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Abstract

This study explores how the COVID-19 shock affected direct lending in the U.S. Using a set of hand-collected data on direct lenders such as business development companies (BDCs) we apply a difference-in-differences model to document the heterogenous impact of the shock on BDCs lending. Our research indicates that, overall, BDCs remain a reliable source of credit following an adverse shock to their fundamentals. Furthermore, we report that BDCs who are more exposed to the shock employ risk control by increasing their portfolio allocation to safer investments.

Keywords: Direct Lending, Business Development Companies, COVID-19

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1. Introduction

Since the end of the financial crisis, the share of credit supply by direct lenders to the U.S. middle market has significantly increased.[1] A rise in regulatory burden led to direct lenders filling the void left by traditional banks (Davydiuk et al., 2020a; Gopal & Schnabl, 2020; Loumioti, 2019). As small and medium-sized businesses (SME) account for large parts of the U.S. economic activity, understanding the liquidity provided by direct lenders during a crisis is crucial to preventing financial distress.[2]

This paper offers a novel perspective on the impact of the COVID-19 shock on direct lenders. By capitalizing on the exogenous nature of the shock we explore the heterogenous impact on the capital supply from direct lenders such as business development companies (BDCs).

With the onset of the COVID-19 crisis, numerous companies' operations were severely disrupted when governments around the world implemented lockdowns and social distancing to slow down the spread of the virus. While some industries were better equipped to deal with the effects of social distancing, others who depend on close face-to-face interaction were more severely affected (Koren & Peto, 2020). In the U.S., this caused predominantly a supply shock to the economy resulting from a reduction in labor supply (del Rio-Chanona et al., 2020). Many firms who were forced to reduce or halt operations felt an immediate impact on their cash flows and were put at risk of default (Gourinchas et al., 2020). Several studies report a rise in demand for liquidity especially among SMEs at the beginning of the pandemic (Acharya & Steffen, 2020; Li et al., 2020). While an increasing number of research documents a decline in credit supply by banks during the pandemic, there has been little research on alternative sources of funding from direct lenders.[3] In this paper, we want to explore the impact of the COVID-19 shock on direct lending in the U.S.

[1] According to the Global Monitoring Report on Non-Bank Financial Intermediation (FSB, 2020), total assets of non-bank financial intermediation have increased by 8.9% to $200.2 trillion (49.5% of global financial assets) as of the end of 2019. Davydiuk et al. (2020a) reported a 25% share of private debt investments in 2017 for BDCs.

[2] The SBA reported a 44% contribution in economic activity by SMEs in the U.S. in 2014 ("Small Businesses Generate 44 Percent of U.S. Economic Activity", 2019).

[3] Chodorow-Reich et al. (2022) and Greenwald et al. (2020) examine bank credit supply based on credit line drawdowns in the U.S. Çolak & Öztekin (2021) study global variations in bank credit supply. Acharya et al. (2021) study stock returns relation to credit line drawdowns during the COVID-19 shock.

Our study focuses on BDCs as direct lenders in the U.S. using a set of hand-collected data from publicly available Securities and Exchange Commission (SEC) filings. Building on the strategy of Davydiuk et al. (2020b) to examine BDC lending, we employ a difference-in-differences (DiD) model to exploit the varied effects of social distancing on businesses. As a result, we categorize BDCs into groups with high and low exposure to affected industries. The identification approach for industries is based on the affected share measure developed by Koren & Peto (2020) for a three-digit North American Industry Classification System (NAICS) level. The authors predict industries' resilience to social distancing based on job descriptions from the Occupational Information Network (O*NET) database.

First, we examine the influence of the COVID-19 shock on the investment activity of BDCs. Our results indicate that overall, the credit supply from BDCs is relatively resilient to adverse shocks to their portfolio. Even though BDCs with greater exposure to the shock exhibit a 29% slower growth in fair value of investments than the control group, this appears to be mostly due to loan size reductions. We find no evidence that exposed BDCs reduce the number of investment transactions relative to the control group. Instead, we find that exposed BDCs maintain their relationships with existing borrowers.

To separate supply and demand effects, we utilize the approach by Khwaja & Mian (2008) using data on a portfolio company level and introducing company-time fixed effects to our model. Thereby, we focus on portfolio companies receiving funding from both treated and control BDCs. Our results show that when allowing for security type demand to vary, affected BDCs exhibit a 14% lower growth in capital supply relative to the control group. This appears to be mainly driven by equity investments as we find no statistically significant differences between both groups for debt investments.

Second, we investigate BDCs adjustments to the investment allocation in response to the COVID-19 shock. Our results suggest that relative to the control group, treated BDCs implement a risk control approach by reducing their portfolio exposure to riskier security types and moving their investment allocation to more secure types. We find this to be the case both on a volume as well as on a number of transaction basis.

Third, we investigate the effect of the COVID-19 shock on the profitability of BDCs. We, thereby focus on the differences in the net interest margin, return on equity (ROE), and return on assets (ROA) as proxies for profitability. We find no evidence that exposed BDCs' profitability is negatively impacted by the shock relative to the control group.

Fourth, we investigate the effects of the COVID-19 shock on BDCs' ability to raise external capital. BDCs need to ask for shareholders' approval prior to issuing new equity when trading at a discount. As investors price-in the risk related to BDCs' portfolio exposure to COVID-19, BDCs might be constrained to obtain funding for their investment activity. Our findings suggest that exposed BDCs experience an increase in the cost of equity and a decrease in equity issuance relative to the control group. Specifically, we show that relative to the control group, exposed BDCs experience a 7% to 8% larger rise in the net asset discount as well as a 2% larger decline in equity issuance scaled by market value equity (MVE). When examining debt financing, we find no statistically significant differences between both groups. This could be potentially because of exposed BDCs' continued access to pre-existing credit lines.

All in all, our findings reveal that treated BDCs manage their portfolio risk exposure prudently. Treated BDCs employ risk control by shifting their investment allocation to more secure investment types. Moreover, we find evidence that BDCs continue to provide capital during market distress that affects their portfolio.

This paper is structured as follows. Section 2 gives an overview of the most relevant literature for direct lending as well as the pandemics' impact on credit supply. Section 3 provides more detailed information on the economics of BDCs as well as the nature of the COVID-19 shock. Section 4 states the hypotheses of this study. In section 5 we describe the data and the methodology used for estimating the impact of the COVID-19 shock on BDCs. Section 6 discusses the findings of our research. In section 7, we analyze the robustness of our findings. Finally, section 8 concludes and provides suggestions on future research areas.

2. Literature Review

Our research focuses on how the COVID-19 shock affected U.S. direct lenders' lending patterns. It, thus, adds to the body of knowledge about the pandemic's effect on loan availability.

Several studies document a rise in bank loan demand in the U.S., especially at the beginning of the pandemic (Acharya & Steffen, 2020; Li et al., 2020). Çolak & Öztekin (2021) discover that during the early stages of the pandemic, banks internationally restricted their credit supply due to an exogenous surge in borrowers' credit risk. Consistent with these findings several studies report that U.S. banks reduce their extension of new credit when experiencing large demand for loans in the form of credit line drawdowns (Acharya & Steffen, 2020; Chodorow-Reich et al., 2022; Greenwald et al., 2020; Li et al., 2020). Moreover, Chodorow-Reich et al. (2022) find a decline in credit for businesses operating in industries highly affected by COVID-19. According to Kapan & Minoiu (2021), the key factor that leads banks with significant drawdowns to tighten their lending requirements and restrict their credit supply is a decrease in risk tolerance.

Our findings add to these studies by documenting the credit supply of direct lenders, in particular BDCs. In contrast to banks, we find no compelling evidence that BDCs with high exposure to affected industries reduce their supply of loans.

Businesses were forced to suspend operations due to lockdowns and social distancing, making especially smaller companies with low cash reserves exposed to falling credit supply.[4] Existing studies show that the decline in credit supply by banks during the COVID-19 shock was even stronger for smaller and medium-sized businesses (Chodorow-Reich et al., 2022; Greenwald et al., 2020). According to Aldasoro et al. (2022), non-bank lenders in the market of syndicated loans decreased their capital supply to risky borrowers after the COVID-19 shock. The authors show that this decrease in liquidity supply was considerably more pronounced than it was for banks. Our work contributes to these findings by providing insight on the supply of capital from alternative sources of credit during an economic downturn, as direct lenders like BDCs often lend to medium-sized enterprises.

Our findings also add to the growing yet small literature trying to shed light on the behavior of direct lenders during different market conditions.

Various studies document that direct lenders increased their credit supply and offered firms an alternative funding source as bank regulation tightened after the global financial crisis (Davydiuk et al., 2020a; Gopal & Schnabl, 2020; Loumioti, 2019).

When hit by an unexpected contraction in funding sources, direct lenders such as BDCs tend to adhere to market discipline, reduce their credit supply to borrowers and allocate more assets towards safer investment types (Davydiuk et al., 2020b).

[4] Bartik et al. (2020) reported the median small business to have cash available for two weeks. Falagiarda et al. (2020) report SMEs to have a stronger demand for loans than larger companies.

Balloch & Gonzalez-Uribe (2021) document that during the pandemic regulatory leverage limits for BDCs restricted their ability to supply credit. In addition to these findings, we show that BDCs lending is relatively resilient to an adverse shock to their portfolio. Moreover, we document that exposed BDCs decrease their allocation to riskier security types after a negative shock to the real economy.

3. Background

Davydiuk et al. (2020a) were one of the first to provide an extensive overview of the structure and business model of BDCs. Therefore, we rely greatly on the information provided by the authors in the following sections on BDCs.

BDCs Regulatory Background. Following the passage of the *Small Business Investment Incentive Act of 1980* (1980 Act) BDCs were established and are regulated by the *Investment Company Act of 1940* (1940 Act). Publicly traded BDCs are typically closed-end investment companies that are required to file extensive quarterly and annual reports with the SEC.

Under the 1940 Act, BDCs must invest at least 70% of total assets in qualifying assets. Those include privately issued securities, distressed debt, and government securities. For portfolio securities to be considered as qualifying assets, BDCs must either control the issuer of the securities or make the issuer an offer of significant managerial assistance. Additionally, the *Small Business Credit Availability Act* (SBCAA), which was enacted in 2018, decreased the asset coverage requirement that applies to BDCs from 200% to 150%.

BDCs in the U.S. may choose to be classified as regulated investment companies (RICs). This allows them to pass on income to investors without being subject to entity-level taxation. To be treated as RIC, BDCs must pass the "90% Income Test". According to the "90% Income Test", BDCs must earn at least 90% of their revenue from dividends, gains from the sale or other exchange of securities, interest, loan income and income from "qualified publicly traded partnerships".

Additionally, BDCs must pass the Diversification Test, which can be subdivided into a 50% test and a 25% test. According to the 50% test, BDCs must maintain 50% of total assets in highly liquid investments (cash, cash equivalents, US government securities, and securities of other RICs). Moreover, it restricts BDCs from holding more than 10% of the voting rights in any single issuer of securities and only 5% of the value of the entire assets in any single issuer of securities. The 25% test mandates that BDC impose a 25% cap on assets held in investments other than U.S. government securities, other RIC, one or more issuers that are not controlled, and securities of one or more qualified publicly traded partnerships.

Moreover, the Annual Distribution Requirement states that BDCs must distribute at least 90% of their taxable income (net ordinary income plus excess of realized net short-term capital) to investors each year. Investors may choose to have dividends distributed as cash or shares of common stock.

In general, BDCs are not able to issue and sell common stock below the current net asset value per share (NAVPS).

Through publicly traded BDCs, retail investors have the opportunity to invest in small and medium-sized private firms. Compared to other investment funds, such as mutual funds or ETFs, BDCs frequently charge larger fees. Investment advisors that manage BDCs often charge advisory fees that range from 1.5% to 2% of the fund's gross asset value, plus specific incentive costs. (*Investor Bulletin: Publicly Traded Business Development Companies (BDCs)*, 2020)

These regulations could lead to some adverse consequences. BDCs might find it difficult to pay the required distributions if the income is recognized before receiving cash. This includes payments in kind (PIK) and warrants. As a result, they might be forced to sell some investments to maintain the RIC status.

BDC Business Model. According to Davydiuk et al. (2020a), BDCs target medium-sized companies that have often been sponsored by private-equity firms. A significant part of their investments into portfolio companies is allocated to debt, followed by equity and to a small extent to structured products. The median loan provided by BDC ranges from $5 million to $10 million and has a maturity of around 4 to 6 years. Moreover, loans often include warrants and have an interest rate of around 8% to 11%.

