Geographically Concentrated Banks and the Amplification of Regional Economic Shocks[1]

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Abstract

When an economic shock hits a local economy, are communities better served by large banks diversified through their national footprint, or by smaller banks committed to serving that specific region? This paper examines whether banks amplify or absorb regional economic shocks by studying the 2014-2016 oil price collapse and its aftermath through 2019. Banks whose branch networks were concentrated in oil-producing regions experienced significant credit quality deterioration—noncurrent loans rose 34 basis points and net charge-offs increased 8.5 basis points—leading to 20.2% reductions in small business lending. Using high-dimensional fixed effects to control for credit demand, we show these reductions were geographically concentrated: banks cut lending an additional 18.5% in oil-dependent counties compared to their lending elsewhere. This pattern had real consequences. Among oil counties experiencing identical commodity price shocks, those dominated by geographically concentrated banks suffered 3.2 percentage points of additional employment losses beyond direct shock effects. Because 96% of oil-producing counties are dominated by such banks, credit supply disruptions caused 1.44 million jobs losses—accounting for essentially all employment losses, as diversified banks would have supported 410,000 jobs through the downturn. Effects persisted through 2019 despite partial price recovery. These findings demonstrate that banking system structure critically determines regional economic resilience: geographic concentration creates correlated losses forcing lending reductions in distressed regions, generating destabilizing feedback loops that transform temporary shocks into persistent damage.

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1 Introduction

Regional economies frequently experience sector-specific shocks—commodity price collapses, natural disasters, industry downturns—that can devastate local economic activity. A critical policy question is whether the banking system helps absorb and redistribute these shocks across regions, or whether it amplifies them through destabilizing feedback loops. If banks are geographically diversified they can cross-subsidize lending across regions, drawing on capital and profits from unaffected areas to support credit supply in distressed regions. On the other hand, banks with concentrated exposures to affected regions may have correlated credit losses that erode capital and force lending reductions in the very places experiencing economic distress, amplifying the initial shock. Which effect dominates matters for financial stability policy, banking regulation, and regional economic resilience.

This paper uses the 2014-2016 oil price collapse to identify how a geographically concentrated and sector-specific shock is transmitted to the broader economy through the banking system. Beginning in mid-2014, oil prices fell precipitously from over $100 per barrel to below $30 by early 2016, imposing severe economic distress on regions dependent on oil and gas production. This setting provides an ideal natural experiment for several reasons. First, the shock was sharp, unexpected, and plausibly exogenous to individual bank and regional economic decisions. Second, upstream oil and gas activities are geographically concentrated in a limited number of counties with hydrocarbon reserves, creating clear treatment and control regions. Third, banks vary in their exposure to oil-producing regions through their branch networks, generating cross-sectional variation in how the shock affected different institutions. We exploit this variation to trace the transmission of the oil price shock from regional economies through bank balance sheets to credit supply decisions and back to regional economic outcomes.

The potential amplification mechanism operates through a four-step feedback loop. First, the oil price collapse directly harms economic activity in oil and gas counties through reduced drilling activity, upstream employment losses, and related spillovers to local businesses. Second, banks with concentrated branch presence in these counties—which we term "oil and gas banks" or "O&G banks"—experience deteriorating asset quality as borrowers in affected regions struggle to repay loans. Third, facing credit losses and potentially binding capital constraints, O&G banks reduce lending to preserve capital adequacy and manage risk. Fourth, if this credit supply reduction is concentrated in oil-dependent regions already experiencing direct economic distress, it can deepen and prolong the regional downturn beyond what the direct shock alone would cause.

The critical empirical question is whether this feedback loop operates in practice and, if so, how large the amplification effects are. Our identification strategy exploits within-region variation in banking system structure: among oil-dependent counties experiencing the same direct oil price shock, we compare outcomes in counties with high versus low presence of O&G banks. If the credit channel amplifies regional shocks, counties dominated by geographically concentrated banks should experience worse outcomes than counties served by more diversified banking systems.

Our analysis proceeds in four steps. First, we establish that the oil price shock caused substantial economic distress in oil and gas counties. Following the mid-2014 price collapse, counties with oil and gas reserves experienced 2.26% slower employment growth, 3.93% slower wage growth, and 5.67% higher bankruptcy filings compared to counties without such reserves. Event study analysis confirms these effects emerged immediately after the shock, with no differential pre-trends, and persisted through the end of our sample period in 2019. In absolute terms, these effects represent approximately 1.04 million jobs lost, $1,447 lower annual wages per affected worker, and 20,500 additional bankruptcy filings annually directly attributable to falling oil prices.

Second, we document that O&G banks—those with above-median branch presence in oil and gas counties—experienced significant performance deterioration following the shock. Return on assets declined by 7.2 basis points for O&G banks relative to other banks. This performance decline was driven entirely by credit quality deterioration: net charge-offs increased by 8.5 basis points and noncurrent loans rose by 34 basis points. Critically, we find no evidence of funding pressures; net interest margins remained stable at 1.2 basis points and deposits in oil and gas regions did not decline after controlling for bank-specific deposit demand. These findings indicate O&G banks faced asset-side problems stemming from borrower distress, not liability-side disruptions.

Third, we examine whether deteriorating asset quality led O&G banks to reduce credit supply. Using bank-county panel data on small business lending and controlling for local credit demand through county-year fixed effects, we find that O&G banks reduced small business lending by 20.2% (loan counts) and 12.3% (loan amounts) more than other banks following the oil price shock. Credit reductions concentrated heavily among the smallest loans: lending to businesses seeking loans under $100K fell by 22.0% (loan counts) and 19.2% (loan amounts), while lending for mid-sized loans showed no significant change and lending for large loans (>$250K) actually increased slightly by O&G banks though not statistically significant. Most importantly, using a difference-in-difference-in-differences framework, we show that O&G banks concentrated these credit supply reductions geographically in oil and gas counties. O&G banks reduced lending by an additional 18.5% (loan counts) to 31.7% (loan amounts) in oil and gas counties compared to their lending in non-oil counties and relative to other banks' lending patterns, even after controlling for local credit demand and bank-specific lending capacity. This geographic pattern reveals that banks reduced credit supply most sharply in the very regions where they faced the greatest losses and where credit was most needed to support economic recovery.

Fourth, we demonstrate that this geographic pattern of credit contraction had significant real economic consequences, providing direct evidence of amplification. Among oil and gas counties experiencing the same direct oil price shock, those with high O&G bank presence experienced substantially worse outcomes than counties with low O&G bank presence.[5] High O&G bank presence counties suffered an additional 3.2 percentage point employment decline (significant at 1%), 2.7% establishment decline (significant at 10%), and 12.8% increase in bankruptcy filings (significant at 1%) beyond the direct shock effects.

Because 96% of oil-producing counties (representing 97% of oil county employment) are dominated by geographically concentrated banks, these amplification effects characterize the typical oil county experience. The credit supply channel caused 1.44 million job losses in high-concentration counties—140% of the 1.03 million net employment decline. This apparent paradox—amplification exceeding net losses—reflects that diversified banks would have supported approximately 410,000 jobs through the commodity downturn. In the small number of low-concentration counties (4% of oil counties), diversified banks maintained credit supply and these counties experienced modest employment gains (+13,000 jobs), demonstrating that banking structure determined whether communities absorbed or amplified the shock. Event study analysis confirms that high and low O&G bank presence counties followed parallel trends before the shock and diverged only afterward, supporting causal interpretation. The effects persist through 2019 even as oil prices partially recovered, suggesting that credit supply disruptions can transform temporary commodity price shocks into persistent regional economic damage through business failures, labor force exit, and foregone investment that cannot easily be reversed.

Our paper contributes to several strands of literature examining the interaction between regional economic shocks, banking system health, and credit supply. A substantial literature examines how regional economic conditions affect local banks and vice versa. Ashcraft (2005) demonstrates that bank failures lead to significant local economic downturns, while Peek and Rosengren (2000) show how Japanese bank shocks transmitted to the U.S. through branch networks. Cetorelli and Goldberg (2012) provide evidence that the impact of bank health on local economies varies with contextual factors such as bank size and portfolio diversity. Cortes and Strahan (2017) examine how bank liquidity shocks affect local employment through reduced small business lending. Methodologically, following Khwaja and Mian (2008) and Amiti and Weinstein (2018), we employ high-dimensional fixed effects to separate credit supply from demand. Our contribution is demonstrating the complete feedback loop: we trace regional shocks through bank balance sheets to credit supply decisions and back to amplified regional economic outcomes.

Our paper is most closely related to recent work examining oil price shocks and banking. Gilje, Loutskina, and Strahan (2016) study how the shale oil boom affected corporate financing, finding that banks' geographic expansion into booming areas increased local firms' access to credit. Adelino and Ferreira (2016) examine commodity price booms more broadly, showing that banks

[5] We define High O&G Bank Presence as counties where more than 25% of branches were operated by O&G banks (median threshold). The distribution is highly bimodal, with most counties at either 0% or 100% (see Figure 3). Among high-presence O&G counties, the average branch share is 88.7%, and most have near-complete O&G bank dominance. See Section 3.3.1 for details.

with exposure to commodity-producing regions experience stronger loan growth and profitability during price increases. Turning to the 2014-2016 bust, Wang (2021) analyzes the oil price decline and finds that local banks in oil-dependent areas experienced deposit outflows and reduced lending, with effects concentrated among smaller institutions. Bidder et al. (2021) examine how banks cope with losses from the oil shock, distinguishing between de-leveraging (reducing total lending) and de-risking (shifting toward safer assets), and find evidence of both responses. Most recently, Marsh et al. (2024) study bank responses to the 2014 oil shock through the lens of the financial accelerator, documenting that oil-exposed banks reduced commercial and industrial lending and that this contraction affected real economic activity in oil-dependent regions.

