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De-leveraging or de-risking? How banks cope with loss

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We explore banks' reactions to a shock arising from their exposure to the sharp oil price declines of 2014. Exposed banks tightened credit on corporate lending and on mortgages to be retained on-balance-sheet, while expanding credit for securitized mortgages. Banks therefore re-balanced their portfolio to lower their risk, rather than scaling back the size of their balance sheet or reducing lending uniformly. Thus, when assessing implications of bank stress for the broader economy, one must consider banks overall strategy, rather than focusing on isolated parts of the balance sheet.

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I. Introduction

Even prior to the recent crisis, it was well understood that the state of the banking system under stress was important for the broader economy. Since the crisis, yet greater emphasis has been put on studying the behavior of financial intermediaries. Understanding how banks behave in response to a shock is therefore of particular current relevance. While banks' responses can be expected to be multifaceted and coordinated across their entire balance sheet, most canonical models simplify matters by envisaging a homogenized 'loan' portfolio rather than the broad class of assets banks in fact hold. Perhaps the most prevalent intuition to arise from such models is that when a bank is damaged it will scale back its operations and reduce lending. Empirical studies inspired by this intuition have generally focused on one particular component of banks' loan books at a time (typically corporate lending) and found support for the idea that damaged banks cut credit.[1] Our paper shows that the reality may be more complicated and that the standard intuition from existing studies is incomplete.

We investigate banks' responses to credit losses induced by the precipitous decline in oil prices of mid-2014 and show that banks do not uniformly reduce credit supply following a damaging shock. Instead, while some types of credit are contracted, others are *expanded*. In particular, corporate loans and *on-balance-sheet* mortgages are reduced, while mortgages to be securitized and shifted off balance sheet are increased. This pattern of adjustment entails a shift from heavily risk-weighted assets, against which banks must hold capital at a high rate, to lower risk-weighted assets. The effect on total lending, total size of the balance sheet, and the degree of leverage appears ambiguous. What is unambiguous, however, is a pattern of 'de-risking'. We observe banks making substantial reductions in their average risk weight rather than reducing their overall quantity of investments. We corroborate these empirical findings with survey evidence from the Senior Loan Officer Opinion Survey (SLOOS), which suggests that banks tightened terms of credit for the types of loans they wished to reduce (portfolio loans) and loosened credit for those they wished to attract (securitizable loans). Interestingly, we find little evidence that the de-risking *across* asset classes was mirrored by de-risking *within* an asset class.

The intuition that a bank might de-risk when damaged follows from basic portfolio theory. A shock to net worth may change the bank's effective risk tolerance

[1] See Khwaja and Mian (2008), Ivashina and Scharfstein (2010), Jimenez et al. (2012) and Chodorow-Reich (2014). See also Holmstrom and Tirole (1997) for theoretical motivation.

as it is shifted closer to some type of funding constraint (see Froot and Stein (1998)). In this sense, a portfolio rebalancing reflects an updated solution to the risk-return tradeoff faced by the bank. One way a damaged bank can pull back is in terms of loan quantities—the traditional focus of the 'bank lending channel' literature.[2] De-risking can be thought of an alternative form of pulling back viewed from the broader portfolio perspective. We show that one can put more traditional bank lending channel studies (which focus on isolated parts of the balance sheet) in a broader portfolio-level analysis and obtain important additional insights. Furthermore, in a world in which banks face multiple regulatory constraints - some risk-weighted and others not - it is especially important to understand how banks tune their risk-weight profile. Even outside explicit banking or regulatory literatures, the importance of distinguishing risk weighted and total assets is also now discussed (see Potter (2013) and Du, Tepper and Verdelhan (2018), for example).[3]

An additional contribution we make is to assess the ultimate impact of the oil shock on borrowers. We find no evidence of an operational 'credit channel' - the term typically given to the indirect effect of a shock on borrowers, via their banks. Specifically, borrowers who were more exposed to damaged banks do not appear to have made significant changes to their total loan balances or total assets after the shock. Since our data provide the identity of the borrowers, we can trace borrowers across banks, helping us to figure out *why* the effect is limited. The data reveal that borrowers facing worsening terms from exposed banks simply switched to other less-exposed banks within our sample. This ability to substitute financing likely reflects the healthy state of the financial system at the time, in contrast to the crisis period studies that typically find an important role for a broader 'credit channel' by which shocks to banks ultimately affect borrowers (see Khwaja and Mian (2008), Chodorow-Reich (2014), Acharya et al. (2018), and Huber (2018)).[4] Our study therefore complements these studies in providing a useful benchmark to understand how fragile banks may impede the economy's recovery from shocks.

We use granular data from the FR Y-14 filings (Y14) obtained from bank hold-

[2]This term was originally coined in the context of monetary policy transmission (Bernanke and Blinder (1992), Kashyap and Stein (1993) and Stein (1998))

[3]See also Landier, Sraer and Thesmar (2013), Drechsler, Savov and Schnabl (2018) and Tella and Kurlat (2017) for analyses of how banks' (interest rate) risk management implies close connections across different aspects of their businesses. Landvoigt and Begenau (2017) also model bank behavior, including the impact on risk-taking incentives of capital regulation.

[4]The importance of the availability of alternative financing also implies that studies based on less developed financial systems may not provide relevant insights for the U.S.

ing companies as part of the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR). This dataset includes a broader array of borrowers and loan types than those typically used in the banking literature, such as the Shared National Credits (SNC) data or Dealscan, and spans a wider range of asset classes. Information about specific loans held on the banks' balance sheets allows us to construct the exposure of the banks' corporate lending to firms in the oil and gas (O&G) sector prior to the sudden decline in oil prices in 2014. Our treatment stems from exploiting variation in this variable across banks, which implicitly induced variation in the impact of the price decline on net worth.

For a variety of loan-types, we isolate the credit supply effects by using borrower fixed effects as in Khwaja and Mian (2008) which strips out possible credit demand effects. Any remaining endogeneity bias would arise from supply factors - specifically, factors associated with the banks' decision to hold O&G loans. Our knowledge of the identities of the borrowers and banks allows us to include a wide range of controls at the bank and bank-borrower level to address these concerns. These observable bank characteristics are not correlated with O&G exposure, indicating that high and low exposed banks appear similar on average. Additionally, we instrument our exposure variable with banks' branch locations from several years prior to the shock (similar to Gilje, Loutskina and Strahan (2016)) with little change in our results. Overall, our results are robust to a variety of alternative exposure measures, standard error constructions and permutation exercises.

II. Relation to literature

Banks' risk management has been studied both theoretically and empirically. Froot and Stein (1998) provide a theoretical framework motivating risk management practices. In applied work, researchers have examined how banks adjust their risk profile in response to shocks. For example De Jonghe et al. (2016) show that Belgian banks reallocated credit to less risky firms during the financial crisis. Liberti and Sturgess (2018) and Ongena, Peydro and van Horen (2013) also suggest some tendency for corporate loan substitution after a shock, towards borrowers that are less risky in some sense. However, the key difference between our paper and these existing studies is that the latter show evidence of de-risking *within* asset classes.[5] In contrast, we find that banks shift risk *between* asset

[5]We also note that De Jonghe et al. (2016) exploit a crisis-era shock and restrict their analysis to banks and firms active in Belgium. Ongena, Peydro and van Horen (2013) consider mainly small and medium-sized firms in Eastern Europe and Turkey, while Liberti and Sturgess (2018) are limited to data from a single multinational bank. As discussed below, our use of data from the especially important

classes, rotating their entire balance sheet away from high risk-weighted asset classes. In fact, we do not see much evidence of risk reallocation within the asset classes we consider.

Our study touches on existing work that examines cross-balance sheet patterns. Using aggregate data, Bernanke and Blinder (1992) show that banks shift from loans into securities after a shock.[6] Haan, Sumner and Yamashiro (2007) also use aggregate data to assess responses to monetary policy shocks across banks' portfolios. Abbassi et al. (2016) use micro data on German banks to show that trading banks increase their holdings of securities whose prices had fallen during the financial crisis. However, they do not assess overall bank balance-sheet effects. More closely related to our work is Peek and Wilcox (2003) who, using data aggregated to the bank level, show the option to securitize mortgages helps stabilize mortgage lending over the business cycle. In this respect we also relate our work to broader studies of banks' motivations in selling loans into secondary markets (see Carlstrom and Samolyk (1995) and Demsetz (1999)) though we focus in particular on the response to a shock and the particular patterns induced across the balance sheet, revealing what banks regard as the most efficient way of reducing their risk-weight profile.[7]

Chakraborty, Goldstein and MacKinlay (2017) observe that banks particularly exposed to MBS increased mortgage origination following the Fed's MBS purchases, while also reducing their C&I lending. While this study examines cross-balance sheet effects, it differs from ours in two regards. First, the shock examined in their study implies a particular type of increased *demand* for MBS and is therefore not necessarily a pure net-worth shock like our shock.[8] Second, the study focuses primarily on loan quantities and does not distinguish between loans originated to be securitized and loans originated to be retained on the portfolio. By contrast, we show a shift within mortgage lending as banks rotate from portfolio to securitizable loans.[9]

- and idiosyncratic - U.S. economy/banking system, post-crisis, provides an important addition to the literature, even when simply considering our data coverage.

[6]Using aggregate data is clearly subject to the important concerns raised by Khwaja and Mian (2008) regarding the conflation of credit demand and supply shocks. Bernanke and Blinder (1992) also attribute portfolio rebalancing (see their figure 4) to differential ease of adjustment among asset classes - not to de-risking.

[7]They could have purchased Treasuries or agency MBS, outright, for example, using resources from cutting their commercial lending even further. Yet we find they choose to use their mortgage origination as a method of implementing their shift.

[8]The Fed implemented its purchases through the to-be-announced (TBA) market so that origination of mortgages was *particularly incentivized* by the purchases. The authors refer to this interesting phenomenon as the 'origination channel' of LSAPs.

[9]Our paper is also somewhat related to a number of studies that have assessed how banks change

We note that de-risking is not completely *a priori* obvious, despite it being consistent with theoretical models, such as Froot and Stein (1998). Indeed, following the work of Jensen and Meckling (1976) (see also Stiglitz and Weiss (1981), Diamond (1989) and Acharya and Viswanathan (2011)) it is well understood that agency problems between creditors and borrowers can lead to 'risk shifting' behavior, whereby borrowers are incentivized to shift activities *towards* risky pursuits. This could particularly be the case after an adverse shock that drives a bank closer to default.[10] Rampini, Viswanathan and Vuillemey (2017) also note that degradation of net worth can also hinder risk reductions by intermediaries and Laeven and Levine (2009) note the effect of capital requirements on risk taking is in some contexts ambiguous and may depend on bank corporate structure.

Our results on banks' changing of their risk (weight) profile in response to the shock provide an important extension to the traditional empirical literature testing for the importance of net worth, as predicted by financial frictions models. While the cross-balance sheet aspect of our analysis takes us beyond the standard 'bank lending channel' literature, our work does include analyses of bank lending. As such, for our corporate and mortgage loan analysis, we implement the fixed-effects identification approach taken by Khwaja and Mian (2008) (KM).[11] It is important to note, also, that where alternative identification approaches have been taken to separate credit demand and supply shocks (notably in Kashyap, Stein and Wilcox (1993) where commercial paper data is used to reveal underlying commercial credit demand) these are tests that again focus on corporate loans, whereas a fundamental insight of our analysis is that looking at one type of lending in isolation can be misleading.

III. Data

We use data from the quarterly FR Y-14Q and monthly FR Y-14M filings required of bank holding companies (BHCs) with more than $50 billion in assets.

their asset liquidity following a shock, though our results indicate adjustment along the average risk weight dimension, rather than in broad measures of liquidity. Cornett et al. (2011) find that banks that had relatively illiquid asset holdings at the start of the crisis were more prone to increase liquidity and reduce lending in response. This is consistent with the work of Loutskina (2011) and Loutskina and Strahan (2009) who emphasize the increased liquidity of loans via securitization in recent years. See also Cebenoyan and Strahan (2004) for the link between liquidity created by loan sales and risk management.

[10]Focusing primarily on insurance companies (though also including more restricted analysis of banks), Kirti (2017) finds similar tendencies of institutions hit hardest in the recent crisis to reduce their risk profile, noting the contrast with traditional theories of 'gambling for resurrection'.

[11]Recent papers that use the KM technique include (among many others): Schnabl (2012), Chodorow-Reich (2014), Jimenez et al. (2014), Iyer et al. (2014), Acharya et al. (2018), Cingano, Manaresi and Sette (2016), Bottero, Lenzu and Mezzanotti (2016), De Jonghe et al. (2016) and Heider, Saidi and Schepens (2017).

The Y14 contains detailed data on balance sheet exposures, capital components and income. Our samples of commercial (residential) loans consist of loans originated by 28 (26) banks and in table 1 we illustrate their characteristics prior to the decline in oil prices. These variables will be used as bank controls in our commercial and residential loan analysis below.

The commercial loan data from the FR Y-14Q provides a 'credit register' - loan-level information identifying borrower and lender and many characteristics of the loans themselves.[12] In 2014:Q2, just prior to the oil price decline, the commercial loans included in the Y14 totaled \$1.17 trillion — nearly 70 percent of the \$1.69 trillion in C&I loans extended by all banks that file FR Y-9C (Y9) reports. For perspective, the total amount of debt owed by U.S. nonfinancial corporations at that time was \$2.39 trillion. The FR Y-14M filings contain loan-level monthly data on banks' mortgage positions, including characteristics (but not the identity) of the borrower and the mortgage.

