Bank Lending to Nonbanks: A Robust Channel Fueled by Constrained Capital?*

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Abstract

This paper documents the way banks are increasingly directing their lending portfolio to nonbanks, fueling recent growth in nonbank assets. Importantly, the shift in lending towards nonbanks is accelerated following unexpected shocks to banks' core capital positions, such as the Basel III regulatory shock, the Oil Shock of 2014, and the COVID-19 crisis. Nonbanks with credit arrangements from bank lenders, in turn, lend more to corporate borrowers, participate more in syndicated loan deals with their bank lenders, and are less likely to sell their shares. These findings highlight a salient channel of banks' lending to nonbanks, driven by banks' constrained capital. (100 words)

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1. Introduction

During the past two decades, nonbank financial institutions (NBFI) have played a growing role in the financial sector and the economy. The global assets of these firms, often referred to as the nonbank sector, reached $200.2 trillion by the end of 2019, comprising 49.5% of the total global financial assets (see Figure 1.)[1] Studies investigating the remarkable growth of the nonbank sector often point to several key differences between banks and nonbanks, including differential adoption rates of new information technology and, importantly for our paper, relatively lighter regulatory scrutiny of the shadow banking sector (e.g., Buchak et al. (2018); Fuster et al. (2019)). However, few studies investigate the *direct* linkages between banks and nonbanks. To a large extent, the rapid growth in the nonbank sector closely correlates with the increase in bank lending to nonbanks, which has more than doubled since 2013, surpassing $2.0 trillion by October 2023.[2] This points to a more complex and symbiotic relationship between banks and nonbanks than a head-to-head competition over market share in the market for loans. While the regulatory costs and technological advantages may be important motives for the financial activities and assets to shift outside of banking perimeters and to nonbnaks, banks remain a crucial source of funding and liquidity provision to NBFIs (Acharya et al. (2023)).

This paper investigates the dynamics of banks' lending to nonbanks, a novel channel that has fueled recent growth in nonbank assets.[3] We conjecture that the significant growth in nonbank assets in the post-GFC era is closely associated with banks increasing lending to nonbanks. We argue that the shift towards nonbank lending is closely linked to the heightened capital regulatory requirement, and lending to nonbanks is particularly accelerated during economic shocks when banks' core capital positions are under pressure. Indeed, while banks are uniquely positioned to channel funds to nonbanks due to their access to deposits and liquidity backstops, they also potentially benefit from engaging in such deals because of the lower capital and regulatory burden associated with lending to nonbanks as opposed to nonfinancial corporates.[4]

[1] See Global Monitoring Report on NonBank Financial Intermediation 2020 (Data Source: Jurisdictions' 2020 submissions (national sector balance sheet and other data); FSB calculations.)

[2] See Financial Stability Report on May 2020 (Data Source: Federal Reserve Board, Form FR Y-14Q (Schedule H.1), Capital Assessments and Stress Testing).

[3] Bank credit and liquidity provision to NBFIs is not limited to loans and is also done through other credit instruments such as federal funds, repos, bonds and holding of Agency- and GSE-backed securities and mutual fund shares. Acharya et al. (2023) provide a detailed view of bank holding of NBFI's liabilities using a flow of funds database called "From Whom To Whom."

[4] The lower regulatory burden associated with lending to NBFIs could be driven by a number of factors. NBFIs have generally narrower and better rating distribution (mostly investment graded) and are generally considered less risky. In addition, due to the higher opacity of financial institutions, the credit deterioration

Our paper has three key findings. First, we document banks are increasingly directing their lending portfolio to nonbanks (see Figure 2.) Second, we demonstrate that the shift in lending towards nonbanks is accelerated following unexpected shocks to banks' core capital positions, suggesting regulatory capital is the key factor behind the effects. Third, nonbanks that are more reliant on banks' credit were better able to continue lending to the economy.

Clear identification of the channel driving bank increased lending to nonbanks is the key to understanding the dynamics of banks' lending to nonbanks. In this paper, we exploit three unexpected shocks to banks' core capital positions: the Basel III regulatory shock, the Oil Shock of 2014, and the COVID-19 crisis.

First, we directly quantify changes in banks' regulatory capital pressure using the introduction of Basel III Capital Accord. We exploit the fact that the banking sector was surprised by the announcement of how U.S. bank regulators planned to implement the Basel III Capital Accord. Banks with relatively greater exposure to the regulatory shock (surprise component of Basel III implementation) responded by shifting lending away from nonfinancial borrowers and towards nonbank borrowers, apparently in an attempt to better optimize their capital positions. This response in the bank loan supply function allowed the nonbanks to lend more to nonfinancial firms. We show that not only did nonbanks expand their market share in commercial loan markets following the adjustment by banks, but nonbanks with access to bank loans had a relatively stronger increase in lending.

Our results are consistent with the notion of there being a complementary relationship between banks and nonbanks. When bank capital positions come under pressure and it becomes more costly to lend, nonbank lenders take steps to absorb the loan demand coming from the real economy, but with the help of increased funding coming from the banks. In other words, as noted in Acharya et al. (2023), this suggests a potential transformation of banks role as providing direct intermediation services to firms and households to providing financing of nonbank activities. Although, the literature has identified regulatory cost as one of the main mechanisms contributing to the shift of financial assets to nonbanks, our paper is the first to document regulatory costs as an incentive for the liabilities to remain within the banks and nonbanks becoming increasingly reliant on banks for funding and liquidity.

The regulatory capital pressure channel driving banks' lending to nonbanks is further illustrated in analyses looking at two other shocks during which certain banks facing higher regulatory costs or tighter capital constraints: the oil price shock of 2014-16 and the COVID-19 episode of early 2020. We identify banks that are exposed to these shocks and explore the changes in lending to nonbank borrowers. We then compare reactions across banks of various

may not be reflect in NBFIs credit rating as fast as nonfinancial corporates.

characteristics and investigate the channel through which banks' loan supply to nonbanks is affected. Our results show that banks exposed to the shocks did not suppress credit supply to nonbank borrowers as they did to other corporate borrowers. Banks with smaller capital buffers exhibit a greater shift of their lending portfolio toward nonbanks, suggesting potential regulatory capital stimulates banks' lending to nonbanks. One important implication of this finding is that banks are now more tightly linked to nonbanks through their lending channel after the two shocks to banks' core capital positions.

The seminal trend of nonbank's increasing reliance on bank funding suggests a potential shift in lending patterns when it comes to nonbanks' credit supply to the real economy. For instance, during economic downturns, nonbanks with access to banks' credit as a liquidity backstop may be able to continuously offer credit to the real economy, as compared to one without. To shed light on the implication for the real economy, we investigate the implication of our finding on the real economy by comparing credit flows by nonbanks reliant on bank credit as a funding source to those that do not rely on bank financing. These tests help us understand whether nonbanks with bank funding are worse able or better able to continuously provide credit to the real economy following a shock to the banks. Our results indicate nonbanks that relied on funding from banks prior to the crisis were better able to continue lending to the economy, providing support for the existence of a robust bank funding channel during periods of stress. This result highlights the importance of bank lending as a stable funding source for nonbanks to support their role as financial intermediaries channeling funds to the real economy, especially during periods of stress.

The paper contributes to several strands of literature that study the growth of shadow banking and also seek to explain that growth and assess the underlying fragility of the sector as well as the more recent literature that highlights a more symbiotic view of bank and nonbank relationship as opposed to the more traditional substitution view. One of the first published references to "Shadow Banking" was at the 2007 Jackson Hole Symposium where Paul McCulley noted that a growing share of financial innovation in the U.S. was being conducted outside of the regulated banking sector. This activity, therefore, was not strongly linked to the safety net and could potentially be fragile in a stressful funding environment. Nonbank funding, of course, famously dried up later in 2007 and eventually led to a crisis in the regulated banking sector as well (Gorton and Metrick (2012)).

Following the events leading up to the financial crisis in 2007-2008, many researchers have studied the role of nonbanks within the larger banking system. The core tradeoff in many of these papers is between regulation that leads to safety and soundness on the one hand but may restrict credit and stifle financial innovation on the other. Depending on the information of the market participants, unregulated nonbanks may have a role in lending side-by-side with traditional banks and shifting risk from the regulated sector to the unregulated sector (Farhi and Tirole (2021), Chrétien and Lyonnet (2017)). Ordonez (2018) develops a model where banks can distinguish between the quality of risky investments, but bank regulators are unable to make this differentiation. Nonbanks serve the useful role of allowing banks to fund higher-quality risky assets and avoid scrutiny from less-informed regulators. Gennaioli et al. (2013) has a related set-up where the nonbank sector exists to allow greater risk-sharing than the banks can provide on their own. This leads to an expansion of credit and can be welfare-improving, even if the greater risk-sharing leads to more interconnectedness and vulnerability to shocks.

Alternatively, nonbanks are relatively new entrants to banking markets and may have access to more recent vintages of lending technology, leading to a comparative advantage in making some types of loans (Buchak et al. (2018); Fuster et al. (2019)). Much of the recent literature on fintech lending stresses the way nonbanks can be more nimble following a change in economic conditions, provided they are able to maintain access to funding (Allen et al. (2022); Erel and Liebersohn (2020)).

Some authors have stressed a more direct motive for the rise of the nonbank sector: regulatory arbitrage. In this strand of the literature, the nonbank sector is not necessarily welfare-improving. Unregulated nonbanks may have a competitive advantage making risky loans simply because they have lower costs. Nonbanks do not face as much regulatory scrutiny (a cost) nor are they required to hold as much capital as the regulated banks (Acharya et al. (2013); Claessens et al. (2012)). These distortions can incentivize banks to offload their risky assets. Empirically, Irani et al. (2021) document the importance of capital constraints in the competition between bank and nonbank lenders. Using shocks to bank capital requirements as instruments for bank credit supply, they find that lower-capitalized banks are less able to retain loans on their balance sheets following a capital shock and that nonbanks enter to fill in the gap.

Most of the empirical papers in the literature on nonbank funding instability use the financial crisis period as a backdrop. Relatively few papers look at nonbank access to funding in stress periods where the shock occurs outside of the nonbanking sector. Along with our paper, an exception to this is Fleckenstein et al. (2020) who document a greater cyclicality of nonbank lending compared to bank lending, including during the COVID-19 period. This greater cyclicality is linked to a similar cyclicality in nonbank funding flows. Our results complement their findings in the sense that nonbank lenders with access to bank funding exhibited less cyclicality in credit provision and, therefore, cut lending less during the COVID-19 pandemic.

Our study sheds lights on the increasingly tighter linkages between banks and nonbanks through *direct* credit provision. Importantly, the direct connection becomes tighter after banks' capital base becomes more constrained during periods of stress.

In the remainder of the paper, Section 3 describes the data, Section 4 introduces the shocks used in the paper and lays out our methodology and main results, Section 5 discusses the further implication on loan sales and credit supply by nonbanks. Section 7 concludes.

2. Institutional Background and Identification

3. Data and Summary Statistics

Our primary data source is the Shared National Credit (SNC) register, sourced by the Federal Deposit Insurance Corporation, the Federal Reserve Board, and the Office of the Comptroller of the Currency. The SNC data has comprehensive coverage of syndicated lending from 1990 to the present and provides information for all syndicated loans in the U.S. with a minimum total commitment of $20 million and at least three federally supervised institutions participating in the syndicate.[5] The administrative agent of a loan - the lead arranger or lead bank - is required to report detailed information about the loan at regular intervals. [6]

The SNC provides comprehensive information on the loan committed and utilized exposure, origination and maturity dates, borrower identity and industry, loan characteristics (e.g., loan type, loan purpose, etc.) and the identity of agent bank and participant lenders. Importantly, SNC data tracks loans and shares of credit held by syndicate lead and participants in each quarter after origination over the life of the credit. This allows us to identify loan-level changes in banks' credit provision in response to shocks. Also essential to our study, detailed information on loan borrowers allows us to analyze banks' portfolio composition and calculate their exposures to specific shocks, including the Basel III regulatory capital shock, oil and gas (O&G) shock, and the COVID-19 crisis. Last but not the least,

[5]See Bord and Santos (2012) in a comparison of SNC and DealScan over 1988-2010 show that the size criterion in SNC relative to DealScan that contains information on credits above $100,000 does not constitute an important difference between the two databases.