We extend this literature in several important ways. First, while Gilje et al. (2016) and Adelino and Ferreira (2016) focus on commodity booms, we examine the bust phase, showing that the banking system's role differs fundamentally: during booms, banks may facilitate growth, but during busts, they can amplify distress. Second, while Wang (2021) examines how the oil shock affected local banks through deposit outflows in regions with high reliance on oil and gas-sector wages, we trace the complete feedback loop: from the oil price shock's impact on regional economies, through its effects on geographically concentrated banks, and back to amplified regional economic outcomes. We find that credit supply reduction—not deposit disruption—was the primary transmission channel. Analyzing deposits at the bank-county level to control for each bank's overall deposit demand, we document that deposits remained stable in oil-producing regions even as banks reduced lending, ruling out liability-side explanations for credit supply contractions. Third, while Bidder et al. (2021) document banks' portfolio adjustments and Marsh et al. (2024) link bank lending reductions to real activity, we provide more granular evidence of the amplification mechanism by exploiting within-region variation in banking system structure. Specifically, among oil-dependent counties experiencing the same direct shock, we show that those with greater exposure to oil-concentrated banks suffered significantly worse outcomes. Our difference-in-difference-in-differences identification strategy—comparing outcomes across banks, counties, and time—provides cleaner identification of the credit channel by controlling for both bank-level and county-level confounding factors simultaneously. Fourth, we demonstrate that amplification effects persist years after the initial shock, suggesting that banking system structure can transform temporary commodity price shocks into permanent regional economic damage. Finally, we quantify the magnitude of amplification, showing that the credit channel caused 1.44 million job losses and accounted for essentially all employment losses in the most affected regions.

Our findings connect to broader work on how financial friction affects real economic activity. Bernanke and Gertler (1989) develop the financial accelerator concept, showing how borrower net worth affects credit access and amplifies economic cycles. Mian and Sufi (2014) demonstrate feedback loops between household debt and the real economy during the housing crisis. We contribute by documenting a regional variant of the financial accelerator: geographic concentration of both economic activity and banking exposures creates conditions for localized feedback loops.

Our findings also speak to debates about banking system structure and regional economic stability. Cortes and Strahan (2017) show that geographically diversified banks reallocate capital to smooth local shocks while Morgan, Rime, and Strahan (2004) find that interstate bank integration reduces state-level business cycle volatility. Loutskina and Strahan (2015) demonstrate that financial integration affects regional economic volatility through the geographic structure of banking markets, with more integrated banking systems dampening the transmission of local shocks.

The tension between diversification benefits and relationship banking is particularly salient for small businesses. Despite increasing geographic integration since the rise of interstate banking, community banks remain the dominant credit provider to small businesses. From 1998 to 2019, while community banks' share of consumer credit fell from 45% to 6% and their deposit share declined from 43% to 16%, their share of small business lending fell more modestly—from 67% to 44%--reflecting their continued comparative advantage in informationally intensive lending (Petersen and Rajan 1994; Berger et al. 2005). For the small business sector, the benefits of community banks' local focus and relationship-based underwriting must be weighted against the procyclical effects of their geographic concentration.

Our empirical work quantifies these costs of geographic concentration within the current banking structure, acknowledging both the benefits of diversification and the vital role of community banks play in small business credit markets. Since geographic concentration is inherent to the community banking model rather than easily adjustable, our key contribution is demonstrating that the balance between concentrated and diversified institutions in local banking systems is a first-order determinant of regional economic resilience. These findings suggest the importance of policies that support community banks' capacity to maintain lending during regional downturns—through counter-cyclical capital buffers calibrated to regional conditions, enhanced liquidity access, or other mechanisms that preserve relationship banking benefits while mitigating geographic concentration costs.

Our contribution is showing that the absence of such diversification—when regional banking systems are dominated by geographically concentrated institutions—creates vulnerability to amplification during regional downturns. Across these literatures, our key contribution is providing comprehensive evidence of amplification through the banking channel and demonstrating that the structure of the local banking system—specifically, the presence of geographically concentrated versus diversified institutions—is a first-order determinant of regional economic resilience.

These findings carry important lessons for financial stability policy and banking regulation. Geographic concentration risk deserves greater attention from banking supervisors. Banks with geographically concentrated operations face correlated credit losses when regional economies suffer shocks, which can quickly erode capital cushions and force lending reductions that transmit shocks back to regional economies. Banking supervisors could enhance monitoring of geographic concentration risk through standardized concentration metrics, incorporate regional economic scenarios into stress testing frameworks, and consider whether banks with high geographic concentration should face higher capital requirements or enhanced supervisory attention. Our results suggest that regulators should track not only sectoral concentrations (commercial real estate, energy lending) but also geographic concentration combined with regional economic correlation. When banks' geographic footprints align strongly with regions vulnerable to correlated shocks—whether from commodity price swings, natural disasters, or industry-specific disruptions—the potential for destabilizing feedback loops increases substantially.

Our results also reinforce the importance of strong capital and liquidity buffers for maintaining credit supply during downturns. Banks entering regional downturns with robust capital positions have greater capacity to absorb credit losses without drastically curtailing lending. Counter-cyclical capital buffers—built during boom periods and released during downturns—could provide banks with concentrated regional exposures the capacity to maintain lending when shocks occur. Our findings suggest such buffers could be calibrated to regional economic conditions rather than only national business cycles. Banks operating in boom regions—whether from commodity price increases, technology sector growth, or real estate appreciation—should build capital specifically designated for release when regional conditions deteriorate, reducing the procyclicality of credit supply in regions vulnerable to sharp reversals.

More broadly, our findings demonstrate that financial system structure materially affects regional economic outcomes. As policymakers consider banking industry structure, the regional stability implications we document deserve consideration alongside more commonly emphasized factors such as competition, efficiency, and access to credit. The U.S. banking industry has consolidated substantially—from over 18,000 FDIC-insured institutions in 1985 to fewer than 5,000 today—raising questions about concentration at both national and regional levels. While much attention focuses on systemic risks posed by the largest institutions, our findings highlight that regional concentration also matters critically for local economic resilience. Building resilient regional economies requires attention not only to economic diversification but also to financial system structure and the concentration of credit provision. Policies to monitor, manage, and potentially limit geographic concentration risk—or to ensure that regions have access to geographically diversified financial institutions—could enhance both financial stability and regional economic resilience, reducing the likelihood that temporary regional shocks are transformed into persistent economic damage through destabilizing feedback loops in the banking system.

The remainder of the paper proceeds as follows. Section 2 provides background on the geographic concentration of oil and gas activity and the 2014-2016 oil price collapse. Section 3 describes our data sources, sample construction, and summary statistics. Section 4 examines the oil price shock's impact on regional economic outcomes. Section 5 analyzes the shock's effects on bank performance and asset quality. Section 6 investigates the impact on small business credit supply. Section 7 presents our main results on amplification, showing that oil and gas counties with high O&G bank presence experienced significantly worse outcomes through both the geographic concentration of credit supply reductions and the resulting real economic consequences. Section 8 presents robustness checks. Section 9 concludes with implications for policy.

2 The Oil and Gas Sector and the 2014-2016 Price Collapse

2.1 Geographic Concentration of Oil and Gas Production

Upstream oil and gas production in the United States is highly concentrated in counties with substantial hydrocarbon reserves. We identify oil and gas regions using the U.S. Energy Information Administration (EIA) county code master list, which documents counties with proven oil and natural gas reserves. Of 3,142 U.S. counties, 1,395 (44.5%) contain oil and gas reserves in our analysis sample.[6] However, as Figure 1 illustrates, these reserves are unevenly distributed, with substantial concentration in the Permian Basin (West Texas and southeastern New Mexico), the Bakken Formation (North Dakota), the Eagle Ford Shale (South Texas), and the Marcellus Shale (Appalachia).

[Figure 1: Geographic Distribution of Oil and Gas Producing Counties]

This geographic concentration of reserves translates into concentrated employment. As documented in Table 1 (and Table A1 in the Appendix), upstream oil and gas employment averaged 7.73% of total employment in O&G counties versus only 1.09% in non-O&G counties. In the most specialized counties, upstream employment exceeded 15%, and in some cases exceeded 25% of total employment. This concentration creates clear treatment and control groups for empirical analysis. Because affected counties represent a small fraction of the U.S. economy, national economic conditions and monetary policy are unlikely to respond to oil-region-specific factors, mitigating reverse causality concerns.

2.2 The 2014-2016 Oil Price Collapse

2.2.1 The Shock and Its Timing

Figure 2 displays WTI crude oil prices and U.S. rotary rig counts from 2010-2019. From 2011 through mid-2014, oil prices remained stable at \$80-\$110 per barrel, and rig counts held steady around 1,800-1,900 active rigs. Beginning in June 2014, prices fell precipitously, reaching \$26 per barrel by February 2016—a 74% decline from the \$107 peak. The rig count collapsed in tandem, falling 79% from 1,930 rigs (October 2014) to 404 rigs (May 2016). The tight co-movement between prices and

[6] The EIA master list identifies 1,424 counties with proven oil and gas reserves nationwide. Our analysis sample contains 1,395 O&G counties due to data availability for certain control variables. Due to data availability for certain variables, our estimation samples range from 3,125 to 3,132 counties depending on the specification. Table A1 in the Appendix provides detailed sample composition as of 2014.

drilling activity demonstrates the direct transmission of price shocks to economic activity in oil-producing regions.

[Figure 2: Oil Prices and Drilling Activity, 2010-2019]

For empirical analysis using annual data, we define the pre-shock period as 2011-2014 and the post-shock period as 2015-2019. While the oil price collapse began in mid-2014, we classify 2014 as pre-shock because the full-year average oil price remained elevated at $93 per barrel, and most economic impacts materialized in 2015 and beyond.

Oil prices began gradual recovery in 2017, reaching approximately $60-70 per barrel by 2018-2019, but remained well below pre-shock levels. The rig counts also recovered to approximately 1,000 by late 2018, substantially below the 2014 peak. This partial recovery allows us to examine whether effects were temporary disruptions or had persistent impacts.

The oil price decline was driven by global supply-demand factors-including OPEC's strategic decision to maintain production despite falling prices and weakening global demand—rather than conditions specific to U.S. oil-producing regions (Gilje, Loutskina, and Strahan 2016; Marsh et al. 2024). While the U.S. shale boom contributed to global supply increases, OPEC's decision not to cut production was the critical factor preventing price stabilization. Our specifications include year fixed effects that absorb national-level shocks, providing a plausibly exogenous shock for identification.

3 Data and Summary Statistics

3.1 Data Sources and Sample Construction

Our empirical analysis draws on multiple datasets covering 2011-2019. County-level economic data comes from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW), which provides near-universal coverage of employment, wages, and establishments based on state unemployment insurance records. Bankruptcy data come from the U.S. Courts' Table F-5A, and demographic controls from the Census Bureau's American Community Survey.

