Zombie Lending to U.S. Firms*

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We show that U.S. banks, including weakly capitalized ones, do not lend to distressed and unprofitable ("zombie") firms. In contrast, unregulated non-bank financial intermediaries do, originating more and cheaper loans to these firms. We establish these results using supervisory data on firm-bank relationships, syndicated lending data for banks and non-banks, and an empirical setting with quasi-random shocks to firm profitability. Relative to banks, non-banks' lending increases the survival rate of zombie firms by delaying their exit through bankruptcy.

Keywords: Zombie lending, Zombie firms, Banks, non-banks.
JEL Codes: G21, G32, G33.

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1 Introduction

Zombie firms are unprofitable businesses that stay afloat due to creditor forbearance. These firms tie up credit that could be channeled to more profitable enterprises, with potentially adverse effects on aggregate productivity and economic growth.[1]

A widely-held view is that zombie firms survive and proliferate because bank lending policies are distorted by capital regulation. According to this view, capital requirements increase the cost of loan loss recognition, creating incentives for weakly capitalized banks to evergreen loans and avoid regulatory pressure to raise capital (Peek and Rosengren, 2005; Caballero *et al.*, 2008; Acharya *et al.*, 2019; Blattner *et al.*, 2023). An alternative view is that lending to zombie firms is unrelated to capital requirements (see Hu and Varas (2021) and Faria-e-Castro *et al.* (2024)). Rather, it arises because the provision of cheap credit to under-performing firms dominates early costly liquidation decisions, especially as lenders' exposure to these firms increases.

In this paper, we contribute to this debate using data for both banks and non-bank financial institutions (NBFIs) to assess whether capital regulation, or lack thereof, fosters zombie lending in the United States. We study how banks' and NBFIs' lending policies change as firm profitability weakens, and how these lending policies vary across regulated and unregulated financial institutions. Our main findings are: (1) U.S. banks, including weakly-capitalized banks and banks with higher exposure to zombie firms, tighten lending terms to such firms; (2) NBFIs partly offset banks' reduced exposure to zombie firms by offering them larger or cheaper loans; (3) bank capital regulations promote credit migration to NBFIs, with NBFIs' participation in the loan market increasing when banks have less capital; and (4) despite the support of NBFIs, zombie firms go bankrupt at a higher rate than other firms, especially when they are more dependent on bank financing.

These results suggest that capital requirements at U.S. banks do not distort the incentives

[1] See Acharya *et al.* (2022) and Albuquerque and Iyer (2024) for reviews of recent research on zombie firms and zombie lending.

of weakly capitalized banks to lend to zombie firms relative to other banks. Instead, capital regulation appears to foster zombie lending through the migration of credit from regulated to unregulated financial institutions. To the best of our knowledge, this is the first paper that studies zombie lending by banks and NBFIs jointly and that highlights the unintended consequences of capital regulation for credit allocation to zombie firms. Our results also suggest that NBFIs' support of zombie firms likely has limited negative spillover effects on the aggregate economy, as zombie firms eventually exit the market through bankruptcy.

Our analysis relies on the universe of bank loans to private and listed firms in the supervisory Federal Reserve Y-14 data set. These data have the most comprehensive coverage of U.S. firms with a banking relationship and offer detailed information on bank loans and firm balance sheets starting in 2012.[2] Data on NBFI lending come from DealScan, a data set of syndicated loans from both banks and non-bank lenders. We focus on the U.S. market because—relative to other jurisdictions—NBFIs are critical intermediaries in the U.S. financial system and, unlike banks, are not subject to capital regulation.

To identify zombie firms, we first select firms that are financially distressed, that is, they have high leverage and struggle to service debt interest payments. Second, we study how banks' and NBFIs' lending policies change when financially-distressed firms suffer a persistent negative profitability shock. We refer to financially-distressed firms that become unprofitable as "zombie firms." This approach follows the seminal paper on evergreening and zombie lending by Peek and Rosengren (2005), but departs from Caballero *et al.* (2008) and Acharya *et al.* (2019), who classify firms as zombies if they receive subsidized credit—that is, credit at interest rates below those paid by the most creditworthy firms. We do not impose this condition because we wish to test—rather than assume—whether lenders offer cheap credit to under-performing firms. Moreover, in our data, very few financially-distressed firms receive subsidized credit.

For empirical identification, we exploit the unanticipated and sustained decline in the

[2]The Federal Reserve Y-14 is a data collection effort originating with the Dodd-Frank Act that gathers detailed information on the lending activities of large bank holding companies subject to stress tests.

global price of crude oil in 2014 and 2015 as a quasi-random shock to firm profitability. The price of oil is determined by global forces, and thus unrelated to firm fundamentals, lender capital positions, and the characteristics of borrowers and lenders that match in the corporate loan market. In this setting, we compare lending to zombie firms by banks with heterogeneous ex-ante capital buffers and by regulated and unregulated financial intermediaries.

Main Results Our first set of results is that banks cut lending to zombie firms. We find that banks reduce their loan exposures to ex-ante financially distressed firms in the oil sector in response to the profitability shock and charge these firms higher interest rates. We estimate that after the oil price decline, banks cut lending to zombie firms by roughly 14% and increase loan rates by 24 basis points (bps). As loan volumes decline and interest rates rise, these post-oil shock changes suggest shifts in credit supply rather than in credit demand. We then test whether these findings depend on banks' capital buffers. Banks in our sample are subject to annual stress tests that determine bank capital needs under adverse economic conditions. Banks with lower capital buffers may therefore follow a policy of forbearance to delay the default of poor-performing firms. We find no evidence of a link between post-stress capital buffers and lending to firms that transition from financially distressed into zombie status. We also find no evidence that banks' lending policies vary with their ex-ante regulatory capital ratios (Tier 1) or with ex-ante loan exposure to zombie firms.

These results are obtained in a difference-in-differences (DD) regression framework that includes a host of granular fixed effects to ensure that the results are not driven by other confounding factors, including unobserved time-varying industry, local, or bank-specific shocks. The identifying assumption is that firms' transition from financially distressed to zombie status is triggered by the oil price shock and not by past bank lending practices nor by unobserved bank and firm characteristics. Our results are robust to alternative definitions of bank capital, approaches to clustering the standard errors, finer fixed effects, and in a more general regression framework outside the 2014–2015 oil shock.

Our second set of results is that NBFIs increase their exposure to distressed firms after the oil shock. Relative to banks, NBFIs are more likely to originate new loans to zombie firms (by about 8%) and offer these firms significantly cheaper loans. In addition, we estimate that, after the oil shock, syndicated loan deals to zombie firms are about 17 percentage points (ppts) more likely to feature at least one non-bank lender and have higher non-bank loan participation shares (by about 7 ppts) compared to loans to other firms.

The data also suggest a direct link between bank capital and NBFI lending. We document that NBFIs participation in syndicated loan deals to zombie firms is higher when participating banks have lower capital. The presence of weakly-capitalized banks in a zombie loan syndicate is associated with a sigificantly higher likelihood of having at least one non-bank participant in the same loan, as well as an increase in the non-bank lending share after the oil shock. This evidence suggests a novel mechanism through which higher bank capital regulations foster zombie lending by promoting credit migration to less regulated financial institutions.

Our third set of results is that while NBFIs' financial support of zombie firms slow their transition into bankruptcy, it does not prevent it. We estimate that zombie firms are 7 ppts more likely to file for bankruptcy compared with firms that are financially distressed but not hit by the oil shock, an effect that is driven by zombie firms historically more dependent on bank debt. These results suggest little persistent misallocation of capital associated with credit migrating from banks to NBFIs.

Contribution to the Literature. Our paper is related to the empirical literature on zombie lending (Peek and Rosengren, 2005; Caballero *et al.*, 2008; Giannetti and Simonov, 2013; Acharya *et al.*, 2019; Schivardi *et al.*, 2020; Blattner *et al.*, 2023). The key finding of this literature is that capital regulation in Japan in the early 1990s and in Europe post-global financial crisis (GFC) has led weakly-capitalized banks to evergreen loans to underperforming firms to avoid capital-eroding losses. To various degrees, zombie lending has

been documented in other developed and emerging economies; see, e.g., McGowan *et al.* (2018), Banerjee and Hofmann (2018), Chopra *et al.* (2021), Bonfim *et al.* (2023), Schmidt *et al.* (2020), De Martiis and Peter (2021), Banerjee and Hofmann (2022), Albuquerque and Iyer (2024), and Amundsen *et al.* (2023). We contribute to this literature by showing that U.S. banks, irrespective of their capital positions and risk exposure, do not engage in zombie lending after the GFC, while unregulated financial intermediaries do, even if their financial support has limited implications for the survival of zombie firms. In a recent paper, Faria-e-Castro *et al.* (2024) exploit cross-sectional variation in U.S. banks' exposure to distressed firms to study banks' incentives to evergreen loans. Unlike this paper, we study how lending outcomes vary with bank capital and between regulated and unregulated financial intermediaries.

Our finding that NBFIs engage in zombie lending adds to the literature that sees capital regulation as reducing banks' capacity to intermediate at the advantage of unregulated financial intermediaries (Irani *et al.*, 2021; Chernenko *et al.*, 2022; Bednarek *et al.*, 2023). This literature examines how capital regulation affects banks' balance sheet and risk-bearing capacity. In contrast, our focus is on credit misallocation. Arguably, while de-risking and deleveraging are intended consequence of bank regulation, credit misallocation, in the form of zombie lending, is not.

Our firms' bankruptcy results contribute to a strand of the zombie lending literature that argues efficient bankruptcy systems encourage creditors to resolve bad loans through insolvency, reducing lenders' incentives to evergreen loans (Andrews and Petroulakis, 2019; Becker and Ivashina, 2021; Li and Ponticelli, 2022).

Our paper is also related to the literature on low interest rates, capital misallocation, and economic stagnation (Gopinath *et al.*, 2017; Aghion *et al.*, 2019; Caggese and Pérez-Orive, 2022). Our analysis covers the post-GFC period, which features low interest rates and accommodative credit conditions. However, we find no evidence that U.S. banks allocate credit to under-performing firms in a low-interest rate environment, while non-banks do.

2 Data

We draw information on firm-lender credit relationships and firm balance sheets from two main data sources: the Y-14 data set, which provides comprehensive supervisory data on commercial and industrial (C&I) loans from large U.S. banks, and DealScan, a dataset with detailed information on the lending activities of banks and non-banks in the syndicated loan market. These and other data sources are described in this section.

Federal Reserve's Y-14Q Since 2012, the FR Y-14Q Schedule H.1 (Corporate Wholesale Risk) collects quarterly data on C&I loans with commitment amounts above $1 million from bank holding companies (BHCs) with at least $50 billion in total consolidated assets.[3] The number of reporting banks in Y-14 fluctuates between 31 and 36 over time. The data account for nearly three-fourths of total C&I lending (Bidder *et al.*, 2021; Favara *et al.*, 2021) and about 85% of total banking-sector assets (Frame *et al.*, 2023). A key advantage of these data is the extensive coverage of private firms that borrow from reporting banks. In any given year, we observe about 70,000 firms, of which about 3% are publicly listed.

We use the Y-14 data in two ways. First, we rely on extensive firm balance sheet information (as reported by the banks) to classify firms as financially distressed and examine their performance (e.g., investment rate, balance sheet growth, etc.). Second, we use data on individual loan agreements to study the terms of bank lending to such firms once they acquire a zombie status.

Bank Balance Sheet Data We use three measures of bank capital. The first one is the "post-stress capital ratio" defined as the minimum common equity Tier 1 capital (CET1) ratio estimated under the adverse scenario (formally, the "Supervisory Severely Adverse" scenario) of the Dodd-Frank Act Stress Test.[4] Stress tests assess banking sector resilience

[3] These stress tests include the Comprehensive Capital Analysis and Review and the Dodd-Frank Act Stress Test. See link for more information on the Y-14 data.