[6]The reporting frequency is annual before 2015, quarterly in 2015, and semi-annual since then. The SNC data report the facility of each loan deal separately. The agencies increased the minimum aggregate loan commitment threshold from $20 million to $100 million effective January 1, 2018. It is also worth noting that the SNC database has snapshots of loan data recorded semi-annually in the earlier years and then switched to a quarterly reporting schedule. Depending on the sample periods used in each test, the number of observation included can thus vary.

since we can track the same borrower across multiple banks, we can exploit within-borrower variation that identifies credit supply without confounding credit demand effects.[7]

In addition to the SNC, we utilize data from other sources. The first is the Federal Financial Institutions Examination Council Consolidated Financial Statements Call Reports of Condition and Income (Form FFIEC 031), which provide quarterly balance sheet data for U.S. banks. We use these data to create bank control variables for our regressions, including measures of size, liquidity, and loan portfolio composition, as well as several bank-level measures of regulatory capital such as the Common Equity Tier 1 (CET 1) capital to risk-weighted assets ratio. Using this, we investigate the impact of bank capital on lending to nonbanks through the analysis of cross-sectional variation in their regulatory capital ratios.

3.1 Sample Selection and Variable Construction

The SNC classifies lenders into three categories: domestic banks, foreign banks, and nonbanks. We keep only the bank lenders and, for better comparison, limit our sample to domestic banks. We run our analysis at top holder level. Our sample includes both term loans and lines of credit. Lines of credit are included because they comprise a significant part of lending to nonbanks. Moreover, this type of lending is instrumental to our study in that credit lines are the main tool for liquidity provision.

We construct three sets of shock exposure variables to reflect the unexpected shocks to banks' core capital positions, such as the Basel III regulatory shock, the Oil Shock of 2014, and the COVID-19 crisis. For the Basel III regulatory capital shock, exposure will be measured by the pre-shock level of capital, and also the capital shortfall denoting the anticipated difference between existing capital and the new capital requirements. For the other two shocks, the exposure variable is constructed as the pre-shock share of a bank's committed exposures to the industries most severely impacted in the stress period. For O&G, the exposure is defined simply as banks' loan portfolio exposure to the O&G sector prior to the shock. For COVID-19, exposure is defined more broadly as banks' exposures to industries negatively affected by the COVID-19 crisis, thus include loans to oil and gas, retail excluding food and drug, entertainment and recreation, restaurant and hotel, transportation, and machinery manufacturing industries, prior to the COVID-19 crisis.

As stated above, SNC dataset tracks syndicate membership on a quarterly basis, allowing

[7] The SNC data do *not* report loan spreads or firm-level financial information in a systematic way, so they are not available in the data. Our understanding of the data and conversations with employees of the Federal Reserve in charge of the SNC exams suggest that loan spread and firm financial information may be reported at firms' discretion for a subset of loans. However, the focus on this subset would likely shrink our sample significantly and may also yield biased results.

for identification of each loan at a share-lender-quarter level. This makes it possible to measure change in loan share held by each lender within a loan syndicate, as well as loan sales in the secondary market by comparing syndicate membership from one period to the next. A sale is recorded when a lender reduces its exposure in a loan syndicate, partially or entirely, relative to the previous period. The definition thus excludes instances where the loan matures in quarter t or entirely drops out of SNCs dataset. We code loan sales at the bank holding company to exclude the cases where a loan is reallocated internally within an organization. Identification of loan sales allows us to analyze changes in the bank lending channel with nonbanks and explore whether this relationship has knock-on effect for nonbanks during times of market stress.

3.2 Summary Statistics

We start the description of our data by illustrating the magnitude and trend of banks lending to nonbanks for our sample, covering time periods around our three shocks: The Basel III shock, O&G price collapse of 2014-16, and the COVID-19 Crisis. Figure 3 plots the year-over-year growth of bank total credit commitments to nonbank borrowers in the syndicated loan market from 2002 to 2022. Banks lending to nonbanks experienced a rapid growth after the financial crisis and increased from approximately $478 billion in 2010 to approximately $1,771 billion in 2022, a growth of 3.7-fold over the course of only 12 years.

Table 2 summarizes the pre-shock financial conditions of the Basel III banks. The Basel III regulatory capital shock applied to all U.S. banks that were large in size and internationally active during that time period. The key variable to be used in later analysis is the Tier 1 Shortfall, constructed as the difference between the old Tier 1 capital requirements under Basel I as of 2012:Q2 and the new proposed capital requirements. As can readily be seen, most banks anticipated having a shortfall in capital, and the shortfall was economically meaningful (average of -3.1 percent).

Table 2 summarizes pre-shock characteristics of the banks in our sample around the O&G price collapse of 2014-16 and the COVID-19 Crisis. These characteristics include bank size, some measures of the banks' risk taking (i.e., return on assets, the non-performing loan rate) and also a measure of banks' capital positions (i.e., CET1 capital buffer). It also presents summary statistics for O&G and COVID-19 exposures of the banks in our sample. Since shock exposure is our main treatment variable and we exploit its cross-sectional variation to perform our analysis, it is important to ensure that the banks in our sample represent a relatively wide variation in terms of their O&G or COVID-19 exposures. Figure 4 shows the distribution of banks exposures to both of these shocks in our sample. As expected, there is a higher variation in COVID-exposure relative to O&G-exposure as there is a wider range of industries impacted by COVID-19 shock.

4. Regulatory capital and bank lending to nonbanks

We begin our analysis by investigating the relationship between banks' Tier 1 capital ratio and lending to nonbank borrowers over the full sample available in our data. Empirical studies have shown that banks with lower Tier 1 capital ratios that are closer to regulatory constraints reduce loan retention and sell their loan shares in the secondary loan market, ceding market share to nonbanks who proceed to expand their own lending (see Irani et al. (2021)). In addition to this substitutional effects between bank and nonbank lending, there might exist a complementarity between the two and the trend could be partly fueled by banks' lending to nonbanks. In other words, could it also be possible that, under capital constraints, banks also change the composition of loan portfolio, shifting lending away from their traditional nonfinancial customers and towards the nonbanks? Indeed, from a capital cost perspective, much of the regulatory change over the past two decades has conferred a cost advantage to the nonbanks over the banks for lending to nonfinancial corporates, especially those at lower spectrum of credit quality. But nonbanks require funding to expand their lending, and the higher credit quality of the nonbank financials makes them relatively more attractive for banks to lend to.

Figure **??** plots the share of non-pass- as a measure of credit quality- exposures in loans to nonbanks versus loans to nonfinancial corporates that are held by banks. A non-pass loan is any loan rated special mention, substandard, doubtful, or loss by SNC examiners. The higher share of non-pass exposures for nonfinancial borrowers means that nonfinancial borrowers in our sample of syndicated loan market generally have lower credit quality relative to nonbank borrowers. The only episode that the credit quality of these borrowers came close was the financial crisis where the source of the shock could be traced back to nonbanks.

To test in the time series whether this channel of banks lending to nonbanks may be operable, we model the change in the share of credit held by a bank as a function of its Tier 1 capital ratio interacted with the indicator variable for nonbank borrowers.

We estimate the regressions using the sample of loan shares held by U.S. banks from 1993 to 2019:

$$\Delta\ Ln\ Credit_{i,j,t} = \alpha_i + \kappa_t + \beta_1\ Tier1Cap_{i,t-1} + \beta_2\ Tier1Cap_{i,t-1} \times\ Nonbank_j + \gamma\ X_{it-1} + \varepsilon_{i,j}, \quad (1)$$

The dependent variable is the change in natural logarithm of bank i's share commitment in loan j, measured at an annual frequency. The variable Tier1Cap variable is the bank's capital position in the previous year. Nonbank is a dummy variable denoting whether the loan commitment is to a nonbank borrower. The model includes year and bank fixed effects and time-varying bank controls, X_{it}. Including bank characteristics alleviates the concern that the results might be driven by factors that simultaneously impact banks' capital levels and lending.

The results shown in Table 3 suggest a clear positive relationship between bank capital constraints and lending to nonbanks. The coefficient estimate on the interaction of the capital constraint dummy and the nonbank loan dummy, β_2 indicates that, holding all else equal, banks with low capital (in the bottom quartile) are more likely to increase lending to nonbanks.

Next, we investigate the knock-on effects of banks' lending to nonbanks. We take the perspective of nonbanks and investigate whether having a loan at a bank allows the nonbank to extend more credit to the real economy. We use the same dependent variable, the change in share commitment of lender i in loan j and restricting lenders to only nonbanks. We regress the variable on dummy variable $BankFunding$ denoting whether the nonbank lender/participant has a bank loan in the previous period as observed in our data. As before, the vector $X_{j,t-1}$ collects the regression controls, only now these controls are with respect to the loan commitment. We also include lender and year fixed effects. The regression takes the form:

$$\Delta\ Ln\ Credit_{i,j,t} = \alpha_i + \kappa_t + \beta\ BankFunding_{i,t-1} + \gamma\ X_{it-1} + \varepsilon_{i,j}, \tag{2}$$

In all the specifications of (2) that we explored in Table 4, we find a strong positive association between nonbank lending and the $BankFunding$ variable. Nonbanks that have some kind of observed borrowing relationship with a bank in a prior year t are able to increase their participation in a given commitment in the range of 7-9 percent. Thus, having a bank funding relationship helps nonbanks expand their own lending in an economically-significant way.

Next, we conduct further test to confirm that banks' lending to nonbanks indeed has led to an increased participation of nonbanks in a syndicate. In particular, we refine the $BankFunding$ variable to denote whether the nonbank has a loan from the Agent, or the lead arranger of the syndication deal, and run our basic regressions using the same framework of equation (2). These regressions thus come closest to establishing the link between how bank funding to nonbanks help the nonbanks support their own lending. Table 5 shows that bank funding can help ease nonbank funding constraints on the same deals arranged by the bank lender.

Our goal in this paper is to explore the motives for banks' lending to nonbanks. Our analysis so far establishes a clear positive relationship between capital constraints and bank lending to nonbanks. We next utilize three important shocks to banks' capital base to understand the driver behind banks' accelerated lending to nonbanks. First, we use the regulatory capital shock related to the U.S. implementation of Basel III. This shock allows us to cleanly identify the effects of unexpected regulatory shock to banks' capital due to Basel III implementation. Then, we supplement the analysis by studying bank lending responses in the aftermath of two other shocks that severely undermined banks' capital base: O&G, and the COVID-19 pandemic. We focus, in particular, on how banks with relatively high exposure to these shocks alter their lending to nonbank borrowers and how those actions, in turn, affect the behavior of the nonbanks. These analysis together provide important insights to banks' lending to nonbanks when facing capital constraints. Relatedly, the resilience of banks funding and liquidity provision for nonbanks has crucial implications on how well nonbanks can continue their role as credit providing intermediaries.

4.1 Lending to nonbanks under the regulatory capital shock from the US implementation of Basel III

In this section, we use a plausibly exogenous shock to bank capital from the realization of uncertainty around the U.S. implementation of Basel III regulations. While the internationally agreed-upon version of Basel III was well known by market participants, U.S. implementation of the rule entailed several adjustments that came as a surprise to banks (see, Berrospide and Edge (2016)). U.S. banking agencies proposed adjustments to both the types of capital counted as Tier 1 capital and the risk weights of various exposures, particularly real estate exposures. These unexpected adjustments affected banks in different ways depending on their ex-ante capital positions. Therefore, the shock created cross-sectional variation in banks' regulatory capital levels. More specifically, two banks with ex-ante similar risk-taking profiles and Tier 1 capital ratios under Basel I could end up with different Tier 1 capital ratios under the proposed Basel III regulations. Therefore, this shock provides variation in bank capital that is orthogonal to other characteristics of the banks that might impact its commercial lending activity. We expect that banks with higher capital shortfalls under the proposed Basel III would shift their loan portfolio toward nonbank borrowers, which would entail lower regulatory capital charges. These unexpected bank capital shocks helps us guard against a potential omitted variable bias where unobserved lender characteristics other than their capital or funding sources can be related to the decision of how much to lend.