Bank-level financial data come from quarterly Call Reports filed by all FDIC-insured institutions. We use performance measures (net interest margin, yield on earning assets, costs of funding earning assets, return on assets) and asset quality measures (noncurrent loans, net charge-offs, loss allowances).[7] Branch-level data from the FDIC's Summary of Deposits (reported annually as of June 30) allow us to measure each bank's geographic footprint and deposit presence across counties.

[7] We winsorize all bank-level ratios at the 5th and 95th percentiles to mitigate outlier influence. Our sample includes commercial banks and savings institutions but excludes credit unions due to data limitations.

Small business lending data comes from Community Reinvestment Act (CRA) disclosures, which report loans with original amounts under $1 million aggregated by bank, county, year, and loan size category (<$100K, $100K-$250K, >$250K) and loans to firms with gross annual revenues ≤$1 million.[8]

Our main sample spans 2011-2019, providing four pre-shock years (2011-2014) and five post-shock years (2015-2019). We classify 2015-2019 as post-shock corresponding to the oil price collapse beginning in mid-2014, when WTI crude prices fell from over $100 per barrel to below $30 by early 2016. Standard errors are clustered at the county level for regional analysis, at the bank level for bank-level analysis, and two-way clustered at bank and county (or commuting zone) levels for bank-county analysis.

3.2 Key Variable Definitions

We define oil and gas counties (O&G counties) as counties with oil and natural gas reserves identified in the U.S. Energy Information Administration's county code master list. This classification is based on proven reserves rather than current production, ensuring treatment group definition is not endogenous to the oil price shock. Of 3,132 counties in our analysis sample, 1,395 (44.5%) are classified as O&G counties (see Table A1 in the Appendix for detailed sample composition).

We define oil and gas banks (O&G banks) as institutions with more than 50% of total branches in O&G counties as of June 2010, four years before the shock. This pre-determined classification ensures bank designation is unaffected by strategic responses to the shock. O&G banks averaged 96.1% of deposits and 95.3% of branches in O&G counties as of 2014, while non-O&G banks had only 2.4% of deposits and 2.8% of branches in O&G counties.

For amplification analysis (Section 7), we define High O&G Bank Presence counties as those where more than 25% of bank branches (median threshold) were operated by O&G banks as of 2014. As Figure 3 illustrates, the distribution of O&G bank branch shares across counties is highly bimodal. Most counties cluster at two extremes: 955 counties (30.5%) have zero O&G bank presence, while 504 counties (16.1%) have exclusively O&G bank branches. The quartiles (Q1=0%, Q2=25%, Q3=81.8%) confirm that relatively few counties fall between these extremes. While our 25% threshold corresponds to the median, it effectively separates two distinct groups: counties dominated by geographically concentrated banks versus those with access to diversified banking systems. Among the 1,395 O&G counties, 1,333 (95.5%) have high O&G bank presence while 55 (3.9%) have low presence. High-presence counties contain 44.5 million workers (96.9% of O&G

[8] The CRA data has limitations: reporting thresholds exclude smaller banks, data are aggregated annually preventing loan-level analysis, and banks may report some loans outside their branch footprint. Despite these limitations, CRA data remains the most comprehensive source of geographically disaggregated small business lending information.

county employment), while low-presence counties contain only 1.4 million workers (3.1%) (Table A1).

[Figure 3: Share of O&G Banks' Branches, 2014]

Throughout the paper, we use the following notation: *b* indexes banks, *c* indexes counties, and *t* indexes time periods (years in our main specification). When we analyze bank-county level outcomes, we use subscripts *b, c, t* to denote bank *b* in county *c* at time *t*.

3.3 Summary Statistics

3.3.1 County Characteristics

Table 1 compares O&G and non-O&G counties during pre-shock (2011-2014) and post-shock (2015-2019) periods. Column 5 reports difference-in-differences (DID) estimates: $(O\&G_{Post} - O\&G_{Pre}) - (Non\ O\&G_{Post} - Non\ O\&G_{Pre})$. Negative values indicate O&G counties experienced worse outcomes (similar increases or larger decreases) relative to non-O&G counties; positive values indicate better relative performance.

Pre-shock characteristics (Columns 1-2) show O&G counties were smaller and more rural, with average populations of 92,734 versus 104,167. Despite being smaller, O&G counties had higher average wages ($36,819 vs. $34,932), reflecting premium wages in the oil and gas sector. O&G counties had substantially higher upstream oil and gas employment concentration (7.37% vs. 1.09% of total employment).

The DID estimates (Column 5) provide preliminary evidence of the oil shock's impact. O&G counties experienced relative declines in employment (906 fewer jobs), wages ($555 lower), and upstream employment share (1.39 percentage points lower). Bankruptcy filings increased by 187 per million population more in O&G counties. These are relative effects—both groups experienced growth during 2015-2019 due to broader economic recovery, but O&G counties grew significantly less. The DID methodology isolates the portion attributable to the oil shock after accounting for national trends.

[Table 1: County Characteristics by Oil and Gas Status, 2011-2019]

3.3.2 Bank Characteristics

Table 2 compares O&G and non-O&G banks during pre-shock and post-shock periods. Column 5 reports DID estimates capturing differential changes for O&G banks.

Panel A confirms that O&G banks are smaller (average assets $338 million vs. $399 million) and operate fewer branches (9.2 vs. 17.2) across fewer counties (8.8 vs. 16.6). By construction, O&G banks have highly concentrated geographic footprints: 96.1% of deposits and 95.3% of branches in O&G counties, compared to 2.4% and 2.8% for non-O&G banks. This stark difference in geographic concentration is the key variation we exploit to identify credit supply effects.

Panels B-C show that O&G banks outperformed non-O&G banks pre-shock on profitability (ROA: 0.85% vs. 0.68%) and asset quality (noncurrent loans: 1.63% vs. 2.14%). This reversed post-shock. While both groups experienced improved profitability due to economic recovery, O&G banks improved significantly less: ROA increased 0.11 percentage points less (DID = -0.11, implying a 7.2 basis point relative decline) and noncurrent loans declined 0.52 percentage points less (DID = +0.52 percentage points less (DID = + 0.52, implying a 34 basis point relative deterioration). Net charge-offs declined 0.15 percentage points less for O&G banks (DID = + 0.15, implying an 8.5 basis point relative increase).

Critically, net interest margins remained virtually unchanged (DID = 0.019 percentage points, or 1.2 basis points), with both groups maintaining margins around 3.7%. The DID for funding costs (+0.030 percentage points) indicates O&G banks' funding costs declined slightly more than non-O&G banks', ruling out liability-side stress. This finding is crucial for identification: performance deterioration was driven by asset-side problems, not funding pressures.

Panel D shows deposits as a share of assets remained stable at 84-85% for both groups (DID = -0.10 percentage points, economically negligible), confirming neither group experienced deposit outflows. Panel E shows both groups maintained capital ratios well above regulatory minimums (Tier 1 capital: 17.7-17.8% vs. 6% minimum; total capital: 18.8-19.0% vs. 10% minimum; leverage: 10.6-11.4% vs. 4% minimum). DID estimates for capital ratios are small (around -0.13 percentage points for risk-based ratios), suggesting O&G banks' capital cushions eroded moderately but remained comfortable.

Panel F shows O&G banks expanded small business lending less than non-O&G banks during the post-shock period. The DID estimate of -$79.9 million in total lending and -4,804 loans represents substantial relative contraction on both extensive and intensive margins. These patterns provide preliminary evidence of credit supply reductions, which we examine rigorously with bank-county level analysis in Section 6.

[Table 2: Bank Characteristics by Oil and Gas Exposure, 2011-2019]

4 Regional Economic Impact of the Oil Price Shock

4.1 Empirical Specification

To investigate the impact of the oil price shock on regional economic activity, we employ a difference-in-differences (DID) framework comparing outcomes in O&G counties to non-O&G counties before and after the shock. Our baseline specification is:

$$Y_{c,t} = \beta_1(Post_t \times O\&G\ County_c) + \beta_2(Post_t \times Z_c) + \alpha_c + \gamma_t + \varepsilon_{c,t} \qquad \cdots (1)$$

where $Y_{c,t}$ represents the outcome of interest for county c in year t. Our primary outcomes include log establishments, log employment, log average weekly wages, and log total bankruptcy filings. $O\&G\ County_c$ is an indicator equal to one if county c has oil and gas reserves and zero otherwise. $Post_t$ is an indicator equal to one for years 2015-2019 (post-shock) and zero for years 2011-2014 (pre-shock).

The coefficient of interest is β_1 on the interaction term $Post_t \times O\&G\ County_c$, which captures the differential change in outcomes for O&G counties relative to non-O&G counties following the oil price shock. A negative (positive) coefficient indicates that O&G counties experienced worse outcomes—slower growth in establishments, employment, or wages (higher bankruptcy rates)—compared to non-O&G counties after the shock.

The vector Z_c captures time-invariant county characteristics measured as of 2010, well before the shock. We include interactions $Post_t \times Z_c$ to allow the impact of the oil price shock to vary with pre-existing county characteristics. Specifically, Z_c includes log population, log median household income, log housing units, log total deposits, and the Herfindahl-Hirschman Index (HHI) of bank deposit concentration. These interactions control for the possibility that counties with different baseline characteristics experienced differential trends during our sample period, ensuring that β_1 captures the shock's impact rather than pre-existing trends.

County fixed effects α_c absorb time-invariant differences across counties, while year fixed effects γ_t capture common macroeconomic trends affecting all counties.

Our sample includes 3,132 counties in the continental United States observed annually from 2011-2019, yielding 28,188 county-year observations for most specifications.[9] Standard errors are clustered at the county level to account for potential serial correlation within counties over time.

[9] The continental United States contains 3,142 counties. Due to data availability for certain variables, our estimation samples range from 3,125 to 3,132 counties depending on the specification. Table A1 in the Appendix provides detailed sample composition as of 2014.

4.2 Baseline Results

Table 3 presents our baseline DID estimates quantifying the oil price shock's regional economic impact. Each column reports results from estimating Equation (1) with a different outcome: establishments (Column 1), employment (Column 2), average weekly wages (Column 3), and total bankruptcy filings (Column 4). The coefficient on O&G County x Post captures the differential change in outcomes for O&G counties relative to non-O&G counties following the shock, after controlling for county characteristics and common time trends.

