value of private BDCs' drawn amount of committed capital and a set of 2019Q4 BDC control variables. The BDC control variables are the founding year, the leverage level, the cash share, the log amount of total assets, the portfolios' Herfindahl-Index, and the number of portfolio firms. Standard errors are robust. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) $h =$ 2020Q1	(2) $h =$ 2020Q2	(3) $h =$ 2020Q3	(4) $h =$ 2020Q4	(5) $h =$ 2021Q1
Drawn Amount in 2019Q4	1.117***	1.254***	1.300***	1.468***	1.494***
	(17.752)	(11.845)	(10.293)	(5.812)	(6.171)
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.978	0.933	0.921	0.844	0.855
N	16	16	16	16	16
SE clustering	Robust	Robust	Robust	Robust	Robust
BDC type	Private	Private	Private	Private	Private

Table 7: Capital versus cash liquidity

The table displays the results of re-estimations of the equations in Table 5 using the undrawn committed capital measure $Undrawn_{b,2019Q4}/Assets_{b,2019Q4}$. All variables are defined accordingly. Columns (1) and (2) additionally control for a BDC's cash share in the previous quarter. Columns (3) and (4) control for a BDC's pre-shock cash share, defined as the cash share on December 31, 2019, interacted with the indicator variable $Shock_t$. $Shock_t$ is defined as in Table 2. All continuous variables are standardized to a mean of zero and a standard deviation of one. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) log(I)	(2) log(I)	(3) log(I)	(4) log(I)
Shock (0/1) × Undrawn/Assets	0.056***	0.031**	0.063***	0.035**
	(3.555)	(2.409)	(3.389)	(2.268)
Shock (0/1) × Pre-shock cash			-0.017	-0.009
			(-1.012)	(-0.640)
L1.Leverage	0.049	0.005	0.055	0.009
	(1.081)	(0.150)	(1.190)	(0.240)
L1.Cash	-0.023*	-0.012		
	(-1.746)	(-1.280)		
BDC FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry-Quarter FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Adj. R^2	0.645	0.916	0.645	0.916
N	4,326	4,249	4,326	4,249
SE clustering	BDC-Firm	BDC-Firm	BDC-Firm	BDC-Firm
Sample	Debt	Debt	Debt	Debt
BDC type	Private	Private	Private	Private

Table 8: Effect of firm information and PE-backing on BDC investment

In Panel A and B, column (1) shows the results of triple difference-in-difference OLS estimations with the debt portfolio of firm f invested by BDC b in quarter t as the dependent variable. In Panel A, a BDC-type indicator variable is interacted with a shock-period indicator variable and an investment-type indicator variable. In Panel B, a BDC-type indicator variable is interacted with a shock-period indicator variable and a firm-type indicator variable. The indicator variable $Equity_{f,b,2019Q4}$ is one if BDC b had an equity investment in firm f by December 31, 2019. The indicator variable $PE\text{-}Backed_{f,2019Q4}$ is one if firm f was backed by a private equity (PE) firm as of December 31, 2019. In both Panels, columns (2) and (3) display the results of difference-in-difference estimations, interacting a BDC-type indicator variable with a shock-period indicator variable. In Panel A, columns (2) and (3) decompose the effect by whether BDC b had an equity investment in firm f as of 2019Q4 (column (2)) or not (column (3)). In Panel B, columns (2) and (3) decompose the effect by whether firm f was PE-backed as of 2019Q4 (column (2)) or not (column (3)). Both panels focus on intensive-margin borrowers. The indicator variables $Private_b$ and $Shock_t$ are defined as in Table 2. The control variables are equivalent to Table 2. In both panels, standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