[4] These data are available on the Federal Reserve's stress test page starting in 2014.

to hypothetical economic downturns and determine the minimum capital ratio that banks must hold to cushion losses without becoming insolvent. The second measure is the BHC-level regulatory CET1 capital ratio from the Consolidated Financial Statements for Holding Companies, FR Y-9C. The third measure we use is the proposed Basel III-compliant Tier 1 regulatory capital ratios for 2012:Q2. This measure is used a source of exogenous variation in bank capital in Irani *et al.* (2021) due to the fact that even though the timing and content of the internationally agreed version of Basel III capital reforms were well understood by banks, the precise implementation of the rule in the United States differed from the international version and contained an element of surprise (Berrospide and Edge, 2016).

Refinitiv LPC DealScan We complement the analysis with data on syndicated loans from Refinitiv DealScan, which provides information on the syndicated lending participation of both banks and NBFIs. Syndicated loans represent a sizeable portion of commercial lending, accounting for about one-quarter of C&I loan commitments in the Y-14 data. Syndicated loans are structured as deals comprising multiple loan tranches. For each loan deal, we observe the characteristics of individual loan tranches (e.g., tranches typically differ in terms of loan amount and type—credit line vs. term loan), the identities of the borrower and lenders in the syndicate, and the loan shares that individual lenders contribute to each loan tranche. Furthermore, the dataset includes information on interest rate spreads, which together with other loan pricing terms, are determined at the deal level (Ivashina, 2005).

DealScan allows us to study differences in lending policies between bank and non-bank lenders and how these policies vary with bank capital positions. To classify lenders as banks or non-banks, we use the "lender institution type" variable coupled with several classification strategies. Appendix C provides details on the processing of DealScan data and the classification of lenders into banks and NBFIs. As shown in Figure C.1, the share of syndicated loans with at least one non-bank participant trends upward between 2012 and 2017, ranging between 14% and 21% over this period, and the aggregate volume of loans originated in such

deals reaches $300 bn in 2017.

Firm Balance Sheet Data DealScan is matched with quarterly firm balance sheet data from Compustat through the Chava and Roberts (2008) crosswalk in the DealScan-Compustat Linking Database. The final DealScan regression sample with Compustat-borrowers has approximately 6,500 loan deals to 3,800 firms over 2012–2017. Appendix C describes in more detail the matching approaches involving DealScan and Compustat and the characteristics of the final samples.

Firm Bankruptcy Data We use data on bankruptcy filings from the S&P Capital IQ U.S. Bankruptcy Tracker to analyze firm exit. Data coverage includes listed firms, private firms with public debt at the time of the bankruptcy filing above $2 million, and private firms with total assets or liabilities at the time of the bankruptcy filing above $10 million. We supplement these data with additional bankruptcy events for public firms recorded in the Mergent FISD data set. To examine firm exit via bankruptcy, we construct a regression sample that retains, from the universe of borrowing firms in the Y-14 data, those firms that meet the criteria for being included in the S&P Capital IQ Bankruptcy Tracker.[5] The regression sample comprises about 14,500 firms per year during 2012–2017 and a total of 293 bankruptcy events over the sample period.

Descriptive Statistics Table 1 reports summary statistics for the Y-14 and DealScan regression samples between 2012 and 2017. In Y-14, the volume of committed credit is on average $34 million across firm-bank pairs and the average interest rate on outstanding loans is 2.8%. Roughly two-thirds of the loan facilities are credit lines, with a mean utilization rate of 28%. The average firm in the Y-14 sample is relatively large, but there is high dispersion,

[5]Specifically, we ensure that the firms have public debt of at least $2 million and total assets of at least $10 million. Because we do not observe the amount of public debt of Y-14 firms, we approximate it as the difference between total debt and total bank debt from Y-14 reporting banks. Since this calculation omits bank debt from non-reporting banks, we likely overestimate the amount of public debt, and, hence, the number of firms eligible to be included in the S&P Capital IQ Bankruptcy Tracker.

with total assets ranging from $5 mn at the 10th percentile of $5.7 bn at the 90th percentile. In DealScan, the probability of a new loan origination in any given year is 7% and average loan spreads are 2.3%. The average firm in DealScan is larger than in Y-14, with total assets of $54 mn at the 10th percentile and $25 bn at the 90th percentile.

3 Zombie Lending by Banks

To study bank lending to zombie firms, we exploit the sharp and sustained decline in the global price of crude oil in 2014 and 2015 as a quasi-random shock to the profitability of oil sector firms. We use this setting to estimate whether bank lending to ex-ante financially distressed firms in the oil sector changes as their profitability deteriorates after the oil shock. We examine the terms of lending by NBFIs in a similar setting in Section 4.

Oil Price Shock Between mid-2014 and early 2015, the global price of crude oil experienced the largest decline in recent history (see Figure A.1). The price drop was largely unanticipated and driven by a combination of factors, including excess oil supply and declining global demand (Baumeister and Kilian, 2016; Prest, 2018). The cumulative price decline of roughly 70% between 2014 and 2015 put severe stress on oil-producing firms and delayed their investments in alternative drilling techniques, stifling the growth prospects of these firms (Baumeister and Kilian, 2016).

We exploit this quasi-natural experiment to identify bank lending policies to ex-ante distressed firms that transition into zombie status after the oil shock. We use the following regression model estimated with data at the firm-bank-quarter level:

$$\begin{aligned} Lending\ outcome_{bft} =& \beta_1 (Distressed_f \times Oil\ Sector_f \times Post_t) + \lambda^c Lower\ level\ controls + \\ &+ (\lambda^x + \lambda^p Post_t) \times X_{ft} + \gamma_{it} + \eta_{st} + \delta_{bt} + \psi_{bf} + \epsilon_{bft} \end{aligned} \tag{1}$$

where the lending outcome between bank b and firm f (in industry i and state s) in quarter

t is either the (log of) total loan commitments or the weighted average loan interest rate. $Distressed_f$ is a dummy variable for firms that are in financial distress during the 2013–2014 period—that is, firms with a debt-to-asset ratio above the cross-sectional median and an ICR below one, before the oil shock—and $Oil\ Sector_f$ is a dummy variable taking value one for firms exposed to the oil price decline, that is, firms that operate in oil and gas (O&G) sector.[6] $Post_t$ is an indicator variable that takes value 1 for the three-year period following the oil shock (2015–2017) and value 0 in the three years before the shock (2012–2014).

In equation (1), *Lower level controls* includes all the double interactions and individual variables of the triple DD term, X_{ft} denotes a vector of firm controls, such as size (log-assets), cash holdings (cash/assets), and tangibility ratio (tangible assets/assets), entering the specification individually and interacted with the $Post_t$ dummy.

We saturate the regression model with an array of fixed effects. To start with, we include industry×quarter and state×quarter fixed effects (γ_{ft} and η_{st}) to control for unobserved time-varying (2-digit NAICS) industry and state-level shocks. As many of the firms in our analysis are private and operate locally, these fixed effects control for local shocks that cannot be diversified away. We also include bank×quarter fixed effects (δ_{bt}) to control for time-varying unobserved heterogeneity across banks (such as quarterly shocks to banks' funding costs or capital). Finally, we add firm×bank fixed effects (ψ_{bf}) to control for unobserved factors that are specific to a firm-banking relationship, such as banks' private information on borrower creditworthiness, or endogenous firm-bank matching (Chodorow-Reich, 2014; Schwert, 2018), which may be driven by bank specialization in some geographies or firm activities (Paravisini *et al.*, 2023; Blickle *et al.*, 2023).

Our regression framework is akin to a triple DD setting, comparing bank lending outcomes

[6]More specifically, we classify firms as oil sector firms if they have one of the following NAICS codes: O&G Extraction (code 211), Drilling O&G Wells (code 213111), Support Activities for O&G Operations (code 213112), Natural Gas Distribution (code 2212), Pipeline Transportation (code 486), O&G Pipeline and Related Structures Construction (code 23712), Mining & O&G Field Machinery Manufacturing (code 33313), Petroleum Refineries (code 32411), Other Petroleum and Coal Products Manufacturing (code 32419), Petrochemical & Industrial Gas Manufacturing (codes 32511, 32512), and Petroleum & Petroleum Products Merchant Wholesalers (code 4247).

before and after the oil shock (first difference) to distressed versus nondistressed firms (second difference) and, among distressed firms, between firms in the oil sector versus other sectors (third difference). Distressed firms in the oil sector are likely to acquire a zombie status, as their ability to generate profits and remain economically viable deteriorates after the oil shock. The identifying assumption is that the transition from distressed to zombie status is induced solely by the oil price decline and not by past bank lending practices nor by unobserved bank and firm characteristics. The coefficient of interest is β_1, which measures the effect of zombie status on bank lending decisions. A negative β_1 for loan quantities and a positive one for loan pricing suggests that banks refrain, on average, from lending to zombie firms.

A key finding of the zombie lending literature (see, e.g., Acharya *et al.* (2019)) is that weakly capitalized banks direct additional credit toward unprofitable firms to avoid loan defaults, as these defaults would deplete capital buffers. In addition, the incentives of weakly capitalized banks to lending to zombie firms are stronger the larger the impact of firms' default on bank equity. To estimate the effects of banks' capital and firm exposure on lending to zombie firms, we split banks in our sample into those that have low capital ratios and high firm exposure (as a share of bank equity) using the cross-sectional distributions of these two variables *before* the oil shock. Accordingly, we define a *low-capital high-exposure bank* dummy variable for banks that at the end of 2014 simultaneously have a low (bottom quartile) post-stress CET1 capital ratio and high (above-median) exposure. Figure A.3 shows that bank capital and bank-firm loan exposure before the 2014–2015 oil price shock exhibit significant cross-sectional variation.

We estimate a modified version of equation (1):

$$
\begin{aligned}
Lending\ outcome_{bft} = & \sum_{\tau=1,2} \beta_\tau (Distressed_f \times Oil\ Sector_f \times Post_t) \times Bank\ Type_{b,\tau} + \\
& + \sum_{\tau=1,2} \lambda^b (Lower\ level\ controls) \times Bank\ Type_{b,\tau} + \\
& + (\lambda^x + \lambda^p Post_t) \times X_{ft} + \gamma_{jt} + \eta_{it} + \delta_{bt} + \psi_{bf} + \epsilon_{bft},
\end{aligned} \tag{2}
$$

where $\tau = 1$ indicates a low-capital high-exposure bank and $\tau = 2$ indicates other banks. In additional specifications, we explore whether low-capital high-exposure bank effects are separately driven by either the bank's level of capital or its exposure to zombie firms. A positive β_1 for loan quantities at low-capital high-exposure banks suggests that such banks extend relatively more credit to distressed borrowers after the oil shock. We also report p-values of two-sided t-tests of the null hypothesis of coefficient equality $\beta_1 = \beta_2$ against the alternative hypothesis that $\beta_1 \neq \beta_2$. Rejecting the null hypothesis of coefficient equality across bank types suggests a lack of evidence for the zombie lending hypothesis.

Results Panel A of Table 2 presents the estimation results for the specification in equation (1).[7] The estimates in column 1 indicate that distressed firms in the oil sector—that is, firms likely to transition into zombie status—experience a reduction in loan amounts of 13.4% higher than other firms, after the oil price shock. Meanwhile, the estimates in column 2 show that banks grant these firms relatively more expensive loans (at interest rates close to 24 bps higher on average), likely as a compensation for the higher credit risk. These results suggest that banks pare back their exposures to distressed firms that are adversely affected by the oil shock, even if these firms and banks are in a pre-existing relationship.

In Panel B of Table 2, we test for differences in lending terms to zombie firms between low-capital high-exposure banks and other banks. These estimates by bank type show that lending terms to zombie firms are not statistically different across the two groups of banks. Both low-capital high-exposure and other banks reduce loan exposures to distressed oil firms by 12-14% and charge them loan rates that are 21 to 32 bps higher after the oil shock.

[7] In Table 2 we only show the main coefficients of interest. Table A.1 additionally reports all the estimated coefficients.