To explore this hypothesis, we define "Basel III Tier 1 capital shortfall" as the difference between a bank's Tier 1 capital ratio under Basel I and under Basel III proposed regulation for the U.S., calculated using banks' capital and risk weighted assets as of 2012:Q2 (see Berrospide and Edge (2016)).[8] Note that our independent variable of interest, Basel III Tier 1 capital shortfall, always takes on a negative value because Basel III capital regulations were in general more stringent than Basel I. Thus, a higher shortfall translates to a bigger negative number and hence a larger exposure to the regulatory shock. The regressions are estimated on a sample of bank-only loan participation decisions, and take the form:

$$\Delta\ Ln\ Credit_{i,j} = \alpha + \beta_1\ Tier1Shortfall_i + \beta_2\ Tier1Shortfall_i \times\ NonBank_j + \gamma\ X_{it-1} + \varepsilon_{i,j}, \qquad (3)$$

The dependent variable is the change in bank participation in commitment j between 2012:Q2 and 2012:Q3. Tables 6 and 7 document the effect of the Basel III regulatory capital shock on banks' lending to nonbanks along intensive and extensive margins. In columns (1) and (2) of Table 6, we estimate $\Delta Ln(Credit)$ at the loan level as a function of the Tier 1 shortfall that interacts with the Nonbank borrower indicator. While the coefficient of interest is negative, implying an increase in nonbank lending as a result of a higher regulatory capital shortfall, it is statistically significant only at 10% confidence level. To capture the potential nonlinearity in this relationship, we run the same analysis for the subsample of banks with above median Tier 1 shortfall in columns (3)–(6). The point estimate of the coefficient on Tier 1 shortfall is positive and statistically significant in columns (3)-(4), and the interaction with Nonbank is negative and statistically significant. This indicates that a higher level of capital shortfall is associated with a decrease in lending to nonfinancial borrowers and an increase in lending to nonbank borrowers. In columns (5)-(6), we perform the same analysis using loan fixed effects to control for borrower and demand side factors. In column (5), which includes all borrowers, we do not find any statistically significant impact on lending; however, column (6) is limited to the subsample of nonbank borrowers, and we find that a higher Tier 1 shortfall is associated with an increase in lending to nonbank borrowers.

Table 7 illustrates the results along the extensive margin. Columns (1)-(2) are performed on the entire sample. The negative and statistically significant coefficient of Tier 1 shortfall and the positive and statistically significant coefficient of its interaction with the nonbank indicator implies that banks with higher Tier 1 shortfalls tend to sell more of their loan shares made to nonfinancial borrowers and retain more of the loans made to nonbank borrowers. Column (3) performs the analysis on the subsample of banks with above median Tier 1 shortfall. The results are consistent and become even stronger. Columns (4)–(5) perform

[8] We thank Jose Berrospide for graciously making this variable available to us.

the analysis with loan fixed effects to control for borrower and demand side factors. In column (4), the negative coefficient of Tier 1 shortfall indicates that, in general, banks with high Tier 1 shortfall tend to sell more loans; however, when we limit the analysis to the subsample of loans to nonbank borrowers, we do not find any statistically significant effect. Overall, all the analyses point to a shift in banks' lending toward nonbank borrowers when facing regulatory capital constraints.

5. Lending to nonbanks when capital is under stress: The O&G and COVID pandemic shocks

We now extend the analysis to understand banks' lending to nonbanks during other periods when banks' core capital positions are under pressure. In particular, we use the O&G shock and the COVID-19 crisis as unexpected shocks that negatively affected the capital position of certain banks with significant exposures to these shocks. Critically, both the O&G shock and the COVID-19 pandemic are plausible exogenous events that unexpectedly hit the capital base of certain banks. The COVID-19 pandemic and the ensuing period of shelter-in-place entailed a sharp fall in (expected) cash flows for many businesses in entertainment, retail, and transpiration in the United States.[9] The O&G shock unexpectedly halted the production of many U.S. shale producers unexpectedly, with the West Texas Intermediate price dropping precipitously from more than \$100 a barrel to less than \$50 a barrel within a few months' time.[10] Unlike the Great Financial Crisis that hit almost all banks, both shocks were idiosyncratic ones that created stress to the capital base of specific banks with sizable exposures. They, therefore, represent unique macroeconomic events to study the effects of unexpected changes to banks' capital base, in addition to the Basel III shock used in our main test.

Both of these shocks had a significant impact on performance of loans in their related industries, and therefore imposed a stress to banks' capital position depending on the banks' exposure to the impacted industries. We show that in both of these shocks, banks reduced lending to nonfinancial borrowers and increased their relative lending to nonbanks.

Our analysis involves comparing credit extended to borrowers from pre- to post-shock periods. The pre-shock period is defined as 2013:Q3-2014:Q2 (2019:Q1-2019:Q4) and the

[9] The exogeneity and timing of COVID-19 crisis have been widely discussed in the literature (see, e.g., Berger et al. (2024), Greenwald et al. (2024))

[10] Although several studies highlight the economic determinants of the oil price throughout history (see, e.g., Baumeister and Kilian (2012), Alquist et al. (2013)), they argue that at least a large part of the cumulative decline of oil price in second half of 2014 was unpredictable and reflected a shock to oil price expectations in July 2014 (see, e.g., Baumeister and Kilian (2016)).

post-shock period is defined as 2015:Q1-2015:Q4 (2020:Q3-2020:Q4) for O&G (COVID-19) shocks respectively. We require the loans to be active as of 2014:Q2 (2019:Q4) for O&G (COVID-19) analysis or enter the sample afterwards.[11]

Our main outcome variable is the (log) change in credit between a bank and its different borrowers. We begin with the full sample of loans in SNC within the pre-shock periods and track these loans over time to construct three measures of credit availability at bank-loan share level that capture the changes along both the intensive and extensive margins.

We first look at changes in the intensive margin. We follow each loan over time and compare the changes in the amount of loans held by distressed banks to nonbanks and other borrowers, before and after the shock. We consider credit growth as the change in log of credit from pre- to post-shock periods. We require the loans to be reported on consecutive quarters throughout the pre- to post periods to be included in intensive margin analysis.

Our baseline DiD specification is:

$$\Delta\ Ln\ Credit_{ij} = \alpha + \beta\ ShockExposure_i \times\ Nonbank_j + \gamma\ X_{ij} + \varepsilon_{ij}, \tag{4}$$

where $Credit_{ij}$ is the outstanding loan amount between bank i and borrower j. The log change in this variable represents the intensive margin in our analysis, and is the change in the log of mean committed exposure for each bank-loan pair. The mean is a simple average across quarters in the relevant sub-periods. $ShockExposure_i$ is the bank i's exposure to the shock, and X_{ij} is a vector of bank and loan/borrower controls. Nonbank takes value of 1 if the borrower is a nonbank and 0 otherwise. So, the interaction term captures the impact of shock exposure on credit extended to nonbanks versus other borrowers.

We then look at the extensive margin and investigate whether distressed banks shifted lending from other borrowers towards nonbanks by increasing holding of loans to nonbank borrowers. We track the existence of the bank-loan pair in the pre- and post-shock periods to capture entry (a bank-loan being initiated after the pre-shock period) or exit (a bank-loan that had been present in the pre-shock period but was not present or came to an end in the post-shock period). These three measures are used as dependent variables in our regression framework.

One concern with a causal interpretation of our findings is the potential endogeneity issue due to missing variables that may affect lending behavior of various banks and the banks with high exposure to the shocks may inherently differ from those with low exposure in terms of their overall portfolio composition, strategy in lending to nonbanks, or risk tolerance. In other words, our treatment variable (i.e., shock exposure) could be correlated

[11] Note that the new entrants are included only in extensive margin analysis.

with the outcome variable (i.e., lending to nonbanks). In that case, the shift of lending toward nonbanks captured in our analysis could be indicative of strategic growth in lending to nonbanks and not driven by net worth shock to the banks.

Conceptually, this bias is unlikely to play a major role in identification. Given the idiosyncratic nature of the two shocks, it would have been challenging, if not impossible, to predict which bank would be negatively affected before the realization of the shocks. To further mitigate the concern, we provide two types of evidence showing that such a bias does not drive our results. First, we show that there are no significant differences between the banks with high exposure to the shock and other banks. That is, the exposure depends on factors uncorrelated with banks' characteristics. Second, we explore the trend in nonbank lending versus other borrowers prior to the period of our analysis. The homogeneity of trends in terms of outcome variables for the treatment and control group prior to the period of our study supports a causal interpretation.

More specifically, for COVID-19 shock, we estimate the banks' exposure to the shock over 2017 as the quarterly mean. Then we define a dummy variable, namely "High Exposure", to be equal to 1 if the bank exposure is above the 85th percentile of the banks in our sample over 2017 and 0 otherwise. We run a similar analysis for the O&G shock, estimating shock exposure over 2011:Q3- 2012:Q2. Next, we estimate the following regression and plot the point estimates and 95% confidence interval for the β's in each quarter from 2018:Q1 to 2020:Q4.

$$\Delta\ Ln\ Credit_{ij} = \alpha + \beta\ HighExposure_i + \gamma\ X_{ij} + \varepsilon_{ij}, \tag{5}$$

The results are illustrated in Figure 5 Panel A for O&G and Panel B for COVID-19 shock. In both graphs, only in 2-3 quarters after the shock, there is significantly higher lending to nonbanks compared to other borrowers. Since our outcome variable is the change in credit, the non-significant results over the subsequent quarters (2020:Q2-2020:Q4) indicate that the shift in lending to nonbanks persists till 2020q4.

Another concern in our setting is associated with disentangling supply- from demand-driven changes in credit. That is, observable or unobservable borrower or loan characteristics may impact the credit allocation. For example, changes in borrower fundamentals that impact the loan credit risk may lead to changes in credit provision by the bank. In particular, the nonbank borrowers who are also credit-providing intermediaries may have correlated shock exposure with their bank lenders. In that case, the nonbank borrowers from highly exposed banks may face relatively higher capital constraints due to those exogenous shocks, which might drive the change in credit availability to them. Although this potential confounding factor likely works against our findings, we use borrower-fixed effects to account for such factors. This approach shares a similar spirit as ofKhwaja and Mian (2008) and relies on firms that borrow from multiple banks to capture within-firm changes in credit across banks. That is, we examine how a change in loan amount for the same firm differs between banks, given differences in their exposure to an exogenous shock. We estimate the following linear probability model via OLS:

$$\Delta\ Ln\ Credit_{ij} = \alpha + \mu_j + \beta\ ShockExposure_i + \gamma\ X_i + \varepsilon_{ij}, \tag{6}$$

where μ_j are the borrower fixed effects intended to capture any cross-sectional shift in the borrowers' credit demand, common across banks.

A remaining identification concern is that a firm's credit demand from its various lenders might be correlated to the intensity of the shock to the lender, hence subjecting our results to endogeneity issues. We address this concern by replacing the borrower fixed effect in our analysis with loan fixed effects. Our assumption is that a borrower's credit demand is not likely to differ across the banks participating in the same loan syndicate. Any changes to the loan should be coordinated and negotiated across all lenders. The only way that a bank can increase/decrease its commitment share to the borrower is through trading in the secondary loan market. This is unlikely to be affected by the borrower.