Panel A: Information

	(1) log(I)	(2) log(I)	(3) log(I)
Private (0/1) × Shock (0/1)	0.076***	0.043	0.077***
	(2.797)	(0.825)	(2.889)
Equity (0/1)	0.530***		
	(2.958)		
Private (0/1) × Equity (0/1)	-0.186*		
	(-1.927)		
Shock (0/1) × Equity (0/1)	0.055		
	(0.816)		
Private (0/1) × Shock (0/1) × Equity (0/1)	-0.016		
	(-0.263)		
BDC FE	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adj. R^2	0.657	0.731	0.645
N	9,327	1,269	7,641
SE clustering	BDC-Firm	BDC-Firm	BDC-Firm
Sample	Debt	Debt	Debt
Split		Equity	No Equity

Panel B: PE-backing

	(1) log(I)	(2) log(I)	(3) log(I)
Private (0/1) × Shock (0/1)	-0.009	0.080***	-0.012
	(-0.183)	(3.084)	(-0.249)
Private (0/1) × PE-Backed (0/1)	0.016		
	(0.181)		
Private (0/1) × Shock (0/1) × PE-Backed (0/1)	0.094		
	(1.645)		
BDC FE	Yes	Yes	Yes
Firm-Quarter FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Adj. R^2	0.659	0.649	0.796
N	8,962	7,569	1,389
SE clustering	BDC-Firm	BDC-Firm	BDC-Firm
Sample	Debt	Debt	Debt
Split		Backing	No Backing

Table 9: Firm performance

The estimation displays the results of OLS regressions of the log fair-value-to-cost ratio of f's debt portfolio invested by BDC b in quarter t. The estimations are based on the subsample of all new BDC-firm relationships formed between 2019Q2 and 2020Q3. The indicator variable $Issued\,Shock_{f,b,t}$ is equal to one if an investment was first formed in 2020Q1, 2020Q2, or 2020Q3, and zero if first formed in 2019Q2, 2019Q3, or 2019Q4. The BDC-type indicator variable is defined as in Table 2. $log(Entry\,valuation_{f,b,t})$ is a continuous variable controlling for the initial fair value to cost percentage share of a debt portfolio. The percentage share is logged and standardized to a mean of zero and a standard deviation of one. The regressions further control for whether a BDC acquired other BDCs in a given quarter using the indicator variable $Acquisition_{b,t}$ as defined in Table 2. All specifications include BDC, firm, and industry-quarter fixed effects. Column (2) additionally includes investment vintage fixed effects, capturing the quarter when a BDC-firm relationship first formed. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) $\log(\frac{I_{FV}}{I_C})$	(2) $\log(\frac{I_{FV}}{I_C})$
Issued Shock (0/1)	0.054***	
	(3.562)	
Private (0/1) × Issued Shock (0/1)	-0.003	-0.004
	(-0.509)	(-0.809)
log(Entry valuation)	0.008*	0.009***
	(1.860)	(3.287)
BDC FE	Yes	Yes
Firm FE	Yes	Yes
Industry-YQ FE	Yes	Yes
Investment Vintage FE	No	Yes
Controls	Yes	Yes
Adj. R^2	0.813	0.841
N	835	835
SE clustering	BDC-Firm	BDC-Firm
Sample	Debt	Debt

Table 10: Robustness - Debt constraints

The table displays the results of triple difference-in-difference OLS estimations with the log debt portfolio amount of firm f invested by BDC b in quarter t as the dependent variable. For the triple interaction term, a BDC-type indicator variable is interacted with a shock-period indicator variable and a continuous measure of a BDC's debt constraint. In column (1), the measure of a BDC's debt constraint, $Distance\,ACR_{b,2019Q4}$, is defined as the distance between a BDC's regulatory and actual asset coverage ratio (ACR) as of 2019Q4. Note that the ACR is not available for BDCs that do not use debt or only rely on SBA debentures, which are exempt from the ACR. In column (2), the measure of a BDC's debt constraint, $Usable\,liquidity_{b,2019Q4}$, is defined as the percentage share of a) the debt a BDC can incur according to its ACR on December 31, 2019, to b) the liquidity a BDC has available under its credit lines as of December 31, 2019. Both continuous measures of a BDC's debt constraint are standardized to a mean of zero and a standard deviation of one. The indicator variables $Private_b$ and $Shock_t$ are defined as in Table 2. The control variables are equivalent to Table 2. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) log(I)	(2) log(I)
Private (0/1) × Shock (0/1)	0.093***	0.100***
	(3.500)	(3.850)
Shock (0/1) × Distance ACR	0.065***	
	(3.155)	
Private (0/1) × Shock (0/1) × Distance ACR	-0.027	
	(-0.936)	
Shock (0/1) × Usable liquditiy		0.040**
		(2.267)
Private (0/1) × Shock (0/1) × Usable liquditiy		-0.013
		(-0.327)
BDC FE	Yes	Yes
Firm-Quarter FE	Yes	Yes
Controls	Yes	Yes
Adj. R^2	0.633	0.652
N	8,356	9,327
SE clustering	BDC-Firm	BDC-Firm
Sample	Debt	Debt