From the perspective of our work, there are several especially important aspects to the data. First, it spans multiple asset classes, including corporate and mortgage lending. Furthermore, among corporate loans we can distinguish credit lines and term lending, and within mortgages we can distinguish those that are securitizable (government loans or conforming to Fannie and Freddie's requirements). Second, for mortgages we know whether the loan is actually held on the balance sheet (a 'portfolio loan') or whether it has been sold off (typically to a GSE) yet remains in our dataset because the bank continues to service the loan. As we will show, if one looks simply at on-balance sheet data, such as in the commonly used Y9 reports, one can be led to believe there is a relative decline in mortgage lending, when in fact there has been an offsetting increase in mortgage origination for securitization. Third, our detailed knowledge of borrowers allows us to construct a measure of bank exposure to oil and gas drillers. In addition, since we can track the same borrower across multiple banks, we can exploit *within borrower* variation that is orthogonal to possibly confounding credit demand effects.[13] Knowing the borrower also allows us to track their substitution of alternative bank lending when switching banks. Finally, the corporate loan data

[12]Other papers that have used these novel regulatory data are Abdymomunov (2014) (operational losses), Black, Krainer and Nichols (2016), Johnson and Sarama (2015), Epouhe and Hall (2016), Calem and Sarama (2016) (real estate) and, making limited use of the corporate loans data to assess the use of private information by syndicate leaders, Balasubramanyan et al. (2016). For contemporaneous work making use of only the corporate loan data available in the Y14 see Berrospide and Edge (2016) and Luck and Zimmermann (2018).

[13]For mortgages we use county fixed effects, as discussed below.

is not restricted simply to syndicated lending (such as the SNC and Dealscan, typically used in the literature) and extends to much smaller borrowers and loans — down to $\$1m$.

In addition to the Y14, we use the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS) to provide insight on lending standards. The SLOOS is a quarterly survey where banks report how various terms and conditions have changed since the previous survey. Importantly, rather than employ the economy-wide aggregate SLOOS responses, we make use of the confidential bank-specific survey responses.[14] We also use the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits data in constructing an instrument for our exposure variable based on branch location, to be discussed further below.

IV. The oil price decline of 2014

Figure 1 shows that the oil price fell suddenly and significantly in the middle of 2014. Furthermore, oil futures prices clearly indicate that the speed and extent of the decline was a surprise. Indeed, much commentary in the early part of 2014 was bullish on oil (see Hamilton (2014), for example). Our analysis does not require that the oil price be exogenous in the broadest sense. Of course, it is possible (though perhaps not likely in this case) that there are feedbacks from the state of the U.S. banking system to the oil price.[15] But that would not undermine our analysis since we exploit variation across the banks in our sample, within the U.S. banking system.

Performance of loans to firms in the O&G industry depend critically on the price of oil. As shown in panel A of figure 1, the rate of loans identified as either past due, charged-off, or in non-accrual status ('problem loans') spiked in the O&G industry following the price decline.[16] The fraction of O&G loans that were in problem status climbed from 0.6 percent in 2014:Q2 to 10.4 percent in 2016:Q3. By contrast, taking all sectors other than O&G we observe essentially no trend. Restricting the sample to net *users* of O&G products we again observe

[14]The SLOOS may not be used for supervisory purposes, and the confidential bank-level survey responses may only be used by Federal Reserve System staff in non-supervisory functions for limited-scope economic research projects.

[15]Slowing growth in China and other large emerging economies, increased oil production (from shale and oil sands) in the US and Canada and toleration of lower prices by Saudi Arabia are commonly-cited reasons for the oil price decline. The state of the US economy and bank health do not typically feature as explanations.

[16]We define firms as being in the O&G industry if the bank reported NAICS codes 211, 213111, and 213112 (O&G extraction, drilling O&G wells, and support activities for O&G operations). In the online appendix we use the Bureau of Economic Analysis' 'Input-Output' tables to illustrate the particular exposure of these industries to the oil price in figure A1.

no obvious pattern. Thus, there was apparently little scope for passive hedging of the shock within the loan book. Loans are debt contracts and given the already low rates of default expected on the typical loan, the upside from having lent to industries whose costs may have declined with the oil price do not offset the downside from exposure to O&G.

In panel B of figure 1 we investigate whether difficulties in the O&G sector led to a liquidity drain for banks. We plot the average utilization rate of credit lines among the same set of sectors as in panel A. While there does appear to be some relative increase in the utilization rate of credit lines in O&G, the difference is not large.

Another concern might be the explicit hedging of credit risk using derivatives. However, Minton, Stulz and Williamson (2009) suggest that derivatives positions were largely held by banks for their dealer activities, rather than to protect against the credit risk of their loan book. In addition, we consulted the FR-Y9C and calculated that all but one of our banks had purchased CDS protection of notional value of around 1 percent or lower of their total loan book and the number was approximately 3 percent for the remaining bank. Thus, hedging of credit exposures via derivatives appears to be limited, as theories of adverse and selection and moral hazard might lead us to expect (see Duffee and Zhou (2001) for discussions of banks' informational advantage). Recent work by Caglio, Darst and Parolin (2017) using Y14 and DTCC data, also suggests that banks appear to be net *sellers* of protection on a substantial fraction of their credit portfolio.

Based on these observations, our analysis will use the banks' loan book exposures to O&G as our treatment variable. Variation in this exposure implies that some banks experienced larger shocks to their loan books than others when oil prices fell. We calculate O&G exposure as the share of each bank's total committed exposure (including term loans as well as both drawn and undrawn lines of credit) reported on the Y14 that is accounted for by lending to firms from the O&G industry over the period 2012:Q3-2013:Q4. We start our sample in 2012:Q3, the date at which the banks that experienced the oil shock period are all present in the Y14 data. We leave a buffer before the period of the price decline to guard against picking up simple reversion to the mean and other concerns of endogeneity.

Average O&G exposure is 5.9 percent and there is considerable variation across banks, with a standard deviation of 4.9 percent. Roughly speaking, a one standard deviation increase in pre-shock O&G exposure represents a 50 basis point increase in the overall problem-loan rate for the 'average' bank over the course of the post period.[17]

It is clear that variation in O&G exposure across banks was important from the perspective of the financial markets, even if *on average* the banking system was not significantly damaged by the shock. In figure 2, we group banks into quartile bins based on their pre-shock O&G exposure. Banks that were more exposed to the O&G industry underperformed in terms of their stock prices and market capitalization following the oil price decline. The timing of the separation in performance is indicative of the repeated guidance given to investors at the time. Further confirmation of the importance of the impact of the oil price decline on bank condition comes from media and survey evidence. The price declines of 2014 drew comment in many quarters and the implications for banks' performance were broadly discussed (Alloway (2014), Jenkins (2014), Noonan and McLannahan (2014)). In fact, in bank surveys the importance of the effects was also emphasized: From the SNC 2016Q1 review - *'The high level of credit risk stems from a large share of risky leveraged finance loans underwritten based on weak practices, and the significant decline in oil prices since mid-2014 that has reduced the repayment capacity of obligors in the oil and gas (O&G) sector'.* Also, from the January 2015 SLOOS *'Some survey respondents specifically noted their concerns about the oil and gas sector resulting from the sharp decline in the price of oil as a reason that they had tightened their lending policies.'*

It is important to point out that the committed exposures reported by the banks include both on and off balance sheet amounts. In particular, undrawn or partially drawn credit lines are reflected in the Y14 as loans with utilized exposures lower than the committed exposure. The off-balance-sheet commitments can sum to particularly large amounts. Indeed, committed O&G loans make up a non-trivial fraction of both total on-balance-sheet loans and total assets, averaging 4.6 and 2.3 percent over the pre-period, respectively. In addition, if one alternatively expresses exposure as a fraction of equity capital, the mean and standard deviation across banks are 19.1 and 21.0 percent, respectively, emphasizing that multiple banks had significant net worth riding on the performance of the O&G sector and, by implication, oil prices.[18]

[17]The fraction of O&G loans in problem status increased by 9.8 percent points between 2014:Q2 and 2016:Q3. A one standard deviation increase in exposure (0.049) would cause a $0.049*9.8 = 0.5$ percentage point increase in the overall rate.

[18]While our exposure variable is committed O&G lending as a share of total committed commercial loans, we also show in a robustness section that our results are robust to using committed O&G/total on-balance-sheet loans and committed O&G/total assets. We also repeat our main regression analyses

V. De-leveraging or de-risking?

We begin our results with a high-level analysis based on publicly available bank-level data. While the insights from these series are suggestive, we will then probe deeper, making use of the more granular data from the Y14 as well as responses from the SLOOS.

A. Descriptive analysis: FR-Y9C data

In figure 3 we show how different components of bank balance sheets behaved around the oil price shock, using information from the FR-Y9C. This aggregate bank-level analysis is meant to highlight the direction and timing of the impact, but does not control for time-varying bank-specific covariates or demand factors. For each bank, we regress the logarithm of the bank-level variable on a linear time trend over the pre-2014:Q2 sample. We then collect the residuals and normalize them by taking the log difference relative to the 2014:Q2 value. The unweighted average for banks in the upper (lower) quartile of exposure are given by the red (blue) dashed line.

Panels A and B show that the more exposed banks exhibited lower commercial and residential lending following the shock, in terms of total *on-balance sheet* loan exposures in these businesses. The timing, again, suggests a noticeable break around the period of the oil shock. While we make no attempt to control for demand factors here, these patterns are consistent with the existence of a bank lending channel to the extent that the reductions in lending reflect a tightening of credit supply. Panel C shows the analogous plot for agency mortgage backed securities (MBS) and is essentially a mirror image of panel B.

Finally, we also note that movements out of corporate lending and (to a lesser extent) residential lending, towards MBS signifies a substantial portfolio shift from high risk weighted assets to low - a form of de-risking. Additionally, we emphasize that the Y9 data relates to *on-balance-sheet* exposures such that any mortgages that are securitized will not show up in panel B. Instead, they would manifest in MBS holdings.

B. Econometric specifications

The results of the previous section are only suggestive of a tightening of bank credit. In particular, they could entangle credit supply and credit demand effects

below using loan exposure as a fraction of equity and find similar results.

and omit possibly influential controls. We account for such potential bias in the more granular analysis that follows.

Regression analysis

We employ a fixed effects regression of the following form (Khwaja and Mian (2008)):

$$\Delta Y_{ij} = \beta_j + \beta_1 Z_i + \beta_2 X_i + \varepsilon_{ij}, \tag{1}$$

where Y_{ij} is a loan amount between bank i and borrower j from the pre- to the post-shock period. β_j is a borrower fixed effect, Z_i is the bank's exposure to oil (the share of its loans accounted for by O&G firms in the pre-shock period), and X_i are bank controls.

As in Khwaja and Mian (2008), we define a particular loan concept for our empirical analysis. Our concept of a loan is a bank-borrower pair based on the underlying raw loan facility data so that, in examining the intensive margin, ΔY_{ij} is the change in the mean individual loan committed balance within the pair. The mean is a simple average across quarters in the relevant subperiods and we require that there be a continuous bank-firm relationship starting before or during the pre-shock period and extending into the post-shock period. We focus on term loans as opposed to lines of credit to avoid complexities related to the decision of whether or when to draw upon the line.

For the extensive margin we track the existence of the bank-firm pair in the pre- and post-shock periods, allowing us to apply a linear probability model where ΔY_{ij} is replaced by an indicator capturing entry (a relationship being initiated in the post-shock period that had not been present in the pre-shock period) or exit (a relationship that had been present in the pre-shock period but was not present or came to an end in the post-shock period).[19]

The importance of the fixed effect in equation (1) is that it absorbs the component of the ΔY_{ij} that is common across i. In particular, it is intended to capture any general shift in the firm's credit demand, common across banks. This addresses concerns that the effects of the oil price shock might induce correlated credit demand and supply shocks, which would lead to endogeneity bias in the regression and confound our measurement of the credit supply effect, captured in

[19] We discard loans that were 90 or more days past due and restrict our sample only to U.S. borrowers. For all econometric specifications, we remove all loans to firms in the oil and gas industry. Further details of how we cleaned the data are in the online data appendix.

β_1. This is the main coefficient of interest as it captures the identified effect on the lending relationship of the credit supply shock arising from the bank's *relative* exposure.[20]

Identification

The inclusion of firm fixed effects controls for any factors due to general shifts in a borrower's demand.[21] However, endogeneity bias could still arise from other supply-side factors. The ideal treatment would entail randomly assigning O&G exposure across banks. Since our banks chose their exposure to the O&G sector, it is important to address potential endogeneity.

First, note that we observe an extensive amount of information about the banks in our sample (see table 1). This includes broad characteristics of the bank (total assets, recent trend in lending, and whether the bank is foreign or domestic), but also characteristics of the banks' risk taking (return on assets, the non-performing loan rate and the charge-off rate) and capital positions (leverage ratio and tier-1 capital ratio). We also observe the banks' balance sheet structure (loan share of assets, share of residential and commercial loans in the loan book, and the deposit ratio) which accounts for the banks' preferences for certain asset classes.[22] Given these observable characteristics, the remaining identification assumption in our empirical analysis is that a bank's O&G exposure is not correlated with any *unobserved* factors influencing how it responds to a shock. This assumption would be undermined by factors, unobserved to the econometrician, that may be correlated with both the bank's decision to hold O&G loans and its decision to change its balance sheet in response to the shock.