[Table 3: Impact of Oil Price Shock on Regional Economic Outcomes]

Column (1) examines business establishments, providing insight into whether firms responded to the shock through closure or adjustment along other margins. The coefficient of -0.0042 is small and statistically insignificant, indicating that the number of business establishments remained relatively stable in O&G counties. This result is economically meaningful: it suggests firms adjusted primarily through employment reductions and wage cuts rather than widespread business closures. The relative stability of establishment counts—despite significant employment and wage declines documented below—indicates that existing businesses contracted operations rather than exiting entirely.

Column (2) reveals substantial employment effects, the primary channel through which the oil shock affected regional economies. The coefficient of -0.0229 is both economically large and statistically significant ($p<0.01$), indicating that O&G counties experienced 2.26% slower employment growth relative to non-O&G counties following the shock.[10] To assess economic magnitude, we translate this percentage effect into job losses. The average O&G county employed 31,935 workers during the pre-shock period (2011-2014) (see Table A1). A 2.26% decline translates to approximately 722 jobs lost per county, or roughly 1.01 million jobs across all 1,395 O&G counties. These employment losses reflect both direct effects—job cuts in the upstream oil and gas sector as drilling activity collapsed—and indirect spillover effects to related industries and local businesses dependent on oil sector spending. The immediate nature of these effects (documented in Section 4.3) and their magnitude underscore the severity of the regional economic shock caused by the oil price collapse.

Average weekly wages also declined significantly in O&G counties relative to non-O&G counties (Column 3). The coefficient of −0.0401 is statistically significant at the 1% level and represents a substantial 3.93% wage decline. Based on the pre-shock average wage of $36,819, this translates to a weekly wage reduction of approximate $28, or an annual wage reduction of approximately $1,447 per worker—a meaningful decline in purchasing power and living standards. This wage

[10] For regression with log-transformed dependent variables, we calculate percentage effects as $[\exp(beta_1) - 1])$ x100%, which gives the exact percentage change. For regression with dependent variables already expressed as percentages or ratios, we interpret coefficients directly as percentage point or basis point changes.

decline likely operates through multiple channels. First, compositional effects: the loss of high-wage oil and gas jobs (which paid premium wages averaging 30-40% above local averages) mechanically reduces average wages as displaced workers find reemployment in lower-wage sectors. Second, general equilibrium effects: weakened labor market conditions put downward pressure on wages across sectors as labor supply exceeds demand. Third, reduced bargaining power: remaining workers face diminished outside options and reduced employer willingness to raise wages in a contracting economy. The 3.93% decline—larger in percentage terms than the employment decline—suggests that workers who retained employment also shared in the economic distress through reduced compensation.

Column (4) examines bankruptcy filings as a direct measure of financial distress among residents and businesses in affected regions. The coefficient of 0.0551 is positive, statistically significant (p<0.01), and economically substantial, indicating that total bankruptcy filings in O&G counties increased by 5.67% more than in non-O&G counties following the oil price shock. Based on the pre-shock average of 259 bankruptcy filings per county annually (Table A1), this represents approximately 15 additional bankruptcy filings per county per year. Across all 1,395 O&G counties, this translates to approximately 20,500 additional bankruptcies annually, or 102,500 over the five-year post-shock period (2015-2019). [11] These bankruptcies—encompassing both business (Chapter 11 and Chapter 7) and personal (Chapter 7 and Chapter 13) filings—provide direct evidence that the economic shock translated into measurable financial distress. Business bankruptcies destroy organizational capital, disrupt supply chains, and eliminate jobs. Personal bankruptcies impose lasting costs on households through credit score damage, asset liquidation, and psychological stress. The elevated bankruptcy rate persisted through 2019 (as documented in Section 4.3), indicating that financial distress was not a temporary phenomenon but rather a persistent feature of the post-shock regional economy.

Note that these are relative effects measured against national trends, not absolute declines in most cases. Both O&G and non-O&G counties experienced economic growth during 2015-2019 due to the broader U.S. economic recovery following the Great Recession. For example, employment in O&G counties grew by an average of 2,716 jobs, while employment in non-O&G counties grew by 3,621 jobs. The DID estimates of -0.0229 (representing approximately 722 jobs per county) captures this differential growth: O&G counties grew significantly less than would be expected based on national trends. This underscores the value of our DID methodology—focusing on absolute levels alone would miss the relative deterioration in O&G counties performance.

The bankruptcy results illustrate this point clearly. Bankruptcy filings actually declined in both O&G and non-O&G counties between periods, reflecting the broader national economic recovery and improved household balance sheets following the Great Recession. However, the positive DID

[11] 259 filings per county x 0.0567 = 14.7 additional filings per county per year. Across 1,395, this translates to 14.7 x 1,395 = 20,506.5 annually. Over five years, additional bankruptcy filings become 20,506.5 x 5 = 102,532.5.

estimate of 0.0551 indicates that bankruptcies declined significantly less in O&G counties—or, equivalently, that O&G counties experienced relative increases in financial distress despite absolute improvements.[12]

These baseline results establish that the oil price shock caused substantial economic distress in O&G counties across multiple dimensions: employment fell, wages declined, and financial distress increased measurably. However, the DID framework's key identifying assumption—that O&G and non-O&G counties would have followed parallel trends absent the shock—requires validation. Section 4.3 presents event study analysis examining year-by-year effects, providing both validation of parallel pre-trends and insights into the dynamic evolution of shock impacts over time.

4.3 Dynamic Effects and Validation of Parallel Trends

A key identification assumption underlying our DID estimates is that O&G and non-O&G counties would have followed parallel trends in the absence of the oil price shock. While this assumption is fundamentally untestable, we can assess its plausibility by examining pre-shock trends and estimating dynamic treatment effects. We estimate an event study specification that replaces the post-shock indicator with a full set of year indicators:

$$Y_{c,t} = \sum_{\tau \neq 2014} \theta_\tau \times (O\&G\ County_c \times 1[t = \tau]) + \beta_2 (Post_t \times Z_c) + \alpha_c + \gamma_t + \varepsilon_{c,t} \qquad \cdots\ (2)$$

where $1[t = \tau]$ is an indicator variable equal to one if the observation is from year τ and zero otherwise. We use 2014 as the base year, so the coefficients θ_τ measure the difference in outcomes between O&G and non-O&G counties in year τ relative to their difference in 2014. Equation (2) includes the same set of controls, county fixed effects, and year fixed effects as the baseline specification.

Figure 4 plots the estimated coefficientsθ_τ and their 90% confidence intervals for establishments (Panel A), employment (Panel B), average weekly wages (Panel C), and total bankruptcy filings (Panel D). Across all outcomes, the pre-shock coefficients (2011-2013) are small in magnitude and statistically indistinguishable from zero, supporting the parallel trends assumption.

[Figure 4: Dynamic Effects of Oil Price Shock on Regional Economic Outcomes]

Panel A shows the dynamic effects for establishments. The pre-shock coefficients are tightly clustered around zero. While post-shock point estimates are negative, they are smaller in

[12] The regression estimates in Table 3 differ somewhat from the raw DID reported in Table 1. For employment, the raw DID from Table 1 is -906 jobs per county, where the regression coefficient implies approximately -722 jobs per county. This difference reflects the inclusion of control variables and county fixed effects in the regression, which explain roughly 20% of the raw difference. The regression estimate isolates the portion attributable specifically to the oil shock after accounting for pre-existing county characteristics and differential trends. Similar patterns hold for other outcomes, with regression estimates generally smaller in magnitude than raw differences but remaining economically substantial and statistically significant.

magnitude than for employment or wages and several are not statistically significant at conventional levels. This pattern is consistent with our baseline estimates in Table 3 (Column 1), confirming that the primary adjustment mechanism was employment and wage reductions rather than widespread business closures. For employment (Panel B), all pre-shock coefficients are within 0.01 of zero in absolute value, and none is statistically significant at conventional levels. Similarly, Panel C shows that wage differentials between O&G and non-O&G counties were stable before the shock, with coefficients near zero and statistically insignificant during 2011-2013. For bankruptcies (Panel D), the pattern reverses: coefficients are near zero pre-shock, then turn positive and statistically significant starting in 2015, indicating elevated financial distress in O&G counties that persists through the sample period.

The post-shock dynamics reveal important patterns. For employment (Panel B), the negative effects emerge immediately in 2015—the first full year after the oil price collapse began—with coefficients becoming statistically significant and deepening through 2016 as oil prices remained depressed. The effects persist through 2019, the end of our sample period, despite partial recovery in oil prices. By 2019, oil prices had recovered to approximately $60 per barrel—roughly 60% of pre-shock levels—yet employment gaps between O&G and non-O&G counties remained nearly as large as at the trough. This persistence suggests that credit supply disruptions and business failures may have transformed a temporary commodity price shock into lasting regional economic damage, consistent with hysteresis effects documented in the literature on regional economic shocks. Similar patterns emerge for wages (Panel C) and bankruptcies (Panel D): effects appear immediately post-shock and persist through 2019.

The absence of differential pre-trends across all outcomes validates our research design and supports a causal interpretation of the baseline results in Table 3. The immediate emergence of effects following the oil price collapse, combined with their persistence years later, indicates that the shock had both immediate and lasting impacts on O&G regional economies. Having established that the oil price shock caused substantial economic distress in oil and gas counties—with employment declining 2.26%, wages falling 3.93%, and bankruptcies rising 5.67%--we next examine how this regional distress affected banks with concentrated exposure to these regions through their branch networks and lending portfolios.

5 Bank Performance and Asset Quality Deterioration

5.1 Empirical Specification

We examine how the oil price shock affected banks with exposure to O&G regions using a difference-in-difference specifications at the bank-level:

$$Y_{b,t} = \beta_1(Post_t \times O\&G\ Bank_b) + \beta_2(Post_t \times Z_b) + \delta X_{b,t-1} + \alpha_b + \gamma_t + \varepsilon_{b,t} \qquad \cdots (3)$$

where $Y_{b,t}$ represents a performance or asset quality measure for bank b in year t. $O\&G\ Bank_b$ is an indicator equal to one if bank b had more than 50% of its branches in O&G counties as of June 2010, well before the oil price shock. This pre-determined classification ensures our bank designation is not affected by strategic responses to the shock itself. $Post_t$ equals one for years 2015-2019 and zero for years 2011-2014.

The coefficient of interest is β_1, which captures the differential change in outcomes for O&G banks relative to non-O&G banks following the shock. Bank fixed effects α_b absorb time-invariant differences across banks (size, business model, charter type), while year fixed effects γ_t capture common macroeconomic trends and changes in the regulatory environment affecting all banks.