Table 3 unpacks the effects on lending terms of bank capital and bank exposure to firms. Regression estimates reveal that neither banks with low capital buffers (panel A) nor banks with high firm exposure (panel B) offer advantageous lending terms to zombie firms. In panel A, coefficient estimates are relatively higher for low-capital banks and we reject the null of coefficient equality across bank groups, which indicates that low-capital banks tighten lending terms to zombie firms even more than high-capital banks. In fact, low-capital banks reduce loan exposures by 21.4% and increase interest rates by almost 35 bps compared to 8.2% and 17 bps for high-capital banks. In panel B, tests of coefficient equality across bank groups indicate statistically insignificant differences in lending outcomes for high versus low-exposure banks.

These results suggest that low-capital banks with significant exposure to zombie firms do not evergreen loans nor do they provide cheaper loans to ex-ante distressed firms with deteriorating profitability.

Ruling Out Potential Confounding Effects We present three sets of tests to allay potential concerns that our baseline results may be driven by other factors.

One concern is that banks with low capital ratios had to cut lending because they had to raise more capital than other banks to comply with stress tests and the phase-in of new regulatory capital requirements post GFC. This adjustment could have limited banks' ability to lend to zombie firms for reasons that are unrelated to firm solvency and profitability. Our regression analysis addresses this concern by including bank×quarter fixed effects, which control for time-varying bank shocks stemming, for instance, from changes in regulatory requirements. In addition, Figure A.2 presents evidence contrary to the view that low-capital high-exposure banks had to make relatively larger adjustments to their capital ratios post-GFC regulation. It shows that these banks adjusted capital ratios by *less* than other banks during the phase-in of the new regulatory regime.

A second concern is that our results may be driven by shifts in credit demand, with

distressed oil firms reducing loan demand from low-capital high-exposure banks after the oil shock. Our main findings that low-capital high-exposure banks not only cut lending but also charge distressed firms higher loan rates after the oil shock (Table 2) rules out this possibility. If a credit demand channel were at work, interest rates would have been lower, not higher. Two additional findings strengthen our confidence that we identify a credit supply channel. First, we examine changes in credit line drawdowns, which (absent covenant violations) likely reflect shifts in credit demand (Sufi, 2009). As shown in Table A.3, we find no evidence that distressed oil firms change their credit line utilization after the oil shock (columns 1 and 3) nor that they do so vis-a-vis a certain type of banks (column 2). Table A.2 also shows that our baseline results continue to hold when we use finer fixed effects than in the benchmark analysis, such as state×industry×quarter fixed effects (panel A) and state×industry×size-group×quarter fixed effects (panel B). As argued by Degryse *et al.* (2019), these finer fixed effects serve as valid alternative demand controls to the traditional Khwaja and Mian (2008) firm×time fixed effects, which are not feasible in our setting.

A third concern is that the results may be driven by low-capital high-exposure banks being more inclined to renegotiate loans and modify contractual terms. This possibility would confound our baseline results insofar as modifications of loan terms stem mainly from loan renegotiations. To alleviate this concern, we re-estimate in Table A.4 our main regressions on a sample of newly originated loans. We find that none of our baseline results are affected.

Additional Tests In additional robustness checks, we show in Panel A of Table A.5 that our results hold up when controlling for differential pre-shock trends in lending outcomes for distressed firms in the oil sector relative to the comparison group (as in Autor *et al.* (2024)). In Panel B of Table A.5 we show that the results are unchanged when we examine lending outcomes in risk-adjusted terms by controlling for ex-ante borrower credit risk rating. Table A.6 shows that levels of statistical significance for our main estimates remain unchanged

for alternative choices of standard error clustering. We also show in Table A.7 that our baseline results are robust to using alternative measures of bank capital, namely the BHC-level regulatory CET1 ratio measured at the end of 2013 (before the phase-in period of new capital requirements and the first Dodd-Frank stress tests), or the proposed Basel III-compliant Tier 1 regulatory capital ratios i 2012:Q2 (used as sources of exogenous variation in bank capital in Irani *et al.* (2021)). Finally, in Appendix B we check the external validity of our main results beyond the oil shock period, using an alternative definition of zombie firms. Table B.1 shows that our core results remain unchanged.

4 Zombie Lending by Non-banks

Do NBFIs tighten lending standards as much as banks do when firms become zombies? To address this question, we begin by documenting differential lending behaviors at non-banks compared to banks using the same quasi-natural experiment introduced in Section 3. We then explore whether NBFIs lending to zombie firms in syndicated loans depends on capital of participating banks.

4.1 Oil Price Shock Analysis

To estimate differences in lending policies to zombie firms between banks and NBFIs, we take advantage of a unique feature of the DealScan dataset, which offers information on the identity and type of the lenders that form a loan syndicate.[8] Similar to the Y-14 analysis, we use the decline in the global price of crude oil in 2014 and 2015 as a quasi-random shock to firm profitability, and estimate a version of equation (2) in which the triple DD term $Distressed_i \times Oil\ Sector_i \times Post_t$ is interacted with a dummy for non-bank lenders.

[8] Appendix C provides detailed information on the approach used to classify lenders into banks and NBFIs and Figure C.1 depicts the evolution of NBFI lending during 2012–2017.

$$
\begin{aligned}
Lending\ outcome_{lit} = {} & \beta_1(Distressed_i \times Oil\ Sector_i \times Post_t) \\
& + \beta_2(Distressed_i \times Oil\ Sector_i \times Post_t) \times Non-bank\ lender_l \\
& + \lambda^c Lower\ level\ controls_{it} + (\lambda^x + \lambda^p Post_t) \times X_{it} \\
& + \alpha_i + \eta_{jt} + \delta_{lt} + \epsilon_{bit}
\end{aligned} \tag{3}
$$

where the outcome variables are *New Loan* or *Loan Spread*. For *New Loan*, we follow Chodorow-Reich (2014), and construct as a dummy variable that is equal to 1 if lender l originates a syndicated loan to firm i in year t and is 0 otherwise. In this specification, which is at the lender-firm-year level, $Non-bank\ lender_l$ is equal to 1 if lender l is a non-bank and 0 if lender l is a bank. For *Loan Spread*, we turn to loan tranche-level data, such that the differential effects between non-banks and banks are estimated from the cross-sectional variation in spreads across syndicated loan deals. $Loan\ Spread_d$ is the all-in drawn spread over the reference rate (typically LIBOR) for loan d. For this specification, $non-bank\ lender_d$ is computed at the loan deal level, given that loan pricing is determined at the deal level and does not vary across tranches (Ivashina, 2005), and takes value 1 for loan deals that have at least one non-bank lender and otherwise.

As in the previous regressions, $Distressed_i$ is a dummy variable for firms that are in financial distress before the oil shock (i.e., with debt-to-asset ratio above the sample median and ICR below one during 2013–2014). $Oil\ Sector_i$ is a dummy variable for firms in the 2-digit SIC industry "Oil and Gas Extraction." $Post_t$ takes value 1 for the 3-year period following the oil shock (2015–2017) and value 0 in the three years before the shock (2012–2014). The coefficient of interest β_2 captures the differential lending policies of NBFIs, relative to banks, to firms that transition into zombie status; that is, to distressed oil firms following the oil shock. The coefficient β_1 represents the baseline effect: the average change in lending outcomes when firms transition into zombie status and their lender is a bank.

We add the same firm controls X_{it} as in the preceding specifications. While the Dealscan data structure prevents us to include lender×firm fixed effects, we control for existing lender-

firm relationships by including a dummy variable ($Prior\ Relationship_{lit}$) that takes value one if the lender was in a relationship with the same borrower in the previous year. We also include fixed effects at the firm (α_i), state×time (γ_{st}), industry×time (η_{jt}), and lender×time (δ_{lt}) levels. The state×time fixed effects controls for unobservable time-varying shocks that are state specific, such state specific business cycles or time-varying state regulations that may affect lenders and borrowers behavior. Industry×time fixed effects control for unobserved time-varying industry-level shocks and lender×time fixed effects absorb time-varying heterogeneity in lender characteristics, including balance sheet characteristics of NBFIs, for which we do not observe financial statements.

Results Estimation results for equation (3) are in Table 4. The first two columns show that NBFIs are significantly more likely than banks to grant new loans to distressed oil firms after the oil price shock. The point estimates in columns 1 and 2 indicate that zombie firms are, on average, about 8% more likely to receive a new loan from a NBFI than they are from a bank. Turning to loan pricing, and focusing on firms borrowing from banks, estimates in columns 3 and 4 suggest that zombie firms face loan spreads that are, on average, 170 to 180 bps higher than non-zombie firms, though these estimates are only marginally statistically significant.[9] In contrast, for firms that borrow from non-banks, the transition into zombie status is associated with a statistically significant decline in spreads of 234 bps ($= 1.822\% - 4.162\%$) in column 3 and 140 bps ($= 1.710\% - 3.114\%$) in column 4.

Ruling Out Potential Confounding Effects To reduce concerns that our results are driven by unobservable factors, including pre-existing trends, and to strengthen the causal interpretation of our findings, we conduct several tests. First, we compare lending policies by NBFIs and banks in the period (2006–2011) that immediately precedes the one used for the oil shock analysis (2012–2017). As shown in Table 5, we do not estimate a statistically

[9]Because of different data structures, the number of observations in the *New Loan* regressions—in which there are multiple observations per loan and observations for each bank-firm-year—is much higher than in the *Loan Spread* regressions—which are at the loan tranche level.

significant change in loan originations by banks and non-banks over this placebo sample, that is between 2006–2008 (pre-shock) and 2009–2011 (post-shock). We interpret these results as suggesting that parallel trends or unobservable firm or lender characteristics are unlikely to drive the results in Table 4. In a second exercise, we check the external validity of our main results by extending the sample period pre-oil shock back to 2010 and post-oil shock sample through 2019 (see Appendix B). Table B.2 shows that the core results hold well beyond the years immediately after the realization of the oil shock. Finally, to allay concerns that our main results are due to non-banks' lending specialization in the oil sector, we compare the share of bank and non-bank lending to oil and gas firms before the oil shock. In our sample, these firms are less dependent on non-bank financing than other firms: during the pre-shock period (2012–2014), the share of non-bank lending volume to oil sector firms is significantly lower (2.8%) than the share of non-bank lending to firms in non-oil sectors (4.7%).

Taken together, the results in this section suggest that NBFIs, unlike regulated banks, originate more loans and charge lower rates to distressed firms of deteriorating profitability.

4.2 Credit Migration to Non-banks

The evidence presented so far—more favorable lending conditions to zombie firms from NBFIs than from regulated entities—points to credit to zombie firms migrating from banks to NBFIs toward zombie firms. In this subsection, we explore the possibility that this credit migration is related to banks' capital positions.

Following Irani *et al.* (2021), we use a specification that allows the share of non-bank lending to zombie firms to vary with the capitalization of participating banks *in the same syndicated loan deal*. Specifically, we estimate the following regression in the DealScan sample over the 2012–2017 period:

$$\begin{aligned} Non-bank\ lending_d = {} & \beta_1(Distressed_i \times Oil\ Sector_i \times Post_t) \\ & + \beta_2(Distressed_i \times Oil\ Sector_i \times Post_t) \times Low\ bank\ capital_d \\ & + \lambda^c Lower\ level\ controls_{itd} + \lambda^x X_{it} + \lambda^z Z_d + \psi_t + \epsilon_d, \end{aligned} \tag{4}$$

where the unit of observation is a loan deal d. The outcome variable $Non-bank\ lending_d$ is either $Deal\ with\ at\ least\ one\ non-bank_d$—which takes value 1 when there is at least one non-bank in the syndicate and 0 otherwise— or $non-bank\ lending\ share_d$—which measures the fraction of the syndicated loan deal funded by non-bank participants. $Low\ bank\ capital_d$ is a dummy variable that takes value 1 for the deals with size-weighted regulatory CET1 ratio across bank participants below the 25^{th} percentile. As in previous specifications, we control for firm characteristics X_{it}. Additionally, we control for average characteristics of banks participating in the loan deal Z_d, which include size (log-assets), deposits as a share of nondeposit liabilities, loan-to-asset ratio, and net interest margins. ψ_t are quarter fixed effects.[10]

We start by estimating how non-bank lending in a loan syndicate responds to firms transitioning into zombie status with a version of equation (4) that omits the term $Low\ bank\ capital_d$. The estimated coefficients for β_1, reported in columns 1–2 of Table 6, are positive and statistically significant, and suggest that zombie credit migrates from banks to NBFIs post-oil price shock. Syndicated loan deals to zombie firms exhibit, on average, a non-bank loan participation share that is about 7 ppts higher than do deals to nonzombie firms (Panel A) and are about 17 ppts more likely to feature at least one non-bank lender compared to loans to other firms (Panel B).