We address this potential endogeneity issue in two ways. First, we examine whether O&G exposure is correlated with any observable characteristics. If exposure is correlated with any observable bank characteristics then it is plausibly more likely to be correlated with unobserved characteristics. Regressing O&G exposure on each of the bank variables discussed above indicates no statistically significant relationship with any of these observable variables. This gives some

[20]In what follows, we will adopt the standard terminology in this literature (which focuses on separating demand from supply effects) and refer primarily to the fixed effect as absorbing firm-specific shifts in credit demand. Our identification allows us to examine the effects of the oil shock, controlling for credit demand effects, systemic supply effects or effects on lending to particular firms that are common across banks. Thus β_1 relates to the marginal effect arising from banks' relative exposure.

[21]Note that this addresses concerns that the industry and geography of borrowers (absorbed by the fixed effect) could confound our analysis. In particular, the location of borrowers in O&G intensive areas is accounted for.

[22]Table C1 in the appendix shows the effects of these control variables on our main estimates.

credence to the idea that exposure is also not correlated with any unobservable factors.

Second, we implement an instrumental variable specification using the banks' 2009 share of branch locations in 'O&G counties' as an instrument for O&G exposure (see Gilje, Loutskina and Strahan (2016) for a similar approach). Specifically, the instrument is the share of bank branches in 2009 that were in counties reporting any income from the O&G sector.[23] This instrument will be strong insofar as certain banks were well placed geographically to originate loans to O&G and valid to the extent that the location of branches in 2009 is independent to how a bank would respond to a net worth shock in 2014. The exclusion restriction relies on the assumption that branch location is an independent historical decision which subsequently caused its corporate loan book to be more concentrated in certain industries. We cannot fully rule out that banks choose branch location *for the sole reason* of obtaining corporate loan exposure in certain industries, in which case the instrument is no more valid than O&G exposure. However, this seems unlikely given that business loans are just one of a multitude of banking services offered at local branches (for example, automatic tellers, consumer loans, and savings accounts). Moreover, it seems even less likely that banks would choose branch location to gain mortgage exposure to households employed in certain industries. Yet, importantly, we find that using branch structure in an instrumental variables regression yields roughly the same conclusions for both corporate loans and mortgages that are retained in the bank portfolios.

C. *Corporate lending*

The first element of the balance sheet we examine is the corporate loan book. Here we find results consistent with the aggregated bank-level data of the Y9.

Main results

In table 3 we show results on the intensive margin. The coefficient of interest, β_1 (in the first row), is estimated to be negative and significant at the 1 percent level for both the fixed-effects instrumental variables (FE-IV, column 1) and FE

[23]These are counties where the fraction of non-farm employee compensation attributable to the O&G industry by county, from 2013 BEA Table CA6N (compensation of employees by industry), was greater than zero. Results were robust to more stringent definitions (e.g. share $> 5\%$ or $> 10\%$). The branch data is from the FDIC's Summary of Deposits. All of the Y14 banks in our sample have grown through mergers or acquisitions over the past several decades. We choose 2009 to sample the branch data because that is the most distant year in which our banks were all in the Summary of Deposits data in their current organizational forms.

regression (column 2).[24] The point estimates under IV and FE are quite similar, indicating that unobservable supply factors are likely not affecting the FE estimates. The IV-FE and FE coefficients imply that a one standard deviation increase in O&G exposure (5 percent from table 1) is associated with about a 4 percent decline on the intensive margin of a randomly selected loan.[25]

Columns 3 and 4 of table 3 show OLS results under two samples: multi-bank firms (i.e. the FE sample) and the entire Y-14 sample, which includes single-bank firms. By comparing the OLS and FE estimators on the same sample we can assess the size of any bias induced by firm credit demand. If anything, the correlation appears negative: firms that experience positive demand shocks appear more concentrated among banks that experienced negative supply shocks. Thus, endogeneity bias from correlated demand, if there is any, may be towards attenuating the measured effect. In this case, and assuming any correlation between credit supply and demand effects is similar in the larger sample, we may expand our sample and treat the estimated OLS coefficients with reasonable confidence as a lower bound (in magnitude) on the credit supply effect. In the larger sample, we again obtain a statistically significant coefficient on O&G exposure, although smaller in magnitude than the FE sample (-0.32).

Table 4 shows results on the extensive margin. Similar to the results on the intensive margin, the point estimates of the FE-IV and FE results are similar. A 1 percent increase in O&G exposure is associated with about a 1 percent increase in the probability of exit (columns 1 and 2) with a similar coefficient using OLS (column 2). When (column 4) we expand the sample to include single bank firms the effect is lower in magnitude and insignificant. The remaining three columns in table 4 relate to new relationships (i.e., entry), which does not appear to be significantly related to bank exposure.

Exploring the mechanism - corporate lending

The decline in the magnitude of the estimates when including single-bank firms in the sample suggests that alternative financing opportunities may influence the results. To explore this, we run a specification with three interactions: a dummy that flags whether or not the firm has access to external finance (has a CUSIP or a stock ticker), the pre-period utilization rate that captures the ability of the firm to

[24]The first-stage estimate shows a strong correlation between O&G exposure and and 2008 branch share, with a t-statistic of 14.

[25]Similar results are obtained when we weight observations by the size of loan, indicating that our results are not being driven by the size of the loan.

draw on existing lines of credit, and the number of pre-existing bank relationships (in the Y14 sample), reflecting the costs of switching from an established banking relationship.

Table 5 shows that most of these interactions are statistically insignificant. However, consistent with the decline in magnitude of the estimate for single-bank firms, there is a statistically significant positive coefficient on the number of pre-existing banking relationships in the exit regression. This suggests that firms with existing alternative banking relationships in the pre-period were more apt to leave their relationship with exposed banks. Since we know the identity of the firms, we can examine if the exiting firm formed a new relationship with another, perhaps less exposed, bank in the Y14 sample. To do so, we run the fixed-effects entry regressions of the type we ran in section V.C above, but on different subsamples of firms. In table 7, we group the firms according to whether they experienced any relationship exit (column 1), did not experience any exit (column 2), experienced any decline in term-loan borrowing from a BHC (column 3), or did not experience any decline in borrowing from a BHC (column 4). Columns 1 and 3 demonstrate that firms that experienced any reduction in lending (by any bank, for any reason) were more likely to strike up new relationships with less-exposed banks.

These results imply that firms with low-switching costs (i.e., low-risk firms with multiple banking partners) switched from more exposed to less exposed banks. The question than arises: what was causing these firms to flee? A plausible hypothesis is that exposed banks varied their terms of lending, inducing those firms to switch. To examine this hypothesis, we look at the Senior Loan Officer Opinion Survey (SLOOS). The SLOOS is qualitative: respondents indicate whether lending standards have tightened or eased ('somewhat' or 'considerably'), or remained about the same. Importantly, the survey questions ask about lending standards for new loan applications, and thus can be interpreted as the willingness of the banks to supply credit. In figure 4 we plot an index of tightening on loan rates and covenant requirements for commercial and industrial (C&I) loans.[26] We again average individual responses of banks in the top and bottom quartiles of exposure. The index shows average cumulative tightening, so a decreasing index depicts banks that have eased terms since the last survey, an increasing index depicts tightening since the last survey.

The banking sector as a whole was generally easing lending standards over this

[26]The BHCs in the indexes are ones where we could merge the bank ID in the Y14 data to the SLOOS data. Almost every Y14 bank was also located in the SLOOS.

period of time. However, on average, those with relatively high exposure to the oil sector (red lines in figure 4) stopped easing in late 2014 and began to tighten the terms of required loan rates and loan covenants.[27] The results from the SLOOS suggest that exposed banks shifted their credit supply function in price relative to less exposed banks.

Finally, we dig deeper by assessing whether the default risk of the firm also played a role in the probability of exit due to O&G exposure. Specifically, we divide all firms in the Y-14 sample into quartiles based on their probability of default (PD), based on the internal credit rating and, where available, PDs provided by banks in the Y14. We run this specification on two samples: the sample of multi-bank firms and single-bank firms.[28] As in the previous results, we find that the probability of exit was larger for multi-bank firms. However, as illustrated in figure 5, this exit effect within multi-bank firms was mainly stemming from the *lower-risk* firms. This result is likely partly due to the fact that low-risk firms have an easier time finding alternative financing than high-risk firms but also suggests that banks were not tuning their terms of credit to deter higher risk borrowers. In contrast to the evidence at the broader balance sheet level (showing that more exposed banks de-risked), we therefore find little evidence that the more exposed banks de-risked at the corporate loan book level. If anything, more exposed banks were increasing their corporate loan risk due to safer loans leaving the loan book.

D. *Residential loan analysis*

A significant advantage of the Y14 data it includes multiple components of banks' balance sheets. Panels B and C of figure 3 indicate that residential lending among more exposed banks decreased relative to the less exposed banks while MBS holdings increased. In this section, we use the micro-data to confirm that this result is not driven by a failure to control for credit demand and bank characteristics. We also show that increased securitizable mortgage lending is associated with the expanded MBS holdings.

[27] For recent work on the role of covenants in the mechanisms by which banks tighten lending in the syndicated loans market, see Chodorow-Reich and Falato (2017). The Y14 has very granular information on loan quantities and loan performance, but does not contain information on covenants.

[28] Specifically, we interact O&G exposure with three dummies, indicating the 2nd through 4th (PD) quartile, the omitted category being the 1st quartile: $Exit_{ij} = \beta_j + \beta_{1,1} Z_i + \beta_{1,2} Z_i * \mathbf{1}(\overline{PD}^{25th} < PD_j < \overline{PD}^{50th} + \beta_{1,3} Z_i * \mathbf{1}(\overline{PD}^{50th} < PD_j < \overline{PD}^{75th}) + \beta_{1,4} Z_i * \mathbf{1}(\overline{PD}^{75th} < PD_j) + \beta_2 X_i + \varepsilon_{ij}$. We then use the delta method to construct standard errors for the implied effects on the 2nd $(\beta_{1,1} + \beta_{1,2})$, 3rd $(\beta_{1,1} + \beta_{1,3})$ and 4th $(\beta_{1,1} + \beta_{1,4})$ quartile firms.

Mortgage regression results

For mortgage lending, we can no longer apply the borrower fixed effects approach at the borrower-bank level because we cannot identify a given household across different banks. However, since mortgage demand is likely to be similar within a county, we include county fixed effects to absorb county-level mortgage demand effects.

In table 8 we show the results of our regression analyses. We partition residential loans into those originated and retained on the banks' portfolios ('portfolio loans') and those originated but either sold or securitized with only servicing rights retained ('non-portfolio loans'). We use only those loans originated by the BHCs themselves, excluding those obtained from correspondent relationships.[29] The different categories of loans are meant roughly to mimic the broad categories included in SLOOS.

For non-government mortgage originations that were retained in the banks' portfolios, the banks are exposed to the credit risk associated with default. The results generally suggest that banks with greater exposure to the oil shock reduced their balance sheet exposure to such mortgages. For both the fixed effects regression in panel A and OLS regression with county controls in panel B of table 8, the estimated coefficient of -2.2 implies that a one standard deviation increase in oil exposure leads to a roughly -11.0 percent decline in portfolio lending. We estimate the balance sheet pullback to be stronger in the non-jumbo category (column 3) than in the jumbo category (column 2).[30]

Conversely, we see the opposite effect for the non-portfolio loans — exposed banks *increased* their origination and securitization activity (columns 4 and 5). The effect is particularly pronounced when we limit the mortgages to non-jumbo loans, which are more likely to be guaranteed by the GSEs. The coefficient estimate implies that a one standard deviation change in O&G exposure is associated with a nearly 14 percent increase in securitization. Similarly, in column 6 of the table we see a significant positive response of changes in loan growth for FHA and VA (i.e. 'government') mortgages-loans likely to be securitized by Ginnie Mae.

[29]We include summary statistics of the log change in mortgage loans and also describe how we partitioned mortgage loans from the Y14 into different types in the online data appendix. We augment our bank-level controls with variables capturing trends in the banks' mortgage lending and MBS holdings (see table 2 for a description of the controls). Results are essentially the same if the correspondent and other loans not originated by the banks themselves are included - available on request.

[30]This is reminiscent of results in Calem, Covas and Wu (2013) where jumbo, as a *share* of total mortgage origination, typically rose after the liquidity shock of 2007, although our broader finding of a pull-back in portfolio mortgage lending is somewhat in tension.

The coefficient implies a one standard deviation increase exposure is associated with a 41 percent increase in these types of loans.

These results are consistent with the patterns observed in figure 3. Recall, in that figure (panel C) we observe a substantial increase in aggregate MBS for banks according to their oil exposure. We find no statistically significant change in overall residential loans (column 7). That is, the decline in portfolio loans was offset by the increase in non-portfolio loans, implying no discernible change in total residential assets. The ultimate effect was a rotation of their balance sheet away from portfolio loans towards non-portfolio loans and, in turn, agency MBS.

Exploring the mechanism - residential lending

Figure 6 shows responses from the SLOOS on how credit terms evolved, depending on banks' exposure to the oil price shock.[31] In panels A and B of figure 6 we show the cumulative tightening of terms for GSE-eligible and Government mortgages. There was a greater tendency on average to loosen terms among the more exposed banks. In contrast, in panels C and D we repeat the analysis for jumbo and non-jumbo, non-GSE lending and observe that the pattern is flipped—the more exposed banks tightened relative to the less exposed.[32] The relative tightening of terms by the more exposed banks is consistent with a decline in their lending as borrowers are less attracted to their loan products. GSE-eligible and government mortgages are largely intended to be securitized and shifted off the banks' balance sheets. Thus, loosening of terms for these products is consistent with an increase in their off-balance-sheet portfolio.