To fund the investments, BDCs utilize both debt and equity funding. BDCs employ initial public offerings (IPOs) to become publicly traded after initially acquiring funds through private means. Thereby, the debt-to-equity ratio of 2:1 must be maintained. However, historically the ratio has been well below the limit for most BDCs. The instruments utilized for debt financing, such as bonds, revolving credit facilities, and notes, typically have a term of 4 to 8 years.

The target company of BDCs has evolved over time. For example, Barings BDC, Inc. stated in its 10-K filing for 2020 that it had previously invested mainly into senior and subordinated debt securities of privately held lower middle-market companies located in the U.S. The target has, however, moved over time to largely senior secured private debt investments in well-established middle-market companies that operate across a wide range of industries (Barings BDC, Inc., 2021).

COVID-19 shock. In this section, we describe the nature of the COVID-19 shock and its implications for the U.S. economy.

With the beginning of the COVID-19 pandemic governments all over the world were facing a serious health crisis that would lead to material disruptions to the global economy. To contain the spread of the virus, countries used strategies including lockdowns and social distancing. However, as some firms depend on in-person encounters for their operations, this had a severe impact on their ability to operate. Productivity dropped as a result of the forced closure or partial reduction of many enterprises' operations. Consequently, the economy experienced a supply shock driven by a reduction in labor supply (del Rio-Chanona et al. 2020; Koren & Peto, 2020). Although consumer preferences also shifted, the decline in the economy was dominated by the supply shock (del Rio-Chanona et al. 2020).

Some industries were better suited to cope with the impact of the crisis, due to their ability to continue operating remotely. Koren & Peto (2020) report that industries like Publishing, Professional Services, and Data processing rely less on face-to-face interaction and, therefore, were able to relocate sizeable portions of their workforce to home offices. Conversely, industries like Clothing Stores, Air Transportation, and Food Services were less prepared to adjust to the effects of social distancing. Correspondingly, the magnitude of the crisis' impact on operations and performance varied across industries (Pagano et al., 2020).

Many businesses' cash flows were adversely affected due to the disruption of operations causing an increase in default risk.[5]

Uncertainty rose sharply as people were unable to forecast factors, such as the duration of the health crisis, the time span of social distancing and the economic impact of government measures (Altig et al., 2020).

Numerous studies find evidence that increasing levels of uncertainty and liquidity problems contributed to a rapid rise in loan demand (Acharya & Steffen, 2020; Chodorow-Reich et al., 2022; Greenwald et al., 2020; Li et al., 2020). Moreover,

[5] Bartik et al. (2020) surveyed SMEs at the beginning of the pandemic, reporting a median duration of available cash of two weeks. Acharya & Steffen (2020) find an increase in cash holdings especially for riskier companies at the start of the crisis.

Chodorow-Reich et al. (2022) show that increased industry exposure predicts higher demand for liquidity.

As firms started increasing their cash holdings, not all were equally able to do so (Acharya & Steffen, 2020). While larger firms were able to access liquidity, banks' ability to exercise discretion, left SMEs unable to access funding from credit lines (Chodorow-Reich et al., 2022). This made SMEs particularly vulnerable to the crisis.

Firms, operating in industries highly exposed to the shock, had a larger reduction in their share price indicating that investors price-in the elevated risk and uncertainty from the exogenous shock (Pagano et al., 2020). This made equity financing a relatively expensive option for many businesses.

To stabilize the economy, the federal reserve reduced the target rate for the federal funds rate to a range of 0% to 0.25% on March 15, 2020. Moreover, on March 27, 2020, the U.S. government released the CARES Act including several financial relief programs like the Payment Protection Program (PPP), designed to provide financial aid to small businesses. Chodorow-Reich et al. (2022) report a reduction in bank loan demand from PPP recipients signaling a relaxation of the liquidity shock for SMEs. Nevertheless, Humphries et al. (2020) document that small businesses continued reducing their headcount even after the passage of the program.

The exogenous character of the COVID-19 shock offers a unique opportunity to learn more about the impact on BDC lending during an economic downturn. Our analysis assumes that nobody could have foreseen COVID-19 and its effects. Therefore, in the absence of the shock, BDCs with different levels of exposure to industries relying on face-to-face interaction would be indistinguishable.

4. Hypotheses

To formally test the impact of the COVID-19 pandemic on BDC lending, we develop testable hypotheses based on previous research and theory. Thus, we attempt to make use of the heterogeneous effects of the exogenous supply shock to establish causality. As discussed in the previous section, social distancing led to a contraction in labor supply. Businesses in severely impacted industries experienced higher degrees of uncertainty and were more vulnerable to cash shortages. As a result, BDCs were indirectly exposed to the shock through their investments. Thus, the varying levels of exposure for BDC depend on the share of investments made in businesses operating in the affected industries. To understand the consequences for exposed BDCs' lending behavior, we explore the various effects of the COVID-19 shock.

We structure the hypotheses as follows. We start by examining the impact of the shock on the investment activity of BDCs. We further explore changes to the investment allocation. Next, we consider how the shock affected BDCs' profitability. As our final step, we look at the effect on BDCs' external funding.

4.1 Investment Activity

Hypothesis 1: Investment Volume. BDCs investment portfolio typically consists of equity and debt investment into small and medium-sized companies. Since the great uncertainty in future economic outlook increased the risk of default of affected portfolio companies, we expect exposed BDCs to have a lower growth in fair value of investments. According to Acharya & Steffen (2020), an increase in uncertainty led to a disruption of affected enterprises' revenue sources, raising the likelihood of default. Furthermore, Balloch & Gonzalez-Uribe (2021) indicate a positive relationship between industry exposure and write-offs for BDCs, following the COVID-19 shock.

Interest rate, the borrower's ability to service its debt and the quality of the collateral are some of the relevant factors that potentially influence the valuation of debt instruments.[6]

Alternatively, a decline in fair value of investments could also be driven by a reduction in lending activity. Pool et al. (2015) show that during the financial crisis, banks reduced their credit supply in response to an increase in the probability of default of their existing borrowers and thereby resulting rise in loan loss provisioning.

Hypothesis 1.a: Post-COVID shock, treated BDCs experience a larger decline in investment volume than the control group as measured by the logarithm of book assets and fair value of investments.

[6] Compare to Barings BDC, Inc. (2021).

Additionally, we expect this uncertainty to be reflected as a decline in investment appreciation for BDCs with higher exposure to industries affected by social distancing.

Hypothesis 1.b: Post-COVID shock, treated BDCs experience a larger decline in relative investment appreciation than the control group as measured by the net realized and unrealized gains (losses) to assets ratio.

Previous research on banks suggests that a higher exposure to the COVID-19 shock caused a reduction in loan supply (Chodorow-Reich et al., 2022). Acharya et al. (2018) suggest that stress-tested banks reduce their exposure to borrowers that face greater risk and uncertainty. We predict that a larger decline in fair value is not only driven by impairments but also by a reduction in borrowers by treated BDCs.

Hypothesis 1.c: Post-COVID shock, treated BDCs have a larger drop in borrowers than the control group as measured by the logarithm of number of borrowers and new borrowers.

Hypothesis 2: Investment Deals. To further determine the drivers for a change in investment volume, we turn to the number of outstanding deals. We hope to determine whether changes are caused solely by volume and valuation changes or also by the number of deals.
A reduction in the number of deals could be a result of exposed BDCs' tighter lending requirements. Deyoung et al. (2015) find credit rationing resulting from increased lender risk aversion and risk overhang effects during the global financial crisis. Bekaert et al. (2022) document a sharp increase in risk aversion at the beginning of 2020.
Alternatively, a decline in the number of deals could be due to a rise in defaults of previous investments as affected borrowers are unable to serve their obligations. According to Gan (2007), banks in Japan that experienced an external shock that negatively impacted the valuation of certain parts of their portfolio also decreased the amount of credit they were willing to extend to other borrowers.
We next investigate whether the COVID-19 shock caused a decrease in the number of newly issued debt deals for exposed BDCs relative to the control group. Davydiuk et al., (2020b) report a reduction in the number of new debt deals for BDCs experiencing a negative shock to their external financing.

Hence, we predict that higher exposed BDCs have a larger decline in the number of deals and new deals than the control group.

Hypothesis 2.a: Post-COVID shock, treated BDCs have a larger reduction in the number of deals and newly originated deals than the control group as measured by the logarithm of number of deals and new deals respectively.

Furthermore, we want to examine whether changes in the number of deals are driven by changes in the number of borrowers. We predict that treated BDCs reduce the number of outstanding loans per borrower to avoid portfolio concentration.

Hypothesis 2.b: Post-COVID shock, treated BDCs have a greater reduction in outstanding deals per borrower than the control group as measured by the logarithm of number of deals per borrower.

Hypothesis 3: Supply and Demand Disentangled. To separate possible capital supply and demand effects, we follow the approach by Khwaja & Mian (2008) and control for the capital demand side. We, then, compare the capital supply to portfolio companies receiving funding from both treated and control BDCs. In comparison to the control group, we anticipate that portfolio companies would get less capital from treated BDCs.

Hypothesis 3: Post-COVID shock, treated BDCs reduce their capital supply to the same portfolio company by more than the control group, as measured by the logarithm of fair value of investments.

4.2 Investment Allocation

Hypothesis 4. Following the COVID-19 shock we expect BDCs to adopt a flight-to-quality approach and reduce their allocation in subordinated debt and equity and increase their allocation to senior debt. Caballero & Krishnamurthy (2008) report a flight-to-quality when Knightian uncertainty is high or liquidity is low. Cortés et al. (2020) document that stress-tested banks reallocate their investments away from riskier to more secure debt investment types. Moreover, recent empirical studies show that banks reduced their capital supply to smaller and riskier borrowers after the COVID-19 shock (Chodorow-Reich et al., 2022; Çolak & Öztekin, 2021). Davydiuk et al. (2020b) find that following a capital supply shock, BDCs reduce their allocation to riskier security types. We want to investigate the impact of the

COVID-19 shock on the portfolio allocation of exposed BDCs on a volume, number of deals and relative level.

Hypothesis 4: Post-COVID shock, treated BDCs allocate relatively less to riskier investments than the control group as measured by the logarithm of fair value of equity, debt, subordinated debt and senior debt investments as well as the number of deals and the ratio of these investments to assets.

4.3 Profitability

Hypothesis 5. Given the increased exposure of BDCs to affected industries, we expect that a shift in investment allocation has an overall negative impact on their profitability in relation to the control group. Davydiuk et al. (2020b) report a reduction in profitability for BDCs that reallocated their portfolio to safer investments in response to a shock to their external funding.

Hypothesis 5: Post-COVID shock, treated BDCs experience a larger decline in profitability than the control group, as measured by the net interest margin, ROA and ROE.

4.4 External Financing

Hypothesis 6: Equity Financing. BDCs rely on external financing to fund investments in portfolio companies. Changes in investors' sentiment and risk perception can significantly influence BDCs' ability to extend credit. Calomiris & Wilson (1998) show that banks adjusted their portfolio risk exposure towards secure investment types following sharp losses to their loan portfolio and a rise in their cost of external financing in the 1930s. Moreover, Bloom (2014) documents that a rise in uncertainty increases the cost of raising capital as investors require a risk premium. Pagano et al. (2020) document a risk premium for companies affected by social distancing. We, therefore, expect share prices of treated BDCs with exposure to affected industries to reflect the increased risk and uncertainty.
Brunnermeier (2009) reports that during the financial crisis, uncertainty about the future access to external financing led to a reduction in the credit supply by banks. Davydiuk et al. (2020b) additionally show that when being subject to an external financing shock, BDCs decrease their investment activity and devote a bigger portion of their portfolio to safer assets.

We predict that raising capital through equity markets should become relatively expensive for treated BDCs relative to the control group.

Hypothesis 6.a: Post-COVID shock, treated BDCs experience a larger drop in valuation than the control group as measured by the logarithm of market value of equity, share price and number of shares outstanding.

To raise equity capital, BDCs rely on shareholder approval in case their shares trade below NAVPS. Therefore, an increase in net asset value (NAV) discount could reflect a difficulty in using equity financing and shows an increase in illiquidity (Haddad et al., 2021). We expect treated BDCs to have a larger increase in NAV discount in comparison to the control group.

Hypothesis 6.b: Post-COVID shock, treated BDCs experience a larger increase in illiquidity than the control group as measured by the share price over NAVPS.