Table 11: Robustness - Portfolio devaluations

The table shows the results of triple difference-in-difference OLS estimations for the log debt portfolio amount of firm f invested by BDC b in quarter t. For the triple interaction term, a BDC-type indicator variable is interacted with a shock-period indicator variable and a measure of a BDC's portfolio devaluation in 2020Q1. The BDC-type indicator variable $Private_b$ is defined as in Table 2. The shock-period indicator variable $Shock2$ is one for 2020Q2 and 2020Q3, and zero otherwise. $Hit_{b,2020Q1}$ is an indicator variable measuring a BDC's portfolio devaluation between December 31, 2019, and March 31, 2020. $Hit_{b,2020Q1}$ is one for public BDCs if a public BDC was in the top quartile of public BDCs' portfolio devaluations and one for private BDCs if a private BDC was in the top quartile of private BDCs' portfolio devaluations, and zero otherwise. $Devaluation_{b,2020Q1}$ continuously measures the change in the fair value of a BDC's investment portfolio between December 31, 2019 and March 31, 2020. $Devaluation_{b,2020Q1}$ is standardized to a mean of zero and standard deviation of one. For both devaluation measures, the calculations use BDCs' portfolio at fair value. The controls are equivalent to Table 2. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) log(I)	(2) log(I)
Private (0/1) × Shock2 (0/1)	0.084***	0.100***
	(3.038)	(3.613)
Shock2 (0/1) × Hit (0/1)	0.040	
	(0.695)	
Private (0/1) × Shock2 (0/1) × Hit (0/1)	-0.018	
	(-0.262)	
Shock2 (0/1) × Devaluation		-0.015
		(-1.068)
Private (0/1) × Shock2 (0/1) × Devaluation		-0.012
		(-0.279)
BDC FE	Yes	Yes
Firm-Quarter FE	Yes	Yes
Controls	Yes	Yes
Adj. R^2	0.652	0.652
N	9,327	9,327
SE clustering	BDC-Firm	BDC-Firm
Sample	Debt	Debt