The vector Z_b includes time-invariant bank characteristics measured as of 2010: log total assets and the HHI of the bank's deposit concentration across counties (measuring geographic diversification). We interact these with Post to allow for differential time trends based on bank size and geographic footprint.

The vector $X_{b,t-1}$ includes lagged bank-level controls: deposit ratio (deposits/assets), core capital ratio (Tier 1 capital/average assets), loss allowance ratio (loan loss allowance/total loans), and liquid asset ratio (liquid assets/total assets). We use one-year lags to mitigate potential endogeneity concerns, as contemporaneous balance sheet ratios could be affected by responses to the shock itself. All bank-level ratios are winsorized at the 5th and 95th percentiles to reduce the influence of outliers.

Standard errors are clustered at the bank level to account for serial correlation in bank outcomes over time.

Our dependent variables fall into two categories. The first set captures overall bank performance: net interest margin (NIM), yield on earning assets, cost of funding earning assets, and return on assets (ROA). The second set measures asset quality and capital adequacy: net charge-offs to total loans, noncurrent loans to total loans (including loans 90+ days past due and loans on nonaccrual status), loss allowance to total loans, and equity capital to total assets.

Bank performance is determined by two primary factors: net interest margin—the rate differential between lending and funding—and credit quality. When credit quality deteriorates, banks must increase provisions for loan losses, which directly reduce net income and profitability. Our empirical strategy allows us to distinguish between liability-side effects (changes in funding costs captured by NIM and its components) and asset-side effects (credit quality deterioration captured by charge-offs, noncurrent loans, and provisions).

5.2 Bank Profitability

Table 4 presents estimates of the oil price shock's impact on bank performance measures. Each column reports results from a separate regression using the bank-level DID specification in Equation (3). The dependent variables are net interest margin (Column 1), yield on earning assets (Column 2), cost of funding earning assets (Column 3), and return on assets (Column 4).

[Table 4: Impact of Oil Price Shock on Bank Performance]

The results show that O&G banks experienced significant deterioration in profitability following the oil price shock, but—critically—this deterioration was not driven by funding pressures or margin compression. Column (1) reveals that net interest margin remained statistically unchanged for O&G banks relative to non-O&G banks. The coefficient on Post × O&G Bank is 0.0124 percentage points (1.2 basis points), which is not statistically significant and economically negligible relative to the pre-shock mean of 3.75%. This stability rules out liability-side stress as the driver of performance deterioration.

To understand the components underlying this stable margin, we decompose net interest margin into its two constituent parts: the yields banks earn on their assets (Column 2) and the cost banks pay to fund those assets (Column 3). Both O&G and non-O&G banks experienced declining yields during 2015-2019, reflecting the low interest rate environment, accommodative monetary policy, and competitive pressures in lending markets. The coefficient on Post × O&G Bank in Column (2) is 0.0345 percentage points for yields, indicating that O&G banks' yields declined 3.5 basis points less than non-O&G banks'—or equivalently, that yields remained slightly higher for O&G banks.

Critically, funding costs also declined for both groups (Column 3), with O&G banks experiencing a relative increase of only 2.2 basis points that is not statistically significant. The near-zero net effect on margins—1.2 basis points in NIM = 3.5 basis points in yield advantage – 2.2 basis points in funding cost increase—confirms that O&G banks did not face elevated funding costs despite their exposure to distressed regions. The absence of differential funding cost increases for O&G banks is crucial for our identification strategy in Sections 6-7: banks reduced lending not because they faced funding pressures, but because they experienced credit losses that impaired profitability and eroded capital cushions.

In contrast to the stable margins, profitability measures show significant deterioration for O&G banks. Column (4) shows that return on assets declined by 0.0717 percentage points (7.2 basis points) for O&G banks relative to non-O&G banks, statistically significant at the 1% level. Given the pre-shock average ROA of 0.849% for O&G banks, this represents an 8.5% relative decline in profitability. Both groups of banks experienced improved profitability during 2015-2019 due to the broader economic recovery and benign interest rate environment, but O&G banks' profitability improved significantly less. In absolute terms, O&G banks' ROA increased from 0.849% to 1.073% (a gain of 22.4 basis points), while non-O&G banks' ROA increased from 0.684% to 0.979% (a gain of 29.5 basis points). The 7.2 basis point difference-in-differences capture this differential improvement.[13]

The control variables reveal additional insights. The coefficient on Post × Log Assets is negative and highly significant for NIM (−0.0282, $p < 0.01$), indicating that larger banks experienced smaller margin improvements during the post-shock period, possibly reflecting more competitive pressures. The lagged balance sheet controls show expected patterns: higher deposit ratios are associated with better performance (positive coefficients), higher core capital ratios support profitability through enabling profitable lending (positive for ROA and NIM), and higher loss allowance ratios signal anticipated credit problems and reduce profitability through provisions (negative coefficients across all columns).

We acknowledge that the control variables reveal supplementary insights about bank performance determinants, though we do not discuss them in detail here given our focused empirical objectives.[14]

The combination of stable net interest margins and declining profitability points unambiguously to asset-side problems as the transmission mechanism for O&G banks' performance decline. If funding costs had risen or margins had compressed substantially, we would conclude that liability-side pressures drove the results. Instead, the deterioration in ROA despite unchanged NIM indicates that credit quality problems—which we examine in detail in the following subsection—drove the performance decline though elevated loan loss provisions and charge offs.

5.3 Credit Quality Deterioration

To investigate the source of declining profitability documented in Table 4, we examine credit quality and capital adequacy measures. Table 5 presents estimates using the same DID specification as Table 4, with four dependent variables: noncurrent loans to total loans (Column 1), net charge-offs

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[13] The regression estimates in Table 4 are smaller in magnitude than the raw difference-in-differences reported in Table 2 (which showed −0.113 percentage points for ROA). This difference reflects the inclusion of control variables and fixed effects in the regression, which explain approximately 35-40% of the raw difference. The remaining differential (7.2 basis points) represents the performance gap attributable specifically to O&G exposure after accounting for bank size, geographic concentration, and balance sheet characteristics.

[14] The control variables display theoretically consistent patterns: deposit ratios positively correlate with margins and profitability (reflecting stable, low-cost funding); core capital ratios show positive effects (indicating well-capitalized banks' lending capacity); loss allowance ratios negatively associate with performance (reflecting anticipated credit losses); and liquid asset ratios demonstrate strong negative coefficients for margins and yields (-1.95 and -2.33, respectively), capturing the opportunity cost of holding low-yielding liquid assets versus loans.

to total loans (Column 2), loss allowance to total loans (Column 3), and equity capital to total assets (Column 4).

[Table 5: Impact of Oil Price Shock on Bank Asset Quality and Capital]

Column (1) shows that noncurrent loans—including loans 90+ days past and loans on nonaccrual status—increased by 0.3375 percentage points (34 basis points) for O&G banks relative to non-O&G banks. Given the pre-shock noncurrent loan ratio of 1.626% for O&G banks, this represents approximately a 21% relative increase. This substantial rise in problem loans indicates that borrowers in O&G regions experienced widespread difficulty servicing debt obligations following the oil price collapse.

Column (2) shows that net charge-offs—representing realized credit losses that directly reduce bank capital and profitability—increased by 0.0850 percentage points (8.5 basis points). The magnitude of this charge-off increase closely corresponds to the decline in ROA documented in Table 4, confirming that credit quality deterioration drove the profitability decline. The increase in charge-offs (8.5 basis points) is smaller than the increase in noncurrent loans (34 basis points), consistent with the typical patterns that loans become noncurrent before banks write them off entirely.

Column (3) examines loss allowances—reserves banks set aside for expected future credit losses. O&G banks increased allowances by 0.0288 percentage points (2.9 basis points) relative to non-O&G banks. This increase is modest relative to the 34 basis point surge in noncurrent loans.[15]

Column (4) shows that the equity capital ratio changed by only 0.0082 percentage points for O&G banks relative to non-O&G banks—economically negligible and statistically insignificant. This indicates that capital constraints were not immediately binding. Both O&G and non-O&G banks maintained equity capital ratios around 11% throughout the sample period, well above the typical 4% regulatory minimum for the leverage ratio documented in Table 2. Similarly, risk-based capital ratios remained well above regulatory minimums (Tier 1 capital ratios around 17-18% versus a 6% minimum; total capital ratios around 19% versus a 10% minimum).

However, deteriorating asset quality combined with stable capital ratios implies erosion of capital cushions above regulatory minimums for O&G banks.[16] While capital constraints were not binding in an accounting sense, this erosion may have influenced lending decisions through several

[15] Berger and Udell (1994) document that banks adjust loan loss reserves gradually in response to credit quality changes, and that regulatory constraints may limit the pace of reserve accumulation. The modest increase in allowance relative to noncurrent loans is consistent with this gradual adjustment process.

[16] We do not observe significant equity issuance by O&G banks during this period. This likely reflects adverse selection costs of equity issuance during distress (Myers and Majluf 1984), small bank aversion to dilution given concentrated ownership (Berger et al. 2005), or uncertain duration of the oil shock making deleveraging cheaper than recapitalization.

channels.[17] In Section 6.3, we investigate whether capital constraints drove lending reductions by examining banks' lending patterns separately for banks above and below median capital ratio as of 2014.

While the control variables provide additional insights into bank performance determinants, we omit their detailed discussion as they fall outside our primary research focus.[18]

Tables 4 and 5 establish that O&G bank performance deterioration was driven by asset-side problems rather than liability-side pressures. The increase in noncurrent loans required higher provisions for loan losses, which directly reduced profitability, while net interest margins remained stable. This pattern—regional economic distress leading to borrower defaults, which generated bank credit losses and reduced profitability—forms the critical link in the transmission of regional shocks through the banking system. The question we address in Section 6 is whether banks facing these credit losses responded by reducing lending, and whether such reductions were concentrated geographically in ways that could amplify the regional downturn.

5.4 Deposit Stability

The stable net interest margin documented in Table 4 suggests that O&G banks did not face elevated funding costs. However, deposit outflows could still affect bank performance if depositors withdrew funds from banks perceived as vulnerable due to exposure to the oil shock. Such deposit withdrawals could force banks to access more expensive funding sources or reduce lending to maintain liquidity (Diamond and Dybvig 1983; Iyer and Puri 2012).