Next, we estimate the full specification in equation (4) to test whether bank capital plays a role in zombie credit migration to NBFIs. The estimates of β_2 in columns 3–4 are positive and statistically significant as well, suggesting that non-bank participation is higher in deals to zombie firms when participating banks in those same deals have lower capital ratios. The economic magnitude of the effect is large; the presence of lower-capital banks in a zombie loan syndicate is associated with (a) an increase in the non-bank lending share of about 50 ppts (panel A), and a higher likelihood (by about 56%) of having at least one non-bank participating in the same loan syndicate (panel B) compared to zombie loan syndicates with

[10]Using the simple average or the assets-weighted average of bank characteristics at the deal level has no material effect on the results.

higher-capital banks.

The evidence in this section brings new insights to the zombie lending literature. It suggests that NBFIs that participate in loan syndicates with banks tend to adopt less strict lending policies than those banks toward distressed firms with deteriorating profitability; it also documents that NBFIs are more likely to fund loans to zombie firms than nonzombie firms, and that this migration of zombie credit from banks to unregulated lenders is related to bank capital positions.

5 Zombie Firms and Bankruptcy

Given the credit support of NBFIs to zombie firms, a natural question is whether this support prolongs the survival of unviable firms and delays their exit from the market through bankruptcy. Bankruptcy serves as the natural mechanism through which firms that are no longer economically viable exit a competitive market. At the same time, a bankruptcy system that enables lenders to quickly resolve firm insolvency may increase lenders' incentives to restructure or liquidate zombie firms rather than evergreen loans to these firms.

We estimate the effect of zombie status on the likelihood of filing for bankruptcy—either Chapter 7 (liquidation) or Chapter 11 (restructuring)—with the following linear probability model in a firm-year panel setting:

$$\begin{aligned} Bankruptcy_{i,t|t+1} = {} & \beta_1(Distressed_i \times Oil\ Sector_i \times Post_t) \\ & + \lambda^c Lower\ level\ controls_{it} + (\lambda^x + \lambda^p Post_t) \times X_{it} \\ & + \alpha_i + \gamma_{st} + \eta_{jt} + \epsilon_{it}, \end{aligned} \tag{5}$$

where $Bankruptcy_{i,t|t+1}$ is a dummy variable that takes value one for firms filing for bankruptcy in year t or $t+1$. A positive β_1 would indicate that firms that are in zombie status after the oil shock are more likely to exit through bankruptcy. The specification includes the same firm-level controls X_{it} from previous specifications interacted with the $Post_t$ indicator variable, and firm (α_i), state×time (γ_{st}), and industry×time (η_{jt}) fixed effects.

Table 7 reports the results. In column 1, we start with the largest sample of firms—both privately-held and public—for which we have bankruptcy data. We estimate a positive and statistically significant relationship between zombie status and the likelihood of exit via bankruptcy over the subsequent two years. Firms that before the oil shock were in financial distress are 7 ppts more likely to file for bankruptcy than other distressed firms that are not hit by the oil shock. The point estimate is economically large, as the unconditional bankruptcy rate in the post-oil shock period is less than 4%. This result suggests that the 2014–2015 oil shock had a non-negligible impact on firm profitability, affecting the economic viability of distressed firms in the oil sector, and validating our interpretation of the oil price decline as sizable and persistent shock to oil firms' profitability.

Next, we explore whether the higher likelihood of entering an insolvency procedure depends on the share of the firm's funding that is provided by banks versus non-banks. We are only able to compute firms' reliance on bank and non-bank funding for the listed firms covered in Dealscan. Therefore, we start by checking that the main bankruptcy result in Column 1 holds in this significantly smaller sample. Column 2 in Table 7 shows that for this sample of firms, we estimate a even larger likelihood of filing for bankruptcy after the oil shock, conditional on being distressed in the years before the shock. Then, we unpack the effect by the the degree of firm reliance on bank debt share. We define $High\ bank\ debt\ share_{it}$ as above-median share of bank debt in total debt, where the share is computed over the ten-year period of syndicated loan originations preceding the oil shock (2005–2014).

Column 3 of Table 7 reports a positive and statistically significant relationship between zombie status and the likelihood of exit via bankruptcy for zombie firms that rely on banks as their main lenders, that is firms that receive less than half of a syndicated loan funding from NBFIs. These findings suggest that, even though zombie firms are more likely to file for bankruptcy than other firms, NBFIs' financial support to these firms increases their survival rate and delays their exit through bankruptcy relative to firms mostly funded by banks.

6 Conclusion

Using supervisory commercial lending data for large U.S. banks, coupled with quasi-random shocks to firm profitability, we document that banks do not keep zombie firms afloat. U.S. banks, irrespective of capital levels and exposure to zombie firms, offer stricter lending terms to financial distressed firms that become economically unviable. By contrast, syndicated loan data reveals that non-banks grow their exposure to zombie firms and offer them more advantageous terms. However, despite the NBFI support, zombie firms file for bankruptcy at a higher rate than other financially-distressed firms.

Overall, our findings provide several novel perspectives to the zombie lending literature. Our results shows that capital regulation does not distort the incentives of weakly capitalized banks to lend to zombie firms to avoid loan losses and regulatory scrutiny. Instead, capital regulation appears to foster zombie lending through the migration of credit from regulated to unregulated financial institutions. Even so, our results also suggest that NBFIs' support of zombie firms likely has limited negative spillover effects on the aggregate economy, as zombie firms eventually exit the market through bankruptcy.

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Table 1: Selected Descriptive Statistics

This table reports summary statistics of the main variables used in the baseline Y-14 (panel A) and DealScan (panel B) analyses over 2012–2017. The Y-14 summary statistics are for the loan-level data, aggregated at the firm-bank-quarter level (for firms with multiple loans in any given quarter from a given bank, we calculate weighted-average interest rates using the relative shares of outstanding loan amounts as weights). Distressed is a dummy that takes value one for firms with ICR below one and above-median leverage during 2013–2014 and zero otherwise. Oil sector is a dummy that takes value one for firms in the oil sector (defined in Section 3). Low-capital high-exposure bank is a dummy for banks with above-median lending exposure to the firm (relative to bank equity) and with post-stress CET1 capital ratio in the bottom quartile before the oil shock (both measured at end-2014). Section 2 describes the data sources in detail.

	(1) N	(2) Mean	(3) SD	(4) p10	(5) p50	(6) p90
			(A) Y-14 data			
Loan commitment amount ($mn)	879503	33.89	86.33	1.50	12.50	79.20
Loan commitment amount (log)	879503	16.29	1.48	14.22	16.34	18.19
Interest rate (percent)	677503	2.81	1.36	1.43	2.70	4.39
Bank is low-capital high-exposure	797918	0.16	0.36	0.00	0.00	1.00
Bank is high-exposure	798663	0.53	0.50	0.00	1.00	1.00
Bank is low-capital (post-stress CET1)	874838	0.33	0.47	0.00	0.00	1.00
Firm is distressed	879503	0.12	0.32	0.00	0.00	1.00
Firm is in oil sector	879503	0.07	0.25	0.00	0.00	0.00
Firm assets ($bn)	873702	3.51	18.37	0.005	0.07	5.69
Firm cash ratio (% assets)	879503	0.10	0.13	0.00	0.05	0.26
Firm tangibility	879503	0.85	0.22	0.47	0.97	1.00
Firm leverage (debt/assets)	871419	0.34	0.27	0.02	0.30	0.67
Firm has ICR<1	720646	0.16	0.36	0.00	0.00	1.00
Credit line utilization rate	701065	0.28	0.33	0.00	0.14	0.80
Probability of default	745727	0.04	0.13	0.00	0.01	0.07
			(B) DealScan & Bankruptcy data			
New loan	139151	0.07	0.26	0.00	0.00	0.00
Nonbank lender	139151	0.20	0.40	0.00	0.00	1.00
Spread (all-in-drawn), percent	17667	2.27	1.36	1.13	1.75	4.00
Nonbank deal	17667	0.31	0.46	0.00	0.00	1.00
Firm is distressed	17667	0.06	0.23	0.00	0.00	0.00
Firm is in oil sector	17667	0.05	0.22	0.00	0.00	0.00
Firm assets ($bn)	17667	13.85	38.65	0.54	3.31	24.45
Firm cash ratio (% assets)	17667	0.09	0.10	0.01	0.06	0.21
Firm tangibility	17667	0.25	0.23	0.04	0.16	0.64
Term loan	17667	0.46	0.50	0.00	0.00	1.00
Syndicate size (# participants)	17667	14	10	4	11	26
Lead bank	17667	0.32	0.47	0.00	0.00	1.00
Deal is refinancing	17667	0.62	0.49	0.00	1.00	1.00
Firm-lender in prior relationship	17667	0.23	0.42	0.00	0.00	1.00
Firm files for bankruptcy	5580	0.003	0.05	0.00	0.00	0.00
Firm with high bank debt share	5580	0.50	0.50	0.00	1.00	1.00

Table 2: Oil Shock Analysis in Y-14: Bank Lending

The table shows coefficient estimates from OLS regressions that link firms' distressed status to bank lending outcomes after the oil shock in Y-14. The outcome variables are loan amount (log) and interest rate (available for all loans other than fully undrawn credit lines). The data are at the firm-bank-quarter level during 2012–2017. Post is a dummy that takes value 1 for 2015–2017 and 0 for 2012–2014. Distressed is a dummy that takes value one for firms in distressed status (with ICR below one and above-median leverage) during 2013–2014 and zero otherwise. Oil sector is a dummy that takes value one for firms in the oil sector, as defined in Section 3. In panel (A) we estimate the baseline DD effect of the oil price shock on bank lending outcomes to ex-ante distressed firms. In panel (B) we break down the triple DD coefficient by banks with low capital and high exposure ("Low-Cap High-Exp") versus other banks. "Low-Cap High-Exp" is a dummy for banks with above-median lending exposure to the firm (relative to bank equity) and with post-stress CET1 capital ratio in the bottom quartile before the oil shock (both measured at end-2014). Firm controls include firm size (log-assets), cash holdings (cash/assets) and tangibility (tangible assets/assets) in levels and interacted with Post. Industry FE are based on 2-digit NAICS classification. Lower level terms for the interactions are included but coefficients are not shown (full specifications showing all controls are reported in Table A.1). Standard errors are triple clustered at the firm, bank, and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)
	Loan amount	**Loan rate**
	(A) Baseline	
Distressed×Oil Sector×Post	-0.134***	0.238**
	(0.046)	(0.094)
Distressed×Post	-0.057***	0.023
	(0.017)	(0.024)
Observations	879,503	675,399
R^2	0.950	0.825
	(B) By Bank Status	
Distressed×Oil Sector×Post×Low Cap–High Exp Bank [1]	-0.121**	0.323***
	(0.049)	(0.091)
Distressed×Oil Sector×Post×Other Bank [2]	-0.136**	0.212*
	(0.050)	(0.112)
Observations	797,870	611,204
R^2	0.950	0.822
pvalue ttest H_0: [1] = [2]	0.737	0.259
Firm controls	Y	Y
Firm controls×Post	Y	Y
Industry×Quarter FE	Y	Y
State×Quarter FE	Y	Y
Bank×Quarter FE	Y	Y
Bank×Firm FE	Y	Y