12 Appendix

12.1 Logged versus scaled asset amounts

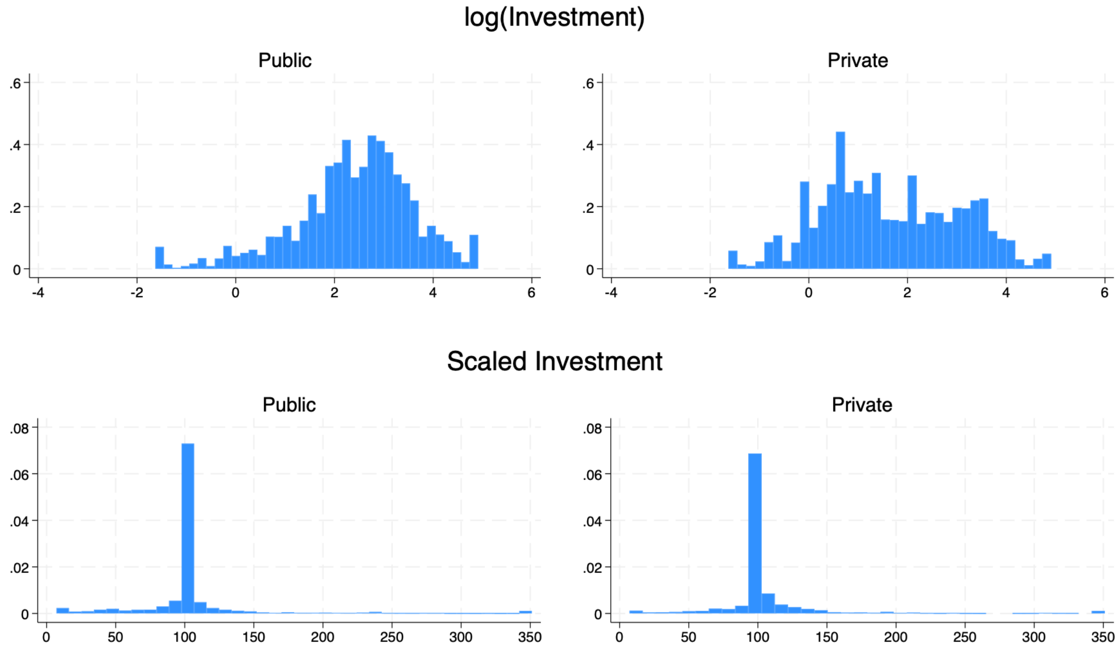
For investment-level estimations, I rely on scaled asset amounts defined as follows:

$$I_{\text{Asset}_{a,f,b,t}} = \frac{I_{a,f,b,t}}{\sum_a I_{a,f,b,2019\text{Q4}}}$$

Since many individual investments, and especially those of private BDCs, are small, log transformations can overemphasize changes in the asset amount, inflating the residual variance and reducing statistical power. Figure A1 displays the distribution of logged and scaled values for public and private BDC investments. The figure corroborates that the log transformation at the investment level introduces noise into the estimation. The left tail of the log distribution is substantially more pronounced for private BDCs and appears almost bimodal. Conversely, the distribution of the scaled values is much more symmetric and centers around 100% for public and private BDCs, with less noise in the tails for private BDCs.

Figure A1: Distributions of logged and scaled asset amounts

The figure displays the distribution of the logged (top two panels) and scaled (bottom two panels) investment amount of public and private BDC assets, defined as $I_{\text{Asset}_{a,f,b,t}} = \frac{I_{a,f,b,t}}{\sum_a I_{a,f,b,2019Q4}}$. The data is winsorized at the 1% and 99% level.



12.2 Tables

Table A1: Industry distribution of BDC portfolio firms

The table shows the industry distribution of BDCs' portfolio firms for the full sample, the sample of public BDC, and the sample of private BDC. The distributions are count-based. Industry codes are based on PitchBook.

Industry	All firms	Public BDC firms	Private BDC firms
Business Products and Services	28.86%	30.06%	23.91%
Information Technology	23.25%	22.00%	27.84%
Consumer Products and Services	18.24%	18.05%	18.61%
Healthcare	16.49%	16.81%	16.40%
Financial Services	6.08%	6.32%	5.9%
Energy	3.56%	3.45%	2.76%
Materials and Resources	3.52%	3.32%	4.55%

Table A2: Portfolio betas

The table displays the betas of public and private BDCs' portfolios and difference in means tests. Betas are assessed with regard to the S&P500. β_{All} refers to the beta of the overall portfolio, encompassing all investment types. β_{Debt} refers to the beta of the debt portfolio. β_{Equity} refers to the beta of the equity portfolio. ***, **, and * indicate the statistical significance for the difference in means tests at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	Public		**Private**		**T-Test**
	Mean	Median	Mean	Median	Difference
Observations	42		16		
β_{All}	0.25	0.18	0.08	0.06	0.16*
β_{Debt}	0.37	0.04	0.02	0.02	0.35
β_{Equity}	1.87	0.64	0.11	0.29	1.77