Given the relative expensiveness of equity financing for treated BDCs, we expect them to reduce their use of equity financing. Moreover, Deyoung et al. (2015) document a reduction in book value equity of banks to compensate for losses on portfolio valuations of banks. Therefore, we anticipate treated BDCs to have a higher decrease in their equity buffer than the control BDCs.

Hypothesis 6.c: Post-COVID shock, treated BDCs have a larger reduction in equity issuance than the control group as measured by book value of equity, net issuance, issuance and repurchase per market value of equity.

Hypothesis 7: Debt Financing. We anticipate that treated BDCs' capacity to issue debt is impacted by the rise in risk in their portfolio composition. As lenders price-in the risk of COVID-19, we expect exposed BDCs to face higher debt costs that affect their debt volume. Additionally, the 2:1 debt-to-equity leverage limit could further restrict their access to external debt capital if the investment valuation declines and exposed BDCs’ equity buffer falls.

Hypothesis 7: Post-COVID shock, treated BDCs have a lower increase in debt financing than the control group as measured by the logarithm of debt and cash as well as their ratio to assets.

5. Methodology & Data

For our empirical strategy, we build on the study by Davydiuk et al. (2020b) to measure the effects of an exogenous shock on BDC lending using the DiD method.

Data. Our empirical setting includes publicly traded and private BDCs in the U.S. We restrict our sample to BDCs with publicly available SEC filings such as 10-Q and 10-K from Q1 2018 to Q4 2020. Our data collection is based on two main sources: CRSP/Compustat North America - fundamental quarterly files and a hand-collected set of quarterly data from SEC filings.

CRSP/Compustat offers a variety of quarterly reported variables from the balance sheet, stock return and shares outstanding.

Additionally, we hand-collected data from the quarterly SEC filings of BDCs. Through the filings, we obtain access to a greater range of variables including more granular investment-level data. We collect data on portfolio investments, such as portfolio company name, industry, investment type, and fair value. Furthermore, we use the industry description from the filings and publicly available information of companies' business activities to assign each company to a three-digit NAICS industry. This lays the basis for the identification method of affected companies following the approach by Koren & Peto (2020), which we discuss in the next section.

Our sample data is divided into a pre-COVID-19 and a post-COVID-19 period. The pre-COVID-19 period starts in Q1 2018 and lasts until Q4 2019. It serves as a reference point for the changes resulting from the COVID-19 shock that started in Q1 2020. We set the ending point of our data to Q4 2020 as vaccinations in the US started to roll out in Q1 2021. We collect data on 52 BDCs during our sampling period, from Q1 2018 to Q4 2020.

Summary statistics and variable descriptions are presented in Table 1. We observe that the average BDC in our sample from Q1 2018 to Q4 20020 has a share price of \$10.77, book equity of \$791.52 million, book assets of \$1,511.78 million and fair value of investments of \$1,418.49 million. Moreover, the average BDC has 126 borrowers and 209 investment deals outstanding.

Treated Variable – Measure of COVID-19 Exposure. Koren & Peto (2020) developed a classification of industry exposure to COVID-19. Their approach is based on a labor supply shock where industries are differently impacted by social distancing. To classify the three-digit NAICS industries by their exposure to

COVID-19, the authors utilized occupational descriptions of U.S. businesses from the O*Net database to assess the dependence on direct human interaction. Thereby, businesses are classified as exposed when they rely on face-to-face interaction or working in short distance from one another. The authors group occupations into three groups, namely, teamwork-intensive, customer-facing, and physical presence. Those groups capture the ability to conform with social distancing. The three sub-measures are summarized in the affected share measure. A high affected share indicates a high vulnerability to operational disruptions from social distancing. We use the affected share measure to first categorize portfolio companies of BDCs by their industry into affected and unaffected companies. Fahlenbrach et al. (2021) point out that the affected share measure shows little variation in the lower quartiles. In Fig. A.1 of the Appendix, we show that the measure is indeed moderately positively skewed. We follow the authors' approach and classify companies operating in an industry with an affected share measure above the 75% percentile as exposed.

For the pre-COVID-19 shock periods (Q1 2018 to Q4 2019) we calculate the percentage share of fair value investments in affected companies by BDCs. BDCs with an average percentage share investment above the median over the pre-shock periods are considered treated. As a result, the treated variable functions as an indicator taking the value of one if the BDC belongs to the treated group and zero otherwise.

Table A.1 of the Appendix presents the pre-shock exposure to the industries affected by social distancing for the treated and control group based on the identification approach described above. The treated group has a mean exposure of 18.12% and a maximum exposure of 27.57% to the affected industries. In contrast, the control group has a mean exposure of 7.12% and a maximum exposure of 13.05%.

It should be noted that the three-digit NAICS affected share measure by Koren & Peto (2020) might be too condensed to capture the variations in shock exposure between sub-industries. Therefore, some firms might have been classified as not affected by social distancing, although their operations were severely disrupted. Moreover, Fahlenbrach et al. (2021) report that the measure does not consider the impact of supply chain disruptions on firms that were otherwise not directly impacted by social distancing.

Table 2 displays the summary statistics on BDCs' characteristics for the treated and control group in Q4 2019. It shows a significant difference between the two groups only for the net interest margin.

Research Design. We exploit the time-series (provided by the COVID-19 shock) and cross-sectional variations in industry exposure (provided by the varied impact of social distancing on operations) to analyze the heterogeneous impact of COVID-19 on BDCs. This allows us to evaluate the average effect and heterogeneity across BDCs. BDCs' characteristics and exposure to the pandemic might influence their lending behavior. Moreover, it could impact their ability to raise capital which in turn might alter their credit extension to portfolio companies.

Difference-in-Differences Regression: Baseline Specification

To implement these comparisons, we utilize the DiD approach, which allows us to split the sample into pre- and post-shock periods, as well as treated and control groups. Through a set of control variables and fixed effects, we can further control for observable and unobservable BDC properties.

The DiD approach is only valid under certain assumptions. As described in the previous section, our analysis relies on the assumption that noone could have foreseen the COVID-19 shock. Moreover, in absence of the COVID-19 shock treated and untreated BDCs would have developed without significant differences. To test if this assumption holds, we employ a range of robustness tests that we discuss in a later section.

We find the following general panel regression for *Hypothesis 1,2,4-7* that we estimate using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t} \quad (1)$$

The dependent variable $y_{j,t}$ is generally a continuous or discrete variable and takes on values for the different aspects of BDCs we want to measure the impact on. The variable $Post_t$ is a time-specific binary variable that takes on the value one for the post-COVID-19 shock starting from Q1 2020 and zero for the pre-COVID-19 shock period.

The variable $Treated_j$ is an indicator variable that takes on the value one for the treated group of BDCs and zero for the control group.

The variable X_{t-1} represents a set of explanatory variables we control for that might vary depending on the regression. Following Davydiuk et al. (2020b) we include observable BDC characteristics such as *size*, *profitability* and *book leverage*.[7] Additionally, we control for unobservable time-invariant BDC attributes through BDC fixed effects and temporal patterns in BDC's attributes through time fixed effects.

Difference-in-Differences Regression: Supply and Demand Disentangled

To test *Hypothesis 3* whether changes in BDC lending are driven by the capital supply or capital demand side we follow the approach by Khwaja & Mian (2008). By estimating the regression on a time-company-BDC-instrument level and including company-time fixed effects we can control for the portfolio company's demand. This allows us to analyze the capital supply to portfolio companies receiving funding from multiple BDCs. Effectively we compare the impact of COVID-19 on the capital supply from exposed BDCs with the capital supply from the control group to the same company. A reduction in loan growth from higher exposed BDCs would indicate a reduction in capital supply.

Additionally, we estimate the regression using company-instrument-time fixed effects to allow firms' demand for security types to vary.

We estimate the following panel regression using OLS:

$$y_{k,i,j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{k,i,j,t} \quad (2)$$

Hence, we evaluate the loan of type *k* originated by BDC *j* to a portfolio company *i* at time *t*.

In addition to company-time, company-instrument-time, BDC and time fixed effects we apply BDC-level controls.

Robustness Test. To ensure the structural validity of our results, we perform several robustness tests. We analyze different approaches to classify BDCs as affected by the COVID-19 shock.

Parallel Trend Assumption

To test the hypothesis using a DiD approach, we rely on the assumption that in absence of the COVID-19 shock treated and control group would have developed

[7] We measure *size* through *Ln* $(Assets_{t-1})$, *book leverage* through $Debt / Assets_{t-1}$, and *profitability* through $Net\ Int.\ Inc. / Assets_{t-1}$.

in parallel following a common trend. To verify this assumption and assess pre-treatment trends we estimate the following regression using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \sum_t \gamma_t \left(\lambda_t \times Treated_j\right) + \delta X_{j,t-1} + \varepsilon_{j,t}, \quad (3)$$

λs are dummy variables for each quarter t of the sample. λ_t is set to one for the period t and otherwise takes on the value zero. We omit the dummy variable for the quarter Q4 2019, which therefore becomes the reference period of the regression.
Additionally, we compare the characteristics of the treated and control group for the pre-COVID-19 shock period Q4 2019 in support of our identification approach.

BDC Classification

In our base classification, we allocate BDCs to the treated group, when the share of their investments to companies in affected industries pre-COVID-19 shock is above the median. Alternatively, we could classify BDCs with a pre-shock exposure above the mean as treated. This allows us to measure the sensitivity of our results to the classification threshold.

Placebo Test

We use a different sorting strategy that is not based on relevant BDCs properties to further explore the robustness of our findings. We sort BDC by their CIK identification number from low to high and split the sample in half. All BDCs with CIKs in the lower range are assigned to the treated group and all others to the control group. Using this approach, we should not observe any meaningful results.

6. Results & Analysis

We first examine the aggregate trend across BDCs during the pandemic. Table 3 presents the results from our baseline-specification Equ. (1) with the natural logarithm of book assets value as well as the natural logarithm of fair value of investments as dependent variables. Column 1 of Panel (a) and Panel (b) shows the aggregate impact of the COVID-19 shock by estimating the regression without fixed effects and control variables. The findings suggest that the average book asset value and the fair value of investment for the control group do not change in the post-treatment period. When controlling for BDC and time fixed effects our results suggest a growth for both the book asset value and the fair value of investments for the control group post-COVID-19 shock.[8] In line, Fig. 1 indicates for both the treated and control groups' average development of investment volume a positive trend. Therefore, BDCs portfolios appear to be on aggregate relatively resilient to the effects of the pandemic.

6.1 Investment Activity

Investment Volume. To assess the COVID-19 impact on exposed BDCs, we first examine changes to the volume of investments. In *Hypothesis 1.a* we predicted a lower growth in investment volume for exposed BDCs in comparison to the control group. We estimate Equ. (1) with the natural logarithm of the book value of assets and the natural logarithm of fair value of investments as our dependent variables. The results are presented in the last columns of Panel (a) and Panel (b) of Table 3. Our results indicate no statistically significant differences between treated and control group for the value of book assets. Accounting for log scale, we find a 29% lower growth in fair value of investments for exposed BDCs in comparison to control BDCs.[9]

Even though these findings suggest that COVID-19 had indeed an effect on exposed BDCs it raises the question on the underlying drivers.

First, we analyze relative changes of realized and unrealized gains (losses) to examine valuation adjustments of the investments. With lockdowns and social distancing causing industries to sharply reduce their output, the probability of default for many firms increased substantially. *Hypothesis 1.b* predicted a decrease in the relative investment appreciation for exposed BDCs following the COVID-19 shock. Panel (c) of Table 3 presents the results of estimating Equ. (1) for the net realized and unrealized gains (losses) to assets ratio as dependent variables. Our results indicate no statistically significant differences between both groups.

This suggests that the overall lower growth in fair value of investments is not due to adjustments to the valuation of existing investments.

Second, we turn to the changes in the number of borrowers following the COVID-19 shock. By examining the impact of the COVID-19 shock on the relationships of exposed BDCs, we aim to understand whether exposed BDCs reduce their risk exposure through a decline in the number of borrowers. Hence, *Hypothesis 1.c*

[8] Note that R-squared increases significantly when BDC and time fixed effects are added to our model.