Table 3: Oil Shock Analysis in Y-14: Bank Capital vs. Loan Exposure

The table shows coefficient estimates from OLS regressions that link firms' distressed status to bank lending outcomes after the oil shock in Y-14 and break down the coefficients by bank capital and exposure to the firm. The outcome variables are loan amount (log) and loan interest rate. The data are at the firm-bank-quarter level during 2012–2017. "Post" is a dummy that takes value 1 for 2015–2017 and 0 for 2012–2014. Distressed is a dummy that takes value one for firms in distressed status (with ICR below one and above-median leverage) during 2013–2014 and zero otherwise. Oil sector is a dummy that takes value one for firms in the oil sector, as defined in Section 3. "High exposure" is a dummy that takes value one for banks with above-median exposure to the firm (relative to bank equity) and "Low capital" is a dummy for banks with capital ratio in the bottom quartile before the oil shock (both measured at end-2014). Firm controls include firm size (log-assets), cash holdings (cash/assets) and tangibility (tangible assets/assets) in levels and interacted with Post. Industry is based on 2-digit NAICS classification. Lower level terms for the interactions are included but coefficients are not shown. Standard errors are triple clustered at the firm, bank, and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)
	Loan amount	**Loan rate**
	(A) By Bank Capital	
Distressed×Oil sector×Post×Low capital [1]	-0.214***	0.349***
	(0.045)	(0.106)
Distressed×Oil sector×Post×High capital [2]	-0.082*	0.174*
	(0.044)	(0.091)
Observations	682,655	521,942
R^2	0.957	0.840
pvalue ttest H_0: [1] = [2]	0.00559	0.0719
	(B) By Bank Exposure	
Distressed×Oil sector×Post×High exposure [1]	–0.114**	0.228**
	(0.052)	(0.086)
Distressed×Oil sector×Post×Low exposure [2]	-0.189**	0.144
	(0.089)	(0.442)
Observations	797,784	611,165
R^2	0.950	0.822
pvalue ttest H_0: [1] = [2]	0.455	0.843
Firm controls	Y	Y
Firm controls×Post	Y	Y
Industry×Quarter FE	Y	Y
State×Quarter FE	Y	Y
Bank×Quarter FE	Y	Y
Bank×Firm FE	Y	Y

Table 4: Oil Shock Analysis in DealScan: Non-bank Lending

The table shows coefficient estimates from OLS regressions that link firms' distressed status to bank lending outcomes after the oil shock in DealScan. The outcome variables are a dummy variable for new loans ("New loan" is a dummy that takes value 1 in the year when a new loan is identified for all bank-firm pairs in the data set and 0 otherwise) and the all-in drawn loan spread over the reference rate (mostly the LIBOR). The data are at the firm-bank-year level in columns 1–2 and at the lender-firm loan-tranche level in columns 3–4 over 2012–2017. "Post" is a dummy that takes value 1 for 2015–2017 and 0 for 2012–2014. "Distressed" is a dummy that takes value 1 for firms in distressed status (with ICR below one and above-median leverage) during 2013–2014. "Oil sector" is a dummy that takes value one for firms in the oil sector, as defined in Section 4.1. Lender-firm controls include a dummy variable that takes value one if the lender has an outstanding exposure to the firm from a past loan in the past year. Loan controls in columns 3–4 include syndicate size (number of syndicate participants) and indicator variables for term loans, lead banks, and deals that are a refinancing. Firm controls include firm size (log-assets), cash holdings (cash/assets) and tangibility (tangible assets/assets). Industry is based on 2-digit SIC classification. Lower level terms are included but coefficients are not shown. Standard errors are triple clustered at the firm, bank, and time level. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
Dependent variables:	**New Loan**		**Loan Spread (percent)**	
Distressed × Oil sector × Post × Non-bank	0.076**	0.076**	-4.162*	-3.114*
	(0.022)	(0.024)	(2.021)	(1.810)
Distressed × Oil sector × Post	-0.031	-0.030	1.822	1.710
	(0.029)	(0.030)	(1.093)	(1.067)
Observations	139,151	139,151	17,667	17,667
R^2	0.181	0.181	0.849	0.849
Firm controls	Y	Y	Y	Y
Firm controls × Post	-	Y	-	Y
Lender-firm prior relationship	Y	Y	Y	Y
Loan controls	-	-	Y	Y
Industry × Time FE	Y	Y	-	-
State × Time FE	Y	Y	Y	Y
Lender × Time FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Table 5: Oil Shock Analysis in DealScan: Placebo Test

The table shows coefficient estimates from running the OLS regressions in the baseline Table 4 on a sample period immediately preceding the period we use for the oil shock estimation: 2006–2008 (pre-shock) versus 2009–2011 (post-shock). The data, from DealScan, are at the firm-bank-year level in columns 1–2 and at the loan-tranche level in columns 3–4. All variable definitions and specification details are the same as in Table 4. Industry is based on 2-digit SIC classification. Lower level terms are included but coefficients are not shown. Standard errors are triple clustered at the lender, borrower, and time level. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
Dependent variables:	**New Loan**		**Loan Spread (percent)**	
Distressed×Oil sector×Post×Non-bank	-0.018	-0.019	-0.138	-0.177
	(0.073)	(0.073)	(0.780)	(0.787)
Distressed×Oil sector×Post	-0.065	-0.066	-0.140	-0.064
	(0.058)	(0.058)	(0.647)	(0.650)
Observations	171,605	171,605	28,023	28,023
R-squared	0.206	0.206	0.859	0.860
Firm controls	Y	Y	Y	Y
Firm controls × Post	-	Y	-	Y
Lender-firm prior relationship	Y	Y	Y	Y
Loan controls	-	-	Y	Y
Industry × Time FE	Y	Y	-	-
State × Time FE	Y	Y	Y	Y
Lender × Time FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Table 6: DealScan Analysis: Non-bank Lending by Bank Capital

The table shows coefficient estimates from OLS regressions that link the share of non-bank lending in syndicated loan deals to oil firms' distressed status and average capitalization of bank participants after the oil shock in DealScan. The data are at the syndicated loan deal level during 2012–2017. The outcome variable is a dummy variable taking value 1 for the total share of non-banks' lending in the deal (panel A) and deals with at least one non-bank participant (panel B). Low bank capital ratio is a dummy variable that takes value one for the deals with size-weighted regulatory CET1 ratio across bank participants below the 25th percentile. "Post" is a dummy that takes value 1 for 2015–2017 and 0 for 2012–2014. "Distressed in oil sector" is a dummy variable that takes value 1 for deals where the borrowing firm is in distressed status (with ICR below one and above-median leverage) and in the oil sector. Firm controls include firm size (log-assets), cash holdings (cash/assets) and tangibility (tangible assets/assets). Bank controls include bank size (log-assets), deposit funding share, and low capital dummy. Lower level terms are included but coefficients are not shown. Standard errors are clustered at quarter level. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
Dependent variable:	**(A) Non-bank lending share**			
Distressed in oil sector×Post	0.069*	0.071*	0.016	0.014
	(0.037)	(0.040)	(0.021)	(0.024)
Distressed in oil sector×Post×Low bank capital			0.493**	0.497**
			(0.224)	(0.225)
Observations	1,980	1,980	1,980	1,980
R-squared	0.049	0.056	0.059	0.066
Dependent variable:	**(B) Deal with at least one non-bank**			
Distressed in oil sector×Post	0.165**	0.177**	0.138**	0.149**
	(0.075)	(0.076)	(0.064)	(0.064)
Distressed in oil sector×Post×Low bank capital			0.561**	0.565**
			(0.229)	(0.230)
Observations	1,980	1,980	1,980	1,980
R^2	0.033	0.038	0.037	0.042
Quarter FE	Y	Y	Y	Y
Bank controls	Y	Y	Y	Y
Firm controls		Y		Y

Table 7: Zombie Firm' Exit Through Bankruptcy

The table shows OLS coefficient estimates from regressions that link oil firms' distressed status to the probability of filing for bankruptcy after the oil shock in DealScan. The data are at the firm-year level during 2012–2017. The dependent variable is a dummy for firms that file for chapter 7 or chapter 11 bankruptcy. "High bank debt share" is defined as above-median historical share of bank debt in total debt originated to a given firm, in a given year, by banks in DealScan. The historical share of bank debt is computed over the ten-year period preceding the oil shock (2005–2014). "Post" is a dummy that takes value 1 for 2015–2017 and 0 for 2012–2014. "Distressed" is a dummy that takes value 1 for firms in distressed status (with ICR below one and above-median leverage) during 2013–2014. "Oil sector" is a dummy that takes value one for firms in the oil sector. Firm controls include firm size (log-assets), cash holdings (cash/assets), and tangibility (tangible assets/assets). Industry is based on 2-digit NAICS classification. Lower level terms for the interactions are included but coefficients are not shown. The bankruptcy rate in the regression sample is 2.2% (3.4% during the Post period). Standard errors are clustered at the firm level. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)
Dependent variable	**0/1 Firm files for bankruptcy**		
	(A) All firms	**(B) Public firms**	
Distressed × Oil Sector × Post	0.0696***	0.1344**	
	(0.021)	(0.057)	
Distressed × Oil Sector × Post × High Bank Debt Share			0.2874***
			(0.075)
Distressed × Oil Sector × Post × Low Bank Debt Share			-0.0425
			(0.027)
Observations	83,556	5,580	5,580
R^2	0.313	0.295	0.317
Firm controls	Y	Y	Y
Firm controls × Post	Y	Y	Y
Firm FE	Y	Y	Y
State × Year FE	Y	Y	Y
Industry × Year	Y	Y	Y

Internet Appendix

A Additional Figures and Tables

Figure A.1: Oil Price, 2012–2019

Notes: The figure plots the Spot Crude Oil Price West Texas Intermediate (WTI) (FRED series WTISPLC retrieved on December 13, 2021) on a monthly basis during 2012–2019. Source: Federal Reserve Bank of St. Louis.

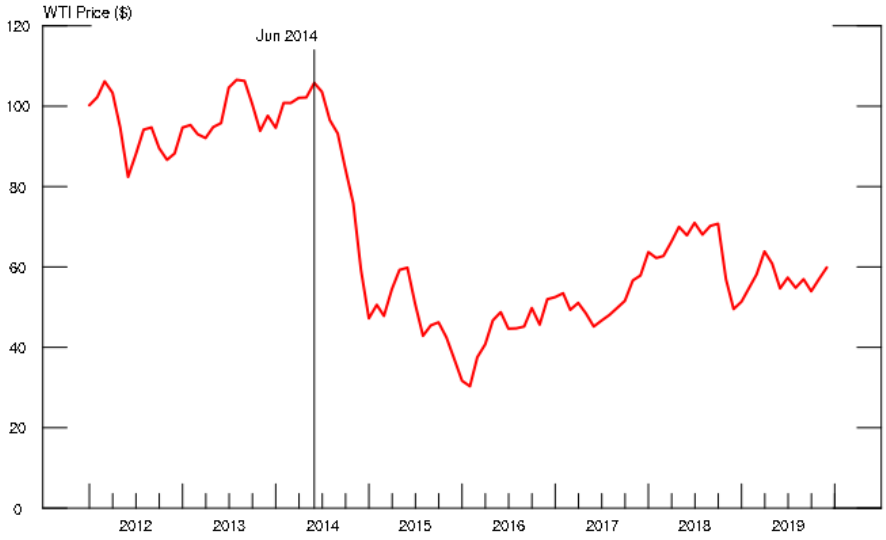


Figure A.2: Increase in Bank Capital, 2013–2017

Notes: The figure plots the 2013 and 2017 BHC-level regulatory CET1 capital ratios for the banks in the regression sample (column 1 of Table 2) along with the 45-degree line. Source: Consolidated Financial Statements for Holding Companies, FR Y-9C.