E. Portfolio implications

Traditionally, studies on the bank lending channel give the impression that a shock to banks induces a uniform reduction in credit. However, we have shown that the bank's overall response is more complex. More exposed banks pulled back

[31] Plots begin in 2015:Q1 because the SLOOS questions on mortgages changed at that date.

[32] The GSE-eligible category of residential mortgages includes loans that meet the underwriting guidelines, including loan limit amounts, of the GSEs-Fannie Mae and Freddie Mac. The government category of residential mortgages includes loans that are insured by the Federal Housing Administration, guaranteed by the Department of Veterans Affairs, or originated under government programs, including the U.S. Department of Agriculture home loan programs. The Qualified Mortgage (QM) non-jumbo, non-GSE-eligible category of residential mortgages includes loans that satisfy the standards for a qualified mortgage and have loan balances that are below the loan limit amounts set by the GSEs but otherwise do not meet the GSE underwriting guidelines. The QM jumbo category of residential mortgages includes loans that satisfy the standards for a qualified mortgage but have loan balances that are above the loan limit amount set by the GSEs.

lending, but this pullback was concentrated among loans against which they would be required to hold regulatory capital at a relatively high rate.[33] In contrast, securitizable lending that was expanded - with relaxation in terms allowing this expansion, as reflected in the SLOOS. This rebalancing is consistent with the Y9 data in that the MBS and residential lending diagrams were essentially mirror images in figure 3. This offsetting pattern adds a subtlety that might be missed, were one only looking at the residential lending data from the Y9. Banks are constantly solving complex optimization problems in their lending behaviors and there is no reason to expect that a pullback in lending will be uniform across all products.

To get a sense of the degree of de-risking we run a simple exercise. We combine our estimated β_1 coefficients from the fixed-effects C&I and mortgage regressions with the pre-shock period loan balances and O&G exposure by bank. This yields an estimated impact of the oil shock arising from the banks' relative exposure.[34] We find that for the banks in the upper quartile of exposure there is a predicted change of about -15 percentage points in the average risk weight among the asset classes considered in our regressions (in comparison with a pre-shock average risk weight of 71%), whereas for the lower quartile banks the predicted change is about -8 percentage points.[35] In terms of loan balances, the equivalent figures are -3 and +0.1 percentage points, respectively, reflecting the reallocation rather than a wholesale reduction in credit that our estimates imply.

The above exercise assesses the degree of de-risking within a portion of the banks' balance sheet: commercial and residential loans. Of course, one would like to extend this analysis to include all elements of the balance sheet, though this would be beyond the scope of this paper. Nevertheless, we can obtain evidence that the patterns we have uncovered reflect a general strategy by the banks. Thus,

[33]Depending on the LTV and other factors, the prevailing risk weights under the Basel standardized approach over the sample period ranged from 35 percent to potentially over 100 percent for mortgages and, according to the particular agency, 0 percent or 20 percent, for agency MBS

[34]The predicted dollar change is pre-shock lending × exposure × β_1.

[35]Note that these calculations are restricted to the parts of the balance sheet for which we have estimated β_1 coefficients. We apply a common set of risk weights to all banks, even though many of these banks actually employ their own risk weights developed for the advanced internal models approach under Basel 3 capital standards. The assumed risk weights w_k for asset class k are as follows. Corporate loans carry a 100% weight, portfolio mortgages carry a 50% weight, GSE-eligible nonportfolio mortgages carry a 20% weight, and government-insured mortgages carry a 0% weight. With these assumptions, our average risk weight measure for bank i is defined by

$$\tilde{w}_i \equiv \sum_k w_k L_{ik} / \sum_k L_{ik}$$

where L_{ik} is bank i's loan exposure in asset category k.

we regress the logarithm of bank-level variables on time-dummies interacted with O&G exposure, time dummies interacted with bank controls, time dummies, bank fixed effects, and bank-specific time trends.[36]

In figure 7 we show coefficients and 95-percent confidence bands of the coefficients on the time dummies interacted with O&G exposure, where the dependent variable is the risk-weighed asset ratio (Panel A), the liquid assets ratio (Panel B), the leverage ratio (Panel C), and log total assets (Panel D). Panel A shows that there is a statistically significant movement downwards in the average risk weight across the balance sheet among banks who were more exposed to the oil shock. A one standard deviation increase in exposure amounts to about a 200 basis point decrease in the risk-weighed asset ratio, interpretable as the average risk weight. The pattern is consistent with our more granular regression evidence. In contrast, the relative behavior of total assets and leverage show no obvious or statistically significant pattern. Thus, we find evidence of de-risking, but little evidence of de-leveraging in the traditional sense.

VI. Evidence of a credit channel

The ability to substitute to alternative funding sources is an important determinant of the ultimate impact of the oil shock on borrowers. To assess the credit channel, we run a specification similar to (1), but aggregated to the level of the borrower:

$$\Delta Y_j = \beta_0^F + \beta_1^F \bar{Z}_j + \beta_2^F W_j + \beta_3^F \bar{X}_j + \eta_j, \tag{2}$$

where ΔY_j is the change (from pre- to post-oil shock) in an attribute Y of firm j.[37] $\bar{Z}_j^F$ is the weighted average O&G exposure of the banks from whom firm j borrowed in the pre-shock period. The variable is meant to capture how exposed the *firm* was to the credit supply effects induced by the oil price shock, via the banks with whom it was associated. W_j are firm controls and $\bar{X}_j$ are weighted

[36]Omitted periods in the regression are 2012:Q3 and 2014:Q2, implying bank-specific time trends capture pre-shock trends. Bank controls include pre-shock loan-weighted average levels of ROA, equity/total assets, NPL/total assets, tier-1 capital/risk-weighted assets, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, and a foreign bank dummy. O&G exposure was normalized to have unit standard deviation. The risk-weighted assets ratio is defined as total risk-weighted assets divided by total assets. The liquid asset ratio is defined as liquid assets divided by total assets, where liquid assets are defined as cash holdings, U.S. Treasuries, U.S. government agency debt, and agency-backed MBS. The leverage ratio is defined as total assets divided by equity. All data are from the FR-Y9. Standard errors are clustered by bank. To correct for a coding change in risk weights implemented by Basel III in 2015:Q1, the risk-weighted asset ratio (panel D) for 2015:Q1 for each bank was spliced with its 2014:Q4 value.

[37]Or county j for the mortgage results.

averages of the characteristics of the banks. β_1^F indicates whether or not firms were systematically affected by being exposed indirectly to the oil shock. One would expect a negative coefficient if firms are unable to substitute alternative financing. However, if the firm can substitute for any reduced financing or away from lending on worsened terms, then one might not expect any effect.

In table 6 we show results for various dependent variables. The first two columns of table 6 relate to the change in firms' total term loan borrowing and total borrowing from Y14 banks, respectively. These regressions show a statistically insignificant relationship with the aggregate exposure variable, implying that firms that were borrowing from more exposed banks in the pre-shock period had no net change in their term loans due to the credit supply shock. This result implies that firms were able to substitute simply from other Y14 banks.

In columns 3-5 we move beyond the Y14 borrowing to look at additional balance sheet objects from Compustat. Here we see no statistically significant estimates, implying essentially no relationship between changes in total liabilities (or assets, or equity) and the aggregate exposure variable. Overall, in spite of the significant adjustments that exposed BHCs were making in the wake of the oil price shock, borrowing firms (at least in the Compustat sample) were apparently able to smooth out the effects of the shift in credit supply using other means.[38]

To pin down a particular channel for substitution, we isolate those firms that switched banks (among the Y14 filers). Returning to table 7 (column 5), we run our firm-level regressions with the dependent variable being a dummy variable equal to one if the firm exited at least one banking relationship and entered at least one banking relationship. The coefficient on aggregate O&G exposure is positive and statistically significant, indicating that those firms more exposed to the credit supply shock were more likely to switch banks.[39]

We also consider the ultimate effect on mortgage borrowing at the county level. Table 9 contains the aggregate regressions, where we relate changes in county-level mortgage balances to the counties' aggregate exposure (analogous to the corporate case). We assess three different categories: portfolio loans, all Y14

[38]We use the Compustat variables in this case because they are obtained from official financial statements and should be more accurate than bank-reported equivalents in the Y-14. The sample size declines substantially in columns 3-5 of table 6 due to the requirement that Compustat firms be publicly traded. Jimenez et al. (2014) suggest a bias adjustment (described in the online descriptive appendix) to the firm level estimated coefficient based on comparing the bank-firm level coefficients from FE and OLS regressions. Making this adjustment does not materially change our insights.

[39]We examined whether firms initially borrowing from more exposed banks drew on open lines of credit. While there seemed to be little evidence overall, there appeared to be an effect for firms with relatively large shares of their borrowing capacity untapped (results are available on request).

loans, and all loans from the Black Knight-McDash Analytics database, which samples loans from the universe of lenders and not just those in the Y14. For all three levels of aggregation there is no statistically significant effect on loan quantity, again suggesting a limited broad credit channel and suggestive of a large degree of substitution to other lenders by households in exposed counties.

There are, of course, a couple of caveats to our result of a limited credit channel. First, it is possible that firms that maintained their relationships with exposed banks still may have suffered due to worsened terms. Second, responses to a larger shock during a systemic tightening could differ from our findings, as suggested by crisis-era papers. Nevertheless, it is interesting that in our case, which may be thought representative of a 'normal shock in normal times', the degree of substitutability of credit seems substantial. Thus we provide a benchmark for studies focusing on more turbulent times.

VII. Robustness

While anecdotal reports and the banks' answers in lending surveys give support to our regressions and our overall story, in this section we carry out a set of robustness checks. First, we consider the implications of defining our exposure variable as a share of total on-balance-sheet loans, of total assets, and of equity capital (all as reported in the FR Y-9C) rather than as a share of total committed commercial loan exposure. The motivation for this (though Chodorow-Reich (2014) also scales his exposure by loans, for example) is that the size of the loan book and capital position of banks may differ, implying noise and possibly bias in our index. Table C2 shows that these changes do not substantially alter our findings.

A possible concern is that our regression specification contains too few clusters, leading to either 'overfitting' of the cluster-robust variance matrix estimate or over-rejection of the critical values (Cameron and Miller (2015)). There is no definitive measure of 'too few', but the general consensus is around 30 clusters - close to the number of banks in our sample. To address this issue, we re-assess our standard errors using the wild cluster bootstrap recommended by Cameron and Miller (2015). The results coincide with our main results above using two-way clustering, showing strong statistical significance for the C&I, portfolio residential, and government residential lending, but noisier results on non-portfolio non-government lending.[40]

[40]Table C3 in the online robustness appendix shows the p-values on β_1 for all of our firm-bank and

There is also a potential concern that the predictive power of our exposure variable was somehow a coincidence. To address this concern, we run a type of permutation test using each bank's loan exposure to other industries as placebos. Analogous to the O&G exposure variable used throughout this paper, for each of the most prevalent other 49 industries (defined by 3-digit NAICS) we create a bank-specific exposure variable analogous to our O&G exposure variable. We then run our main fixed-effects specification 50 times - once replicating our original specification, and 49 subsequent regressions using the alternative industry exposures. To be conservative, we collected the associated t-statistic based upon the standard errors obtained from the wild cluster bootstrap. In figure 8 we show the distribution of t-statistics obtained from our intensive and extensive corporate lending regressions. Clearly, sampling variability associated with this test means that, even if our O&G exposure variable were the 'true' exposure variable, it would not necessarily emerge as having the largest t-statistic. However, we would at least hope for it to be in the tail. In fact, the results are extremely strong. In the intensive regressions, our exposure variable is a clear outlier in the left tail (where the left tail is most relevant given the limited upside to a debt contract) and in the right tail in the extensive regressions.

Roughly contemporaneous to the oil price shock, U.S. banking regulators were in the process of phasing in new balance sheet liquidity requirements for many of the banks in our sample. The new regulations stipulated that banks maintain a liquidity coverage ratio (LCR) whereby liquid assets could be used to offset possible funding outflows in a period of stress. The rule may have influenced the demand for liquid assets for certain banks, which include agency MBS. In the U.S., BHCs with assets over \$250 billion needed to meet 80 percent of their liquidity requirements in 2015 (i.e., in our post-shock window). BHCs with assets above \$50 billion but below \$250 billion were subject to a modified and less severe LCR requirement with a phase-in period in 2016 (i.e., outside our post-shock window).

In response, we construct an indicator variable to identify banks with assets over \$250 billion and subject to the LCR phase-in in 2015, and then interact this variable with a proxy for exposure to the LCR in the pre oil-shock period. This

county-bank pair regressions, under the wild cluster bootstrap. We also include in the table p-values under the amended definition of bank exposure, in which we scale committed balances by bank equity, rather than total committed C&I loan balances. Although clustering should guard against an individual bank driving our results we also ran our commercial intensive and extensive fixed effect regressions repeatedly, each time removing a different bank from the sample. We retained significance in all cases and the coefficient value was consistent (average and standard deviation of -0.81 and 0.06, respectively, for intensive and 0.84 and 0.08 for the exit regressions).

proxy consists of a measure of high-quality liquid assets (Treasury Securities + Agency MBS) which is then scaled by a measure of possible funding outflows (Total Liabilities - Deposits). Thus, BHCs with large values for the proxy have ample liquidity, or are more reliant on deposits (or both), and thus would be less constrained by the LCR. When we include these variables among the bank controls in our regressions we find only small quantitative differences in the estimates of the sensitivity of lending to O&G exposure and no differences in statistical significance. Indeed, the coefficients on the LCR controls are not statistically significant in any of the mortgage regressions.