[9] Our findings are reported as raw coefficients. For the analysis of all our log results we convert the coefficients to account for the log scale (-0.29 = $e^{-0.34} - 1$)

predicted a reduction in the number of borrowers for exposed BDCs relative to the control group. Using Equ. (1) we conduct a test with the natural logarithm of the number of borrowers and the number of debt borrowers as dependent variables. Table 4 suggests that rather than reducing their investment relationships, treated BDCs have a 9% and 8% higher growth in the number of borrowers and debt borrowers respectively relative to the control group. To determine whether this rise is due to a relative increase in new relationships we next estimate Equ. (1) with the natural logarithm of new borrowers and the natural logarithm of new debt borrowers as dependent variables. Our results indicate no statistically significant differences in trend for the number of new borrowers between the treated and control group. Hence, these findings suggest that exposed BDCs continue to extend credit, especially to their existing borrowers.

These observations align with the findings by Elliott et al. (2021) who document that in the global syndicated lending market non-bank lenders increase their credit supply in response to adverse policy shock. Moreover, the authors note that a substitution to non-bank credit is especially strong for riskier borrowers.

Investment Deals. Instead of reducing their investment relationships, exposed BDCs could reduce their risk exposure through a decline in the number of deals. In *Hypothesis 2.a* we predicted a reduction in the number of deals and new deals by exposed BDCs relative to the control group. We estimate Equ. (1) with the natural logarithm of number of deals, equity deals, debt deals and new deals as dependent variables. Table 5 Panel (a) and Panel (d) report no statistically significant findings for all three dependent variables.

Another channel through which exposed BDCs could reduce their risk exposure is by reducing their transactions per portfolio company. In our previous findings, we have reported a higher growth in the number of borrowers but no statistically significant differences in the number of deals for exposed BDCs. This would imply a reduction in the number of deals on a per-borrower basis.

Hypothesis 2.b predicted a lower growth in the number of deals per borrower in comparison to the control group. In Table 5 Panel (c) we present the results from estimating Equ. (1) with the natural logarithm of the number of deals per borrower and the natural logarithm of the number of debt deals per borrower as dependent variables.[10] Our findings show a 2% lower growth in the number of deals per borrower for exposed BDCs in comparison to the control group.

Taken together, our results indicate that loan size modifications to new agreements may have contributed to the lower growth in treated BDCs' fair value of investments post-COVID-19 shock. Overall, exposed BDCs remain a dependable source of credit, with the number of transactions falling only on a per-borrower basis.

Supply and Demand Disentangled. To determine whether our results are driven by the demand or supply for loans we follow the approach by Khwaja & Mian (2008) to control for capital demand and analyze the provision of loans on investment-level data. By introducing company-time fixed effects we investigate if companies, receiving funding from both groups, experience a larger decline in funding from exposed lenders. Furthermore, we introduce company-instrument-time fixed effects to allow the company's demand to vary across instrument types. In *Hypothesis 3* we predicted that portfolio companies receive less capital from BDCs with a higher COVID-19 exposure than the control group. Table 6 reports the results of estimating Equ. (2).

Panel (a) of Table 6 indicates a 14% lower growth for all investment types of exposed BDCs when allowing for instrument type demand to vary. This outcome seems to be driven by equity investments as we find no statistically significant results when calculating exclusively for debt instruments. It suggests that in comparison to the control group, exposed BDCs provide less capital to borrowers who receive funding from multiple lenders. Surprisingly, as shown in Panel (b) of Table 6 we find that multi-relationship borrowers receive 93% more subordinated debt funding by exposed BDCs following the COVID-19 shock relative to the control groups.

Overall, our findings show a decline in capital supply by exposed BDCs relative to the control group when allowing for the investment type demand to vary. However, our results only analyze the effect of the shock on multi-relationship borrowers.

[10] To estimate the number of deals per borrower we summarize the average number of deals across companies – How many deals BDC_j is extending to a borrower on average at time t.

6.2 Investment Allocation

While our previous findings suggest that BDCs do not constrain the number of outstanding deals, it leaves open how the debt deal composition might be impacted by the COVID-19 shock. In *Hypothesis 4* we predicted a decline in the allocation to riskier security types by exposed BDCs relative to the control group. We first regress Equ. (1) using the natural logarithm of subordinated and senior deals as dependent variables. Panel (b) of Table 5 reports a 13% to 14% lower growth in the number of subordinated debt deals for exposed BDCs than the control group. Moreover, we find a 21% higher growth in the number of senior debt deals for exposed BDCs relative to the control group. This suggests a risk control approach for exposed BDCs through a shift to more secure investment types.

Our findings on investment deals indicate a varied effect of the COVID-19 shock on the allocation to security types. We next analyze how this shift is reflected in the overall volume of those investments. Our dependent variables consist of the natural logarithm of fair value of equity investments, the total fair value of debt investments, as well as its breakdown into senior and subordinated debt. The findings are illustrated in Table 7 Panel (a) and are estimated using Equ. (1). Following the COVID-19 shock we find no statistically significant differences in growth for debt investments. However, in comparison to the control group, our findings show an 82% to 85% lower growth in the fair value of subordinated debt in contrast to a 68% higher growth for the fair value of senior debt investments for treated BDCs. Despite being statistically insignificant, our findings indicate a 27% to 29% lower growth in fair value of equity investments. Together with our findings on the investment deals, this confirms that exposed BDCs reduce their investments in riskier security types. Moreover, it suggests that exposed BDCs do not reduce their investment activity but shift their investments to more senior secured investment types.

We continue to examine the investment allocation relative to total assets. The data presented in Table 7 Panel (b) reveals that exposed BDCs invest 4% less in equity relative to the control group. For the overall debt investments, we observe no statistically significant differences after the COVID-19 shock. However, the share of subordinated debt over assets has experienced a larger decline of 1.5% for the treated BDCs relative to the control BDCs. Moreover, although it is not statistically significant, we find a 1% to 2% larger increase in percentage of senior debt investments of total assets.

Overall, these results suggest that in response to a negative exogenous shock to the portfolio, exposed BDCs employ risk control by shifting their portfolio allocation to more secure assets. Similarly, Davydiuk et al. (2020b) report a reallocation towards securer investments by BDCs affected by a credit supply shock. Moreover, our results support Papadamou et al. (2021) who report a flight-to-quality from stock to bonds during the pandemic.

6.3 Profitability

We expand our research to test whether profitability is impacted by losses on existing deals, a decrease in investment activity, and a shift towards more secure types of investments due to treated BDCs' higher exposure to the COVID-19 shock. In *Hypothesis 5* we predicted a lower growth in net interest margin and a lower ROE and ROA for exposed BDCs relative to the control group. The results from estimating Equ. (1) are illustrated in Table 8. Surprisingly, we find no evidence of differences in the ratio of interest income to assets between the two groups as shown in Panel (a). Our previous findings suggest that exposed BDCs prioritize more secured assets and shift from subordinated debt to senior debt. We would, therefore, expect them to forego higher expected returns for less risky and more stable returns, which would lead to a decline in profitability for exposed BDCs relative to the control group. One plausible explanation could be a possible counter-effect through an increase in credit spread of new deals by treated BDCs. Exposed BDCs might have raised interest spreads in response to the COVID-19 shock and the elevation in overall uncertainty. The assumption is consistent with the findings of Beck & Keil (2022) who find that banks with larger exposure to government policies in response to the COVID-19 pandemic issued loans with smaller sizes and higher spreads. In addition, we find no evidence of differences in the interest expenses to assets ratio between treated and control BDCs either. Ultimately, the absence of any changes in both ratios suggests that there is no difference in the net interest margin for exposed BDCs relative to the control BDCs.

Furthermore, we look at how profitable overall investments of exposed BDCs are relative to their total assets in comparison to the control group. Table 8 Panel (b) illustrates the outcomes for the dependent variables ROE and ROA. We find no statistically significant differences between control and treated groups. In summary, these findings suggest that the profitability of exposed BDCs was not negatively impacted by the COVID-19 shock relative to the control group.

6.4 External Financing

BDC Equity Financing. We want to investigate whether BDCs' exposure to the COVID-19 shock also hampered their ability to raise capital to meet increased loan demand. An inability to raise external capital either through equity or debt could lead to a reduction in lending.

BDC shares should trade close to their NAVPS or at least trade at a similar distance over time. As closed-ended funds, they need to seek prior approval from shareholders if they want to issue new shares while trading at a discount on their NAV. Therefore, a drop in share price and an increase in NAV discount would make it more difficult to raise equity capital. Moreover, an increase in NAV discount could signal an increase in illiquidity.

We proceed by first analyzing the impact of the COVID-19 shock on the market valuation of exposed BDCs. *Hypothesis 6.a* predicted a lower growth in the valuation of exposed BDCs relative to the control group. In Table 9 Panel (a) we report the results for estimating Equ. (1) with the natural logarithm of MVE, the share price and the number of shares outstanding as dependent variables. We find a significantly lower growth in market equity value of 10% for exposed BDCs relative to the control group. This finding seems to be mainly driven by a drop in share price, which shows a 9% to 11% lower growth for treated BDCs. We find no statistically significant differences in the number of shares outstanding between the two groups. The results indicate that investors indeed price-in the risk exposure to industries highly affected by social distancing, making external financing through equity capital expensive. The results are in line with Pagano et al. (2020) who find a risk premium for nonfinancial firms impacted by social distancing. An alternative explanation could be a reduction in cash flows.

Next, we investigate differences in NAV discount as measured by the share price over NAVPS. In *Hypothesis 6.b* we predicted that after the COVID-19 shock exposed BDCs would experience an increase in illiquidity relative to the control group. Panel (c) of Table 9 presents the regression results from estimating Equ. (1) with the share price to NAVPS ratio as the dependent variable.

The results demonstrate a 7% to 8% larger increase in NAV discount for exposed BDCs in comparison to the control group. This increase in NAV discounts could be due to two possible explanations. Firstly, the increase could indicate greater illiquidity for exposed BDCs negatively impacting their ability to raise equity capital. Haddad et al. (2021) claim that increased NAV discounts of closed-ended funds are a sign of illiquidity and constrained balance sheets. Secondly, exposed BDCs could have reported inflated fair values. According to Balloch & Gonzalez-Uribe (2021), BDCs constrained by leverage limits, report higher investment values than without them.

We further investigate whether these findings have an impact on the issuance of new stocks. On the one hand, BDC can issue new stocks and draw from investors' commitments. On the other hand, BDCs use dividends and repurchases of stocks to distribute earnings that they are obliged to maintain their status as RIC.

In *Hypothesis 6.c* we predicted a lower growth in equity issuance for exposed BDCs relative to the control group. To measure issuance and repurchases we follow the approach by Boudoukh et al. (2007).[11] We estimate Equ. (1) with the book value of equity, the net issuance to MVE ratio, the issuance to MVE ratio and the repurchases to MVE ratio as dependent variables. As shown in Panel (a) of Table 9, we find a 21% lower growth in book value of equity in comparison to the control group. Moreover, we find 2% larger decline in the share of net issuance for exposed BDCs relative to the control group as reported in Panel (b) of Table 9. For the share of repurchases, our results show a slightly larger decline of 0.4% for exposed BDCs in comparison to the control group. Although not statistically significant, our results also indicate that the share of equity issuance declines by 1% to 2% more for exposed BDCs relative to the control group.

These results indicate that market participants seem to price-in an exposure to the risk and uncertainty arising from the COVID-19 pandemic that is partially reflected in BDCs' issuance of new stocks.

Moreover, the drop in book value of equity does not seem to be solely driven by a reduction in stock issuance. Instead, BDCs might partially use the equity buffer to cover for decreases in the fair value of investments on the asset side.

To sum up, it appears that the relatively higher cost for external financing and the reduction in external equity capital to exposed BDCs contributed to a slowdown in

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[11] To calculate net issuance we utilize the adjustment factor *adjexq* from the Compustat/CRSP database to account for stock splits and other events. We first adjust the share price ($share\ price^*_{jt} = share\ price_{jt}\ /\ adjexq_{jt}$) as well as the number of shares outstanding ($num\ shares^*_{jt} = num\ shares_{jt} \times adjexq_{jt}$). We can then calculate net issuance using the adjusted variables $\left(num\ shares^*_{jt} - num\ shares^*_{jt-1}\right) \times share\ price^*_{jt}$. Issuances (Repurchases) are periods with positive (negative) changes in the number of shares outstanding.

investment activity. Similarly, Davydiuk et al. (2020b) document BDCs passing on a decrease in external capital to their portfolio companies.

BDC Debt Financing. We further investigate the impact of COVID-19 exposure to BDCs' ability to raise debt and cash holdings. With an increased exposure to riskier investments, we expect creditors to increase interest spreads, making debt financing relatively expensive. This would make it even more difficult for BDCs to extend capital to portfolio companies. In *Hypothesis 7* we predicted a lower growth in debt financing for exposed BDCs relative to the control group. Results are reported in Table 10 and estimated using Equ. (1) for the natural logarithm of debt and cash as well as the debt to assets ratio and the cash to assets ratio as dependent variables.