Tables 8 and 9 illustrate the impact of bank distress on credit availability to their borrowers during the O&G and COVID-19 shocks. First, as indicated in columns (1) to (4) of Table 8, there is a negative and statistically significant (at the 1% level) relation between a bank O&G exposure and its overall credit provision. In other words, compared to banks that did not have significant exposure to O&G portfolio prior to the oil shock, O&G exposed banks reduced credit supply to their borrowers more during the oil price shock of 2014-16. Second, the positive and significant coefficients of nonbank dummy interaction with O&G exposure in regressions (3) and (4) suggest that nonbanks borrowers did not experience a similar decline in credit availability like the other borrowers.

To further control for the heterogeneity related to borrowers or loans and associated demand-side effects, we include loan or borrower fixed effects in columns (5)-(7). This approach exploits the fact that the borrowers in our sample always have multiple lenders either within the same loan syndicate or across multiple loan syndicates if the borrower has multiple loans in our sample. As noted earlier, this approach boils down to comparing changes in lending across banks while keeping borrowers and, therefore, the demand fixed. Regressions (5) and (6) show similar results in that shock exposure is associated with lower credit provision by the banks. As a further check, the subsample analysis including only nonbank borrowers in column (7) does not indicate any significant effects of shock exposure on loan funding to nonbanks. Thus, the results suggest that most of the adjustments along the intensive margin following the O&G shock occurred from more exposed banks shifting their portfolios away from other borrowers and towards nonbanks, in a relative sense.

These findings are generally very similar to those of the COVID-19 shock. Table 9 indicates that COVID-19 shock has an adverse impact on credit availability to borrowers in general. Also, both the coefficients of nonbank and its interaction with COVID exposure are positive and significant, indicating that the adverse effect of COVID-19 shock on credit supply does not hold for nonbanks as much as the other borrowers. The overall reduction in credit provision also holds after controlling for borrower and bank fixed effects. However, consistent with the findings for the O&G shock period, limiting borrowers to nonbanks in regression (7), the impact of COVID-19 shock on credit availability is no longer significant.

In Table 10, we examine the rate at which loans exit the SNC sample over O&G shock period. The bank shock exposure is not associated with any statistically significant change in loan exit rate. However, the negative and significant interaction term in column (2) indicates a lower exit rate for nonbank borrowers. The regression results using borrower fixed effects in columns (3) and (4) are in line with OLS results, although they are not statistically significant. Regressions (5)-(8) examine the entry rate for the borrowers. Consistent with findings on loan exit, we also observe lower entry rates for the banks impacted by the shock, although the entry rate is not statistically different for nonbank borrowers as the interaction term in columns (1)-(2) is not statistically significant. The fixed effects regressions (7)-(8) indicate that while entry rates are, in general, lower for exposed banks, they are not so for nonbank borrowers.

The results on Exit and Entry rates of loans over COVID-19 shock are presented in Table 11. Although the OLS regressions indicate a positive but marginally significant change in loan exit rates as the result of COVID-19, the fixed effect regressions show that the exit rate as the result of COVID-19 exposure generally increases, however, not for loans to nonbanks. The results on entry margin are stronger, showing a lower entry for all borrowers except nonbanks, which seems to have a higher entry rate for the exposed banks (the positive coefficient on interaction term in columns (5)-(6).) The fixed effect results also show a positive and significant entry for nonbank borrowers.

5.1 Heterogeneous Tests Across Banks of Various Levels of Capital Buffer

Banks' exposure to adverse shocks translates to losses, which consequently lowers their risk-weighted capital levels. Given earlier results on the positive relationship between banks' capital constraints and their lending to nonbanks, we should expect that, facing adverse shocks, banks with a lower capital buffer would be more likely to shift lending to nonbanks.

This is reasonable given that, in general, loans to nonbank borrowers carry lower regulatory capital charges relative to loans to other borrowers.[12] This, to some extent, is driven by the overall better rating distribution of nonbanks.[13]

We test whether the regulatory capital constraints lead distressed banks to shift their loan portfolio composition toward nonbank borrowers. We use CET1 buffer as a measure of capital constraints and calculate it as follows:

$$CET1buffer = CET1actual - [minCET1 + ConservationBuffer(orSCBin2020:Q4) + GSIBsurcharge], \tag{7}$$

We estimate the following regression using OLS:

$$\Delta\ Ln\ Credit_{ij} = \alpha + \beta\ ShockExposure_i \times Nonbank_j \times CET1Buffer_i + \gamma\ X_{ij} + \varepsilon_{ij}, \tag{8}$$

where CET1 buffer is estimated as of 2014:Q2 for O&G and 2019:Q4 for COVID-19 shock. We also replace CET1 Buffer by a dummy variable called *Low Buffer* which is equal to 1 if the CET1 buffer is in the lowest quartile and 0 otherwise.

Tables 12 and 13 present the results for O&G and COVID-19 shocks, respectively. Although the triple interaction term $ShockExposure_i \times Nonbank_j \times CET1Buffer_i$ is not statistically significant, using the *Low Buffer* dummy results in a positive and statistically significant triple interaction term. This result implies that distressed banks, within the lowest quartile of the CET1 buffer, exhibit a higher reallocation of credit to their nonbank borrowers after being hit by the shock.

6. Implications on Nonbanks' Credit Provisioning

In this section, we test whether the channel of banks' lending to nonbanks has spillover effects in terms of nonbanks' credit provisioning during economic downturns.

First, we investigate whether the bank lending channel has an impact on preventing nonbanks from loan sales and their subsequent adverse effects. The central empirical challenge is that loan trading could be driven by changes in borrower characteristics or by loan characteristics, irrespective of lender-side factors. To overcome this challenge, as in the previous section, we utilize an approach similar to the Khwaja and Mian (2008) and incorporate loan-quarter fixed effects in estimation. This specification should control for all

[12] Given that estimation of expected losses relies on historical data, comparing the historical aggregate loss rate of loans to NBFIs vs. other C&I borrowers, implies lower capital charges for NBFI borrowers.

[13] Furthermore, given the opacity of nonbanks, it is relatively harder to catch signs of credit deterioration in a timely manner. This may lead to an upward bias in nonbank ratings when the overall credit condition deteriorates, which presents an opportunity for regulatory capital arbitrage.

observable and unobservable borrower and loan characteristics in our analysis and, therefore, capture supply-side effects. Our regression analysis compares the trading activity between the nonbanks within a given syndicate at a given point in time.

We estimate the following linear probability model using OLS:

$$LoanSales_{ijt} = \alpha + \mu_i + \psi_j + \beta \; LenderBankLoan_{jt} \times EBP_t + \gamma \; X_{ijt} + \varepsilon_{ijt}, \tag{9}$$

where $LoanSales_{ijt}$ is an indicator variable equal to one if any portion of the loan i held by nonbank j in quarter $t-1$ is sold in quarter t and 0 otherwise. *Lenderbankloan* is the sum of the committed exposure of all loans that lender has received as of quarter t. This variable takes the value of 0 if we can't find any loans associated with the lender in SNC data. In this analysis, we use the Excess Bond Premium (EBP) from Gilchrist and Zakrajsek (2012) as a proxy for overall credit condition.

Table 14 presents the results. In all specifications, the coefficient of EBP is positive and significant, implying that loan sales by nonbanks increase when the credit condition tightens. Our main coefficient of interest is the one related to the interaction of EBP and *Lenderbankloan* as we are especially interested in how the presence of bank loans as a potential liquidity backstop for nonbanks may affect their loan sales during bad times. This coefficient is negative and statistically significant in all specifications, implying that the existence of bank loans is associated with lower loan sales by the nonbanks during times of stress.

In specification (4) we distinguish between nonbanks that have stable funding versus those with unstable funding and incorporate *Unstable* dummy variable as well as its interaction with EBP and *Lenderbankloan* variables.[14] The negative and significant coefficient on the triple interaction term implies that the existence of bank loans does have a higher impact on loan sales by the nonbanks with unstable funding.

Next, we test whether the channel of bank lending to nonbanks has spillover effects in terms of credit provision and origination of new credits to borrowers in bad times. We are especially interested in credit provision during bad times as the literature has shown nonbanks' lending fragility during those times. We run a similar regression substituting the dependent variable by New Origination which is a dummy variable equal to one if loan i is originated in quarter t and lender j participates in the loan syndicate.

$$NewOrigination_{ijt} = \alpha + \mu_i + \beta \; LenderBankLoan_{jt} \times EBP_t + \gamma \; X_{it-1} + \nu Y_{it} + \varepsilon_{ijt}. \tag{10}$$

[14] Our classification of nonbanks into stable and unstable is crude as we don't have data on their liability structure. We classify Insurance companies and pension funds as stable and the rest of the institutions as unstable.

Table 15 presents the results. In columns (1) to (3), we find that nonbank participation in newly originated credits declines during bad times, however, less so for those that have a bank loan. The latter result is implied by positive and significant coefficients on *Lenderbankloan* and its interaction with EBP.

In columns (4) and (5), we restrict the sample to newly originated loans and test whether the amount of credit provided by nonbanks with bank loans is higher than the rest of nonbanks. Our results are in line with Fleckenstein et al. (2020) showing that the cyclicality in nonbank lending is explained by nonbanks' access to financing. While their study compares the nonbanks with banks, we make the comparison between nonbanks with access to bank funding versus those without. We find that nonbanks with access to bank funding demonstrate relatively less cyclical behavior in terms of credit origination.

7. Conclusion

The nonbank sector, including fintech firms, has experienced significant growth lately, and a major driving force behind this growth has been financing from banks. The growth in bank funding to nonbanks raises several important policy questions, including how the regulatory capital constraints banks face may be related to the growth in nonbanking. Our analysis here presents a large amount of evidence on this relationship. Over a set of three shocks to bank capital and net worth, the bank's response was to lend more to nonbanks. We find that the shift towards nonbank lending is closely linked to the height- ened capital regulatory pressure, and lending to nonbanks is particularly accelerated during economic shocks when banks' core capital positions are weaker. The strongest evidence for this comes from our analysis around the time of the Basel III implementation shock, which was a pure shock to bank capital and unrelated to ex-ante conditions of nonbank or nonfinancial creditworthiness. This increase in bank funding to nonbanks has served to make the two sectors more integrated. we demonstrate that the shift in lending towards nonbanks is accelerated following unexpected shocks to banks' core capital positions, suggesting regulatory capital is the key factor behind the effects. We show that nonbanks with access to bank funding are better able to lend to the real economy and are less likely to liquidate their loan shares in times of stress, when fire sale dynamics may possibly be in play.

Our paper also points to an interesting implication of the growing linkages between the banks and the nonbanks. Rather than cutting off lending to the nonbanking sector in times of stress, our results show that banks actually lend more to nonbanks, in a relative sense. Thus, one byproduct of these connections between the regulated banking sector and shadow banking may be a lessening of the concerns about fragility at the nonbanks due to their lack of access to low-cost deposits and vulnerability to the runs.