Finally, although it is less a robustness test than a useful re-expression, we recast our shock in terms of its relative impact on bank valuations. To do so, we run a two-stage specification of our model, first regressing the bank's change in log market capitalization (between the pre and post period) on the bank's O&G exposure and then using this fitted change in valuation to explain the various changes in loans discussed above. In this way, we obtain an elasticity of lending with respect to a change in market capitalization attributable to the oil price shock. This allows us to map the oil shock into a common scale that might be transferrable to other studies, rather than leaving it in terms of exposure to a particular industry.

In table 10, we repeat our main regressions under this two stage approach. We lose some power through this procedure but qualitatively our results are confirmed and in most cases we retain statistical significance. Our results imply that a 1 percent hit to net worth leads to a 0.90 percent decline in corporate lending on the intensive margin and a 0.95 percent increase in the probability of exit. In terms of mortgage lending, the response is a 1.8 percent decline for non-government portfolio loans, 0.6 percent increase for non-government non-portfolio, and a 3.5 percent increase for government loans. Our aggregate regressions again suggest that the ultimate impact on exposed borrowers was minimal, relative to those borrowing from less exposed banks.

VIII. Conclusions

Banks damaged by exposure to industries adversely affected by the oil price decline made significant adjustments to their balance sheets. Banks de-risked their balance sheet by undertaking actions that reduced their average risk weight. We document a significant pull-back in commercial lending by exposed banks, both on the intensive and the extensive margins. Importantly, however, the balance sheet adjustments by banks exposed to the oil price shock were not confined to the corporate loan portfolio where the shock might be expected to have its most direct impact. Exposed banks tightened credit supply for those mortgages that they would have to hold in their own portfolios, while expanding credit for loans that were government-backed and could be securitized. Overall, it appears there was a tendency of the damaged banks to de-leverage by de-risking. This is a new insight relative to the traditional 'bank lending channel' view which emphasizes a general de-leveraging and pull back in lending.

Ultimately, the relative impact on borrowers who were particularly exposed to damaged banks appears to have been limited. The ability to substitute to alternative financing sources largely allowed borrowers to smooth through any credit tightening imposed by the exposed banks—although it is still possible that firms unable to switch banks easily may have suffered from worsened credit terms even as they maintained their quantity of borrowing. This likely reflects the health of the U.S. financial system in 2014 and the moderate size of the shock, but nevertheless we provide a benchmark for studies of larger shocks in more turbulent periods.

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Table 1—Bank summary statistics - average values pre-oil shock

	Commercial Loan Analysis		Residential Loan Analysis	
	Mean	Std. Dev.	Mean	Std. Dev.
Total assets (\$*billions*)	474	675	466	694
Non-performing loan ratio (commercial loans)	.010	.007	.010	.007
Tier-1 Capital Ratio	.129	.020	.126	.016
Mean ROA (quarterly)	.002	.001	.002	.001
Equity/Total assets	.116	.023	.118	.022
On-balance-sheet total loans/Total assets	.526	.225	.561	.192
On-balance-sheet commercial loans/Total on-balance-sheet loans	.240	.104	.252	.096
On-balance-sheet residential loans/Total on-balance-sheet loans	.285	.135	.306	.116
Total charge-offs/Total on-balance-sheet loans	.006	.005	.006	.005
Deposit share of total liabilities	.726	.231	.748	.201
Foreign bank dummy	.214		.231	
Lag Δ log commercial loans (2012:Q3 to 2014:Q2)	.326	.662		
Lag Δ log residential loans (2012:Q3 to 2014:Q2)			-.025	.201
Lag Δ log MBS (2012:Q3 to 2014:Q2)			.038	.700
Committed O&G loans/Total committed commercial loans	.059	.049	.060	.049
Committed O&G loans/Total on-balance-sheet loans	.046	.042	.045	.041
Committed O&G loans/Total assets	.023	.027	.025	.027
Committed O&G loans/Equity	.194	.210	.205	.213
Observations	28		26	

Notes: Data are from the Y9-C and are taken as the average from the 2012:Q3 to 2014:Q2 period. Lag Δ log commercial loans, lag Δ log residential loans, and lag Δ log MBS are constructed as the change between 2012:Q3 and 2014:Q2.

TABLE 2—REGRESSION SAMPLES - FIRM AND LOAN CHARACTERISTICS

	Intensive Margin		Exit Margin		Entry Margin	
	FE Sample	OLS Sample	FE Sample	OLS Sample	FE Sample	OLS Sample
			Firm Variables			
Number of firms	3,541	42,111	7,802	65,724	5,901	60,121
Assets ($ millions)	720	179	569	178	619	182
	(745)	(455)	(711)	(454)	(722)	(479)
Access to external finance	.56	.11	.44	.11	.47	.10
	(.49)	(.31)	(.50)	(.31)	(.50)	(.30)
Share of credit lines utilized (pre-shock period)	.72	.89	.74	.88		
	(.28)	(.22)	(.29)	(.23)		
Number of bank relationships (pre-shock period)	4.5	1.5	3.6	1.4		
	(3.2)	(1.5)	(2.7)	(1.4)		
			Loan Variables			
Number of loans	10,169	48,739	20,006	77,928	17,132	74,407
Loan size ($ millions, pre-shock period)	22.9	10.8	18.9	9.9		
	(47.0)	(41.2)	(41.4)	(36.7)		
Δ Log loan size	-.05	-.07				
	(.47)	(.35)				
Exit in post-shock period			0.39	0.41		
			(0.49)	(0.49)		
Entry in post-shock period					0.26	0.28
					(0.44)	(0.45)

Notes: Listed are means and standard deviations in parentheses of variables used in the six main commercial loan samples. A "loan" is defined as a bank-firm pair. The pre and post data are averaged over 2012:Q3 to 2014:Q2 and 2015:Q1 to 2015:Q3, respectively. Access to external finance = dummy for whether the firm has either a CUSIP or a ticker; Share of credit lines utilized = total utilized commercial loan exposure in the pre-period (2012:Q3 to 2014:Q2) divided by total committed commercial loan exposure over the pre-period.

Table 3—The bank lending channel - commercial loans, intensive margin

	Δ Log loan Size			
	FE-IV	FE	OLS	OLS
O&G Exposure	-0.713***	-0.824***	-0.586***	-0.326***
	(0.248)	(0.162)	(0.172)	(0.059)
Log Total Assets	0.057***	0.060***	0.043***	0.035***
	(0.011)	(0.009)	(0.009)	(0.004)
ROA	-13.676***	-14.124***	-7.346**	-7.446***
	(4.338)	(4.001)	(3.746)	(1.426)
Equity/Total Assets	-1.236**	-1.299***	-0.421	-0.999***
	(0.544)	(0.488)	(0.555)	(0.136)
Lag Δ Log Commercial Loans	-0.044	-0.055	-0.043	-0.009
	(0.047)	(0.040)	(0.031)	(0.016)
NPL/Total Assets	-4.098	-4.522**	-3.940**	-1.859**
	(2.508)	(2.223)	(1.780)	(0.749)
Tier-1 Capital/RWA	1.041	1.144	0.484	1.327***
	(0.794)	(0.731)	(0.679)	(0.204)
Total Loans/Total Assets	0.433***	0.456***	0.221**	0.209***
	(0.132)	(0.116)	(0.108)	(0.041)
Charge Offs/Total Loans	-6.836***	-7.113***	-3.213***	-1.908***
	(1.578)	(1.442)	(1.213)	(0.733)
Commercial Loans/Total Loans	-0.576***	-0.617***	-0.504***	-0.312***
	(0.142)	(0.116)	(0.106)	(0.043)
Residential Loans/Total Loans	-0.652***	-0.714***	-0.566***	-0.514***
	(0.230)	(0.181)	(0.169)	(0.055)
Deposits/Total Liabilities	0.117**	0.123**	0.108**	0.151***
	(0.049)	(0.048)	(0.048)	(0.028)
Foreign Bank Dummy	0.214***	0.230***	0.182***	0.145***
	(0.049)	(0.038)	(0.034)	(0.013)
Number of Observations	10162	10162	10162	48739
R-squared	0.59	0.59	0.18	0.06
Fixed Effects	Firm	Firm	Firm Controls	Firm Controls
Instrument	Branch Share			

Notes: The dependent variable is the change in log term-loan size. All quarterly data for a given loan were collapsed to a single pre and post period, defined as 2012:Q3 to 2014:Q2 and 2015:Q1 to 2015:Q3, respectively. We removed from the sample loans to firms in the oil and gas industry and data was restricted to term loans for consecutive quarters throughout both the pre- and post period (i.e., no exiting and re-entering). O&G exposure is constructed as total committed loans to O&G firms divided by total committed commercial loans in 2012 and 2013. Column 1 is estimated under IV, where O&G exposure is instrumented by the share of the BHC's branches in 2009 in counties with any O&G income. Columns 1 and 2 are run on the sample of firms that borrow term loans from multiple banks and include firm fixed effects. Column 3 is run on the same sample of firms as columns 1 and 2 (but excluding firms in the O&G industry) and includes firm controls instead of firm fixed effects. Column 4 includes firms that borrow from single banks and includes firm controls. All bank controls listed are measured in the pre-shock period. Firm controls in columns 3 and 4 include industry-times-region fixed effects (across 322 industries—3-digit NAICS codes, and 9 regions—the first digit of firm's zip code) and a dummy indicating whether the firm borrows from multiple banks. Standard errors in parentheses are two-way clustered at the bank (28 banks in total) and firm level. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$.

TABLE 4—THE BANK LENDING CHANNEL - COMMERCIAL LOANS, EXTENSIVE MARGIN

	Exit?				Entry?			
	FE-IV	FE	OLS	OLS	FE-IV	FE	OLS	OLS
O&G Exposure	1.003***	0.843***	0.728***	0.110	0.012	-0.107	0.033	0.199
	(0.198)	(0.158)	(0.197)	(0.072)	(0.226)	(0.175)	(0.211)	(0.279)
Log Total Assets	-0.030***	-0.027**	0.007	0.012*	-0.052***	-0.050***	-0.039**	-0.054**
	(0.011)	(0.011)	(0.011)	(0.007)	(0.012)	(0.012)	(0.017)	(0.026)
ROA	8.150	7.655	4.368	0.931	6.867	6.582	2.060	6.130
	(5.963)	(6.088)	(7.410)	(2.846)	(5.236)	(5.370)	(6.800)	(7.803)
Equity/Total Assets	0.304	0.223	-0.365	-0.403	0.779	0.729	-0.201	0.782
	(0.741)	(0.752)	(0.854)	(0.321)	(0.612)	(0.611)	(0.757)	(0.841)
Lag Δ Log Commercial Loans	0.076**	0.062*	0.053	0.009	0.064*	0.054*	0.055	0.040
	(0.037)	(0.036)	(0.035)	(0.021)	(0.037)	(0.033)	(0.044)	(0.060)
NPL/Total Assets	3.513*	3.047	2.203	3.086**	7.756***	7.400***	9.277***	12.730***
	(2.016)	(1.998)	(2.430)	(1.524)	(2.171)	(1.938)	(2.376)	(2.856)
Tier-1 Capital/RWA	1.156*	1.308**	2.401***	1.219***	-0.475	-0.353	0.301	-0.284
	(0.598)	(0.581)	(0.788)	(0.421)	(0.946)	(0.883)	(1.340)	(1.662)
Total Loans/Total Assets	-0.231	-0.201	0.055	0.026	-0.152	-0.129	0.057	-0.174
	(0.150)	(0.154)	(0.127)	(0.060)	(0.144)	(0.138)	(0.158)	(0.190)
Charge Offs/Total Loans	1.052	0.672	-1.501	0.080	-0.504	-0.803	-2.398	-3.159
	(2.069)	(2.001)	(1.900)	(1.232)	(1.973)	(1.799)	(2.525)	(2.844)
Commercial Loans/Total Loans	0.511***	0.461***	0.470***	0.142*	-0.146	-0.185	-0.153	0.155
	(0.143)	(0.140)	(0.154)	(0.076)	(0.156)	(0.142)	(0.178)	(0.254)
Residential Loans/Total Loans	0.550***	0.469***	0.282	0.078	0.231	0.170	0.175	0.471**
	(0.168)	(0.161)	(0.187)	(0.094)	(0.203)	(0.175)	(0.193)	(0.184)
Deposits/Total Liabilities	-0.123*	-0.114	-0.109	0.033	-0.151**	-0.145**	-0.217**	-0.339***
	(0.068)	(0.069)	(0.077)	(0.050)	(0.060)	(0.060)	(0.097)	(0.122)
Foreign Bank Dummy	-0.150***	-0.130***	-0.092**	-0.012	-0.054	-0.040	-0.037	-0.128***
	(0.038)	(0.039)	(0.038)	(0.021)	(0.046)	(0.041)	(0.044)	(0.042)
Number of Observations	20004	20004	20004	77927	17129	17129	17129	74404
R-squared	0.60	0.60	0.11	0.04	0.56	0.56	0.12	0.11
Fixed Effects	Firm	Firm	Firm Controls	Firm Controls	Firm	Firm	Firm Controls	Firm Controls
Instrument	Branch Share				Branch Share			

Notes: The dependent variable in columns 1-4, "exit," is an indicator whether the term loan is not renewed and the firm exits its banking relationship in the post-shock period. The dependent variable in columns 5-8, "entry," is an indicator if the term loan was made for the first time in the post-shock period. We removed from the sample loans to firms in the O&G industry. O&G exposure is constructed as total committed loans to O&G firms divided by total committed commercial loans in 2012 and 2013. Columns 1 and 5 are estimated under IV, where O&G exposure is instrumented by the share of the BHC's branches in 2009 in counties with any O&G income. FE regressions are run on the sample of multi-bank firms. Columns 4 and 8 include single-bank firms. All bank controls listed are measured in the pre-shock period. Firm controls include industry-times-region fixed effects (across 322 industries—3-digit NAICS codes, and 9 regions—the first digit of firm's zip code) and a dummy indicating whether the firm borrows from multiple banks. Standard errors in parenthesis are two-way clustered at the bank (28 banks in total) and firm level. $^{*}p < 0.10, ^{**}p < 0.05, ^{***}p < 0.01$.