Surprisingly, we find no statistically significant evidence that exposed and control BDCs differ in debt financing after the COVID-19 shock. These results are similar to Balloch & Gonzalez-Uribe (2021) who report no decline in debt volume for BDCs constrained by leverage limits following the COVID-19 shock. One possible explanation could be that BDCs were able to draw on existing credit lines. Furthermore, Table 10 shows a 2% increase in the cash-to-asset ratio, but no statistically significant difference in cash holdings between the two groups. With neither cash nor book assets being statistically significant, it remains open what the underlying driver of this result is.

7. Robustness Analysis

To ensure the validity and robustness of our results, we conduct a range of robustness tests. The results of the analysis are in support of our main findings.

Parallel Trend Assumption

First, we formally test the parallel trend assumption to support the validity of our model. Fig. B.1 of the Appendix plots the coefficients from the regression result of Equ. (3) with a 95% error bar. Panel (a) shows for the natural logarithm book value of equity no statistically significant differences between the treated and control group for the pre-COVID shock period. The same is confirmed for the natural logarithm of book asset value and the natural logarithm of fair value of investments as can be seen in Panel (b) and Panel (c) respectively. The trend for the fair value of book assets and book equity shows a drop at the beginning of the pandemic but a recovery during later stages of the pandemic. This could indicate low persistency of the effects of the COVID-19 shock on exposed BDCs relative to the control group. Bekaert et al. (2022) report a significant level of risk aversion at the start of the COVID-19 crisis, which quickly declined as the crisis continued.

In addition, we compare the relative properties of the control and treated group for the pre-COVID period Q4 2019 to support our method. The results reported in Table 2 indicates no statistically significant differences other than the net interest margin.

Alternative Allocation of BDCs

Our identification approach of treated BDCs is based on the mean share of industry exposure. Panel (a) in Table 11 supports the robustness for a range of dependent variables.

Furthermore, we use a placebo test based on sorting BDCs by a variable unrelated to any meaningful grouping such as the CIK number of BDCs. The findings presented in Panel (b) of Table 11 for a range of dependent variables show no meaningful results. Therefore, they support the robustness of our main findings.

8. Conclusion

Direct lenders have established themselves in recent years as an important source of credit to the U.S. middle market. Therefore, having a clear comprehension of the liquidity offered by direct lenders during a crisis is vital to avoid financial distress. Given the limited research on direct lenders, this represents a unique area for further investigation.

This paper documents the effects of the COVID-19 pandemic and its subsequent economic supply shock on direct lenders in particular BDCs. We use a set of hand-collected data from publicly available SEC filings on BDCs in the U.S. Using a difference-in-differences approach based on BDCs' heterogeneous exposure to industries affected by social distancing we attempt to capture the varied impact on BDC lending.

Our analysis reveals that BDCs show a certain level of resilience to the adverse effects caused by COVID-19. On aggregate, BDCs do not contract their capital supply following a shock to the real economy. Nevertheless, exposed BDCs experience a lower growth in investments compared to control BDCs. According to our research, the majority of this can be attributed to a decrease in loan size. Meanwhile, exposed BDCs control their portfolio risk by reallocating larger portions of investments to safer securities. In addition, the relatively higher cost of equity and the reduction in equity issuance for exposed BDCs in comparison to the control group might also contribute to a decrease in investment activity.

The COVID-19 pandemic caused substantial disruptions to the global economy. Therefore, there has been an increased need for liquidity, particularly among SMEs. Although larger firms managed to secure liquidity, SMEs faced difficulties accessing funds from banks. As a result, SMEs rely on alternative funding sources such as direct lending. Our findings show that following the COVID-19 shock, BDCs have consistently proven to be a sustainable source of credit and demonstrated their ability to provide much-needed financing during the COVID-19 pandemic.

Our research is subject to several limitations that should be acknowledged. One limitation of the current research is that it focuses solely on BDCs as representatives of direct lenders in the market, which may result in overgeneralization. Secondly, as mentioned by Fahlenbrach et al. (2021), the measure by Koren & Peto (2020) is not very granular. For example, a firm operating in a four-digit NAICS industry might be highly affected by social distancing, however, based on the aggregate three-digit NAICS code it is classified as not affected. Moreover, the authors point out that the measure does not include the effects on suppliers, which in turn could have reduced the ability of firms to continue operating even though they themselves are not directly impacted by social distancing. Finally, it remains open how the COVID-19 shock impacted exposed BDCs' capital supply to single-relationship borrowers. Those are expected to be even more vulnerable to the shock, as they might find it difficult to obtain alternative funding.

We propose several recommendations for future research to further enhance the understanding of the subject matter. Expanding the scope of research beyond BDCs to include a wider range of direct lenders would provide a more comprehensive picture of the effects of the COVID-19 shock on the direct lending market. Another recommendation for future research would be to analyze interest rates in conjunction with credit spreads for both current and new deals within direct lending following the COVID-19 shock. This comprehensive analysis would provide valuable insights into the profitability and risk-return dynamics of direct lenders. Additionally, conducting an analysis of an environment with rising interest rates would be highly valuable. This analysis would shed light on the effectiveness of risk management and the overall financial sustainability of direct lending institutions.

References

Acharya, V. V., Berger, A. N., & Roman, R. A. (2018). Lending implications of US bank stress tests: Costs or benefits? *Journal of Financial Intermediation*, *34*, 58–90.

Acharya, V. V., Engle III, R. F., & Steffen, S. (2021). *Why did bank stocks crash during COVID-19?* National Bureau of Economic Research.

Acharya, V. V., & Steffen, S. (2020). The Risk of Being a Fallen Angel and the Corporate Dash for Cash in the Midst of COVID. *The Review of Corporate Finance Studies*, *9*(3), 430–471. https://doi.org/10.1093/rcfs/cfaa013

Aldasoro, I., Doerr, S., & Zhou, H. (2022). *Non-bank Lending During Financial Crises* (SSRN Scholarly Paper No. 4008248). Social Science Research Network. https://doi.org/10.2139/ssrn.4008248

Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., Davis, S. J., Leather, J., Meyer, B., & Mihaylov, E. (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics*, *191*, 104274.

Balloch, C., & Gonzalez-Uribe, J. (2021). *Leverage Limits in Good and Bad Times*.

Barings BDC, Inc. (2021). *Annual Report FY2020*. Barings BDC, Inc. https://www.sec.gov/Archives/edgar/data/1379785/000137978521000016/a202010-k.htm

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences*, *117*(30), 17656–17666. https://doi.org/10.1073/pnas.2006991117

Beck, T., & Keil, J. (2022). Have banks caught corona? Effects of COVID on lending in the US. *Journal of Corporate Finance*, *72*, 102160.

Bekaert, G., Engstrom, E. C., & Xu, N. R. (2022). The time variation in risk appetite and uncertainty. *Management Science*, *68*(6), 3975–4004.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, *28*(2), 153–176.

Boudoukh, J., Michaely, R., Richardson, M., & Roberts, M. R. (2007). On the importance of measuring payout yield: Implications for empirical asset pricing. *The Journal of Finance*, *62*(2), 877–915.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008. *Journal of Economic Perspectives*, *23*(1), 77–100.

Caballero, R. J., & Krishnamurthy, A. (2008). Collective risk management in a flight to quality episode. *The Journal of Finance*, *63*(5), 2195–2230.

Calomiris, C. W., & Wilson, B. K. (1998). *Bank Capital and portfolio management: The 1930's capital crunch and scramble to shed risk*. National Bureau of Economic Research Cambridge, Mass., USA.

Chodorow-Reich, G., Darmouni, O., Luck, S., & Plosser, M. (2022). Bank liquidity provision across the firm size distribution. *Journal of Financial Economics*, *144*(3), 908–932.

Cortés, K. R., Demyanyk, Y., Li, L., Loutskina, E., & Strahan, P. E. (2020). Stress tests and small business lending. *Journal of Financial Economics*, *136*(1), 260–279.

Davydiuk, T., Marchuk, T., & Rosen, S. (2020a). Direct Lending in the U.S. Middle Market. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3568718

Davydiuk, T., Marchuk, T., & Rosen, S. (2020b). Market Discipline in the Direct Lending Space. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3729530

del Rio-Chanona, R. M., Mealy, P., Pichler, A., Lafond, F., & Farmer, J. D. (2020). Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective. *Oxford Review of Economic Policy*, *36*(Supplement_1), S94–S137. https://doi.org/10.1093/oxrep/graa033

Deyoung, R., Gron, A., Torna, G., & Winton, A. (2015). Risk overhang and loan portfolio decisions: Small business loan supply before and during the financial crisis. *The Journal of Finance*, *70*(6), 2451–2488.

Elliott, D., Meisenzahl, R., & Peydró, J.-L. (2021). *Nonbank lenders as global shock absorbers: Evidence from US monetary policy spillovers*. working paper, Imperial College London.

Fahlenbrach, R., Rageth, K., & Stulz, R. M. (2021). How Valuable Is Financial Flexibility when Revenue Stops? Evidence from the COVID-19 Crisis. *The Review of Financial Studies*, *34*(11), 5474–5521. https://doi.org/10.1093/rfs/hhaa134

Falagiarda, M., Köhler-Ulbrich, P., & Maqui, E. (2020). Drivers of firms' loan demand in the euro area–what has changed during the COVID-19 pandemic? *Economic Bulletin Boxes*, *5*.

FSB. (2020). *Global Monitoring Report on Non-Bank Financial Intermediation 2020*. https://www.fsb.org/2020/12/global-monitoring-report-on-non-bank-financial-intermediation-2020/

Gan, J. (2007). The real effects of asset market bubbles: Loan-and firm-level evidence of a lending channel. *The Review of Financial Studies*, *20*(6), 1941–1973.

Gopal, M., & Schnabl, P. (2020). The rise of finance companies and fintech lenders in small business lending. *NYU Stern School of Business*.

Gourinchas, P.-O., Kalemli-Özcan, Ṣebnem, Penciakova, V., & Sander, N. (2020). *Covid-19 and SME failures* (Vol. 27877). National Bureau of Economic Research Cambridge, MA, USA.

Greenwald, D. L., Krainer, J., & Paul, P. (2020). *The credit line channel*.

Haddad, V., Moreira, A., & Muir, T. (2021). When selling becomes viral: Disruptions in debt markets in the COVID-19 crisis and the Fed's response. *The Review of Financial Studies*, *34*(11), 5309–5351.

Humphries, J. E., Neilson, C., & Ulyssea, G. (2020). *The evolving impacts of COVID-19 on small businesses since the CARES Act*.

Investor Bulletin: Publicly Traded Business Development Companies (BDCs). (2020). SEC.Gov. https://www.sec.gov/oiea/investor-alerts-and-bulletins/investor-bulletin-publicly-traded-business-development-companies

Kapan, T., & Minoiu, C. (2021). Liquidity insurance vs. credit provision: Evidence from the COVID-19 crisis. *Credit Provision: Evidence from the COVID-19 Crisis (September 30, 2021)*.

Khwaja, A. I., & Mian, A. (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, *98*(4), 1413–1442.

Koren, M., & Peto, R. (2020). Business disruptions from social distancing. *PloS ONE*, *15*(9), e0239113.

Li, L., Strahan, P. E., & Zhang, S. (2020). Banks as lenders of first resort: Evidence from the COVID-19 crisis. *The Review of Corporate Finance Studies*, *9*(3), 472–500.

Loumioti, M. (2019). Direct Lending: The Determinants, Characteristics and Performance of Direct Loans. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3450841

Pagano, M., Wagner, C., & Zechner, J. (2020). Disaster resilience and asset prices. *ArXiv Preprint ArXiv:2005.08929*.

Papadamou, S., Fassas, A. P., Kenourgios, D., & Dimitriou, D. (2021). Flight-to-quality between global stock and bond markets in the COVID era. *Finance Research Letters*, *38*, 101852. https://doi.org/10.1016/j.frl.2020.101852

Pool, S., De Haan, L., & Jacobs, J. P. (2015). Loan loss provisioning, bank credit and the real economy. *Journal of Macroeconomics*, *45*, 124–136.