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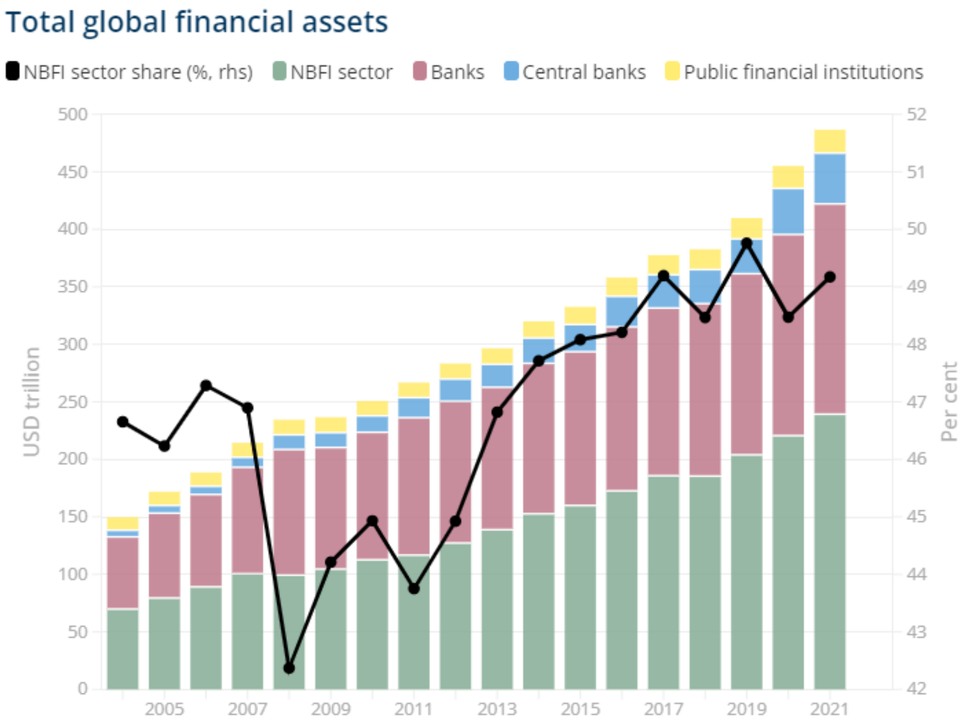
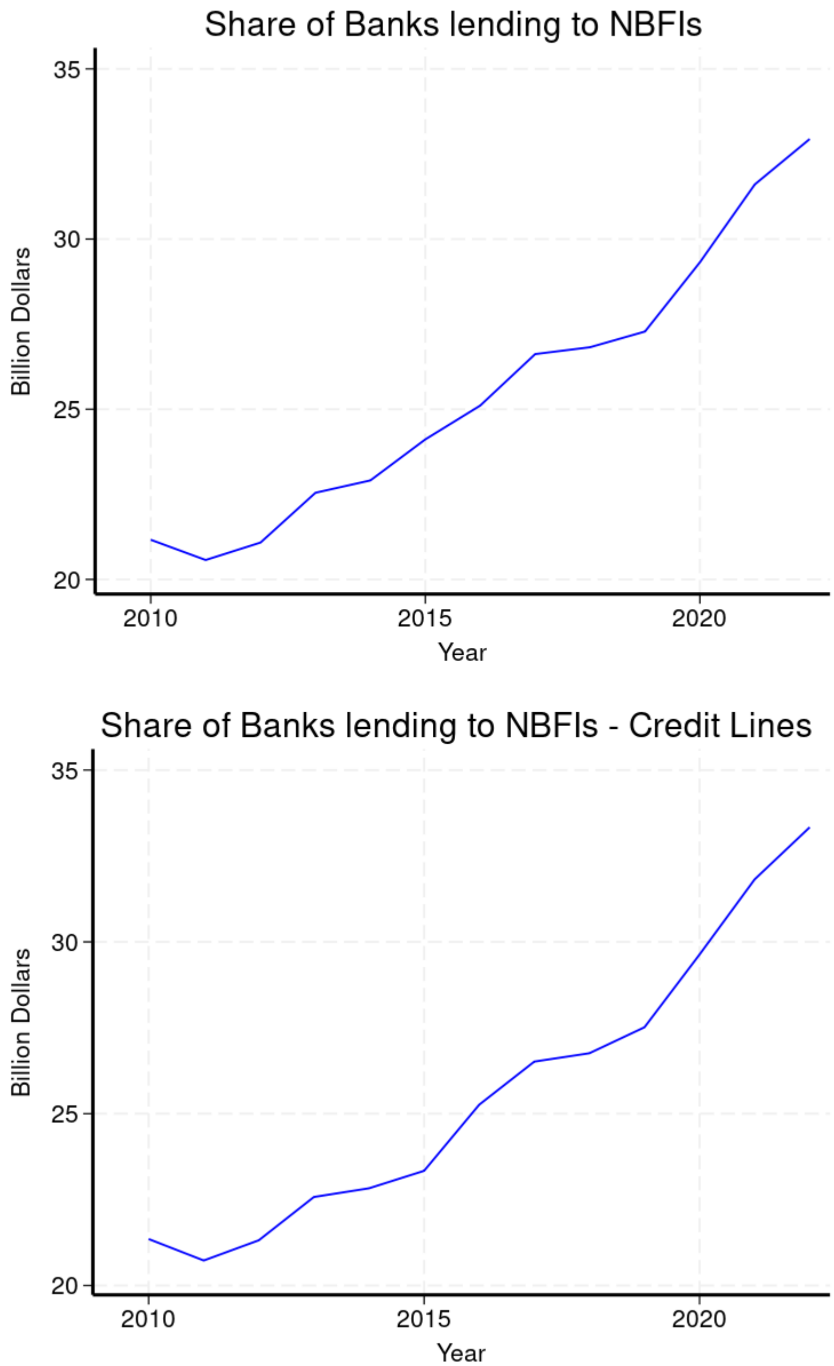
Figure 1: **Global growth of NBFI and bank sectors assets**



Source: Financial Stability Board report on non-bank financial intermediation (2022) based on jurisdictions' 2022 submissions (national sector balance sheet and other data); FSB calculations.

Figure 2:



This graph shows the share of bank lending to NBFIs using SNC data from 2010 to 2022.

Figure 3: **Banks total credit commitments to NBFIs**

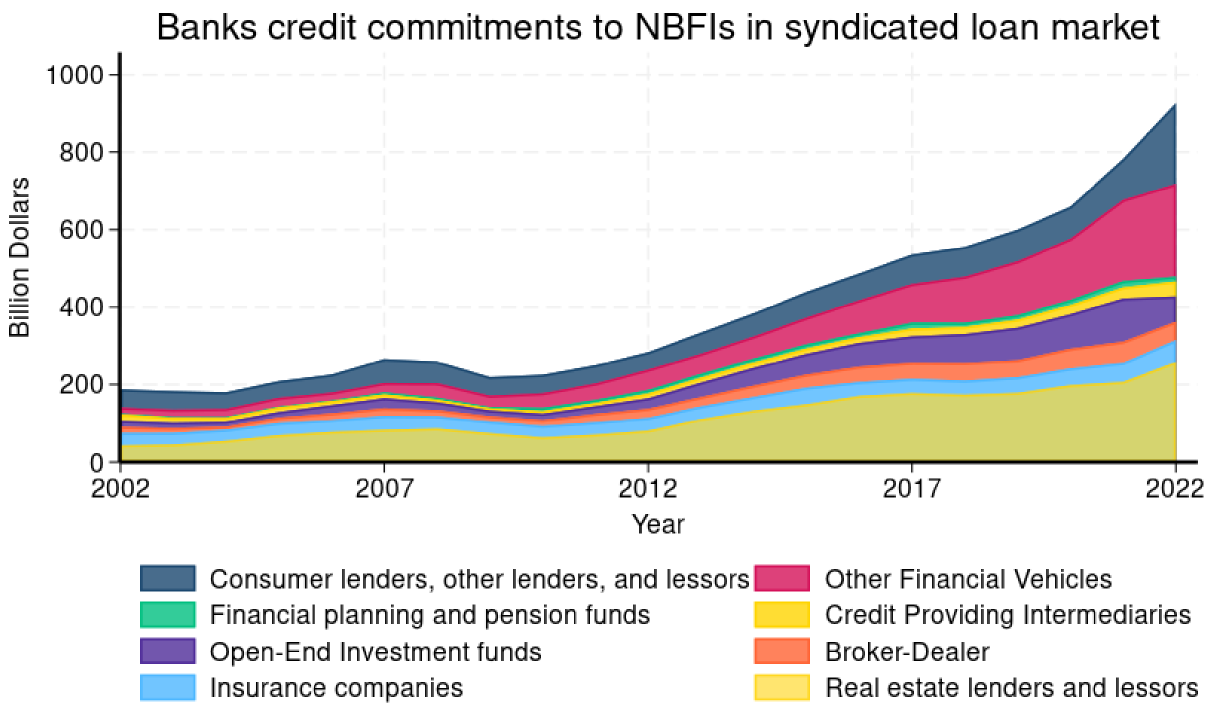


Table 1: **Banks summary statistics - Basel III shock**

Loan-level variables

	Observations	mean	p10	p90	sd
Loan Sale	32340	.18	0	1	.38
Loan Size	32340	5.6	3.9	7.2	1.3

Bank-level variables

	Observations	mean	p10	p90	sd
Tier1 Shortfall	243	-.031	-.052	-.015	.014
Tier1 Ratio	243	14	10	20	3.1
Bank Size	243	16	14	18	1.5
Wholesale Funding	243	.1	.035	.19	.099
Realestate loan share	243	.65	.39	.79	.18
C&I loan share	243	.2	.085	.36	.12
Non-Interest Income/NI	243	2	.26	3.7	3.5
Loan Share	243	.61	.41	.77	.15

This table summarizes bank characteristics of our Basel III shock sample with valid covariates as of 2012q2. The sample includes data from 2012q2 to 2012q3. All variables are defined in Table 16.

Table 2: **Banks summary statistics - O&G and COVID shocks**

Panel A: O&G Shock

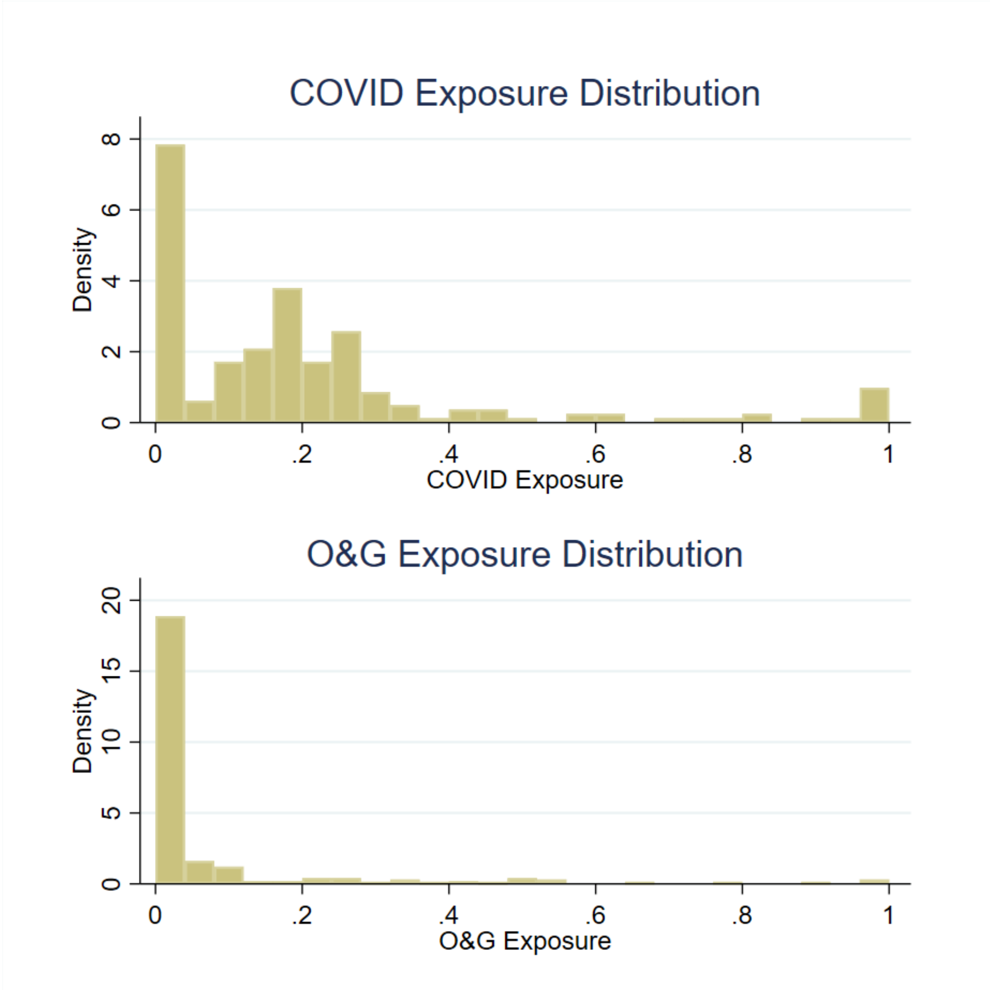
	Observations	mean	p10	p90	sd
O&G Exposure	249	.068	0	.24	.17
CET1 buffer	12	8.7	6.9	11	1.8
Bank Size ($Bn)	249	58	.81	39	274
Return-on-Assets	249	.0044	.0018	.0067	.002
Non-Interest Income/NI	249	1.7	.32	3.7	2
Equity/Total Assets	249	.11	.079	.14	.028
Wholesale Funding	249	.1	.025	.2	.091
NPL/Total Assets	249	.0096	.0024	.015	.012