Table 5—The bank lending channel - commercial loans, interaction effects

	Intensive Margin		Exit?	
	FE	OLS	FE	OLS
O&G Exposure	-1.105**	-0.137	1.023**	0.310
	(0.480)	(0.361)	(0.428)	(0.311)
O&G Exposure*External Finance Firm	0.044	0.126	0.047	0.255
	(0.245)	(0.131)	(0.298)	(0.336)
External Finance Firm		-0.002		-0.033*
		(0.011)		(0.019)
O&G Exposure*(Pre-period # of Bank Relationships)	-0.016	-0.025	0.042	0.056**
	(0.026)	(0.033)	(0.026)	(0.027)
Pre-period # of Bank Relationships		0.008***		-0.024***
		(0.003)		(0.002)
O&G Exposure*(Pre-period Utilization Rate)	0.515	-0.136	-0.668	-0.363
	(0.480)	(0.348)	(0.423)	(0.337)
Pre-period Utilization Rate		-0.092***		-0.154***
		(0.023)		(0.023)
Number of Observations	10162	48739	20004	77927
R-squared	0.59	0.06	0.60	0.05
Fixed Effects	Firm	Firm Controls	Firm	Firm Controls

Notes: The dependent variable for columns 1 through 4 is the change in log term-loan size and for columns 5 through 8 is an indicator whether the term loan is not renewed and the firm exits its banking relationship in the post-shock period (i.e., "exit."). All quarterly data for a given term loan were collapsed to a single pre- and post-shock period, defined as 2012:Q3 to 2014:Q2 and 2015:Q1 to 2015:Q3, respectively. We removed from the sample loans to firms in the O&G industry. Data for the FE regressions were restricted to term loans in the sample for consecutive quarters throughout both the pre- and post-shock period (i.e., no exiting and re-entering). O&G exposure is constructed as total committed loans to oil and gas firms divided by total committed commercial loans in 2012 and 2013. Columns 1 and 3 are run on the sample of firms with term loans from multiple banks and include firm fixed effects. OLS regressions include firms that borrow from single banks and includes firm controls. Firm controls include industry-times-region fixed effects (across 322 industries—3-digit NAICS codes, and 9 regions—the first digit of firm's zip code) and a dummy indicating whether the firm borrows from multiple banks. Small firm = total borrowing by firm from all banks is in bottom 70%, external finance firm = dummy for whether the firm has either a CUSIP or a ticker; pre-period utilization rate = total utilized commercial loan exposure in the pre-period (2012:Q3 to 2014:Q2) divided by total committed commercial loan exposure over the pre-period; pre-period # of banks = number of banks the firm has at least one loan with in the pre-shock period; length of relationship = years between date of first origination and 2014:Q2. Bank controls include pre-shock period ROA, equity/total assets, NPL/total assets, tier-1 capital/risk-weighted assets, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, lag change in log commercial loans (defined between 2012:Q3 and 2014:Q2), and a foreign bank dummy. Standard errors in parentheses are two-way clustered at the bank and firm level (28 banks in total). $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$.

TABLE 6—THE CREDIT CHANNEL - FIRM REGRESSIONS

	Y14		Y14 & Compustat		
	Term Loans	All Loans	Liab	Eqty	Assets
Agg O&G Exposure	0.056	0.044	-0.181	-0.332	0.243
	(0.066)	(0.074)	(0.499)	(0.614)	(0.435)
Constant	0.147	0.523***	-0.062	-0.821	-0.249
	(0.136)	(0.153)	(0.647)	(0.767)	(0.500)
Number of Observations	47208	47191	1466	1435	1466
R-squared	0.06	0.07	0.40	0.38	0.41
Bank Controls	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes

Notes: These regressions are run at the firm level. We removed from the sample loans to firms in the O&G industry. The dependent variable is the change in log total term-loan borrowing (column 1), the change in log total-loan borrowing (column 2), the change in log total liabilities (column 3), the change in log total equity (column 4), and the change in log total assets (column 5) by firm across the pre- and post-shock period. Total term loan borrowing includes all term loans across all banks in the Y14 sample. Total-loan borrowing includes utilized loans of all types (i.e., not just term loans) across all banks in the Y14 sample. Liabilities, equity, and assets are taken from Compustat, limiting the sample of firms. All quarterly data for a given loan were collapsed to a single pre and post period, defined as 2012:Q3 to 2014:Q2 and 2015:Q1 to 2015:Q3, respectively. Firm controls include industry-times-region fixed effects (across 322 industries—3-digit NAICS codes, and 9 regions—the first digit of firm's zip code) and a dummy indicating whether the firm borrows from multiple banks. Agg-exposure is the loan-size weighted O&G exposure across all banks by the firm. Bank controls include pre-shock period loan-weighted average levels of ROA, equity/total assets, NPL/total assets, tier-1 capital/risk-weighted assets, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, lag change in log commercial loans (defined between 2012:Q3 and 2014:Q2), and a foreign bank dummy. Robust standard errors in parentheses. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Table 7—Substitute financing - alternative banks

	Entry?				Switch?
	FE	FE	FE	FE	OLS
O&G Exposure	-0.523**	0.292	-0.346*	0.417	
	(0.246)	(0.200)	(0.182)	(0.268)	
Agg O&G Exposure					0.089***
					(0.020)
Number of Observations	7285	8437	12011	5118	
R-squared	0.41	0.42	0.36	0.63	
Fixed Effects	Firm	Firm	Firm	Firm	Firm Controls
Bank Controls	Yes	Yes	Yes	Yes	Yes

Notes: Fixed-effects (FE) regressions are run at the loan level. The dependent variable of the FE regressions is an indicator if the term loan was made for the first time in the post-shock period (i.e., entry). All FE regressions are run with multiple banking relationships using firm fixed effects. Column 1 is run on the sample of firms that exited from at least one banking relationship in the post period. Column 2 is run on the sample of firms that did not exit any banking relationship. Column 3 is run on a sample firms with at least one loan that declined in size. Column 4 is run on a sample of firms without any loans that decreased in size. Bank controls include pre-shock period ROA, equity/total assets, NPL/total assets, tier-1 capital/RWA, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, lag change in log commercial loans (defined between 2012:Q3 and 2014:Q2), and a foreign bank dummy. Column 5 is a regression run at the firm level, where the dependent variable is a dummy equal to one if the firm exited at least one banking relationship and entered at least one banking relationship between the pre- and post-shock period. Bank controls are loan-size weighted in the OLS specification. We removed from the sample loans to firms in the O&G industry. Standard errors in parentheses are two-way clustered at the bank (28 banks in total) and firm level for FE regressions and robust standard errors reported for the OLS regression. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$.

TABLE 8—THE BANK LENDING CHANNEL - RESIDENTIAL LOANS

	Non-Government						Government	All Loans
		Portfolio Loans			Non-Portfolio Loans			
	All (IV)	All	Jumbo	Non-Jumbo	All	Non-Jumbo		
Panel A: County Fixed Effects								
O&G Exposure	-3.111***	-2.247***	-1.451	-2.521**	1.073	3.042**	8.426***	-1.502
	(0.716)	(0.538)	(0.920)	(1.019)	(0.933)	(1.185)	(1.190)	(0.944)
Number of Observations	19929	19929	5555	18913	23353	23247	13712	29056
R-squared	0.23	0.23	0.29	0.26	0.23	0.26	0.40	0.24
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	County	County	County	County	County	County	County	County
IV	Branch Share							
Panel B: OLS								
O&G Exposure	-2.979***	-2.223***	-1.522*	-2.512**	0.965	2.941**	8.295***	-1.518
	(0.705)	(0.531)	(0.911)	(1.039)	(0.924)	(1.232)	(1.133)	(0.955)
Number of Observations	19928	19928	5555	18912	23351	23245	13710	29053
R-squared	0.09	0.09	0.09	0.13	0.11	0.14	0.23	0.16
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	State	State	State	State	State	State	State	State
County Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV	Branch Share							

Notes: The dependent variable is the change in log residential loans by bank-county. All quarterly data for loans was aggregated by bank-county and then collapsed to a single pre- and post-shock period, defined as 2012:Q3 to 2014:Q2 and 2015:Q1 to 2015:Q3, respectively. O&G exposure is constructed as total committed loans to oil and gas firms divided by total committed commercial loans in 2012 and 2013. Column 1 is estimated under IV, where O&G exposure is instrumented by the share of the BHC's branches in 2009 in counties with any O&G income. Portfolio loans are divided between non-government jumbo loans, non-government non-jumbo loans, and government loans (i.e., FHA and VA loans). We include only loans originated by the BHC (i.e., we removed mortgages with loan source marked as correspondent, servicing rights purchased, and bulk purchased). Bank controls include pre-shock period ROA, equity/total assets, NPL/total assets, tier-1 capital/RWA, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, lag change in log residential loan (defined between 2012:Q3 and 2014:Q2), lag change in log MBS (defined between 2012:Q3 and 2014:Q2), and a foreign bank dummy. County controls include pre-period log population, log population density, percent veterans, log housing density, percent urban housing units, percent occupied housing units, percent vacant housing units, log median house value, log median rental value, fraction of housing with 3 or more individuals, percent in poverty, unemployment rate, percent disabled, log median household income. Standard errors in parentheses are two-way clustered at the bank (26 banks in total) and county level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9—The credit channel - county regressions

	Y-14		LPS
	Portfolio	All	
Aggregate O&G Exposure	-0.477	-0.263	-0.105
	(0.901)	(0.428)	(0.532)
Number of Observations	2951	3010	3003
R-squared	0.15	0.10	0.08
Bank Controls	Yes	Yes	Yes
Fixed Effects	State	State	State
County Controls	Yes	Yes	Yes

Notes: The dependent variable is the change in log residential loans by county. All quarterly data for loans were aggregated by county and then collapsed to a single pre- and post-shock period, defined as 2012:Q3 to 2014:Q2 and 2015:Q1 to 2015:Q3, respectively. In column 1, we include only portfolio loans, and in column 2 all Y14 mortgages. In column 3, we include all loans in the LPS McDash Analytics database. Agg-exposure is the loan weighted O&G exposure across all banks in the county. Bank controls include pre-shock period (weighted to county level) ROA, ROE, NPL/total assets, tier-1 capital/RWA, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, lag change in log residential loan (defined between 2012:Q3 and 2014:Q2), lag change in log MBS (defined between 2012:Q3 and 2014:Q2), and a foreign bank dummy. County controls include pre-period log population, log population density, percent veterans, log housing density, percent urban housing units, percent occupied housing units, percent vacant housing units, log median house value, log median rental value, fraction of housing with 3 or more individuals, percent in poverty, unemployment rate, percent disabled, log median household income. Robust standard errors in parentheses. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$.

TABLE 10—THE BANK LENDING CHANNEL- INSTRUMENTAL VARIABLES

A: Commercial Loans

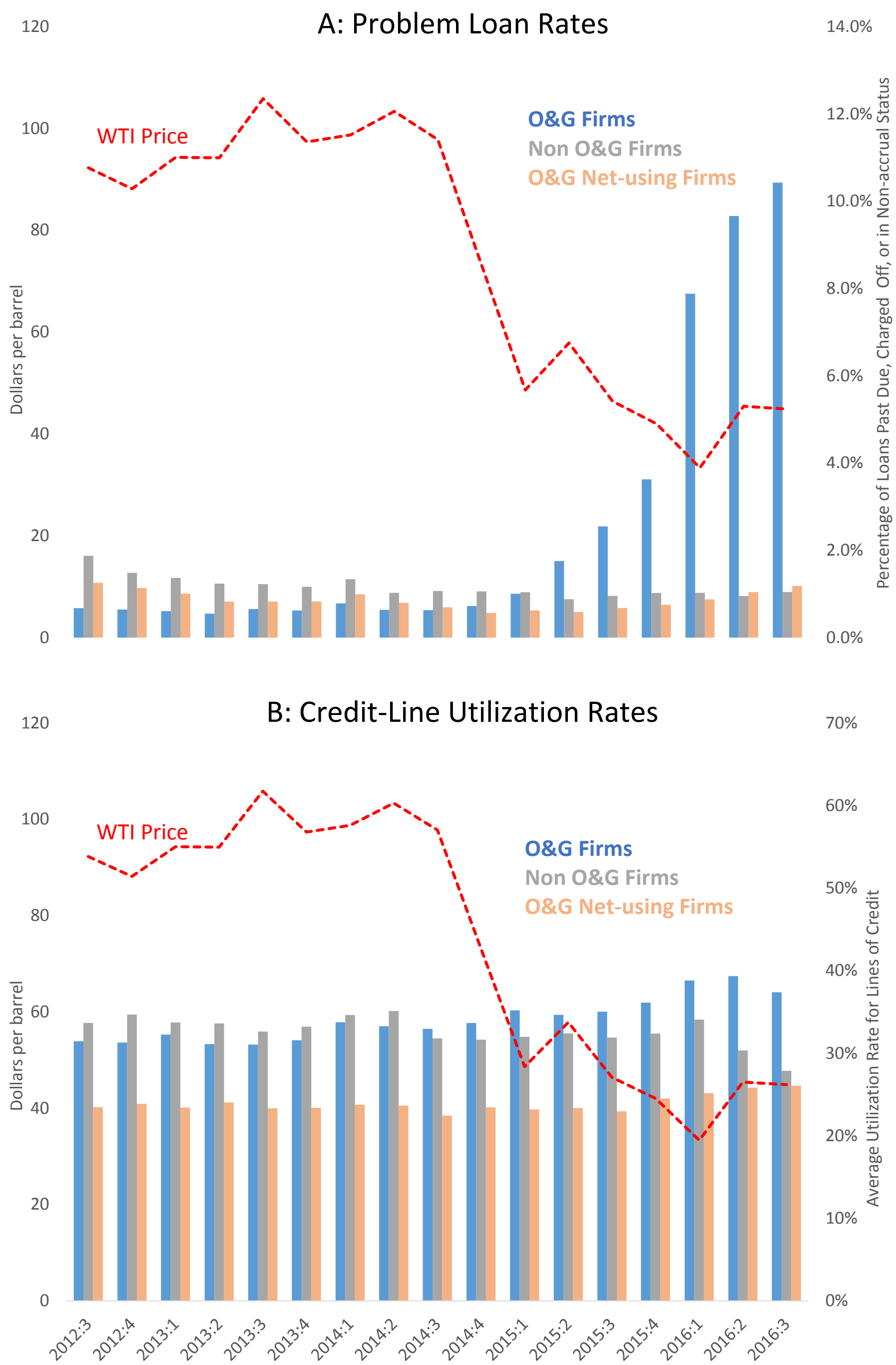
	Δ Log loan size	Exit?	Entry?
	FE-IV	FE-IV	FE-IV
		Second Stage	
Δ Log Market Cap	0.901***	-0.953**	0.056
	(0.328)	(0.410)	(0.209)
		First Stage	
O&G Exposure	-0.956***	-0.907**	-0.907**
	(0.368)	(0.353)	(0.367)
Number of Observations	9719	19222	16412
R-squared (second-stage)	0.60	0.61	0.57
Bank Controls	Yes	Yes	Yes
Fixed Effects	Firm	Firm	Firm