To examine deposit dynamics directly, we use bank-county-level deposit data from the FDIC Summary of Deposits. We estimate a specification that includes bank-year fixed effects to control for bank-specific time-varying deposit demand:

$$Log(Deposits_{b,c,t}) = \beta_1(Post_t \times O\&G\ County_c) + \beta_2(Post_t \times Z_c) + \alpha_c + \gamma_{b,t} + \varepsilon_{b,c,t} \quad \cdots\ (4)$$

where $Deposits_{b,c,t}$ represents bank b's deposits in county c at time t. Bank-year fixed effects $\gamma_{b,t}$ absorb all factors that affect a bank's overall deposit demand in a given year, including lending opportunities, liquidity needs, deposit rate setting, or bank financial condition. With these fixed effects, identification comes from within-bank variation across counties: we compare how the same bank's deposits evolved in O&G counties versus non-O&G counties after the shock. If deposit

[17] First, banks may reduce lending to rebuild capital cushions through precautionary risk management even when not required to do so by regulators (Bernanke and Lown 1991; Peek and Rosengren 1995). Second, bank supervisors may apply informal pressure on banks to maintain strong capital ratios as asset quality deteriorates and uncertainty remains elevated (Peek and Rosengren 1995; Berger and Udell 1994). Third, forward-looking banks anticipating further credit losses may preemptively reduce lending to preserve capital for absorbing future losses, particularly when uncertainty about the duration of adverse conditions remains high (Holmstrom and Tirole 1997).

[18] The control variables display theoretically consistent patterns; deposit and capital ratios correlate positively with asset quality (reflecting stable funding and stronger risk management capacity); loss allowances naturally correlated with current asset quality problems; and liquid asset ratios show mixed effects depending on specification.

outflows occurred specifically in O&G counties—whether due to regional distress reducing depositors' savings or concerns about bank exposure to the oil shock—the coefficient β_1 should be negative and significant.

Table 6 presents the results. Column (1) includes bank-year fixed effects and county fixed effects. Column (2) adds interactions between Post and 2010 county characteristics (log population, log median household income, log housing units, log total county deposits, and HHI of bank deposit concentration). Column (3) replaces county fixed effects with commuting zone fixed effects as a robustness check.

[Table 6: Impact of Oil Price Shock on Bank Deposits (Bank-County Level)]

The coefficient on Post × O&G County is small and statistically insignificant across all specifications. In Column (1), the coefficient is −0.0152. Column (2), our preferred specification with the full set of controls, yields a coefficient of −0.0176. Column (3) with commuting zone fixed effects produces a similar estimate of −0.0184. None of these estimates is statistically distinguishable from zero at conventional significance levels.

The point estimates suggest deposits in O&G counties grew approximately 1.5-1.8% less than deposits in non-O&G counties for the same bank over the five-year post-shock period. This represents less than 0.4% annual growth differential—economically negligible. More importantly, after controlling for bank-specific deposit demand through bank-year fixed effects, there is no statistical evidence of systematic deposit outflows from O&G counties.

This finding indicates that deposits in O&G regions remained stable despite significant regional economic distress, deteriorating bank asset quality, and declining bank profitability.[19] This rules out deposit flight as a driver of credit supply reductions. Combined with stable net interest margins (Table 4) and minimal funding cost increases, the evidence points unambiguously to asset-side problems—deteriorating loan quality and capital concerns—rather than liability-side pressures as the transmission mechanism.

The absence of deposit outflows during this period of economic and banking distress likely reflects the presence of federal deposit insurance, which covered up to $250,000 per account (Iyer and Puri 2012). Depositors with insured deposits had limited incentive to withdraw funds even if banks experienced credit losses, as deposits were guaranteed by the FDIC. For uninsured deposits—typically held by large businesses and high-net-worth individuals—the absence of outflows suggests that depositors did not perceive O&G banks as facing imminent failure risk.

[19] The Summary of Deposits data capture domestic retail deposits but exclude wholesale funding (15-1% of O&G bank liabilities). However, stable net interest margins and funding costs (Table 4) indicate wholesale funding stress was minimal. Federal deposit insurance ($250,000 per account) likely explains retail deposit stability. Robustness checks using less demanding specifications (bank FE + year FE rather than bank x year FE) yield similar results, confirming deposits remained stable even at the bank level.

This result is critical for interpreting our findings: the banking channel through which the oil shock transmitted to regional economies operated primarily through credit supply contraction driven by asset-side problems rather than liability-side pressures. Combined with the stable net interest margins documented in Table 4, these results rule out funding disruptions as a driver of O&G bank behavior and allow us to focus on credit supply responses in Section 6.

6 Credit Supply Responses of Oil and Gas Banks

Having established that O&G banks experienced deteriorating asset quality without facing liability-side disruptions, we now examine whether these banks reduced their supply of credit to small businesses. The findings in Section 5 indicate that O&G banks faced asset-side problems stemming from borrower distress in oil-dependent regions, not funding pressures or deposit outflows.

6.1 Identification Strategy: Separating Supply from Demand

Distinguishing credit supply from credit demand is central to our analysis. Loan originations reflect the equilibrium outcome of both supply (banks' willingness to lend) and demand (firms' desire to borrow). In regions experiencing economic distress, loan demand may decline as businesses faced reduced investment opportunities and heightened uncertainty (Bernanke and Gertler 1995). Our goal is to isolate whether O&G banks contracted credit supply beyond any changes in demand.

We employ a DID specification at the bank-county level:

$$Log(Lending_{b,c,t}) = \beta_1(Post_t \times O\&G\ Bank_b) + \delta X_{b,t-1} + \alpha_b + \gamma_{c,t} + \varepsilon_{b,c,t} \quad \cdots\ (5)$$

where b indexes banks, c indexes counties, and t indexes years. The dependent variable is the natural logarithm of bank b's small business loan originations in county c at year t, measured by either the number of loans or total dollar amounts. We use data from the Community Reinvestment Act (CRA) disclosure files, which report small business loans (original amounts ≤\$1 million) aggregated by bank, county, and year.

The coefficient of interest is β_1, which captures the differential change in lending by O&G banks relative to non-O&G banks following the shock.

The critical identification challenge is controlling for county-specific credit demand. Economic conditions in O&G regions deteriorated following the shock (as documented in Section 4), which likely reduced firms' demand for credit. To isolate credit supply, we include county-year fixed effects ($\gamma_{c,t}$) that absorb all time-varying factors affecting credit demand in a given county and year, including local economic conditions, investment opportunities, firm creditworthiness, and demographic changes. With these fixed effects, identification comes from within-county variation across banks: we compare how O&G banks' lending in the same county evolved relative to non-

O&G banks' lending after the shock. A negative coefficient β_1 indicates that O&G banks reduced lending more than non-O&G banks to the same local borrower pool, which we interpret as a credit supply reduction.

This identification strategy follows the approach pioneered by Khwaja and Mian (2008) and widely adopted in the banking literature (Amiti and Weinstein 2018; Cortes and Strahan 2017). By saturating the regression with county-year fixed effects, we effectively compare the lending behavior of O&G versus non-O&G banks to the same borrower pool in the same time period, holding constant all demand-side factors. The key identifying assumption is that all banks operating in a given county face the same local credit demand conditions, and any differential change in lending by O&G banks reflects supply-side factors.

We also include bank fixed effects (α_b) to absorb time-invariant bank characteristics such as size, business model, charter type, and historical market presence. The vector $X_{b,t-1}$ includes the same lagged bank-level control variables introduced in Section 5 to account for differences in bank financial conditions that might affect lending capacity.

Standard errors are two-way clustered at the bank and commuting zone levels to account for correlation in lending outcomes both within banks across counties and within local labor markets (commuting zones) across banks. This conservative clustering approach allows for arbitrary correlation structures in both dimensions (Cameron, Gelbach, and Miller 2011).

6.2 Small Business Lending Responses

Table 7 presents estimates of the oil price shock's impact on small business lending by O&G banks. Panel A reports results using the number of small business loans as the dependent variable, while Panel B uses the total dollar amount of loans. Column (1) examines all small business loans (original amounts ≤$1 million). Columns (2)–(4) disaggregate lending by loan size category: ≤$100K, $100K–$250K, and >$250K. This decomposition allows us to assess whether credit supply reductions were uniform across borrower types or concentrated among particular segments.

[Table 7: Impact of Oil Price Shock on Small Business Credit Supply]

6.2.1 Overall Credit Supply Reduction

Column (1) of Panel A shows that O&G banks originated 20.2% fewer small business loans (in terms of loan counts) relative to non-O&G banks after the shock, conditional on local credit demand absorbed by county-year fixed effects. Panel B reveals a similar but somewhat smaller pattern for loan dollar amounts: O&G banks reduced total lending by 12.3%. The smaller magnitude for dollar amounts compared to loan counts indicates that O&G banks reduced lending on both the extensive margin (number of borrowers served) and the intensive margin (average loan size), with particularly sharp reductions in the number of smaller loans.

These estimates represent substantial credit supply contractions occurring after controlling for county-specific demand conditions through county-year fixed effects and bank-specific characteristics through bank fixed effects and lagged balance sheet controls. The R-squared values of 0.47–0.48 indicate that the high-dimensional fixed effects explain nearly half of the variation in lending outcomes, underscoring the importance of controlling for both demand and supply factors.

6.2.2 Heterogeneity by Loan Size: Flight to Quality

Columns (2)–(4) reveal striking heterogeneity in credit supply responses across loan size categories, consistent with banks reallocating credit toward less risky borrowers when facing asset quality pressures. For loans ≤$100K (Column 2), O&G banks reduced lending by 22.0% in terms of loan counts (Panel A) and 12.3% in terms of dollar amounts (Panel B). These are the largest effects across all loan size categories. Small loans typically go to smaller businesses with limited collateral and shorter credit histories—borrowers who are more vulnerable during economic downturns and have fewer alternative financing sources (Berger and Udell 2006; Petersen and Rajan 1994).

In contrast, for loans between $100K and $250K (Column 3), the coefficients are small and statistically insignificant: -2.5% for loan counts and -1.7% for dollar amounts, neither significantly different from zero. This middle category of loans appears largely unaffected by the shock.

For loans exceeding $250K (Column 4), the point estimates are positive—O&G banks increased lending by 3.7% (loan counts) and 4.4% (dollar amounts)—though these estimates are not statistically significant at conventional levels. While we cannot reject the null hypothesis of no effect for this category, the positive point estimates contrast sharply with the large negative effects for small loans.