Panel B: COVID Shock

	Observations	mean	p10	p90	sd
COVID Exposure	204	.2	0	.46	.24
CET1 buffer	20	3.1	1.8	5.4	1.3
Bank Size ($Bn)	204	84	3.5	109	332
Return-on-Assets	204	.012	.007	.016	.0035
Non-Interest Income/NI	204	1.1	.31	1.8	1
Equity/Total Assets	204	.12	.091	.16	.024
Wholesale Funding	204	.13	.046	.21	.086

This table summarizes pre-shock characteristics of the banks in our sample for both O&G and COVID-19 shocks. These banks include domestic banks reported in SNCs with valid covariates as of the last quarter of the relevant pre-shock period. The reported characteristics include bank size, some measures of the banks' risk taking (i.e., return on assets, the non-performing loan rate) and also a measure of banks' capital positions (i.e., CET1 capital buffer). It also presents summary statistics for O&G and COVID-19 exposures of the banks in our sample. All variables are defined in Table 16.

Figure 4: **Distribution of Banks' Exposure to the Shocks**



These graphs illustrate the distribution of shock exposure of the banks in our sample for both O&G and COVID-19 shocks. These banks include domestic banks reported in SNCs with valid covariates as of the last quarter of the relevant pre-shock period.

Regression Sample: Loan Characteristics - O&G and COVID shocks

Panel A: O&G Shock

Intensive Margin	All Loans			Nonbanks		
	Number of Loans	mean	sd	Number of Loans	mean	sd
Loan Size (MM)	21709	604	917	3978	655	1,080
Δ Ln(Loan Size)	21709	.01	.38	3978	.014	.34
Exit Margin						
	Number of Loans	mean	sd	Number of Loans	mean	sd
Loan Size (MM)	18056	498	807	2858	482	692
Entry Margin						
	Number of Loans	mean	sd	Number of Loans	mean	sd
Loan Size (MM)	1166	529	1,058	117	675	1,060

Panel B: COVID Shock

Intensive Margin	All Loans			Nonbanks		
	Number of Loans	mean	sd	Number of Loans	mean	sd
Loan Size (MM)	38426	668	960	8214	662	834
Δ Ln(Loan Size)	38426	-.04	.39	8214	-.023	.33
Exit Margin						
	Number of Loans	mean	sd	Number of Loans	mean	sd
Loan Size (MM)	7628	652	1,294	1342	699	1,388
Entry Margin						
	Number of Loans	mean	sd	Number of Loans	mean	sd
Loan Size (MM)	1487	862	1,225	229	1,117	1,132

This table provides summary statistics of the lender-loan observations in our sample for intensive, exit and entry margins. All variables are defined in Table 16.

Table 3: **Bank Capital and Lending to Nonbanks - Intensive Margin**

	(1)	(2)
Tier1 Ratio	0.0205***	
	(2.92)	
Tier1/rwa * Nonbank	-0.0269***	
	(-2.68)	
Nonbank	0.329***	-0.0711
	(2.76)	(-1.10)
Low_tier1		-0.0836***
		(-2.82)
Low_tier1 * Nonbank		0.209***
		(2.89)
Bank Size	-1.442***	-1.458***
	(-36.98)	(-38.17)
Wholesale Funding	0.402**	0.397**
	(2.04)	(2.01)
Realestate loan share	-0.490**	-0.515***
	(-2.57)	(-2.71)
C&I loan share	-6.089***	-6.159***
	(-24.22)	(-25.13)
Non-Interest Income/NI	0.00126***	0.00127***
	(3.20)	(3.22)
Loan Share	-0.946***	-0.985***
	(-5.11)	(-5.31)
Bank Controls	Yes	Yes
Bank FE	Yes	Yes
Year FE	Yes	Yes
Loan-Year FE	No	No
Observations	855446	855446
Adjusted R2	0.035	0.035

This table shows the effects of bank regulatory capital on it's lending in the syndicated loan market. The dependent variable is $\Delta Ln(Credit)$ estimated as a change in a bank's share commitment from the previous year. The time horizon is from 1993 to 2019 using the SNC annual data and the analysis is performed on both term loans and revolvers. *Low_tier1* is a dummy variable equal to 1 if a bank's tier1 capital ratio is within 25th percentile of the banks cross section within a year, and 0 otherwise. Regressions (5)-(6) are performed over the subset of banks within the lowest quartile of tier 1 capital ratio. Standard errors are clustered at the loan level and t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 4: **Bank Funding and Nonbanks Syndicate Participation**

	(1)	(2)	(3)
Bank Funding	0.0733***	0.0848***	0.0747***
	(3.16)	(4.15)	(3.00)
Loan Size		0.819***	0.813***
		(44.89)	(43.66)
Rating		-0.0319***	-0.0306***
		(-2.94)	(-3.18)
Syndicate Size		-0.682***	-0.661***
		(-32.58)	(-28.59)
Remaining Maturity		0.0676***	0.0537***
		(5.94)	(4.54)
Loan Type		0.195***	0.193***
		(5.38)	(5.40)
Loan Controls	No	Yes	Yes
Participant FE	Yes	Yes	Yes
Year FE	No	No	Yes
Observations	3344791	3297106	3297106
Adjusted R2	0.481	0.622	0.624

This table shows the effects of having a loan from a bank on NBFIs loan syndicate participation. The dependent variable is the natural log of share commitment. *FundingfromAbank* is a dummy variable equal to 1 if the participant has a loan from a bank, and 0 otherwise. The time horizon is from 1993 to 2019, and the analysis is limited to NBFIs credit provision. We ensure that loan is received before or at the time of syndicate participation and remains active. *Rating* presents a number between 1 to 5 where 1 indicates highest and 5 lowest credit quality based on final SNC exam rating. *Loan Type* is a dummy variable equal to 1 if the loan is a revolver and 2 if it is a term loan. Standard errors are clustered at agent bank and year level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 5: **Bank Funding and Nonbanks Syndicate Participation (lender is lead arranger)**

	(1)	(2)	(3)
Bank Funding	0.556***	0.100***	0.566***
	(14.50)	(5.58)	(14.93)
Loan Size	0.918***	0.872***	
	(32.33)	(32.70)	
Rating	-0.0140***	-0.0189***	
	(-4.80)	(-5.51)	
Syndicate Size	-0.746***	-0.528***	
	(-31.18)	(-23.94)	
Remaining Maturity	0.000364	0.00798	
	(0.04)	(0.87)	
Loan Type	-0.00840	0.0100	
	(-0.47)	(0.74)	
Loan FE	Yes	Yes	No
Year FE	Yes	Yes	No
Loan-Year FE	No	No	Yes
Participant FE	No	Yes	No
Observations	3293764	3290515	3312992
Adjusted R2	0.261	0.651	0.245

This table shows the effects of having a loan from a bank on NBFIs loan syndicate participation where the lending bank is the lead arranger of the syndicate. The dependent variable is the natural log of share commitment. *FundingfromAgent* is a dummy variable equal to 1 if the participant has a loan from the lead arranger of the syndicate, and 0 otherwise. The time horizon is from 1993 to 2019, and the analysis is limited to NBFIs credit provision. *Rating* presents a number between 1 to 5 where 1 indicates highest and 5 lowest credit quality based on final SNC exam rating. *Loan Type* is a dummy variable equal to 1 if the loan is a revolver and 2 if it is a term loan. Standard errors are clustered at loan & year level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 6: **Basel III shock - Intensive Margin**

	All Banks		Above Median Shortfalls			
	(1)	(2)	(3)	(4)	(5)	(6) NBFI
Tier1 Shortfall	0.250	0.128	1.854***	0.719**	0.297	-1.413**
	(1.56)	(0.79)	(5.85)	(2.42)	(0.70)	(-1.98)
Tier1 Ratio	-0.000892	-0.00100	0.00276***	0.00553***	0.00491**	-0.00135
	(-1.11)	(-0.99)	(2.92)	(3.22)	(2.08)	(-0.48)
Nonbank	-0.00892	-0.0109	-0.0604***	-0.0562***		
	(-0.94)	(-1.15)	(-3.19)	(-2.92)		
Tier1 shortfall * Nonbank	-0.353	-0.430*	-1.418***	-1.349***		
	(-1.45)	(-1.76)	(-3.90)	(-3.61)		
Bank Size		-0.00261**		0.00205	0.00144	-0.0126
		(-2.26)		(1.15)	(0.45)	(-1.54)
Wholesale Funding		-0.0343***		-0.0817***	-0.0710*	0.0939
		(-2.63)		(-3.65)	(-1.70)	(0.82)
Realestate loan share		0.0209*		0.00397	0.0422**	-0.0200
		(1.89)		(0.28)	(2.25)	(-0.59)
C&I loan share		0.000810		-0.0712***	-0.0527*	-0.0485
		(0.06)		(-3.67)	(-1.71)	(-0.74)
Non-Interest Income/NI		0.00158***		0.00107***	0.00216**	0.00522*
		(4.20)		(2.70)	(2.24)	(1.72)
Loan Share		0.00149		0.0636**	0.0242	0.0975
		(0.13)		(2.41)	(0.56)	(1.08)
Bank Controls	No	Yes	No	Yes	Yes	Yes
Loan FE	No	No	No	No	Yes	Yes
Observations	29395	29395	10893	10893	8601	1567
Adjusted R2	0.000	0.002	0.002	0.004	0.221	0.323

This table shows the effects of the 2012q2 proposed changes in bank capital regulation under Basel III on bank lending. *Tier 1 shortfall*, measures the bank-level difference between the tier 1 capital ratio under Basel I and under proposed Basel III capital calculation framework. The unit of observation in each regression is loan share-bank. The data includes 2012q2 and 2012q3 where a lender is a U.S. Bank with valid covariates as of 2012q2. The dependent variable is $\Delta Ln(Credit)$ estimated as a change in natural logarithm of credit from 2012q2 to 2012q3. Regressions (3)-(6) are performed on a subset of banks with below median capital shortfall. Regressions (5)-(6) are performed with loan fixed effects and regression (6) is limited to the subset of loans where the borrower is a nonbank. Standard errors are clustered at the loan level and t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 7: **Basel III shock - Loan Sales**