Table A3: Growth of BDC portfolios - Additional control variables

The table re-estimates Table 2 column (2), including additional control variables. The additional BDC control variables are the previous quarter ($t-1$) values of the following variables: level of leverage ($Leverage_{b,t}$), cash share ($Cash_{b,t}$), a portfolio's Herfindahl-Index ($HHI_{b,t}$), the value-weighted portfolio share of PIK loans ($PIK\,share_{b,t}$), and the number of portfolio firms ($\#Firms_{b,t}$). Also, the regression controls for whether the portfolio of firm f provided by BDC b in quarter t contained a PIK loan ($PIK_{f,b,t}$). The remainder is equivalent to Table 2 column (2). Again, standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) log(I)
Private (0/1) × Shock (0/1)	0.055**
	(2.273)
L1.Leverage	-0.006
	(-0.166)
L1.Cash	0.010
	(0.630)
L1.HHI	-0.051**
	(-2.326)
L1.PIK Share	0.058**
	(1.999)
L1.# Firms	0.218**
	(2.409)
PIK (0/1)	0.034
	(0.214)
L1.# Tranches	0.346***
	(7.445)
Acquisition (0/1)	0.252***
	(6.227)
BDC FE	Yes
Firm-Quarter FE	Yes
Adj. R^2	0.653
N	9,327
SE clustering	BDC-Firm
Sample	Debt

Table A4: Private BDCs' undrawn capital commitments as of 2019Q4

The table shows summary statistics for private BDCs' committed but undrawn capital as of December 31, 2019. $Undrawn_{b,2019Q4}$ is defined as the percentage share of a BDC's undrawn capital to its overall committed capital on December 31, 2019. $Undrawn_{b,2019Q4}/Assets_{b,2019Q4}$ is defined as the percentage share of a BDC's undrawn capital to its total assets on December 31, 2019. The data is winsorized at the 1% and 99% level.

	N	Mean	SD	Min	p25	Median	p75	Max
Undrawn (%)	16	36.03	25.08	0.00	16.16	32.57	56.00	84.82
Undrawn/Assets (%)	16	47.26	50.23	0.00	11.60	33.64	58.33	177.62

Table A5: Capital versus cash and debt liquidity

The table extends the estimations from Table 7 columns (3) and (4) by including the interaction term of the indicator variable $Shock_t$, as defined as in Table 2, and the debt measure $Usable\,liquidity_{b,2019Q4}$, as defined in Table 10. All specifications are defined as in Table 7. All continuous variables are standardized to a mean of zero and a standard deviation of one. Standard errors are clustered at the BDC-firm level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	(1) log(I)	(2) log(I)
Shock (0/1) × Undrawn/Assets	0.055***	0.034**
	(2.923)	(2.200)
Shock (0/1) × Pre-shock cash	-0.004	-0.008
	(-0.229)	(-0.564)
Shock (0/1) × Usable liqudity	-0.018	-0.000
	(-1.387)	(-0.011)
BDC FE	Yes	Yes
Firm FE	No	Yes
Industry-Quarter FE	Yes	Yes
Controls	Yes	Yes
Adj. R^2	0.645	0.916
N	4,326	4,249
SE clustering	BDC-Firm	BDC-Firm
Sample	Debt	Debt
BDC type	Private	Private

Table A6: BDCs' debt constraints as of 2019Q4

The table displays summary statistics for the debt constraints of public and private BDCs as of December 31, 2019, and difference in means tests. $Distance\,ACR_{b,2019Q4}$ is defined as the distance between a BDC's regulatory and actual ACR as of 2019Q4 in percentage points (pp). $Usable\,liquidity_{b,2019Q4}$ is defined as the percentage share of a) the debt a BDC can incur according to its ACR on December 31, 2019, to b) the liquidity a BDC has available under its credit lines as of December 31, 2019. ***, **, and * indicate the statistical significance for the difference in means tests at the 1%, 5%, and 10% level, respectively. The data is winsorized at the 1% and 99% level.

	Public		**Private**		**T-Test**
	Mean	Median	Mean	Median	Difference
Observations	42		16		
Distance ACR (pp)	191.73	49.00	84.68	56.30	107.05
Usable liqudity (%)	126.84	83.85	144.05	53.67	-17.20