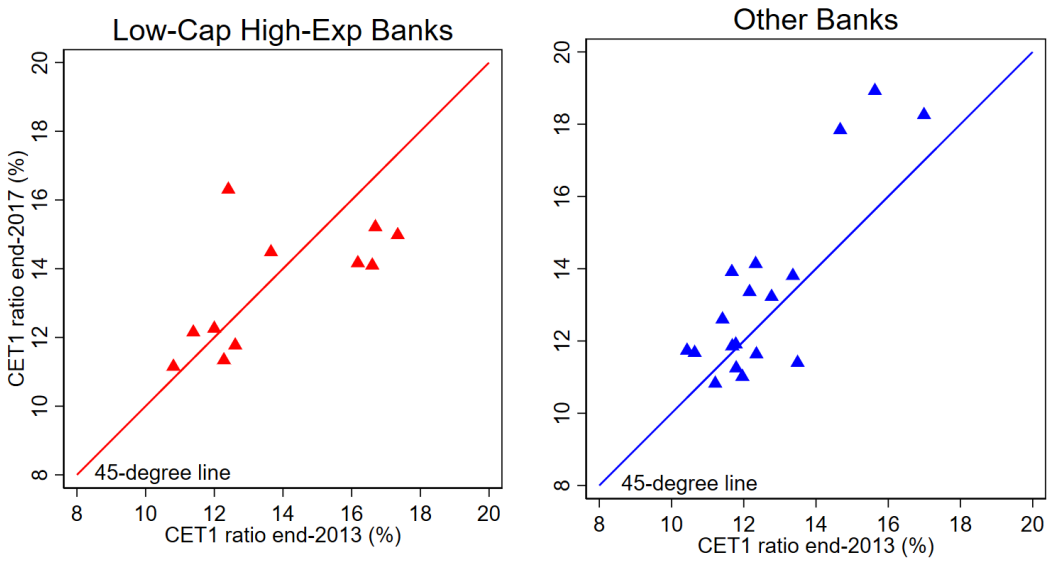
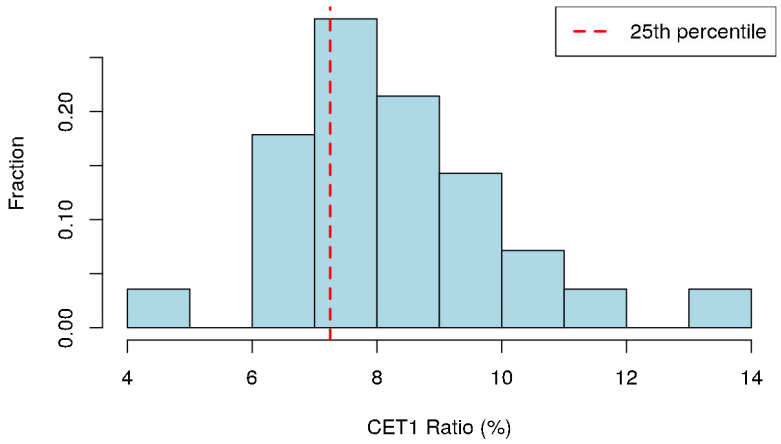


Figure A.3: Pre-Shock Bank Capital and Loan Exposure to Firms

Notes: This figure depicts the cross-sectional variation in bank capital and bank-firm loan exposure before the 2014–2015 oil price shocks. Panel (A) shows a histogram of the post-stress CET1 capital ratios across banks (at end-2014), on the basis of which we define low-capital banks as those banks with post-stress CET1 capital in the bottom 25th percentile of the distribution. Panel (B) shows a histogram of bank-firm loan exposures (calculated in percent of bank equity, at end-2014), on the basis of which we define high-exposure banks as those banks with loan share to individual firms above the sample median. The cutoff points for low-capital and high-exposure are shown as vertical lines. Source: Authors' calculations using the Federal Reserve Y-14 and the Federal Reserve's stress test webpage.

(A) Post-stress CET1 Capital



(B) Bank Loan Share to Firms

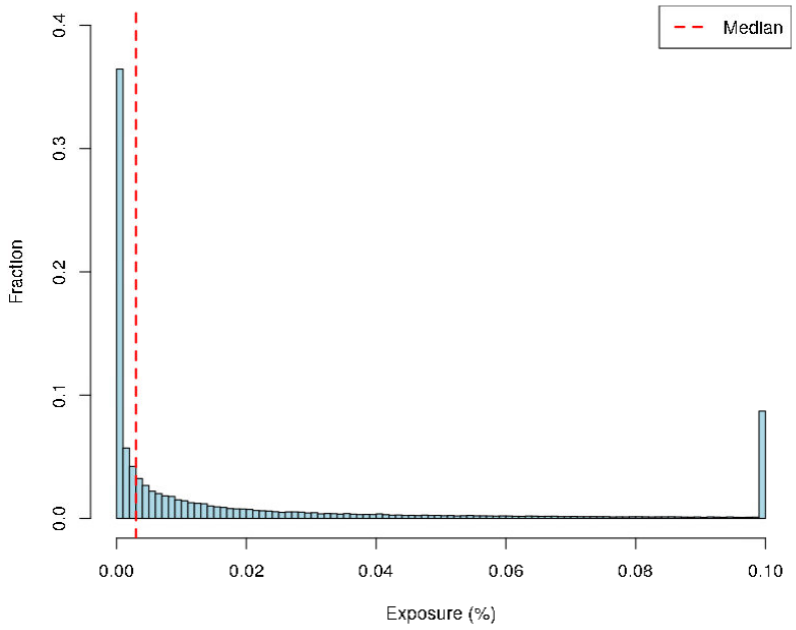


Table A.1: Bank Lending to Distressed Firms—Full set of controls

This table replicates baseline Table 2 and reports the estimates coefficients for lower level terms and additional controls. p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
Dependent variables:	**Loan Amount**	**Loan Rate**	**Loan Amount**	**Loan Rate**
Distressed×Oil Sector×Post	-0.134***	0.238**		
	(0.046)	(0.094)		
Distressed×Oil Sector×Post×Low Cap–High Exp Bank [1]			-0.121**	0.323***
			(0.049)	(0.091)
Distressed×Oil Sector×Post×Other Bank [2]			-0.136**	0.212*
			(0.050)	(0.112)
Distressed×Post	-0.057***	0.023		
	(0.017)	(0.024)		
Distressed	0.018*	-0.040*		
	(0.010)	(0.022)		
Distressed×Oil Sector	-0.063**	0.067		
	(0.024)	(0.040)		
Oil Sector×Post	-0.081***	0.109***		
	(-0.023)	(0.036)		
Distressed×Post×Zombie Bank			-0.063**	0.045
			(0.027)	(0.032)
Distressed×Post×Other Bank			-0.057***	0.011
			(0.015)	(0.020)
Oil Sector×Post×Zombie Bank			-0.079***	0.055
			(0.028)	(0.054)
Oil Sector×Post×Other Bank			-0.057**	0.067
			(0.026)	(0.039)
Distressed×Oil Sector×Zombie Bank			0.030	-0.079
			(0.041)	(0.088)
Distressed×Oil Sector×Other Bank			0.029	-0.052
			(0.030)	(0.051)
Distressed×Zombie Bank			0.132**	-0.173
			(0.054)	(0.149)
Distressed×Other Bank			0.018	-0.029
			(0.010)	(0.021)
Non-distressed×Zombie Bank			0.105*	-0.089
			(0.056)	(0.162)
Firm size (log-assets)	0.029***	-0.007	0.030***	-0.008
	(0.010)	(0.005)	(0.010)	(0.005)
Firm cash	-0.002***	-0.002*	-0.002***	-0.002*
	(0.000)	(0.001)	(0.000)	(0.001)
Firm tangibility	-0.001**	-0.002***	-0.001***	-0.002***
	(0.001)	(0.000)	(0.001)	(0.000)
Firm size×Post	0.019***	-0.009	0.018***	-0.009
	(0.003)	(0.007)	(0.003)	(0.007)
Firm cash×Post	-0.001***	-0.002**	-0.001***	-0.002**
	(0.000)	(0.001)	(0.000)	(0.001)
Firm tangibility×Post	0.000**	0.001	0.000**	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
pvalue ttest H_0: [1] = [2]			0.737	0.259
Observations	879,503	675,399	797,870	611,204
R^2	0.950	0.825	0.950	0.822
Firm controls	Y	Y	Y	Y
Firm controls×Post	Y	Y	Y	Y
State×Quarter FE	Y	Y	Y	Y
Industry×Quarter FE	Y	Y	Y	Y
Bank×Quarter FE	Y	Y	Y	Y
Bank×Firm FE	Y	Y	Y	Y

Table A.2: Finer Fixed Effects

This table shows that the baseline results in Table 2 are including more granular fixed effects to account for common shocks affecting all firms in a given industry, geography, and of size group. In panel (A) we include interacted state×industry×quarter FE; in panel (B) we include interacted state×industry×size group×quarter FE (where the size groups are defined based on total assets in the following groups: below \$50mn, \$50–\$250mn, \$250mn–\$1000mn, \$1000mn–\$5000mn, and above \$5000mn, following Chodorow-Reich *et al.* (2022)). The outcome variables are loan amount (log) and interest rate. The data are at the firm-bank-quarter level over 2012–2017. All variables as in baseline Table 2. Standard errors are triple clustered at the firm, bank, and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	Loan Amount	**Loan Rate**	**Loan Amount**	**Loan Rate**
			(A) state×industry×quarter FE	
Distressed×Oil Sector×Post	-0.134***	0.226**		
	(0.045)	(0.089)		
Distressed×Oil Sector×Post×Other Bank [2]			-0.136**	0.196*
			(0.050)	(0.108)
Distressed×Oil Sector×Post×LowCap-HighExp Bank [1]			-0.123**	0.319***
			(0.049)	(0.089)
pvalue ttest H_0: [1] = [2]			0.771	0.211
Observations	877,482	673,126	795,726	608,869
R^2	0.952	0.834	0.952	0.831
Firm controls	Y	Y	Y	Y
Firm controls×Post	Y	Y	Y	Y
State×Industry×Quarter FE	Y	Y	Y	Y
Bank×Quarter FE	Y	Y	Y	Y
Bank×Firm FE	Y	Y	Y	Y
			(B) state×industry×size-group×quarter FE	
Distressed×Oil Sector×Post	-0.135***	0.234**		
	(0.043)	(0.091)		
Distressed×Oil Sector×Post×Other Bank [2]			-0.134**	0.198*
			(0.048)	(0.109)
Distressed×Oil Sector×Post×LowCap-HighExp Bank [1]			-0.132**	0.328***
			(0.048)	(0.091)
pvalue ttest H_0: [1] = [2]			0.959	0.206
Observations	864,730	661,520	783,592	597,707
R^2	0.956	0.844	0.956	0.842
Firm controls	Y	Y	Y	Y
Firm controls×Post	Y	Y	Y	Y
State×Industry×Size-Group×Quarter FE	Y	Y	Y	Y
Bank×Quarter FE	Y	Y	Y	Y
Bank×Firm FE	Y	Y	Y	Y

Table A.3: Credit Line Utilization of Distressed Firms

This table examines changes in credit line utilization rates of ex-ante distressed firms after the oil shock relative to other firms. The outcome variable is the credit line utilization rate, defined as the ratio between the utilized amount and the committed amount across a firms' outstanding bank credit lines. The data are at the firm-bank-quarter level (columns 1–2) or at the firm-quarter level (column 3) during 2012–2017. All variables as in baseline Table 2. Standard errors are double-clustered at the firm and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)
	Credit line utilization rate		
	(A) Bank-firm-quarter		**(B) Firm-quarter**
Distressed×Oil Sector×Post	0.032		0.012
	(0.024)		(0.021)
Distressed×Oil Sector×Post×LowCap-HighExp Bank [1]		0.014	
		(0.037)	
Distressed×Oil Sector×Post ×Other Bank [2]		0.040	
		(0.024)	
pvalue ttest H_0: [1] = [2]		0.431	
Observations	699,218	640,492	506,003
R^2	0.765	0.761	0.743
Firm controls	Y	Y	Y
Firm controls×Post	Y	Y	Y
Firm FE	Y	Y	Y
State×Quarter FE	Y	Y	Y
Industry×Quarter FE	Y	Y	Y
Bank×Quarter FE	Y	Y	-
Bank×Firm FE	Y	Y	-