This pattern is consistent with a “flight to quality” phenomenon documented in earlier banking literature (Bernanke, Gertler, and Gilchrist 1996; Rajan 1994). Larger loans typically go to more established businesses with stronger balance sheets, longer banking relationships, more tangible collateral, and greater transparency. During periods of heightened risk and capital pressure, banks rationally shift their portfolios toward such safer borrowers (Berger and Udell 2004). By maintaining credit to larger borrowers while cutting credit to smaller borrowers, O&G banks managed their risk exposure but concentrated the credit supply disruption precisely where it would have the greatest impact on employment and economic activity, as small businesses account for approximately 47% of private-sector employment in the United States (U.S. Small Business Administration 2019).

The R-squared values vary across loan size categories, from 0.26 for loans >$250K to 0.52 for loans ≤$100K, reflecting differences in the predictability of lending across borrower types. The consistently high R-squared values validate our identification strategy: the county-year and bank fixed effects capture the primary drivers of lending variation, allowing us to cleanly identify the differential effects on O&G banks.

We acknowledge that the control variables reveal supplementary insights about bank lending determinants, though we do not discuss them in detail given our focused empirical objectives.[20]

6.2.3 Economic Magnitude and Implications

To assess the economic significance of these credit supply reductions, we focus on the smallest loan category (<$100K), which experienced the largest reductions. The 24.8% reduction in the number of small loans represents a substantial credit supply shock to micro-enterprises and small businesses. For O&G counties where O&G banks dominate the banking system—operating the majority of branches and holding the majority of deposits (as documented in Table 2)—this credit contraction directly affected thousands of small businesses seeking to maintain operations, meet payroll, or invest during the regional downturn.

The concentration of credit cuts among the smallest loans carries important distributional implications. Larger businesses (those receiving loans >$250K) maintained or even slightly increased access to credit, while the smallest and most vulnerable businesses faced sharp credit constraints. This pattern suggests that credit market friction during downturns disproportionately harm smaller firms (Gertler and Gilchrist 1994), potentially leading to increased market concentration as smaller competitors exit.

The flight to quality pattern we document reflects banks' rational response to heightened uncertainty and capital pressure (Bernanke, Gertler, and Gilchrist 1996). While individually rational from each bank's perspective, this collective behavior may amplify regional economic distress by denying credit precisely to the firms that need it most and have the fewest alternatives (Holmstrom and Tirole 1997). Section 7 examines whether this credit supply contraction had differential effects across regions, providing direct evidence of amplification through the banking channel.

6.3 Capital Constraint Mechanisms

To further examine whether capital constraints drove lending reductions, we test whether effects concentrated among banks with smaller capital cushions. Table 8 re-estimates the credit supply regressions (Table 7, Column 1) separately for banks above and below median capital ratios as of 2014.

[Table 8: Credit Supply Reduction by Bank Capital Position]

Panel A examines risk-based Tier 1 capital ratios. Banks with below-median capital ratios (median: 13.8%) reduced lending by 21.07% following the shock, compared to 1.73% for above-median

[20] The lagged bank-level controls show expected patterns were statistically significant. However, most control variable coefficients are not statistically significant in these demanding specifications with high-dimensional fixed effects, as the primary drivers of differential lending behavior are captured by time-invariant bank characteristics (bank fixed effects) and time-varying county conditions (county-year fixed effects).

banks. The difference is economically meaningful and statistically significant at 10 percent level, suggesting constrained banks with smaller cushions reduced lending more severely than others.

Panel B examines the leverage ratio (Tier 1 capital to average assets). Banks with below-median leverage ratio (median: 9.97%) reduced lending by 19.37%, compared to 13.7% for above median banks. The difference is economically meaningful yet statistically insignificant.

These patterns suggest that while capital considerations influenced lending decisions, the channel operated more concentrated among O&G banks closest to regulatory minimums. This is most consistent with binding regulatory constraints.

7 Amplification Through the Banking Channel

The results in Section 6 demonstrate that banks with concentrated exposure to oil-producing regions reduced small business credit supply following the oil price shock, even after controlling for local credit demand through county-year fixed effects. Credit reductions were substantial and concentrated among the smallest loans. This section investigates whether these credit supply reductions created a destabilizing feedback loop that amplified the initial shock through two mechanisms: geographic concentration of credit cuts in already-distressed regions, and measurable deterioration in real economic outcomes beyond direct shock effects.

7.1 Geographic Distribution of Credit Supply Reductions

A substantial literature examines whether financial systems amplify or absorb economic shocks. Bernanke and Gertler (1989) demonstrate theoretically how credit market imperfections magnify initial disturbances through the financial accelerator mechanism. Empirical evidence predominantly supports amplification: Ashcraft (2005) finds that bank failures cause significant local economic contractions, Peek and Rosengren (2000) document international shock transmission through bank lending channels, and Chodorow-Reich (2014) shows that firms dependent on distressed lenders experience employment losses. However, banking system structure may mediate these effects. Cortes and Strahan (2017) demonstrate that geographically diversified banks reallocate capital across regions to smooth local shocks, while Morgan, Rime, and Strahan (2004) find that interstate bank integration reduces state-level business cycle volatility.

Having established that O&G banks reduced credit supply following the oil price shock (Section 6), we examine where these reductions occurred. If O&G banks reduced lending primarily in non-O&G counties—perhaps deliberately diversifying away from oil exposures—the credit channel would not amplify regional distress in oil-dependent areas. Conversely, if credit reductions concentrated in O&G counties already experiencing direct economic damage, this would indicate a destabilizing feedback loop. Specifically, the oil shock harms regional economies, which causes bank asset quality deterioration. Banks then contract credit supply in affected regions, and this credit contraction deepens the regional downturn, creating further economic harm.

7.1.1 Empirical Specification

To examine the geographic distribution of credit supply reductions, we estimate a difference-in-difference-in-differences (DDD) specification that exploits variation across banks, counties, and time:

$$Log\left(Lending_{b,c,t}\right) = \beta_1(Post_t \times O\&G\ Bank_b \times O\&G\ County_c) + \beta_2(Post_t \times O\&G\ Bank_b) + \beta_3(O\&G\ Bank_b \times O\&G\ County_c) + \alpha_b + \gamma_{c,t} + \varepsilon_{b,c,t}. \quad \cdots (6)$$

The specification compares the same bank's lending across different types of counties over time, isolating the geographic targeting of credit supply reductions.

The specification includes three sets of high-dimensional fixed effects. Bank fixed effects (α_b) absorb all time-invariant characteristics of banks. County-year fixed effects ($\gamma_{c,t}$) absorb all time-varying county-specific factors, including local credit demand—crucial for isolating credit supply shifts from demand shifts.

The coefficient of interest is β_1 on the triple interaction term. This coefficient captures the differential change in lending by O&G banks in O&G counties relative to three benchmarks: (1) O&G banks' lending in non-O&G counties, (2) non-O&G banks' lending in O&G counties, and (3) non-O&G banks' lending in non-O&G counties. Because county-year fixed effects absorb local credit demand, a negative β_1 indicates that O&G banks reduced credit supply more severely in O&G counties—precisely the regions where credit was most needed and where these banks faced the greatest asset quality deterioration.

7.1.2 Credit Supply Reduction Concentrated in Oil-Dependent Regions

Table 9 presents the results. Panel A examines loan counts, while Panel B examines loan amounts. Across all specifications, the coefficient on the triple interaction term is negative and statistically significant, indicating that O&G banks reduced lending more sharply in O&G counties than elsewhere.

[Table 9: Geographic Distribution of Credit Supply Reductions]

In Column (1) of Panel A, the triple interaction coefficient is -0.2045, indicating that O&G banks reduced loan counts by an additional 18.5% in O&G counties compared to their lending elsewhere and relative to other banks' geographic patterns. Panel B shows an even larger effect for dollar amounts, with a coefficient of -0.3819 implying a 31.7% additional reduction in lending volume to O&G counties. The larger magnitude for dollar amounts suggests that O&G banks reduced both the number of borrowers served (extensive margin) and average loan size (intensive margin) in oil-dependent regions.

The coefficient on $\text{Post} \times \text{O\&G Bank}$ reveals how O&G banks adjusted lending in non-O&G counties. For large loans (>$250K, Column 4), this coefficient is +0.1160 (significant at 1%), indicating that O&G banks increased lending to larger borrowers in non-O&G counties by approximately 12.3% while simultaneously cutting lending in O&G counties by 10.6%. This pattern provides direct evidence of geographic reallocation: O&G banks deliberately shifted credit away from oil-exposed regions toward non-oil regions, concentrating new lending among larger, presumably safer borrowers. This represents a double retrenchment—away from risky geographies and away from risky (small) borrowers.

The triple interaction coefficient estimates in Columns (2)-(4) reveal that geographic concentration occurred across all borrower types. For the smallest loans (≤$100K, Column 2), O&G banks reduced lending in O&G counties by an additional 18.0% (loan counts) to 27.1% (dollar amounts) beyond their reductions elsewhere. For mid-sized loans ($100K-$250K, Column 3), additional reductions were 10.6% (loan counts) to 20.0% (dollar amounts). Even for the largest loans (>$250K, Column 4), O&G banks reduced lending in O&G counties by approximately 11.2% while increasing such loans in non-O&G counties by 12.3%. The net effect for large loans was approximately zero overall (as documented in Table 7, Column 4), but this masked substantial geographic reallocation.

These findings reveal that O&G banks concentrated credit supply reductions in regions experiencing direct economic distress from the oil price collapse. Rather than acting as shock absorbers by maintaining credit in affected areas—as geographically diversified banks might through cross-subsidization (Cortes and Strahan 2017)—O&G banks intensified the geographic concentration of economic hardship through deliberate portfolio reallocation away from oil-dependent regions.

7.2 Amplified Impact on Regional Economic Outcomes

The preceding analysis demonstrates that O&G banks concentrated credit supply reductions in oil-dependent counties. We now examine whether this geographic pattern translated into differential real economic outcomes, providing direct evidence of amplification through the banking channel.

Our identification strategy compares economic outcomes across O&G counties with different levels of exposure to O&G banks. The key insight is that if credit supply reductions amplified regional economic distress, then O&G counties with greater presence of O&G banks should have experienced worse outcomes than O&G counties with less exposure to these banks, even though both types of counties experienced the same direct oil price shock.