B: Residential Loans

	Non-Government		Government	All Loans
	Portfolio	Non-Portfolio		
	FE-IV	FE-IV	FE-IV	FE-IV
		Second Stage		
Δ Log Market Cap	1.812***	-0.581*	-3.453***	1.181
	(0.630)	(0.316)	(0.436)	(0.775)
		First Stage		
O&G Exposure	-1.427***	-2.772***	-2.679***	-1.749***
	(0.448)	(0.316)	(0.159)	(0.486)
Number of Observations	19451	22830	13514	28378
R-squared (second-stage)	0.24	0.24	0.41	0.25
Bank Controls	Yes	Yes	Yes	Yes
Fixed Effects	County	County	County	County

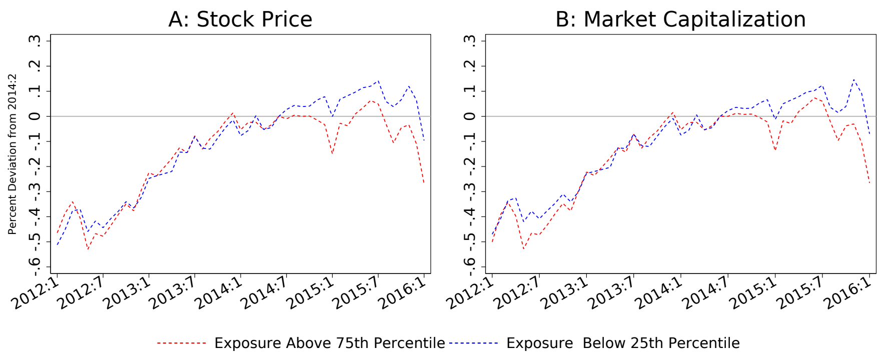
Notes: All regressions were run under two-stage least squares using O&G exposure as an instrument for the change in bank's market capitalization—defined as the difference in log average quarterly market capitalization in the post-period (2015:Q1 and 2015:Q3) and pre-period (2012:Q3 and 2014:Q2). The dependent variables are the change in log term-loan size (column 1, panel A), an indicator whether the term loan is not renewed and the firm exits its banking relationship in the post period (column 2, panel A), and an indicator if the term loan was made for the first time in the post-period (column 3, pane A), and the change in log residential loans (originated by the BHC) by county and type of loan (panel B). Bank controls include pre-shock period ROA, equity/total assets, NPL/total assets, tier-1 capital/RWA, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, and a foreign bank dummy. Residential loan regressions in include the lag change in log residential loan (defined between 2012:Q3 and 2014:Q2) and lag change in log MBS (defined between 2012:Q3 and 2014:Q2) as controls, and the commercial loan regressions include the lag change in log commercial loans (defined between 2012:Q3 and 2014:Q2) as a control. Standard errors in parentheses are two-way clustered at the bank and firm level. $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$.

Figure 1. Oil Prices, Problem Loans, and Credit-Line Utilization Rates



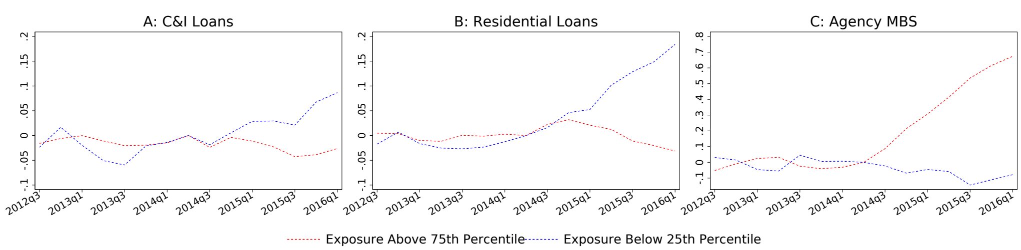
Notes: The red dashed line represents the price per barrel of crude West Texas Intermediate oil, collapsed to the quarterly level. Panel A: Blue bars represent the percentage of loans (i.e., including undrawn commitments) to oil and gas (O&G) firms (defined by NAICS codes 211, 213111, and 213112) that are either past due, charged off, or in non-accrual status (referred to as "problem loans"). Gray bars represent the percentage of loans to all non-O&G firms that are problem loans. Orange bars represent the percentage of loans to all net users of the O&G industry—defined as firms in industries with less than -0.10 in net trade (i.e., make minus use) with the O&G industry, as defined by the 2007 BEA make and use tables—that are problem loans. Panel B: Blue bars represent the average utilization rate on a line of credit (defined as total utilized amount divided by total committed amount) to O&G firms. Gray bars and orange bars represent the average utilization rate for non-O&G and net users of the O&G industry.

FIGURE 2. STOCK PRICE AND MARKET CAPITALIZATION - DEPENDENCE ON OIL EXPOSURE



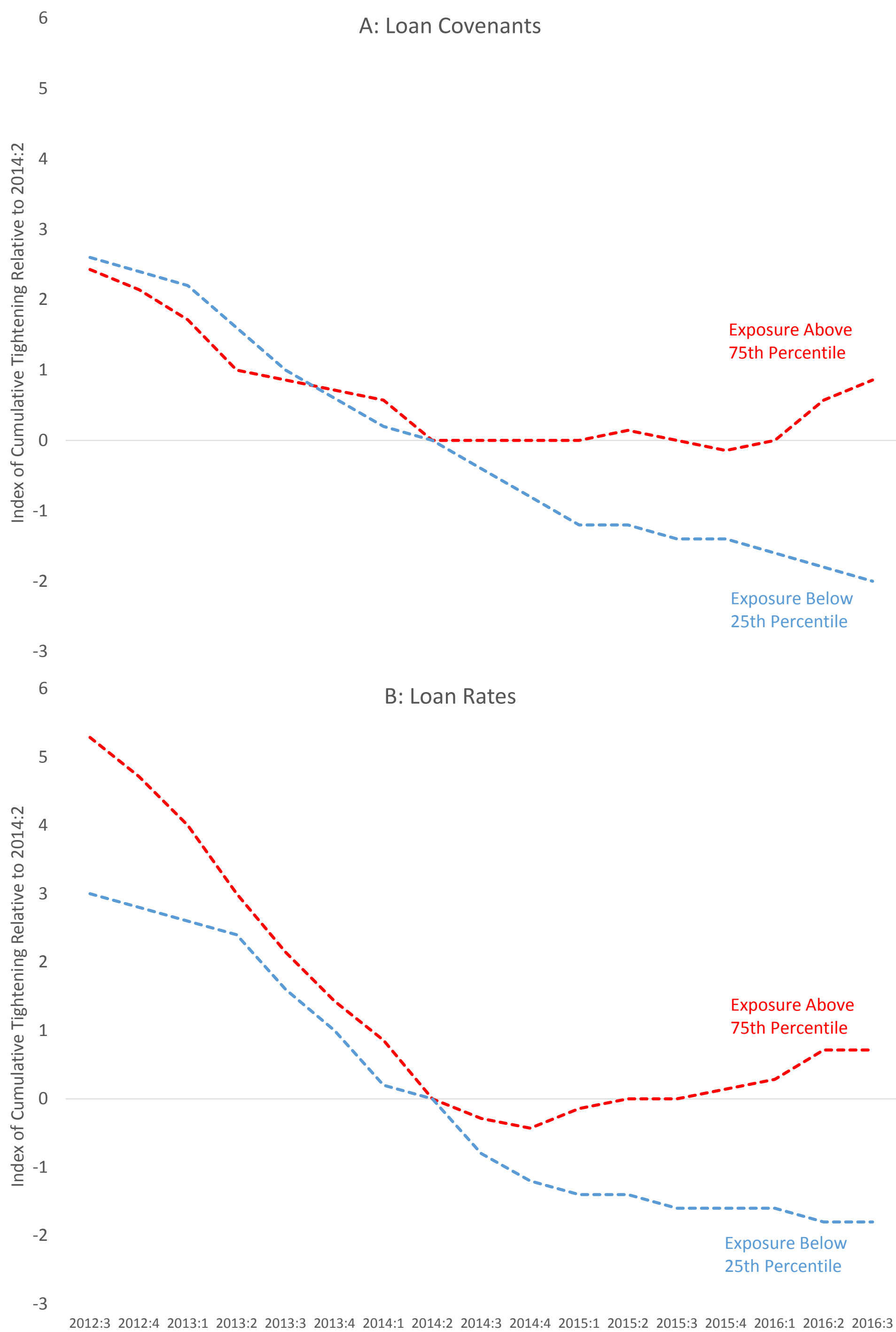
Notes: This figure illustrates the impact of a bank's oil and gas extraction (O&G) exposure to bank stock prices (panel A) and market capitalization (panel B). For each bank in each month, we calculate the deviation of its stock price or market capitalization from 2014:M6. The red dashed line represents the average deviation for banks in the upper-quarter in terms of exposure to the O&G sector, the blue dashed line represents the average deviation for banks in the bottom quartile.

FIGURE 3. BANK BALANCE SHEET VARIABLES - DEPENDENCE ON OIL EXPOSURE



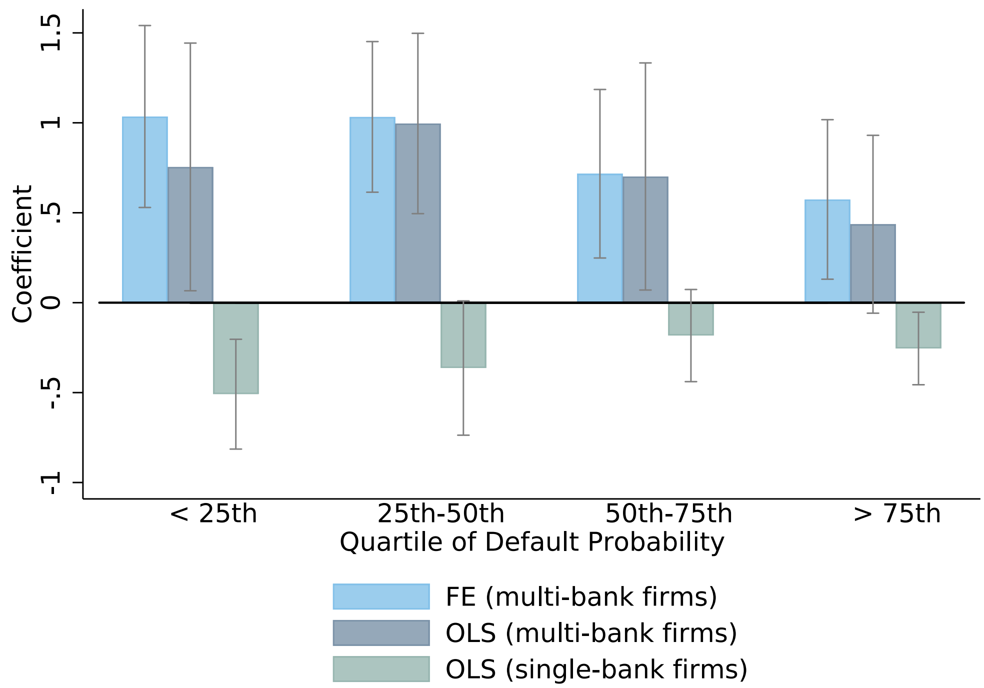
Notes: This figure illustrates the impact of a bank's oil and gas extraction (O&G) exposure to commercial and industrial loans (C&I), portfolio residential loans, and agency-backed MBS. All data are from the FR-Y9. For each bank, we regress the logarithm of the bank-level variable on a linear time trend over the pre-2014:Q2 sample. We collect the residuals and then normalize them by taking the difference relative to the 2014:Q2. We then sort banks into two groups—banks in the upper quartile (red-dashed line) and bottom quartile (blue-dashed line) O&G exposure—and average for each group.