Table A.4: New Loan Originations

This table shows that the baseline results in Table 2 are robust to estimating the main specifications on the sample of new loans only. The outcome variables are loan amount (log) and interest rate. The data are at the firm-bank-quarter level over 2012–2017. All variables as in baseline Table 2. Standard errors are triple clustered at the firm, bank, and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)
	Loan amount	**Loan rate**
	(A) Baseline	
Distressed×Oil Sector×Post	-0.239***	0.279**
	(0.068)	(0.105)
Distressed×Post	-0.021	-0.044
	(0.029)	(0.042)
Observations	77,203	58,879
R^2	0.952	0.853
	(B) By Bank Status	
Distressed×Oil Sector×Post×Low Cap–High Exp Bank [1]	-0.187**	0.410**
	(0.089)	(0.149)
Distressed×Oil Sector×Post×Other Bank [2]	-0.213**	0.281**
	(0.083)	(0.124)
pvalue ttest H_0: [1] = [2]	0.797	0.381
Observations	70,341	53,738
R^2	0.953	0.854
Firm controls	Y	Y
Firm controls×Post	Y	Y
State×Quarter FE	Y	Y
Industry×Quarter FE	Y	Y
Bank×Quarter FE	Y	Y
Bank×Firm FE	Y	Y

Table A.5: Robustness to Additional Controls

This table shows that the baseline results in Table 2 are robust to controlling for a firm-bank-specific linear pretrend (panel A) and to additional controls (panel B). In panel A, the pretrend control variable is the log-diff growth rate in loan amounts, the difference in loan rates, and in probabilities of default at the bank-firm level over the pre-oil shock period (2012–2014) multiplied by a linear time trend. In panel B, we additionally control for loan type (a dummy for term loans) and probability of default. The (one-year ahead) probability of default is the bank-reported borrower rating according to the bank's internal risk rating system and empirical default models. The outcome variables are loan amount (log) and interest rate. The data are at the firm-bank-quarter level over 2012–2017. All variables as in baseline Table 2. Standard errors are triple-clustered at the firm, bank, and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	Loan Amount	**Loan Rate**	**Loan Amount**	**Loan Rate**
			(A) Control for pre-trends	
Distressed×Oil Sector×Post	-0.101**	0.255***		
	(0.039)	(0.090)		
Distressed×Oil Sector×Post×LowCap-HighExp Bank [1]			-0.116***	0.295***
			(0.039)	(0.091)
Distressed×Oil Sector×Post×Other Bank [2]			-0.093**	0.245**
			(0.042)	(0.102)
Pretrend control	0.028***	0.025***	0.027***	0.024***
	(0.005)	(0.006)	(0.005)	(0.006)
pvalue ttest H_0: [1] = [2]			0.482	0.563
Observations	844,375	554,562	797,269	524,739
R-squared	0.955	0.843	0.955	0.841
			(B) Control for borrower risk and loan type	
Distressed×Oil Sector×Post	-0.146***	0.272**		
	(0.047)	(0.102)		
Distressed×Oil Sector×Post×LowCap-HighExp Bank [1]			-0.181***	0.317**
			(0.048)	(0.118)
Distressed×Oil Sector×Post×Other Bank [2]			-0.136**	0.266**
			(0.051)	(0.111)
pvalue ttest H_0: [1] = [2]			0.331	0.637
Observations	720,632	553,794	672,498	516,253
R-squared	0.962	0.837	0.962	0.837
Firm controls×Post	Y	Y	Y	Y
State×Quarter FE	Y	Y	Y	Y
Industry×Quarter FE	Y	Y	Y	Y
Bank×Quarter FE	Y	Y	Y	Y
Bank×Firm FE	Y	Y	Y	Y

Table A.6: Alternative Clustering of Standard Errors

This table replicates panel A of baseline Table 2 (where standard errors are triple-clustered at the firm, bank and quarter levels) with alternative clustering approaches for the standard errors. In panel A, the standard errors are double clustered at the firm-bank and quarter levels. In panel B, the standard errors are double clustered at the firm and quarter level. All variables as in baseline Table 2. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	Loan Amount	**Loan Rate**	**Loan Amount**	**Loan Rate**
	(A) Double cluster on firm-bank and quarter			
Distressed×Oil Sector×Post	-0.134***	0.238***		
	(0.034)	(0.078)		
Distressed×Oil Sector×Post×LowCap-HighExp Bank [1]			-0.121**	0.323***
			(0.043)	(0.092)
Distressed×Oil Sector×Post×Other Bank [2]			-0.136***	0.212**
			(0.037)	(0.089)
pvalue ttest H_0: [1] = [2]			0.744	0.218
Observations	879,503	675,399	797,870	611,204
R^2	0.950	0.825	0.950	0.822
	(B) Double cluster on firm and quarter			
Distressed×Oil Sector×Post	-0.134***	0.238**		
	(0.046)	(0.094)		
Distressed×Oil Sector×Post×LowCap-HighExp Bank [1]			-0.121**	0.323***
			(0.055)	(0.106)
Distressed×Oil Sector×Post×Other Bank [2]			-0.136**	0.212**
			(0.049)	(0.102)
pvalue ttest H_0: [1] = [2]			0.762	0.206
Observations	879,503	675,399	797,870	611,204
R^2	0.950	0.825	0.950	0.822
Firm controls	Y	Y	Y	Y
Firm controls×Post	Y	Y	Y	Y
State×Quarter FE	Y	Y	Y	Y
Industry×Quarter FE	Y	Y	Y	Y
Bank×Quarter FE	Y	Y	Y	Y
Bank×Firm FE	Y	Y	Y	Y

Table A.7: Alternative Measures of Bank Capital

This table shows that the baseline results in panel B of Table 3 are robust to two alternative measures of capital. In panel A, we use the BHC-level regulatory CET1 ratio as a measure of capital instead of post-stress CET1 capital. The BHC-level CET1 ratio is measured at end-2013, before the phase-in period of new capital requirements and the first Dodd-Frank stress tests. In panel B, we use the proposed Basel III-compliant Tier 1 regulatory capital ratios for 2012:Q2. This measure is used a source of exogenous variation in bank capital in Irani *et al.* (2021) due to the fact that even though the timing and content of the internationally agreed version of Basel III capital reforms were well understood, the precise implementation of the rule in the United States differed from the international version and surprised banks (Berrospide and Edge, 2016). The outcome variables are loan amount (log) and interest rate. The data are at the firm-bank-quarter level over 2012–2017. All variables as in baseline Table 2. Standard errors are triple clustered at the firm, bank, and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)
	Loan Amount	**Loan Rate**
	(A) BHC-level CET1 ratio	
Distressed×Oil Sector×Post×LowCap [1]	-0.123**	0.270**
	(0.047)	(0.099)
Distressed×Oil Sector×Post×HighCap [2]	-0.181**	-0.024
	(0.079)	(0.117)
Observations	797,784	611,165
R-squared	0.950	0.822
pvalue ttest H_0: [1] = [2]	0.445	0.0248
	(B) Proposed Basel-III Tier1 capital ratio	
Distressed×Oil Sector×Post×LowCap [1]	-0.136**	0.313***
	(0.063)	(0.098)
Distressed×Oil Sector×Post×HighCap [2]	-0.136***	0.206*
	(0.047)	(0.112)
pvalue ttest H_0: [1] = [2]	0.998	0.327
Observations	872,699	669,964
R-squared	0.950	0.826
Firm controls	Y	Y
Firm controls×Post	Y	Y
State×Quarter FE	Y	Y
Industry×Quarter FE	Y	Y
Bank×Quarter FE	Y	Y
Bank×Firm FE	Y	Y

B Additional Results: External Validity

In this section, we assess the external validity of the baseline analysis by leveraging the Y-14 and DealScan data to study zombie lending outside the oil shock episode. To identify zombie firms, we follow the approach in Section 3 and select firms in a pre-existing banking relationship that are financially distressed and unprofitable. More precisely, we require zombie firms to be (1) highly indebted (leverage is above-median); (2) unable to service debt (ICR is less than one), and (3) have negative (three-year average) sales growth.[11] The share of zombie firms thus defined ranges between 3.9% and 6.5% during 2014–2019.

Bank Lending To test zombie lending at banks, we use the full sample of Y-14 data over the 2014–2019 period. The estimation sample starts in 2014 because we require three consecutive years of sales growth data (2012–2014) to classify firms as unprofitable. The sample ends in 2019 to exclude the unprecedented policy response related to the Covid-19 pandemic that likely influenced bank lending to all firms. We regress bank lending outcomes on zombie firm status with data at the bank-firm-quarter level using the following linear regression model:

$$\begin{aligned} Lending\ outcome_{bit} = \sum_{\tau=1,2} \beta_\tau Zombie_{it} \times Bank\ Type_{b,\tau} + \\ + \lambda^x \times X_{it} + \gamma_{jt} + \eta_{jt} + \delta_{bt} + \psi_{bi} + \epsilon_{bit}, \end{aligned} \tag{6}$$

where the lending outcomes of interest are (log of) loan amounts and interest rates on loans from bank b to firm i in quarter t. $Bank\ Type_{b,\tau}$ refers to either *low-capital high-exposure* banks ($\tau = 1$) or *other* banks ($\tau = 2$). The dummy variable $Zombie_{it}$ takes value one for zombie firms and zero otherwise. Control variables and fixed effects are the same as in the oil analysis specifications. Here, an important caveat is that firms' transition to zombie status may be nonrandom, unlike in the baseline oil shock analysis. Therefore, the findings should be interpreted as generalizing those of the previous section and not as establishing causal evidence.

Table B.1 reports coefficient estimates of the regression model in equation (6). Estimates in columns 1–2 show that zombie firms receive, on average, smaller and more expensive bank loans than other firms. In addition, columns 3–4 show that both *low-capital high-exposure* and other banks tighten the terms of lending to zombie firms (with effects that are not statistically significantly different from each other). These results confirm those reported in the oil shock analysis and suggest that the banks in our data neither increase their exposure to zombie firms nor offer lower rates to such firms, regardless of the approach used to identify zombie firms. Instead, the evidence supports the view that banks lend to zombie firms at risk-adjusted terms.

[11] Sales growth is a reliable predictor of firm productivity (Goyal and Yamada, 2004; Whited and Wu, 2006). Imposing a profitability requirement reduces the risk of incorrectly classifying temporarily unprofitable firms with good future growth prospects as zombies. In a similar vein, Schivardi *et al.* (2020) use return on assets as a gauge of profitability, while Banerjee and Hofmann (2018) use Tobin's q for publicly listed firms.

Table B.1: External Validity in Y-14

The table shows coefficient estimates from OLS regressions that link firms' zombie status to bank lending outcomes in the full Y-14 sample and break down the coefficients by bank capital and bank exposure to the firm. The outcome variables are loan amount (log) and loan interest rate. The data are at the firm-bank-quarter level during 2014–2019. "Low-Cap High-Exp" is a dummy variable taking value 1 for banks with above-median lending exposure to the firm (relative to bank equity) and with post-stress CET1 capital ratio in the bottom quartile. Firm controls include firm size (log-assets), cash holdings (cash/assets) and tangibility (tangible assets/assets) in levels and interacted with Post. Industry FE are based on 2-digit NAICS classification. Standard errors are triple clustered at the firm, bank, and quarter levels. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
	Loan Amount	**Loan Rate**	**Loan Amount**	**Loan Rate**
Zombie	-0.067***	0.155***		
	(0.009)	(0.019)		
Zombie × Other Bank [2]			-0.063***	0.152***
			(0.009)	(0.017)
Zombie × Low Cap–High Exp Bank [1]			-0.089***	0.166***
			(0.025)	(0.033)
pvalue ttest H_0: [1] = [2]			0.329	0.580
Observations	832,156	625,374	832,156	625,374
R-squared	0.955	0.865	0.955	0.865
Firm controls	Y	Y	Y	Y
State × Quarter FE	Y	Y	Y	Y
Industry × Quarter FE	Y	Y	Y	Y
Bank × Quarter FE	Y	Y	Y	Y
Bank × Firm FE	Y	Y	Y	Y

Non-bank Lending We check the external validity of our oil shock analysis results in DealScan by extending the sample period to 2010–2019—a period of stricter bank capital regulation post-GFC. Here, we estimate a version of the baseline specifications where the triple DD term is replaced with a $Zombie_{it}$ dummy variable and its interaction with the non-bank lender dummy.