Small Businesses Generate 44 Percent of U.S. Economic Activity. (2019, January 30). *SBA's Office of Advocacy*. https://advocacy.sba.gov/2019/01/30/small-businesses-generate-44-percent-of-u-s-economic-activity/

Çolak, G., & Öztekin, Ö. (2021). The impact of COVID-19 pandemic on bank lending around the world. *Journal of Banking & Finance*, *133*, 106207.

Table 1: Variable descriptions and descriptive statistics

This table illustrates descriptions and descriptive statistics of the variables for the periods from Q1 2018 to Q4 2020. The source of the data is SEC filings, if not stated otherwise. The data is expressed in US dollars.

Variable	Description	Mean	Median	St.dev	Min	Max
Panel A. Equity Financing						
Market equity	Total dollar value of BDC's equity (market capitalization), in millions.	714.36	289.81	1,225.64	12.84	8,038.15
Book equity	Total book value of equity, in millions.	791.52	316.79	1,222.00	27.75	7,467.00
Share price	Share price of BDCs. (Source: Compustat/CRSP)	10.77	10.03	6.78	0.58	43.21
Assets	Total book value of assets, in millions.	1,511.78	629.87	2,348.37	38.66	16,196.00
Net Issuance	Total new securities issued less securities repurchased, in millions. (Source: Compustat/CRSP)	13.50	0.00	113.54	-86.24	1,514.24
Issuance	Total new securities issued, in millions. (Source: Compustat/CRSP)	14.83	0.00	113.20	0.00	1,514.24
Repurchase	Total securities repurchased, in millions. (Source: Compustat/CRSP)	-1.33	0.00	6.24	-86.24	0.00
NAVPS	Net assets value per share of BDCs.	97.91	13.59	354.86	2.50	2,380.58
Shares	Total number of shares outstanding, in millions. (Source: Compustat/CRSP)	66.71	24.60	106.57	0.10	531.48
Panel B. Debt Financing						
Debt	Total value of debt (borrowings) of BDCs, in millions. (Source: Compustat/CRSP)	670.13	314.38	1,086.77	0.00	8,491.00
Cash	Total value of cash of BDCs, in millions. (Source: Compustat/CRSP)	93.02	28.48	232.57	0.00	1,964.19
Panel C. Investment Activity						
Investments	Total fair value of investment: sum of total fair value of debt, equity and other investments, in millions.	1,418.49	586.79	2,258.29	7.00	15,515.00
Borrowers	Total number of borrowers (portfolio companies).	126.33	72.00	271.91	1.00	2,676.00
Debt borrowers	Total number of debt borrowers (portfolio companies).	112.31	62.00	272.96	1.00	2,668.00
New borrowers	Total number of new borrowers (portfolio companies) per quarter.	10.39	5.00	31.93	0.00	661.00
New debt borrowers	Total number of new debt borrowers (portfolio companies) per quarter.	9.84	4.00	31.87	0.00	662.00
Panel D. Investment Allocation						
Equity investments	Total fair value of equity investments, in millions.	188.77	68.94	328.07	0.00	2,283.30
Debt investments	Total fair value of debt investments: sum of total value of senior, subordinated and other debt investments, in millions.	1,246.70	517.49	1,971.24	0.00	13,231.80
Subordinated debt investments	Total fair value of subordinated debt investments, in millions.	167.47	7.21	489.79	0.00	3,677.30
Senior debt investments	Total fair value of senior debt investment, in millions.	1,079.78	457.22	1,660.89	0.00	11,158.30
Deals	Total number of deals (transactions): debt, equity and other deals.	209.42	133.00	350.48	1.00	3,128.00
Debt deals	Total number of debt deals (transactions).	166.85	93.50	341.31	0.00	3,110.00
Senior debt deals	Total number of senior debt deals (transactions).	148.22	92.00	332.47	0.00	3,110.00
Subordinated debt deals	Total number of subordinated debt deals (transactions).	18.69	3.00	77.81	0.00	658.00

(continued)

(continued)

Variable	Description	Mean	Median	St.dev	Min	Max
Equity deals	Total number of equity deals (transactions).	44.98	32.00	49.60	0.00	245.00
New debt deals	Total number of new debt deals (transactions) per quarter.	21.91	10.00	41.80	0.00	675.00
New senior debt deals	Total number of new senior debt deals (transactions) per quarter.	19.35	10.00	40.11	0.00	675.00
New subordinate debt deals	Total number of new subordinated debt deals (transactions) per quarter.	2.41	0.00	11.04	0.00	103.00
Panel E. Profitability						
Gross income	Total investment income (income from investment activities), in millions.	37.51	16.15	60.28	-0.31	440.00
Net investment income	Total net investment income (income from investment activities), in millions.	30.88	9.86	55.79	-31.05	417.00
Interest income	Interest income from total value of investments, in millions.	31.97	14.42	50.04	-45.49	324.95
Interest expenses	Interest expenses from total value of debt (borrowings), in millions.	8.69	4.32	13.56	-24.10	96.51
Net interest income	Net interest income from total value of investments, in millions.	24.06	10.93	37.39	-1.23	227.00
Net realized gains/losses	Total net realized gains or losses from investment activities, in millions.	-7.75	-0.01	48.17	-646.00	373.00
Net unrealized gains/losses	Total net unrealized gains or losses from investment activities, in millions.	-1.94	-0.02	79.95	-889.00	468.63
ROE	Return on equity calculated as net investment income over total book equity, in %.	0.03	0.03	0.03	-0.14	0.14
ROA	Return on assets calculated as net investment income over total book assets, in %.	0.02	0.01	0.02	-0.08	0.07

Table 2: Treated vs. Control: Descriptive Statistics

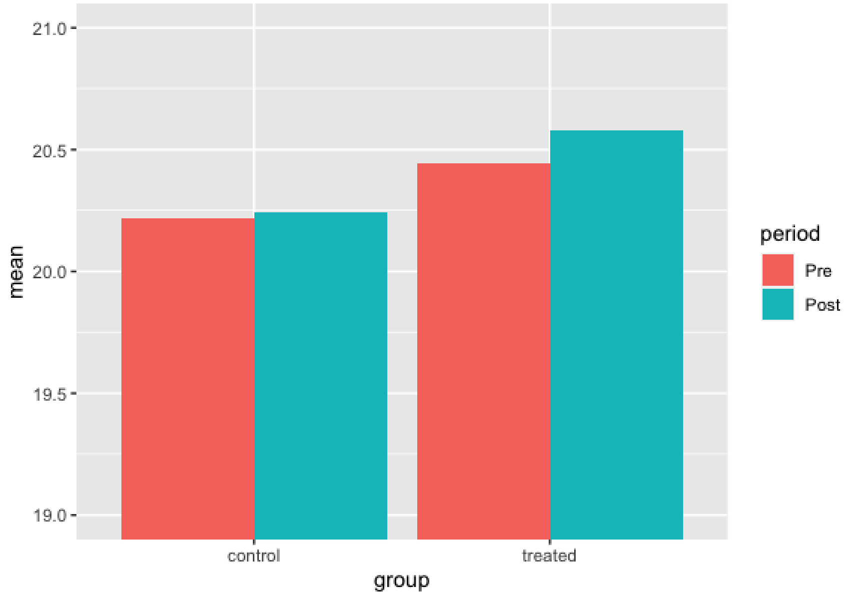
The table illustrates the descriptive statistics of two groups of BDCs as of Q4 2019. A BDC *j* is in the treated group if its average share of investments in industries affected by the COVID-19 shock is above the median over the pre-shock periods.

	Control			Treated			
	N	Mean	St. Dev.	N	Mean	St. Dev.	Difference
Total Assets, $ Billions	26	1.38	1.86	26	1.99	3.24	0.60
(Cash+Securities)/Total Assets, %	26	97.14	4.00	26	98.05	13.87	0.92
Cash/Total Assets, %	26	7.82	10.74	26	8.65	13.76	0.83
Securities/Total Assets, %	26	89.32	11.58	26	89.41	10.60	0.09
Other Assets/Total Assets, %	26	2.86	4.00	26	1.95	13.87	–0.92
MVE/BE, %	19	94.98	37.29	18	96.36	31.31	1.38
Equity/Total Assets, %	26	54.31	16.46	26	53.71	16.82	–0.60
Debt/Total Assets, %	26	40.29	15.27	26	43.44	16.80	3.15
Total Revenue/Total Assets, %	26	2.79	1.75	26	2.18	0.72	–0.62
Interest Income/Total Assets, %	26	2.34	1.88	26	1.73	0.54	–0.61
Interest Expense/Total Assets, %	26	0.62	0.45	26	0.51	0.26	–0.11
Net Interest Income/Total Assets, %	26	1.85	1.43	26	1.20	0.50	-0.66^{**}

Figure 1: Aggregate Trends

The Figures show the average natural logarithm of book assets and fair value of investments for the treated and control group pre- (Q1 2018 to Q4 2019) and post-COVID-19 shock (Q1 2020 to Q4 2020).

Panel (a): Ln (Fair Value of Book Assets)



Panel (b): Ln (Fair Value of Investments)

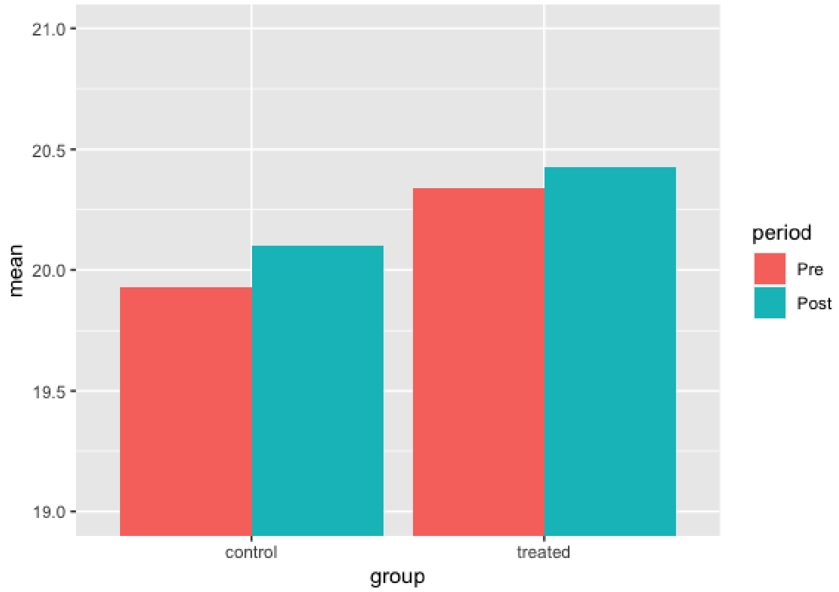


Table 3: Investment Volume

The Tables display the regression results from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t},$$

The dependent variables used in the regression are the natural logarithm of book assets and fair value of investments of BDC *j* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Dependent variables are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel (a): Investment Valuation

	Ln(Book Assets)					
Post	0.02	0.02	0.27	0.27***		–0.05*
	(0.16)	(0.05)	(0.28)	(0.09)		(0.03)
Treated	0.23	2.01***	0.23*	2.01***		–0.05
	(0.13)	(0.18)	(0.13)	(0.18)		0.06
Post × Treated	0.11	0.11	0.11	0.11	–0.03	–0.03
	(0.22)	(0.07)	(0.23)	(0.07)	(0.02)	(0.02)
Ln ($Assets_{t-1}$)					0.94***	0.94***
					(0.01)	(0.05)
Debt / $Assets_{t-1}$					0.96***	0.96***
					(0.05)	(0.05)
Net Int. Inc. / $Assets_{t-1}$					0..83***	0.83***
					(0.02)	(0.02)
BDC FE	No	Yes	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
R^2	0.01	0.90	0.01	0.90	0.99	0.99
N	624	624	624	624	624	624

Panel (b): Investment Valuation

	Ln(Fair Value of Investments)					
Post	0.17	0.16	0.95**	0.90***		0.27
	(0.21)	(0.14)	(0.38)	0.24		(0.19)
Treated	0.41**	2.98***	0.41**	2.98***		–0.53
	(0.17)	(0.47)	(0.17)	0.47		(0.40)
Post × Treated	–0.09	–0.07	–0.09	–0.07	–0.34**	–0.34**
	(0.30)	(0.20)	(0.30)	(0.19)	(0.15)	(0.15)
Ln ($Assets_{t-1}$)					1.57***	1.57***
					(0.09)	(0.09)
Debt / $Assets_{t-1}$					2.88***	2.88***
					(0.33)	(0.33)
Net Int. Inc. / $Assets_{t-1}$					1.44***	1.44***
					(0.13)	(0.13)
BDC FE	Yes	Yes	No	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	Yes	Yes
R^2	0.01	0.61	0.03	0.63	0.79	0.79
N	624	624	624	624	624	624