Figure 4. Bank Lending Standards for Commercial Loans - dependence on oil exposure



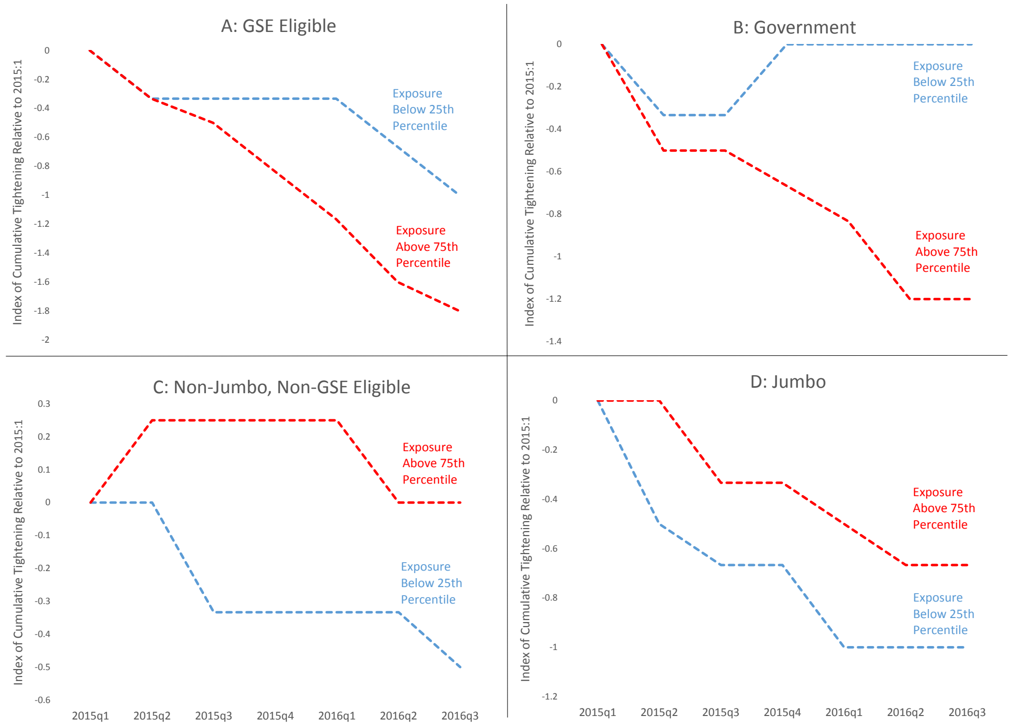
Notes: This figure illustrates the impact of a bank's oil and gas extraction (O&G) exposure to banks lending standards for commercial loans. All data are from the Senior Loan Officer Opinion Survey (SLOOS). For each bank we measured the cumulative amount of survey responses in which the response was a tightening of the specified variable—loan covenants (panel A) or loan rates (panel B)—relative to 2014:Q2. The red-dotted line represents the average for banks in the upper-quarter in terms of exposure to the O&G sector, the blue-dotted line represents the average for banks in the bottom quartile.

FIGURE 5. IMPLIED COEFFICIENTS ON O&G EXPOSURE BY BORROWER DEFAULT RISK



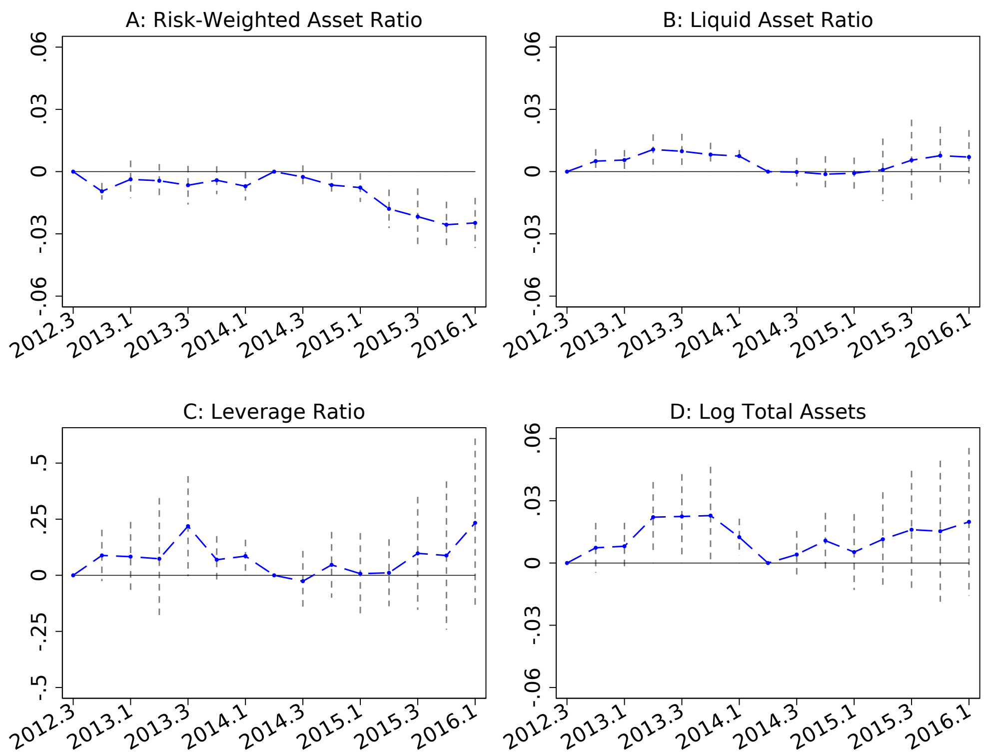
Notes: This figure plots estimates from the following regression: $Exit_{ij} = \beta_j + \beta_{1,1}Z_i + \beta_{1,2}Z_i * \mathbf{1}(\overline{PD}^{25th} < PD_j < \overline{PD}^{50th} + \beta_{1,3}Z_i * \mathbf{1}(\overline{PD}^{50th} < PD_j < \overline{PD}^{75th}) + \beta_{1,4}Z_i * \mathbf{1}(\overline{PD}^{75th} < PD_j) + \beta_2 X_i + \varepsilon_{ij}$. "FE (multi-bank firms)" are estimates with firm-fixed effects over the sample of multi-bank firms. "OLS (multi-bank firms)" reports estimates where with industry-region controls on the sample of multi-bank firms. "OLS (multi-bank firms)" reports estimates with industry-region controls on the sample of single-bank firms. The first quartile reports $\hat{\beta}_{1,1}$, the second quartile reports $\hat{\beta}_{1,1} + \hat{\beta}_{1,2}$, the third quartile reports $\hat{\beta}_{1,1} + \hat{\beta}_{1,3}$, and the fourth quartile reports $\hat{\beta}_{1,1} + \hat{\beta}_{1,4}$) quartile firms, where standard errors are constructed using the delta method.

Figure 6. Bank Lending Standards for Mortgages - dependence on oil exposure



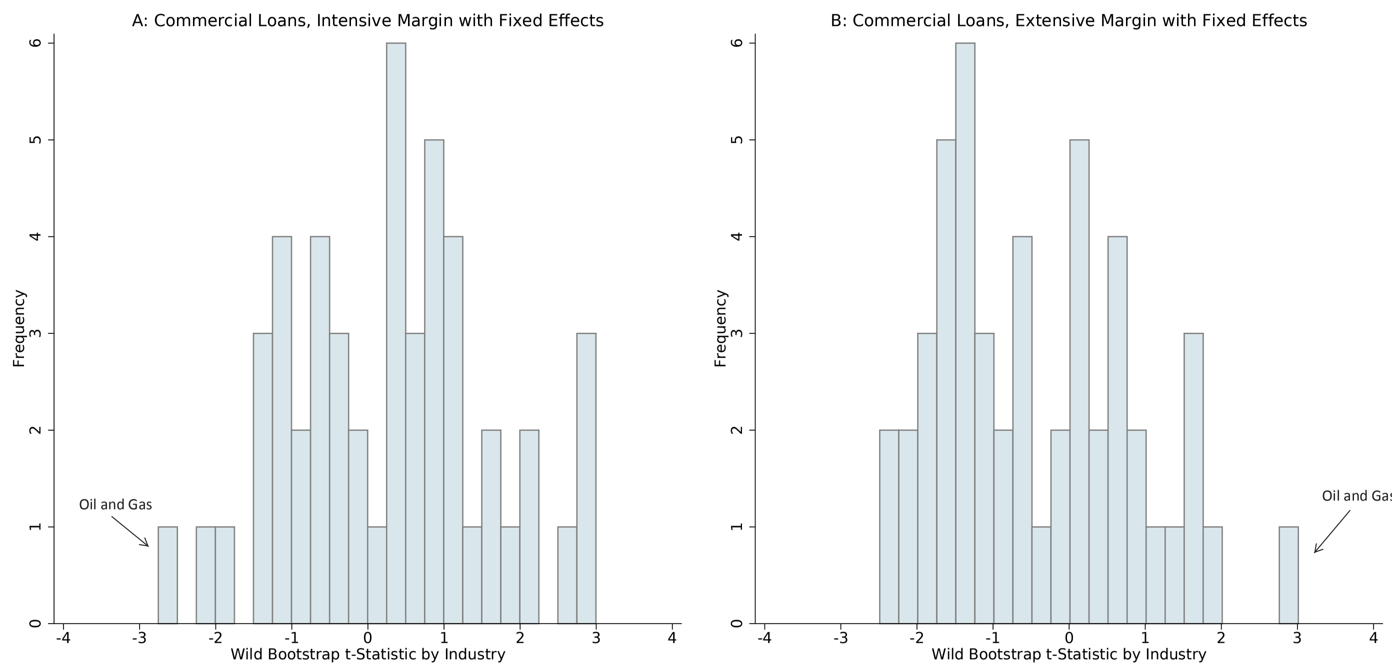
Notes: This figure illustrates the impact of a bank's oil and gas extraction (O&G) exposure to bank lending standards for mortgages. All data are from the Senior Loan Officer Opinion Survey (SLOOS) questions about qualifying mortgages. A positive slope indicates tightening. For each bank we measured the cumulative amount of survey responses in which the response was a tightening of the specified variable relative to 2015:Q1, the first date available. The GSE-eligible category of residential mortgages includes loans that meet the underwriting guidelines, including loan limit amounts, of the GSEs—Fannie Mae and Freddie Mac. The government category of residential mortgages includes loans that are insured by the Federal Housing Administration, guaranteed by the Department of Veterans Affairs, or originated under government programs, including the U.S. Department of Agriculture home loan programs. The non-jumbo, non-GSE-eligible category of residential mortgages includes loans that satisfy the standards for a qualified mortgage and have loan balances that are below the loan limit amounts set by the GSEs but otherwise do not meet the GSE underwriting guidelines. The jumbo category of residential mortgages includes loans that satisfy the standards for a qualified mortgage but have loan balances that are above the loan limit amount set by the GSEs. The red dashed line represents the average for banks in the upper-quarter in terms of exposure to the O&G sector, the blue dashed line represents the average for banks in the bottom quartile.

Figure 7. Response of Average Risk Weight, Liquidity Ratio, Leverage Ratio, and Total Assets to Oil Shock



Notes: This figure illustrates the impact of a bank's oil and gas extraction (O&G) exposure to the risk-weighted asset ratio (total risk-weighted assets divided by total assets), the liquid asset ratio (defined as liquid assets divided by total assets), the leverage ratio (total assets divided by equity) and log total assets. Liquid assets are defined as cash holdings, U.S. Treasuries, U.S. government agency debt, and agency-backed MBS. All data are from the FR-Y9. We regress the logarithm of the bank-level variable on time dummies interacted with O&G exposure, time dummies interacted with bank controls, time dummies, bank fixed effects, and bank-specific time trends. Shown are the coefficients and 95 percent confidence bands of the coefficients on the time dummies interacted with O&G exposure. Omitted periods in the regression are 2012:Q3 and 2014:Q2, implying bank-specific time trends capture pre-shock period trends. Bank controls include pre-shock period loan-weighted average levels of ROA, equity/total assets, NPL/total assets, tier-1 capital/risk-weighted assets, total loans/total assets, charge offs/total loans, commercial loans/total loans, residential loans/total loans, deposits/total liabilities, and a foreign bank dummy. O&G exposure was normalized to have a mean of one standard deviation. Standard errors are clustered by bank. To correct for a coding change in risk weights implemented by Basel III in 2015:Q1, the risk-weighted asset ratio (panel D) for 2015:Q1 for each bank was spliced with its 2014:Q4 value.

Figure 8. Wild Cluster Bootstrap t-Statistic Permutation Test by Industry



Notes: This figure shows histograms of wild cluster bootstrap t-statistics for each of the 50 most common industries (defined by 3-digit NAICS code) in the commercial loan Y14 data. Analogous to the O&G exposure variable used throughout this paper, for each of the other 49 industries we create a bank-specific exposure variable. We then run the fixed fixed-effects specification 50 times—once as our original specification, and 49 subsequent regressions, each time replacing O&G exposure with one of the 49 other industry exposures. t-statistics for each regression were constructed using the wild cluster bootstrap resampling method (clustered by bank) as described in Cameron and Miller (2015). This sequence of steps was performed twice: producing two histograms, one for the intensive margin (Panel A) and one for the extensive margin (Panel B). The wild cluster bootstrap t-statistic for the O&G exposure variable is marked in each panel.