Estimation results in column 1 of Table B.2 show that firms that transition into zombie status are as likely to receive new loans from banks compared to other firms, but are more likely (by 2.0% ($\approx -0.009 + 0.029$)) to be granted new loans by non-banks than firms that do not transition to zombie status. Loan pricing results in column 2 suggest that zombie firms face higher loan spreads from banks (close to 40 bps) but lower spreads from non-banks (about 20 bps $\approx 0.399 - 0.220$) compared to other firms.

Overall, these results corroborate our main findings in the oil shock analysis.

Table B.2: External Validity in DealScan

The table shows coefficient estimates from OLS regressions that link firms' zombie status to bank lending outcomes in the full DealScan sample and interact the "Zombie" dummy with non-bank lender dummies. Estimates on interest rates are omitted for the credit-subsidy definition of zombie firms because this definition uses low interest rates on bank debt as a criterion to identify zombie firms. The outcome variables are "New Loan" (a dummy variable for whether a given borrower signs a new loan in a given year with a given bank) and the loan (all-in drawn) spread over the reference rate. The sample period is 2010–2019. Loan controls include syndicate size (the number of syndicate participants) and indicator variables for term loans, lead banks, and refinancings. Firm controls include firm size (log-assets), cash holdings (cash/assets) and tangibility (tangible assets/assets). Industry is based on 2-digit SIC classification. Standard errors are triple clustered at the firm, lender, and quarter level. Significance: *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)
Dependent variables:	**New Loan**	**Loan Spread**
Zombie × Non-bank Lender	0.029***	-0.220*
	(0.008)	(0.127)
Zombie	-0.009	0.399**
	(0.006)	(0.183)
Observations	217,918	26,669
R-squared	0.193	0.827
Firm controls	Y	Y
Loan controls	-	Y
Firm FE	Y	Y
Industry × Year FE	Y	Y
State × Year FE	Y	Y
Lender × Year FE	Y	Y

C Data Appendix: DealScan

Initial Data Processing We start with the DealScan masterfile (downloaded from WRDS on December 18, 2022) with information on more than 300,000 loan tranches (tranches) organized in 240,000 loan deals extended since 1980. Data before the early 1990s is very sparse, therefore we follow Chava and Roberts (2008) and start the sample period in 1994. We end the sample period in 2019 as in the Y-14 analysis, to avoid potentially confounding effects from the Covid-19 pandemic period and related policies.

We apply several filters to the data. Following Elliott *et al.* (2024) and Roberts (2015), we remove loan amendments as those reflect renegotiations of loans over time as opposed to new loan originations. Thus, we retain only those loan observations that correspond to purely new credit, representing about 75% of all observations. We drop any loan deals and tranches with negative or zero amounts, we keep "closed" deals (we drop cancelled, in-process, no further info, on-hold and pre-mandate deals), we replace negative loan spreads with missing, and we drop loans in foreign currencies. In addition, we use the variable "lead role" to construct a lead bank dummy which takes value 1 for those banks with the following main syndicate roles: book-runner, administrative agent, agent, lead arranger, lead manager, manager, mandated lead arranger, mandated arranger, syndication agent, and sole lender.

We also construct dummies for term loans (versus credit lines). Term loans are identified as those loans classified according to the "tranche type" variable as term loans (types A-K), bridge loans, delayed draw term loans, demand loans, other loans, and a minority of other types of loans (such as loan style floating rate notes, loan-style floating rate CDs, Sukuks, and Wakalas). The majority of credit lines are 364-day tranches, revolvers with a maturity of either less or more than one year, and other loan types such as revolver/term loans, standby letters of credit, leases, and guarantees. A minority of other types of loans such as trade letters of credit, mezzanine tranches, limited lines, export credit, and acquisition/advance/bills/bonding/CAPEX/construction tranches are also classified as credit lines.

Classifying Lenders as non-banks The starting point for classifying lenders into banks versus non-banks is the variable "lender institution type." This string variable identifies the institution type for the lenders in each syndicate. Institution types include the following categories:

- **Banks**: Investment bank, U.S. bank, Western European bank, European bank, East. Europe or Russian Bank, Canadian bank, African bank, Asia-Pacific bank, Middle Eastern Bank, Latin America & Caribbean bank, Australian/New Zealand bank, Japanese bank, Multinational investment bank, Multinational investment bank & Fi-

nancial services, Mortgage bank, Farm credit bank, Thrifts and S&L associations, Export-import bank, Credit union, Government sponsored lender, and Foreign bank;

- **Non-banks**: Finance Company, Corporation, Asset manager, CDO, Business development company, Insurance company, Specialty Lender, Development Finance Institution, Diversified financial services company, Hedge fund, Diversified (vulture) fund, Institutional Investor (CDO, Hedge fund, Insurance company, Prime fund, and Other), Business corporation, Law firm, Leasing company, Mutual fund, Pension fund, Private equity, and Trust company.

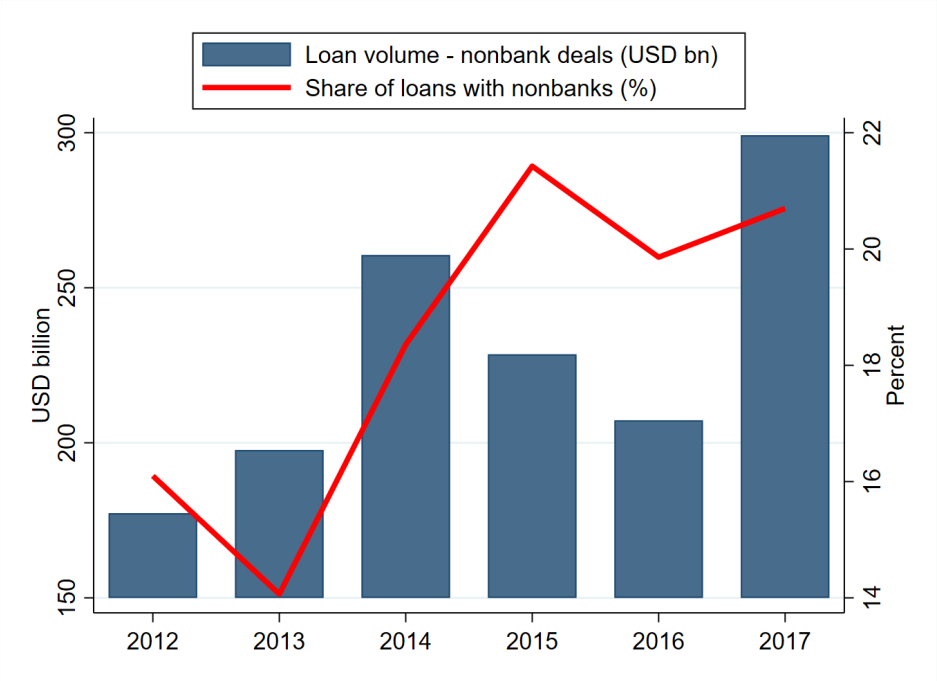
The assignment of lenders to the bank/non-bank category is straightforward for single-lender loans and for loans in which all lenders are banks. In the case of loan deals with at least one non-bank lender, it is not possible to carry out an automatic assignment because there is no one-to-one mapping between the syndicate lenders and the types listed in "lender institution type" variable. In these cases, we extract the lenders and assign them a bank/non-bank classification as follows. First, all lenders that have bank-related word stems in the name (such as bank, banc, banque, banco, banca, bancorp, banken, or bankia), all thrifts and S&L associations, credit cooperatives, and financial institutions that primarily provide farm credit, are classified as banks. We drop international financial institutions such as the World Bank (International Finance Corporation).

Second, we classify as non-banks those lenders with stems in the name such as financing, financial, business, credit, investor, investment, insurance, capital, advisors, asset, management, income, trust, prime, senior, secured, debt, leveraged, lease, leasing, loanco, floating, services, high yield, insurance, infrastructure, opportunities, funding trust, trustee, agency, equity, guarantee, securities, funding, and fund. Lastly, we carefully inspect all the non-banks identified with this approach and make manual corrections or additional classifications for unassigned lenders based on web searches and research of individual lenders. This approach yields a share of non-bank lenders in data at the lender-borrower level over the sample period 2012–2017 of 5.9%, which is close to the 5.7% share reported by Elliott *et al.* (2024) for the 1990–2019 period.

Third, we clean the lender type variable which sheds light on the types of non-banks with lending activities in DealScan. Our starting point is the "lender institution type" variable, which we carefully check and apply manual corrections based on web searches and research of individual lenders. The non-banks with the highest lending volumes during the 2012–2017 are finance companies and other non-banks.

Figure C.1: Non-bank participation in syndicated loan market

This figure depicts the total syndicated lending volume across deals with non-bank participation ("nonbank deals") and the share of such deals during 2012–2017. Loan deals are classified as "nonbank" if the syndicated has at least one NBFI lender. Source: Authors' calculations using Refinitiv DealScan.



Matching Borrowers to Compustat After classifying all lenders as banks and non-banks, we keep only U.S. borrowers and lenders as reported in the lender and borrower country variables. Then, as described in Section 2, we link the borrowers in DealScan (using the borrower name or the borrower parent's name) with their balance sheet characteristics using the DealScan-Compustat Linking Database from Chava and Roberts (2008) (dated August 31, 2012), which contains matches through 2017. In Compustat, we focus on nonfinancial firms by excluding utilities (SIC codes 4900–4999), financial firms (SIC codes 6000-6999), and public administration firms (SIC codes 9000-9999). Zombie status is assigned to firms using data on ICR, leverage, and sales growth on a four-quarter rolling window.

Matching Lenders to Call Report For the analysis in Table 6, we need to compute average capitalization level of bank participants in syndicated loan deals. To maximize sample size, we bring balance sheet data for DealScan bank lenders from the merger-adjusted U.S. Call Report (available at the Federal Reserve Board). To start with, we follow Dell'Ariccia *et al.* (2018) and clean and uniformize the names of bank lenders in DealScan and the Call

Report and conduct a string match on bank name. We inspect the matches manually to resolve uncertain and multiple matches using additional information on city-state location, web searches, and the NIC National Information Center (link). We augment this initial match with the cross-walk linking DealScan lenders with RSSD IDs from Keil (2018) (available on link) and covering the period between 1982 and 2016. We are able to match 385 banks in DealScan with RSSD IDs in the Call Report over the 2012–2017 sample period.

In Table 6, we also use the loan share that is contributed by individual lenders (available in the "lender share" variable). We use the loan shares as reported in DealScan when available. When the loan share is missing, we follow Ivashina and Scharfstein (2010) and focus on the loan contributions of lead banks. When a loan has more than one lead bank, we assume each lead bank extends the loan pro rata as in Giannetti and Laeven (2012a,b). For single-lender loans, 100% of the loan amount is always assigned to the lender.

Final Sample Characteristics Over the sample period 2012–2017, the final DealScan sample with Compustat-matched borrowers has 6,545 loan deals (structured in 10,498 loan tranches) extended by 1,183 lenders to 3,849 borrowers identified by GVKEY ID. In the deal-level analyses, the regression sample of approximately 2,050 loan deals is significantly smaller than the starting sample because it fulfills additional requirements for the construction of the non-bank loan share and participating banks' average regulatory Tier 1 capital positions during the oil shock period 2012–2017. These requirements are as follows: (a) loan deals must be syndicated as opposed to single-lender loans, (b) loan deals must include at least one non-bank lender; and (c) participating banks are matched to Call Reports.