Panel (c): Valuation Adjustments

	Net Realized and Unrealized Gains / Assets		Net Unrealized Gains / Assets	
Post × Treated	0.24	0.10	3.87	3.00
	(0.68)	(0.68)	(2.11)	(2.15)
Ln ($Assets_{t-1}$)		−0.56		−0.01
		(0.39)		(0.02)
Debt / $Assets_{t-1}$		6.81^{***}		0.02
		(1.52)		(0.05)
Net Int. Inc. / $Assets_{t-1}$		−0.32		−0.01
		(0.58)		(0.03)
BDC FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.36	0.39	0.13	0.13
N	624	624	624	624

Table 4: Number of Borrowers

The Table displays the regression result from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t},$$

The dependent variable used in the regression is the natural logarithm of number of borrowers of a BDC *j* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Dependent variables are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Ln(# of Borrowers)		Ln(# of New Borrowers)		Ln(# of Debt Borrowers)		Ln(# of New Debt Borrowers)	
Post × Treated	0.09^{**}	−0.01	0.14	0.08	0.08^{**}	−0.03	0.11	0.02
	(0.04)	(0.03)	(0.10)	(0.10)	(0.03)	(0.03)	(0.11)	(0.10)
Ln ($Assets_{t-1}$)		0.56^{***}		0.21^{***}		0.59^{***}		-0.20^{***}
		(0.03)		(0.06)		(0.03)		(0.06)
Debt / $Assets_{t-1}$		0.60^{***}		1.34^{***}		0.59^{***}		1.52^{***}
		(0.06)		(0.23)		(0.03)		(0.23)
Net Int. Inc. / $Assets_{t-1}$		0.34^{***}		0.20^{**}		0.37^{***}		0.20^{**}
		(0.03)		(0.09)		(0.03)		(0.09)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.95	0.98	0.71	0.73	0.97	0.98	0.73	0.75
N	624	624	624	624	624	624	624	624

Table 5: Number of Investment Deals

The Tables display the regression results from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t},$$

The dependent variables used in the regression are the natural logarithm of number of outstanding deals in Panel (a), decomposed debt deals in Panel (b), the number of deals per borrower in Panel (c) and the number of newly originated debt deals in Panel (d) by a BDC *j* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Dependent variables are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel (a): Number of Outstanding Deals

	Ln(# of Deals)		Ln(# of Equity Deals)		Ln(# of Debt Deals)	
Post × Treated	0.03	–0.05	0.04	0.02	0.04	–0.04
	(0.06)	(0.04)	(0.06)	(0.05)	(0.06)	(0.04)
Ln ($Assets_{t-1}$)		0.53^{***}		0.16^{***}		0.53^{***}
		(0.02)		(0.03)		(0.02)
Debt / $Assets_{t-1}$		0.86^{***}		0.04		0.88^{***}
		(0.08)		(0.12)		(0.09)
Net Int. Inc. / $Assets_{t-1}$		0.29^{***}		0.15		0.29^{***}
		(0.03)		(0.05)		(0.03)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.91	0.96	0.95	0.95	0.93	0.97
N	624	624	624	624	624	624

Panel (b): Decomposing Debt Deals

	Ln(# of Sub Debt Deals)		Ln(# of Senior Debt Deals)	
Post × Treated	-0.14^{**}	-0.15^{**}	0.19^{***}	–0.01
	(0.06)	(0.06)	(0.04)	(0.04)
Ln ($Assets_{t-1}$)		0.08^{**}		0.53^{***}
		(0.04)		(0.02)
Debt / $Assets_{t-1}$		0.05		0.94^{***}
		(0.14)		(0.09)
Net Int. Inc. / $Assets_{t-1}$		0.06		0.30^{***}
		(0.05)		(0.03)
BDC FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.94	0.94	0.97	0.98
N	624	624	624	624

Panel (c): Number of Outstanding Deals per Borrower

	Ln(# of Deals per Borrower)		Ln(# of Debt Deals per Borrower)	
Post × Treated	–0.01	-0.02^{***}	0.00	–0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Ln ($Assets_{t-1}$)		0.05^{***}		0.04^{***}
		(0.01)		(0.01)
Debt / $Assets_{t-1}$		0.04^{**}		0.05^{**}
		(0.02)		(0.02)
Net Int. Inc. / $Assets_{t-1}$		0.03^{***}		0.02^{*}
		(0.01)		(0.01)
BDC FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.95	0.95	0.96	0.96
N	624	624	624	624

Panel (d): Number of Newly Originated Deals

	Ln(# of New Debt Deals)		Ln(# of New Sub. Debt Deals)		Ln(# of New Senior Debt Deals)	
Post × Treated	−0.05	−0.09	−0.10	−0.10	0.00	−0.05
	(0.10)	(0.09)	(0.08)	(0.08)	(0.10)	(0.10)
Ln ($Assets_{t-1}$)		0.34***		0.06		0.34***
		(0.06)		(0.51)		(0.06)
Debt / $Assets_{t-1}$		1.11***		0.01		1.17***
		(0.28)		(0.25)		(0.29)
Net Int. Inc. / $Assets_{t-1}$		−0.02		0.05		−0.02
		(0.08)		(0.07)		(0.08)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.80	0.83	0.73	0.73	0.80	0.83
N	624	624	624	624	624	624

Table 6: Investment Volume Controlling for Firms' Demand

The Tables display the regression results from estimating the following difference-in-differences model using OLS and within transformation:

$$y_{k,i,j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{i,t-1} + \varepsilon_{k,i,j,t},$$

The dependent variabl is the natural logarithm of the fair value of investments of type *k* originated by a BDC *j* to a portfolio company *i* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Dependent variables are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel (a): Fair Value of Investments

	All		Debt	
	(1)	(2)	(3)	(4)
Post × Treated	–0.04	–0.15**	–0.01	0.01
	(0.15)	(0.09)	(0.07)	(0.06)
Ln ($Assets_{t-1}$)	0.31*	0.26**	0.32***	0.22***
	(0.14)	(0.07)	(0.07)	(0.08)
Debt / $Assets_{t-1}$	0.28	0.31*	0.34**	0.68***
	(0.30)	(0.16)	(0.15)	(0.19)
Net Int. Inc. / $Assets_{t-1}$	0.28	0.24**	030***	0.22*
	(0.22)	(0.11)	(0.10)	(0.12)
BDC FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Company-Time FE	Yes	No	Yes	No
Company-Instrument-Time FE	No	Yes	No	Yes
R^2	0.02	0.15	0.11	0.17
N	90000	90000	69211	69211

Panel (b): Fair Value of Debt Investments by Type

	Subordinated	Senior
Post × Treated	0.66***	–0.02
	(0.54)	(0.06)
Ln ($Assets_{t-1}$)	0.57*	0.28***
	(0.30)	(0.06)
Debt / $Assets_{t-1}$	1.69***	0.41***
	(0.56)	(0.13)
Net Int. Inc. / $Assets_{t-1}$	–19.23	0.26***
	(19.03)	(0.08)
BDC FE	Yes	Yes
Time FE	Yes	Yes
Company-Time FE	Yes	Yes
R^2	0.45	0.17
N	5500	63711

Table 7: Investment Decomposition

The Tables display the regression results from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t},$$

The dependent variables are the natural logarithm of fair value of equity and debt investments in Panel (a) and the share of equity and debt investments in terms of the fair values in Panel (b) of a BDC *j* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. The equity and debt shares are expressed in percentages. Dependent variables in Panel (a) are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel (a): Fair Value of Investments by Type

	Ln(Equity)		Ln(Debt)		Ln(Sub. Debt)		Ln(Senior Debt)	
Post × Treated	−0.31	−0.34	0.00	−0.12	-1.74^{***}	-1.87^{***}	0.52^{**}	−0.03
	(0.29)	(0.29)	(0.01)	(0.18)	(0.65)	(0.65)	(0.21)	(0.25)
Ln ($Assets_{t-1}$)		0.38^{**}		0.81^{***}		2.70^{***}		1.64^{***}
		(0.17)		(0.37)		(0.73)		(014)
Debt / $Assets_{t-1}$		−0.91		0.08^{***}		1.76		3.12^{***}
		(0.65)		(0.03)		(1.92)		(0.55)
Net Int. Inc. / $Assets_{t-1}$		0.37		0.02^{*}		32.51		1.50^{***}
		(0.25)		(0.01)		(31.33)		(0.21)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.90	0.90	0.72	0.92	0.80	0.80	0.85	0.85
N	624	624	624	624	624	624	624	624

Panel (b): Portfolio Shares

	Equity / Assets		Debt / Assets		Sub. Debt / Assets		Senior Debt / Assets	
Post × Treated	-4.38^{***}	-4.45^{***}	0.02	−0.75	-1.48^{**}	-1.41^{**}	1.70	0.66
	(0.94)	(0.94)	(0.01)	(1.18)	(0.62)	(0.62)	(1.34)	(1.16)
Ln ($Assets_{t-1}$)		0.01		0.08^{***}		0.00		0.08^{***}
		(0.01)		(0.01)		(0.00)		(0.01)
Debt / $Assets_{t-1}$		−0.01		0.08^{**}		-0.04^{***}		0.12^{***}
		(0.02)		(0.03)		(0.01)		(0.03)
Net Int. Inc. / $Assets_{t-1}$		0.01		1.79^{***}		0.00		0.02^{*}
		(0.01)		(0.45)		(0.01)		(0.01)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.92	0.92	0.90	0.93	0.94	0.94	0.93	0.94
N	624	624	624	624	624	624	624	624

Table 8: Profitability

The Tables display the regression results from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{i,t-1} + \varepsilon_{j,t},$$

The dependent variables are the net interest margin and its components in Panel (a), net realized gain/loss over assets in Panel (b) and the returns on assets and equity in Panel (c) of a BDC *j* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Financial ratios are expressed in percentages. Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel (a): Net Interest Margin

	Net Interest Income / Assets		Interest Income / Assets		Interest Expense / Assets	
Post × Treated	0.08	0.06	0.06	0.04	0.00	−0.01
	(0.09)	(0.09)	(0.11)	(0.10)	(0.03)	(0.03)
Ln (Assets$_{t-1}$)		0.36***		0.41***		0.04***
		(0.04)		(0.04)		(0.01)
Debt / Assets$_{t-1}$		−0.21*		−0.04		0.11*
		(0.19)		(0.24)		(0.06)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.73	0.76	0.70	0.73	0.68	0.69
N	624	624	624	624	624	624

Panel (b): Return on Assets and Equity

	ROE		ROA	
Post × Treated	0.07	0.00	−0.48	−0.96
	(0.34)	(0.00)	(0.77)	(0.61)
Ln (Assets$_{t-1}$)		0.64***		5.17***
		(0.16)		(0.29)
Debt / Assets$_{t-1}$		0.36		2.39*
		(0.76)		(1.38)
BDC FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
R^2	0.64	0.65	0.18	0.48
N	624	624	624	624

Table 9: Equity Financing

The Tables display the regression results from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t},$$

The dependent variables are the logarithm of the market value of equity, share price, number of shares outstanding, and book value of equity in Panel (a), the ratio of equity net issuances, issuances, and repurchases to market value of equity in Panel (b) and the ratio of the share price over NAVPS in Panel (c) of a BDC *j* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Ratios are expressed in percentages. Dependent variables in Panel (a) are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel (a): Market and Book Value of Equity

	Ln(MVE)		Ln(Price)		Ln(# of Shares)		Ln(BVE)	
Post × Treated	−0.03	−0.10**	−0.09*	−0.12**	0.01	−0.01	−0.01	−0.24***
	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.12)	(0.14)	(0.07)
Ln ($Assets_{t-1}$)		0.94***		0.21***		0.63***		1.59***
		(0.06)		(0.07)		(0.08)		(0.04)
Debt / $Assets_{t-1}$		0.03		−0.61***		0.72***		1.44***
		(0.12)		(0.15)		(0.16)		(0.16)
Net Int. Inc. / $Assets_{t-1}$		10.59***		5.30**		4.59**		1.55***
		(1.79)		(2.16)		(2.33)		(0.06)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.96	0.98	0.85	0.86	0.87	0.88	0.72	0.93
N	444	444	444	444	444	444	624	624