	OLS			Fixed Effects	
	(1)	(2)	(3)	(4)	(5)
			Above Median Shortfall		NBFI
Tier1 Shortfall	-0.917***	-0.911***	-1.860**	-0.714***	-0.160
	(-4.81)	(-3.85)	(-2.28)	(-4.63)	(-0.52)
Tier1 Ratio	0.00788***	0.00915***	-0.00423	-0.00315***	-0.000913
	(6.53)	(5.10)	(-0.97)	(-2.66)	(-0.37)
Nonbank	-0.00330	-0.00160	0.0152		
	(-0.21)	(-0.10)	(0.42)		
Tier1 shortfall * Nonbank	1.454***	1.507***	1.908**		
	(4.08)	(4.18)	(2.47)		
Bank Size		-0.00573***	-0.0164***	0.00300**	0.00426*
		(-2.69)	(-5.04)	(2.44)	(1.65)
Wholesale Funding		-0.00477	0.166***	-0.0129	-0.00845
		(-0.17)	(3.03)	(-0.69)	(-0.20)
Realestate loan share		-0.0160	-0.0848**	-0.0742***	-0.0206
		(-0.73)	(-2.54)	(-5.04)	(-0.75)
C&I loan share		-0.0617**	-0.000719	-0.0674***	-0.0234
		(-2.17)	(-0.01)	(-3.77)	(-0.68)
Non-Interest Income/NI		-0.000835	0.00450***	-0.000465	-0.000503
		(-1.56)	(3.50)	(-1.19)	(-0.63)
Loan Share		0.0246	0.0561	0.00820	-0.00693
		(0.92)	(0.85)	(0.43)	(-0.16)
Bank Controls	No	Yes	Yes	Yes	Yes
Loan FE	No	No	No	Yes	Yes
Observations	31006	31006	11531	29872	4991
Adjusted R2	0.005	0.006	0.009	0.734	0.790

This table shows the effects of the 2012:Q2 proposed changes in bank capital regulation under Basel III on bank loan share sales. *Tier 1 shortfall*, measures the bank-level difference between the tier 1 capital ratio under Basel I and under proposed Basel III capital calculation framework. The unit of observation in each regression is loan share-bank. The data includes 2012:Q2 and 2012:Q3 where a lender is a U.S. Bank with valid covariates as of 2012:Q2. The dependent variable is the *Loan Sales*, an indicator variable equal to one if a lender reduces its ownership stake in a loan in 2012q3 that was funded in 2012q2. This does not include the instances where the total exposure of the loan itself has reduced over this time period. Standard errors are clustered at the loan level and t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 8: **Intensive Margin (O&G Shock)**

	OLS				Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
O&G Exposure	-0.00807***	-0.0173***	-0.0188***	-0.0188***	-0.00666**	-0.00838***	-0.00311
	(-2.80)	(-5.40)	(-5.48)	(-5.48)	(-2.54)	(-2.89)	(-0.51)
Nonbank			0.0290	0.0287			
			(1.50)	(1.49)			
O&G Exposure * Nonbank			0.0119**	0.0120**			
			(2.10)	(2.13)			
Rating				-0.00899			
				(-0.50)			
Loan controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan FE	No	No	No	No	Yes	No	No
Borrower FE	No	No	No	No	No	Yes	Yes
Observations	21709	20358	20358	20358	19840	20112	3892
Adjusted R2	0.002	0.023	0.023	0.023	0.426	0.274	0.310

The dependent variable is $\Delta Ln(Credit)$ estimated as a change in credit over pre- and post-period, defined as 2013:Q3-2014:Q2 and 2015:Q1-2015:Q3, respectively. Loans to firms in the O&G industry are removed from the sample. O&G exposure is constructed as total committed loans to O&G firms divided by total committed commercial loans in pre period. Columns 1-4 are run using OLS over the entire loan sample. Regression (5) includes loan fixed effects and naturally using the sample of loans with multi-bank lenders. Regressions 6-7 include borrower fixed effects. Regression (6) includes all loans where the borrower have borrowed from multiple banks. Regression (7) is limited to the nonbank borrowers. Bank controls include pre-shock period bank size, ROA, non-interest income/net income, equity/total assets, NPL/total assets, wholesale funding, share of nonbank lending. Loan controls include loan size, remaining maturity, syndicate size, loan type, relationship length, obligor credit share, bank credit share, main lender dummy variable and collateral. All bank controls listed are measured in the pre-shock period. Standard errors are clustered at loan level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 9: **Intensive Margin (COVID Shock)**

	OLS				Fixed Effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
COVID Exposure	-0.00911**	-0.00978***	-0.0133***	-0.0133***	-0.00759***	-0.00650**	-0.00543
	(-2.47)	(-2.94)	(-3.21)	(-3.21)	(-2.63)	(-2.14)	(-1.22)
Nonbank			0.0328**	0.0285**			
			(2.46)	(2.16)			
Covid Exp. * Nonbank			0.0112*	0.0118**			
			(1.85)	(1.97)			
Rating				-0.0714***			
				(-3.85)			
Loan controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan FE	No	No	No	No	Yes	No	No
Borrower FE	No	No	No	No	No	Yes	Yes
Observations	38426	34880	34880	34880	33931	34491	8027
Adjusted R2	0.002	0.016	0.016	0.020	0.441	0.266	0.293

The dependent variable is $\Delta Ln(Credit)$ estimated as a change in credit over pre- and post-period, defined as 2019Q1-2019Q4 and 2020Q3-2020Q4, respectively. COVID exposure is constructed as total committed loans to firms in COVID impacted industries divided by total committed commercial loans in pre period. Columns 1-4 are run using OLS over the entire loan sample. Regression (5) includes loan fixed effects and naturally using the sample of loans with multi-bank lenders. Regressions 6-7 include borrower fixed effects. Regression (6) includes all loans where the borrower have borrowed from multiple banks. Regression (7) is limited to the nonbank borrowers. Bank controls include pre-shock period bank size, ROA, non-interest income/net income, equity/total assets, NPL/total assets, wholesale funding, share of nonbank lending. Loan controls include loan size, remaining maturity, syndicate size, loan type, relationship length, obligor credit share, bank credit share, main lender dummy variable and collateral. All bank controls listed are measured in the pre-shock period. Standard errors are clustered at loan level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 10: **Extensive Margin (O&G Shock)**

	Exit				Entry			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FE	FE-NBFI	OLS	OLS	FE	FE-NBFI
O&G Exposure	-0.00257	-0.00221	0.000707	-0.00281	-0.00414***	-0.00361***	-0.00161**	-0.00180
	(-0.81)	(-0.64)	(0.56)	(-0.78)	(-3.44)	(-2.83)	(-2.48)	(-1.26)
Nonbank	-0.0538**	-0.130***			-0.0212***	-0.0140*		
	(-2.11)	(-5.25)			(-2.79)	(-1.92)		
O&G Exposure * Nonbank	-0.0105	-0.0154**			-0.00297	-0.00160		
	(-1.47)	(-2.13)			(-1.14)	(-0.67)		
Loan controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	43636	38484	37922	6815	43636	38484	37922	6815
Adjusted R2	0.012	0.188	0.830	0.814	0.003	0.019	0.529	0.519

The dependent variable is Exit for regressions 1-4 and Entry for regressions 5-8. Entry is a dummy variable equal to 1 if a bank-loan being initiated after the pre-shock period and 0 otherwise. Exit is a dummy variable equal to 1 if a bank-loan that had been present in the pre-shock period exits the sample in post-shock period and 0 otherwise. Pre- and post-periods are defined as 2013Q3-2014Q2 and 2015Q1-2015Q3, respectively. Loans to firms in the O&G industry are removed from the sample. O&G exposure is constructed as total committed loans to O&G firms divided by total committed commercial loans in pre period. Columns 1-2 and 5-6 are run using OLS over the entire loan sample. Regressions 3-4 and 7-8 include borrower fixed effects. Regressions 3 and 7 includes all loans where the borrower have borrowed from multiple banks. Regressions 4 and 8 are limited to the nonbank borrowers. Bank controls include pre-shock period bank size, ROA, non-interest income/net income, equity/total assets, NPL/total assets, wholesale funding, share of nonbank lending. Loan controls include loan size, remaining maturity, syndicate size, loan type, relationship length, obligor credit share, bank credit share, main lender dummy variable and collateral. All bank controls listed are measured in the pre-shock period. Standard errors are clustered at loan level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 11: **Extensive Margin (COVID Shock)**

	Exit				Entry			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	FE	FE-NBFI	OLS	OLS	FE	FE-NBFI
COVID Exposure	0.00439	0.00691*	0.00956***	0.000680	-0.00605**	-0.00507**	-0.00143	0.00293**
	(1.03)	(1.69)	(4.59)	(0.25)	(-2.55)	(-2.20)	(-0.98)	(2.01)
Nonbank	-0.0336**	-0.0484***			0.00875	0.00582		
	(-2.22)	(-3.58)			(1.50)	(1.04)		
Covid Exp. * Nonbank	-0.00382	0.00104			0.0103***	0.00731***		
	(-0.53)	(0.16)			(3.66)	(2.72)		
Loan controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	51159	45307	44879	10245	51159	45307	44879	10245
Adjusted R2	0.001	0.196	0.683	0.747	0.005	0.020	0.383	0.316

The dependent variable is Exit for regressions 1-4 and Entry for regressions 5-8. Entry is a dummy variable equal to 1 if a bank-loan being initiated after the pre-shock period and 0 otherwise. Exit is a dummy variable equal to 1 if a bank-loan that had been present in the pre-shock period exits the sample in post-shock period and 0 otherwise. Pre- and post-periods are defined as 2019Q1-2019Q4 and 2020Q3-2020Q4, respectively. COVID exposure is constructed as total committed loans to firms in COVID impacted industries divided by total committed commercial loans in pre period. Columns 1-2 and 5-6 are run using OLS over the entire loan sample. Regressions 3-4 and 7-8 include borrower fixed effects. Regressions 3 and 7 includes all loans where the borrower have borrowed from multiple banks. Regressions 4 and 8 are limited to the nonbank borrowers. Bank controls include pre-shock period bank size, ROA, non-interest income/net income, equity/total assets, NPL/total assets, wholesale funding, share of nonbank lending. Loan controls include loan size, remaining maturity, syndicate size, loan type, relationship length, obligor credit share, bank credit share, main lender dummy variable and collateral. All bank controls listed are measured in the pre-shock period. Standard errors are clustered at loan level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 12: **Capital Channel (O&G Shock)**

	(1)	(2)
O&G Exposure	0.225*	-0.0197***
	(1.69)	(-5.67)
Rating	0.00570	-0.00846
	(0.26)	(-0.47)
Nonbank	0.0120	0.0263
	(0.05)	(1.36)
O&G Exposure * Nonbank	0.0177	0.0109*
	(0.20)	(1.94)
CET1 buffer	-0.0672**	
	(-2.35)	
CET1 buffer * Nonbank	0.00986	
	(0.36)	
CET1 buffer * O&G Exp.	-0.0236*	
	(-1.96)	
O&G Exp. * Nonbank *CET1 buffer	0.00202	
	(0.21)	
low_buffer		0.161**
		(2.53)
Low buffer * Nonbank		0.211**
		(2.13)
Low buffer * O&G Exp.		0.0589***
		(2.59)
O&G Exp. * Nonbank *Low buffer		0.0772**
		(2.14)
Loan controls	Yes	Yes
Bank controls	Yes	Yes
Borrower FE	No	No
Observations	13398	20358
Adjusted R2	0.032	0.023

The dependent variable is $\Delta Ln(Credit)$ estimated as a change in credit over pre- and post-period, defined as 2013Q3-2014Q2 and 2015Q1-2015Q3, respectively. Loans to firms in the O&G industry are removed from the sample. O&G exposure is constructed as total committed loans to O&G firms divided by total committed commercial loans in pre period. Bank controls include pre-shock period bank size, ROA, non-interest income/net income, equity/total assets, NPL/total assets, wholesale funding, share of nonbank lending. Loan controls include loan size, remaining maturity, syndicate size, loan type, relationship length, obligor credit share, bank credit share, main lender dummy variable and collateral. All bank controls listed are measured in the pre-shock period. Standard errors are clustered at loan level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 13: **Capital Channel (COVID Shock)**

	(1)	(2)
COVID Exposure	0.435***	-0.0139***
	(5.80)	(-3.37)
Rating	-0.0721***	-0.0712***
	(-3.44)	(-3.84)
Nonbank	-0.0623	0.0431***
	(-0.38)	(3.24)
Covid Exp. * Nonbank	-0.0382	0.0131**
	(-0.40)	(2.19)
CET1 buffer	-0.213***	
	(-5.73)	
CET1 buffer * Nonbank	0.0254	
	(0.57)	
CET1 buffer * COVID Exp.	-0.128***	
	(-5.71)	
COVID Exp. * Nonbank *CET1 buffer	0.0145	
	(0.57)	
low_buffer		-0.0372
		(-0.24)
Low buffer * Nonbank		0.501**
		(2.02)
Low buffer * COVID Exp.		-0.0385
		(-0.41)
COVID Exp. * Nonbank *Low buffer		0.311**
		(2.14)
Loan controls	Yes	Yes
Bank controls	Yes	Yes
Borrower FE	No	No
Observations	27849	34880
Adjusted R2	0.025	0.021

The dependent variable is $\Delta Ln(Credit)$ estimated as a change in credit over pre- and post-period, defined as 2019Q1-2019Q4 and 2020Q3-2020Q4, respectively. COVID exposure is constructed as total committed loans to firms in COVID impacted industries divided by total committed commercial loans in pre period. Bank controls include pre-shock period bank size, ROA, non-interest income/net income, equity/total assets, NPL/total assets, wholesale funding, share of nonbank lending. Loan controls include loan size, remaining maturity, syndicate size, loan type, relationship length, obligor credit share, bank credit share, main lender dummy variable and collateral. All bank controls listed are measured in the pre-shock period. Standard errors are clustered at loan level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 14: **Nonbank loan sales**

	(1)	(2)	(3)
ExcessBondPremium (EBP)	0.0669***	0.0646***	0.0523***
	(8.45)	(7.92)	(6.01)
Lender Bank loan	-1.857**	-1.351**	-0.480
	(-2.27)	(-2.15)	(-0.75)
EBP * Lender Bank loan	-7.560***	-8.147***	-4.361**
	(-3.80)	(-4.77)	(-2.48)
Rating	0.000608	0.00221	0.00234
	(0.14)	(0.74)	(0.79)
Unstable			-0.0273**
			(-2.22)
Unstable * Lender Bank Loan			-12.10*
			(-1.95)
Unstable * Lender Bank Loan * EBP			-50.84***
			(-4.31)
Unstable*EBP			0.0142***
			(5.88)
Loan controls	Yes	Yes	Yes
Borrower FE	Yes	No	No
Loan FE	No	Yes	Yes
Lender FE	Yes	Yes	Yes
Observations	10309043	10859614	10514760
Adjusted R2	0.158	0.227	0.227

The dependent variable is Nonbank loan sales which is an indicator variable equal to 1 if a lender reduces its exposure in a loan that it funded in the previous quarter. Our sample includes all syndicated term loan sales by Nonbanks between 2010Q1 and 2020Q3. Excess Bond Premium (EBP) from Gilchrist and Zakrajsek (2012) captures macroeconomic credit conditions. Unstable is equal to 1 if a nonbank is a broker-dealer or an investment fund and 0 if it is an insurance company or a pension fund. All columns include an indicator variable for whether the bank has undergone a merger in the past quarter. Loan controls include loan size, remaining maturity, syndicate size, rated indicator and voter rating. Standard errors are clustered at the loan level.t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

Table 15: **Nonbank New Originations**

	All Observations			New Loans	
	(1)	(2)	(3)	(4)	(5)
				Ln(Share commitment)	Ln(Share commitment)
ExcessBondPremium (EBP)	-0.0758***	-0.0859***	-0.144***	0.0525	
	(-11.87)	(-13.00)	(-13.09)	(1.56)	
Lender Bank loan	0.765**	1.485***	1.011***	-111.5***	-136.8***
	(2.49)	(5.63)	(2.59)	(-11.11)	(-12.47)
EBP * Lender Bank loan	1.957*	2.357***	2.965**	220.1***	294.3***
	(1.95)	(2.66)	(2.13)	(6.10)	(7.33)
Total Lending	-1.394***	-2.495***	-2.464***	377.6***	449.4***
	(-5.99)	(-14.54)	(-14.36)	(39.81)	(49.11)
Rating	-0.00666***	-0.000158	0.00355	-0.0143	
	(-2.62)	(-0.05)	(1.15)	(-0.45)	
EBP * Rating			0.0546***		
			(8.73)		
Lender Bank Loan * Rating			0.706**		
			(2.38)		
EBP * Lender Bank Loan * Rating			-0.720		
			(-0.80)		
Loan controls	Yes	Yes	Yes	Yes	Yes
Borrower FE	No	Yes	Yes	Yes	No
Loan FE	No	No	No	No	Yes
Observations	10505416	10505178	10505178	940180	938136
Adjusted R2	0.057	0.120	0.122	0.223	0.240

The dependent variable is Nonbanks' new loan originations. Our sample includes all syndicated loans between 2010Q1 and 2020Q3. Excess Bond Premium (EBP) from Gilchrist and Zakrajsek (2012) captures macroeconomic credit conditions. Unstable is equal to 1 if a nonbank is a broker-dealer or an investment fund and 0 if it is an insurance company or a pension fund. All columns include an indicator variable for whether the bank has undergone a merger in the past quarter. Loan controls include loan size, remaining maturity, syndicate size, rated indicator and voter rating. Standard errors are clustered at the borrower level. t-statistics in parentheses, and *p<0.10, **p<0.05, ***p<0.01.

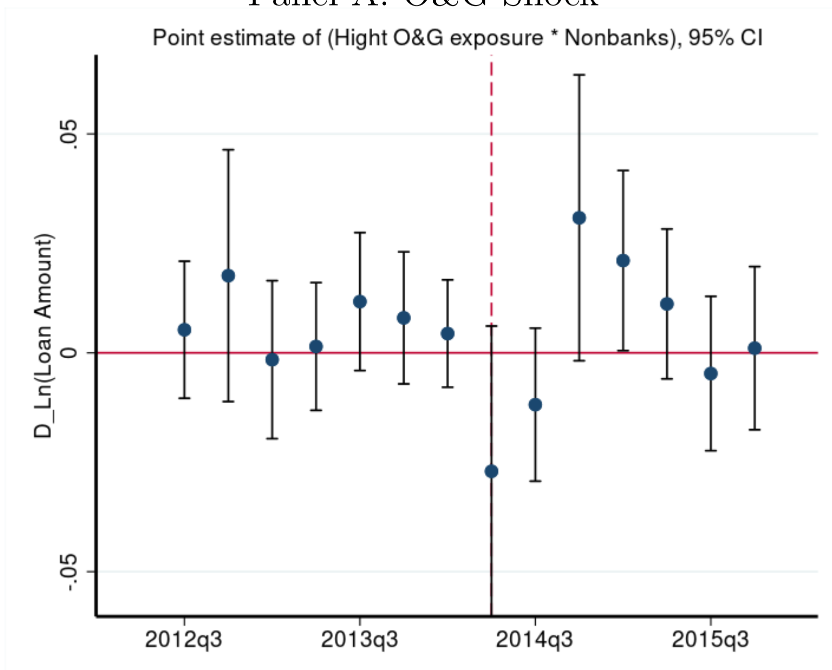
A. Appendix

Table 16: Variable Definitions

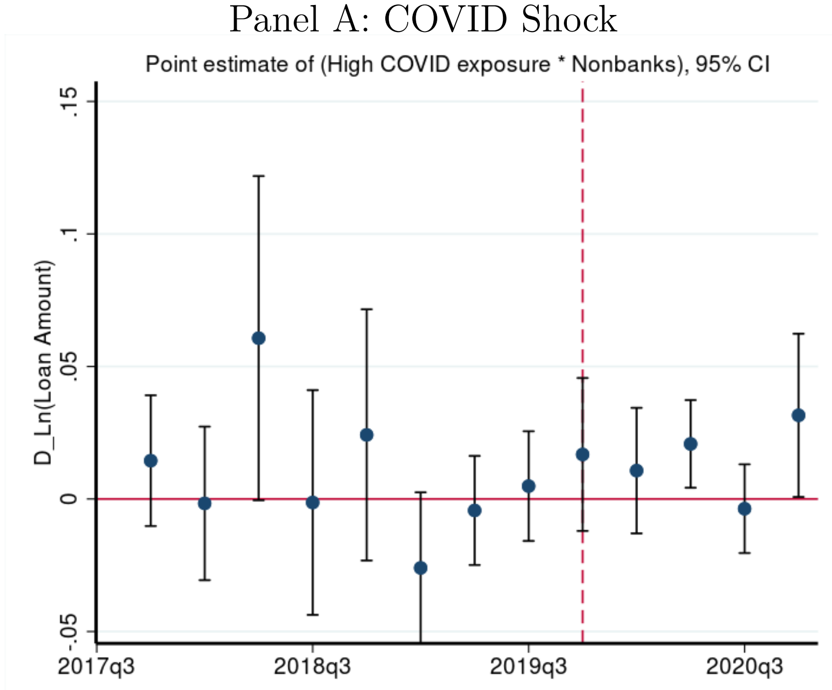
Variable	Definition
Bank-level Measures:	
O&G Exposure	Share of bank committed exposure to the O&G sector in pre-period (2013Q3-2014Q2)
COVID Exposure	Share of bank committed exposure to COVID-19 impacted industries in pre-period (2019Q1-2019Q4)
Basel III Tier 1 Shortfall	Difference between current Tier 1 capital under Basel I and proposed Tier 1 capital requirement under Basel III (as of 2012q2)
Bank Size	Natural logarithm of total assets
ROA	Net income divided by total assets
Non-Interest Income/Net Income	Non-interest income divided by net income
Equity/total assets	Shareholders equity divided by total assets
NPL/total assets	Non-performing loans divided by total assets
Wholesale Funding	Sum of large time deposits, foreign deposits, repo sold, other borrowed money, subordinated debt, and federal funds purchased divided by total assets
Loan-level Measures:	
Loan Sale	Indicator variable equal to 1 if bank reduces its share in a loan syndicate that it participated in in previous period while loan continues to exist in the current period
Loan Size	Natural logarithm of committed exposure in millions of dollars
Loan Share	Share of loan committed exposure that is held by the lender during pre-shock period
Syndicate Size	Natural logarithm of number of all syndicate participants
Remaining Maturity	Natural logarithm of number of quarters remaining from report date till maturity date
Refinance	Indicator variable equal to 1 if loan's committed exposure in a quarter is different from the previous quarter, and 0 otherwise
Loan Type	Indicator variable equal to 1 if a loan is a revolver and equal to 2 if it is a term loan
Relationship Length	Number of quarters in which we observe a lending relationship between an obligor and a bank
Obligor Credit Share	Share of an obligor's loan balance in the bank's loan portfolio
Bank Credit Share	Share of a bank in an obligor's loan portfolio
Main Lender	Indicator variable equal to 1 if a bank is the firm's largest lender and 0 otherwise
Collateral	Indicator variable equal to 1 if a loan is secured by a collateral and 0 otherwise.
Rating	Presents a number between 1 to 5 where 1 indicates highest and 5 lowest credit quality based on final SNC exam rating. It is calculated as (1 * pass + 2 * special mention + 3 * substandard + 4 * doubtful + 5* loss)/100 where each of pass, special mention, substandard, doubtful and loss represents the percent of credit's committed exposure that has such final exam rating.

Figure 5: **Pre-trend Analysis**

Panel A: O&G Shock



Panel A: COVID Shock



These graphs depict the point estimate and 95% confidence interval of the βs of interaction term, HighExposure * Nonbank, in each quarter for the following regression. $\Delta Ln(Credit_{ij}) = \alpha + \beta HighExposure_i * Nonbank_j + \gamma X_{i,j} + \epsilon_{ij}$ where "High Exposure" is equal to 1 if a bank exposure is above 85th percentile of the banks in our sample over and 0 otherwise. We estimate shock exposure for O&G (COVID) over 2011Q3-2012Q2 (2017Q1-2017Q4).