Panel (b): Equity Issuance

	Net Issuance / MVE		Issuance / MVE		Repurchases / MVE	
Post × Treated	−2.44*	−1.52	−2.06	−1.12	−0.38*	−0.40*
	(1.42)	(1.27)	(0.01)	(1.25)	(0.20)	(0.21)
Ln ($Assets_{t-1}$)		−0.02		−0.02		0.01
		(0.02)		(0.02)		(0.00)
Debt / $Assets_{t-1}$		0.36***		0.35***		0.00
		(0.04)		(0.04)		(0.01)
Net Int. Inc. / $Assets_{t-1}$		1.45**		1.41**		0.03
		(0.56)		(0.55)		(0.09)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.14	0.33	0.13	0.33	0.28	0.28
N	444	444	444	444	444	444

Panel (c): Net Asset Discount

	Share Price / NAVPS	
Post × Treated	−6.99***	−7.81***
	(2.49)	(2.48)
Ln ($Assets_{t-1}$)		0.02
		(0.04)
Debt / $Assets_{t-1}$		−0.24***
		(0.08)
Net Int. Inc. / $Assets_{t-1}$		2.22**
		(1.09)
BDC FE	Yes	Yes
Time FE	Yes	Yes
R^2	0.88	0.89
N	444	444

Table 10: Debt Financing and Cash Holdings

The Table displays the regression result from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t},$$

The dependent variables are the logarithm of total debt, the ratio of total debt to total assets, the logarithm of cash-like securities, and the ratio of cash-like securities to total assets of a BDC *j* at time *t*. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if BDC *j* has pre-shock average exposure to the affected industries above the median. The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Ratios are expressed in percentages. Dependent variables are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

	Ln(Debt)		Debt-to-Assets		Ln(Cash)		Cash-to-Assets	
Post × Treated	0.10	–0.22	0.22	–0.75	–0.06	–0.20	1.56	2.36**
	(0.31)	(0.24)	(1.36)	(1.18)	(0.19)	(0.18)	(1.18)	(0.96)
Ln ($Assets_{t-1}$)		1.82***		0.08***		0.54***		–0.09***
		(0.14)		(0.01)		(0.11)		(0.01)
Debt / $Assets_{t-1}$		5.80***		0.08***		2.00***		–0.01
		(0.53)		(0.01)		(0.41)		(0.02)
Net Int. Inc. / $Assets_{t-1}$		0.16		0.02*		0.79		–0.02**
		(0.20)		(0.01)		(0.15)		(0.01)
BDC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.89	0.94	0.90	0.93	0.79	0.81	0.73	0.82
N	624	624	624	624	624	624	624	624

Table 11: BDC Outcomes: Alternative Allocation to Treatment

The Tables display the regression results from estimating the following difference-in-differences model using OLS:

$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \beta_3 Post_t \times Treated_j + \delta X_{j,t-1} + \varepsilon_{j,t},$$

The dependent variables are the ratio of cash to assets (1), the natural logarithm of book value of assets (2), the natural logarithm of fair value of investments (3) the natural logarithm of fair value of subordinated debt (4), the natural logarithm of number of subordinated debt deals (5) of a BDC j at time t. The dummy variable $Post_t$ takes on the value of one for the periods Q1 2018 to Q4 2019 and zero otherwise. The indicator variable $Treated_j$ takes on the value of one if (i) BDC j has pre-shock average exposure to the affected industries above the mean in Panel (a); (ii) BDC j has lower CIK number in Panel (b). The data is based on quarterly observations for the periods Q1 2018 to Q4 2020. Dependent variables are calculated as the natural logarithm of (1+ *Variable*). Standard errors are reported in parentheses. ***, **, * denote significance at the 1%, 5% and 10% level, respectively.

Panel (a): Pre-Shock Average Industry Exposure

	(1)	(2)	(3)	(4)	(5)
Post × Treated	2.63***	–0.02	–0.38**	1.92***	–0.16**
	(0.96)	(0.02)	(0.15)	(0.65)	(0.06)
Ln (Assets$_{t-1}$)	–0.09***	0.94***	1.57***	0.81**	0.08**
	(0.01)	(0.01)	(0.09)	(0.38)	(0.04)
Debt / Assets$_{t-1}$	–0.01	0.96***	2.91***	1.42	0.07
	(0.02)	(0.05)	(0.33)	(1.46)	(0.14)
Net Int. Inc. / Assets$_{t-1}$	–0.02**	0.83***	1.43***	0.68	0.06
	(0.01)	(0.02)	(0.13)	(0.55)	(0.05)
BDC FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
R^2	0.82	0.99	0.79	0.80	0.94
N	624	624	624	624	624

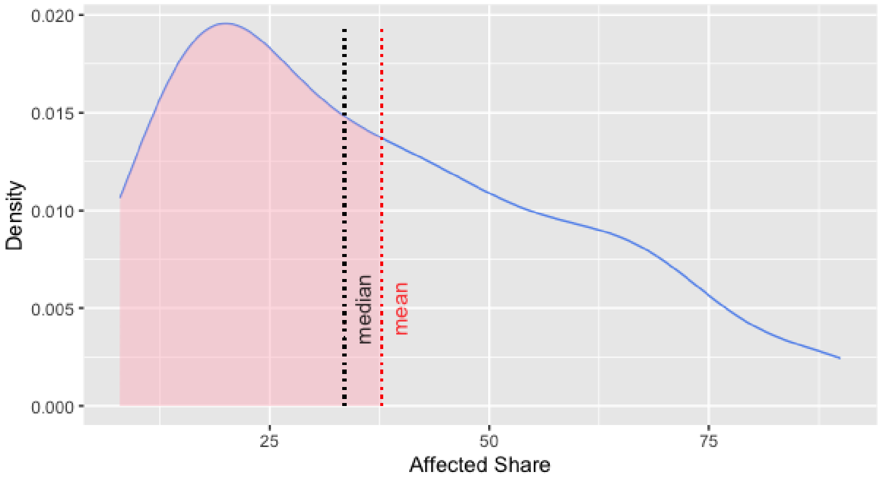
Panel (b): Placebo Test – CIK Sorted

	(1)	(2)	(3)	(4)	(5)
Post × Treated	0.99	–0.02	–0.14	0.44	0.06
	(0.96)	(0.02)	(0.15)	(0.65)	(0.06)
Ln (Assets$_{t-1}$)	–0.08***	0.94***	1.55***	0.76**	0.08**
	(0.01)	(0.01)	(0.09)	(0.38)	(0.04)
Debt / Assets$_{t-1}$	–0.00	0.96***	2.84***	0.94	0.02
	(0.02)	(0.05)	(0.33)	(1.46)	(0.14)
Net Int. Inc. / Assets$_{t-1}$	–0.02**	0.82***	1.42***	0.57	0.05
	(0.01)	(0.02)	(0.13)	(0.55)	(0.05)
BDC FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
R^2	0.82	0.99	0.79	0.80	0.94
N	624	624	624	624	624

Appendix A

Figure A.1: Industry Affected Share Density

This figure represents the distribution of the affected share, which measures industries vulnerability to social distancing.



Note: The data for the affected share measure is taken from Koren & Peto (2020) and based on the three-digit NAICS industries.

Table A.1: Pre-Shock Industry Exposure

The table presents descriptive statistics of the average pre-shock affected industry exposure (Q1 2018 to Q4 2019) for the regression groups used in the DiD model. BDC *j* is in the treated group if its average percentage share of fair value investments in affected industries is above the median over the pre-shock periods. The statistics describing the industry exposure are presented as percentages.

	N	Min	25%	Median	Mean	75%	Max	St. Dev.
Treated	26	13.40	15.15	17.21	18.12	20.85	27.57	3.58
Control	26	0.00	4.99	7.92	7.12	10.22	13.05	4.04
All	52	0.00	8.03	13.23	12.62	17.09	27.57	6.72

Appendix B

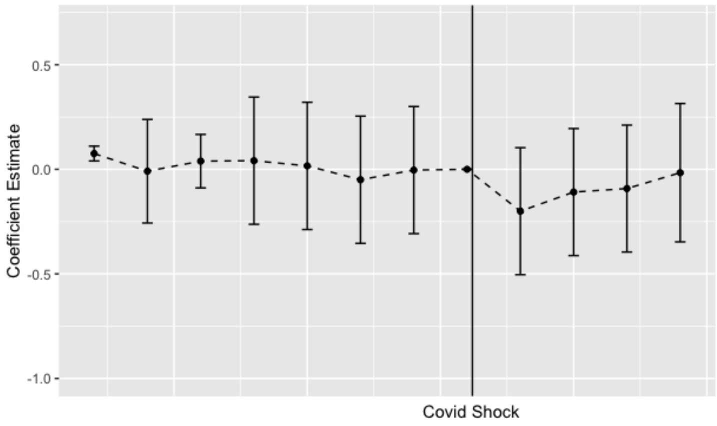
Figure B.1: Parallel Trends

The Figures depict the regression coefficients of γs together with the 95% error bar from the following panel regression:

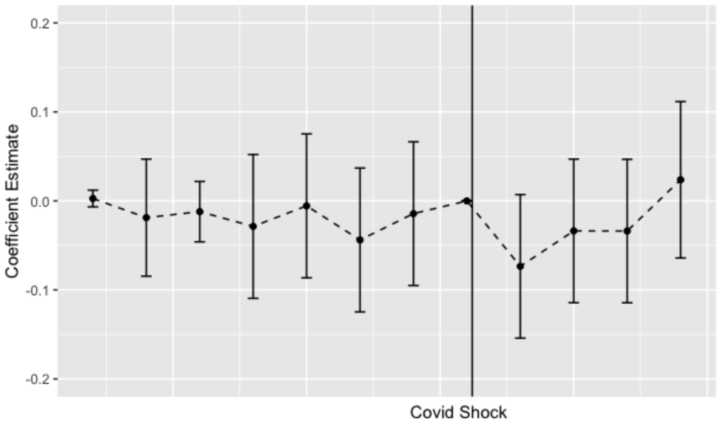
$$y_{j,t} = \beta_1 Post_t + \beta_2 Treated_j + \sum_t \gamma_t \left(\lambda_t \times Treated_j\right) + \delta X_{j,t-1} + \varepsilon_{j,t},$$

where λs are dummy variables for each quarter t of the sample. λ_t is set to one for the period t and otherwise takes on the value zero. We omit the dummy variables for the quarter Q4 2019, which therefore becomes the reference period of the regression.

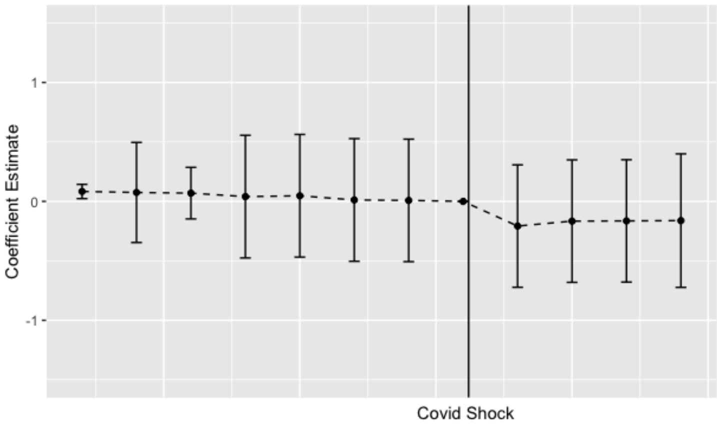
Panel (a): Book Value of Equity



Panel (b): Book Value of Assets



Panel (c): Fair Value of Investments



Appendix C

Table C.1: Investment Portfolio of BDCs

The Table reports summary statistics for portfolio of BDC investments. It represents the cross-sectional statistics on investment instruments across BDCs as of Q4 2019.

	Count	Mean	St.Dev.	Median	25%	75%	90%
Portfolio Companies, Count	52	132.85	274.24	79.00	46.00	120.00	208.00
Outstanding Deals, Count	52	221.44	363.27	136.50	75.75	210.50	342.70
Outstanding Debt Deals, %	52	70.03	23.66	75.61	54.44	85.72	97.02
Senior Debt Deals, %	52	87.86	22.49	98.04	87.56	100.00	100.00
Subordinated Debt Deals, %	52	12.14	22.49	1.96	0.00	12.44	28.93
Outstanding Equity Deals	52	29.97	23.66	24.39%	14.28	45.56	61.98

Figure C.1: NAV Discount

The Figure illustrates the average NAV discount for treated and control BDCs for the periods Q1 2018 to Q4 2020.