7.2.1 Measuring Banking System Structure

We construct a county-level measure of exposure to O&G banks based on branch presence. For each county, we calculate the share of bank branches operated by O&G banks as of 2014 (immediately before the shock). Among the 3,132 counties in our sample with available banking data, the distribution is highly bimodal: 955 counties (30.5%) have zero O&G bank presence, while 504 counties (16.1%) have exclusively O&G bank branches. The median branch share is 0.25.

We define High O&G Bank Presence as an indicator variable equal to one if a county's O&G bank branch share exceeds the median (25%), yielding 1,566 high-presence counties and 1,566 low-presence counties. We measure this variable before the shock to ensure our treatment definition is not affected by endogenous responses.

Among the 1,395 O&G counties in our sample, 1,333 (95.5%) are classified as high O&G bank presence, while only 55 (3.9%) are low O&G bank presence. This overwhelming concentration reflects the historical development of community banking in oil-producing regions: local banks established to serve oil and gas communities naturally concentrated their operations in areas with hydrocarbon reserves. High-presence O&G counties contain 44.5 million workers (96.9% of all O&G county employment), while low-presence O&G counties contain only 1.4 million workers (3.1%). High-presence counties exhibit higher average employment per county (33,412 vs. 24,828), higher average annual wages per employee ($49,715 vs. $41,802), and higher average annual bankruptcy filings (262 vs. 220).

The dominance of geographically concentrated banks in oil-producing regions means that credit supply amplification effects characterize the typical O&G county experience. When we examine differential outcomes between high and low O&G bank presence counties, we are effectively comparing the 96% of oil counties (by employment) where credit supply disruptions occurred against the 4% where diversified banks maintained credit access.

7.2.2 Empirical Specification

We estimate a DDD specification at the county-year level:

$$\begin{aligned} Y_{c,t} = \beta_1(&Post_t \times High\ O\&G\ Bank\ Presence_c \times O\&G\ County_c) \\ &+ \beta_2(Post_t \times High\ O\&G\ Bank\ Presence_c) + \beta_3(Post_t \times O\&G\ County_c) \\ &+ \beta_4(Post_t \times Z_c) + \alpha_c + \gamma_t + \varepsilon_{c,t} \qquad \cdots (7) \end{aligned}$$

where $Y_{c,t}$ represents regional economic outcomes: the log of establishments, employment, average weekly wages, or total bankruptcy filings. The coefficient of interest is β_1 on the triple interaction term, which captures the differential economic impact in O&G counties with high O&G bank presence relative to three comparisons: (1) O&G counties with low O&G bank presence, (2) non-O&G counties with high O&G bank presence, and (3) non-O&G counties with low O&G bank presence.

The specification includes county fixed effects (α_c) and year fixed effects (γ_t). The vector Z_c includes 2010 county characteristics (log population, log median household income, log housing units, log total deposits, and HHI of bank deposit concentration) interacted with $Post_t$ to allow for differential time trends based on pre-existing conditions. Standard errors are clustered at the county level.

7.2.3 Amplification Results

Table 10 presents the results for four economic outcomes. The triple interaction coefficient provides evidence of amplification through the banking channel, with the strongest effects for employment and bankruptcies.

[Table 10: Amplification Effects on Regional Economic Outcomes]

Establishments (Column 1). The triple interaction coefficient is -0.0274 ($p<0.10$), indicating that O&G counties with higher O&G bank presence experienced a 2.7% decline in establishments beyond baseline effects. High O&G bank presence counties had 3.31 million establishments in 2014 (average 2,483 per county). The 2.7% amplification effect represents approximately additional 89,000 business closures attributable to credit supply disruptions beyond direct shock effects. While the statistical significance is weaker than for employment—reflecting that establishment counts are "stickier" than employment levels—the economic magnitude is substantial. These closures represent permanent destruction of organizational capital, customer relationships, and entrepreneurial activity.

Employment (Column 2). The triple interaction coefficient is -0.0329, statistically significant at the 1% level. This indicates that O&G counties with high O&G bank presence experienced a 3.2% employment decline relative to their peers' counties, beyond whatever baseline effects they faced from the oil price shock.

To interpret the magnitudes, we examine the components of the total effect. The coefficient on $Post_t \times O\&G\ County_c$ is 0.0092, positive but statistically insignificant. This represents the direct effect experienced by low O&G bank presence O&G counties. The positive coefficient indicates these counties experienced modest employment gains (+0.92%) following the oil shock, demonstrating that diversified banks successfully insulated these communities from the commodity price decline. The amplification coefficient (-3.24%) captures the additional employment loss in high O&G bank presence counties attributable specifically to credit supply disruptions.

Figure 5 illustrates these employment dynamics. While both O&G and non-O&G counties experienced employment growth from 2011 to 2019—reflecting the broader national economic recovery—O&G counties grew substantially less. Total employment in non-O&G counties increased from 63.0 million to 73.5 million (a gain of 16.7%), while actual employment in O&G counties increased from 42.7 million to 49.5 million (a gain of 15.9%). However, this aggregate masks critical heterogeneity driven by banking system structure. The counterfactual trajectory (red line) shows that O&G counties would have reached 51.2 million jobs by 2019 had they maintained credit access comparable to low O&G bank presence counties. The gap between actual (49.5 million, orange line) and counterfactual (51.2 million, red line) employment—1.7 million jobs—represents the cumulative impact of credit supply disruptions through 2019. Both the actual and counterfactual trajectories include the small base of employment in low O&G bank presence counties (shown as the green segment), which experienced positive employment effects and grew steadily throughout the period.

[Figure 5: Employment Dynamics and the Credit Channel: Actual vs. Counterfactual Outcomes]

The net effect in high O&G bank presence counties is the sum of these components: +0.92% (direct effect) -3.24% (amplification effect) = -2.32%. High O&G presence counties (1,333 counties with 44.5 million workers in 2014) experienced total employment losses of 44,500,000 x 0.0232 = 1,032,400 jobs, or approximately 1.03 million jobs. This total decomposes into:

- Direct effect: +0.92% = +409,400 jobs (what these counties would have experienced with diversified banks)
- Amplification effect: -3.24% = -1,441,800 jobs (credit supply disruption)
- Net effect: -2.32% = -1,032,400 jobs

The credit channel accounts for 140% of net employment losses in high-concentration counties (1,441,800 / 1,032,400 = 1.40). This apparent paradox—amplification exceeding net losses—reflects the fact that diversified banks would have supported approximately 410,000 jobs through the commodity downturn. Equivalently, credit supply disruptions were responsible for essentially all employment losses, as diversified banks would have largely insulated these counties from the oil shock.

In contrast, low O&G bank presence counties (55 counties with 1.4 million workers) experienced employment gains of 1,400,000 x 0.0092 = 12,880 jobs, or approximately 13,000 jobs. These counties demonstrate that diversified banking systems can effectively buffer regional economies from sector-specific shocks.

The coefficient on $Post_t \times High\ O\&G\ Bank\ Presence_c$ (capturing effects in non-O&G counties with high O&G bank presence) is -0.0006, small and statistically insignificant. This result indicates that high O&G bank presence did not systematically affect economic outcomes in non-O&G counties, supporting the interpretation that amplification operated specifically through the interaction of regional economic shocks and concentrated banking systems.

While our baseline analysis (Table 3) found that O&G counties experienced a 2.26% employment decline on average, the decomposition in Table 10 reveals this aggregate masks substantial heterogeneity:

- 96% of O&G counties (by employment) experienced -2.32% decline
- 4% of O&G counties (by employment) experienced +0.92% gain
- Weighted average: (-2.32% x 0.969) + (0.92% x 0.031) = -2.22%

This closely matches the -2.26% baseline effect, validating our decomposition. The small difference reflects sample composition variations and the inclusion of banking structure controls in Table 10.

Wages (Column 3). The triple interaction coefficient is -0.0123, suggesting a 1.2% wage decline though not statistically significant at conventional levels. The lack of statistical significance likely reflects that wage adjustments occur more gradually than employment adjustments, and that compositional effects (loss of high-wage oil jobs) affect both high and low O&G bank presence counties similarly.

Bankruptcies (Column 4). The triple interaction coefficient is 0.1205, statistically significant at the 1% level, indicating that bankruptcy filings increased by 12.8% more in O&G counties with high O&G bank presence. This large effect demonstrates that credit constraints forced businesses and households into financial distress at substantially higher rates in counties where the banking system was dominated by O&G banks.

High O&G bank presence counties experienced 349,000 bankruptcy filings annually in 2014 (pre-shock). The 12.8% amplification effect translates to approximately 45,000 additional bankruptcy filings per year, or 224,000 additional bankruptcies over the five-year post-shock period (2015-2019), attributable to credit supply disruptions beyond the direct impact of falling oil prices. These bankruptcies—encompassing both business (Chapter 11 and Chapter 7) and personal (Chapter 7 and Chapter 13) filings—impose lasting costs on households through credit score damage, asset liquidation, and psychological stress, and destroy business organizational capital and jobs.

The direct effect ($Post_t \times O\&G\ County_c$) is 0.0547 (p<0.01), indicating that even low O&G bank presence counties experienced increased bankruptcies (5.6%) from the direct economic shock. However, the amplification in high-presence counties more than doubled this effect, demonstrating that credit supply constraints significantly exacerbated financial distress.

7.3 Dynamic Effects

Figure 5 presents event study estimates showing the triple interaction coefficients by year for all four outcomes: establishments (Panel A), employment (Panel B), average weekly wages (Panel C), and total bankruptcy filings (Panel D). Across all outcomes, the pre-shock coefficients (2011-2013) are small and statistically indistinguishable from zero, supporting parallel pre-trends and validating our research design.

[Figure 6: Dynamic Amplification Effects on Regional Economic Outcomes]

The post-shock patterns are consistent with amplification through the banking channel. For establishments, employment, and wages (Panels A-C), coefficients become negative and significant starting in 2015, deepening through 2016 as oil prices remained depressed and persisting through 2019 despite partial oil price recovery. For bankruptcy filings (Panel D), the pattern reverses: coefficients turn positive and significant starting in 2015, indicating elevated financial distress that persists through the sample period.

The persistence of effects through 2019 is particularly striking. By 2019, oil prices had recovered to approximately $60 per barrel (60% of pre-shock levels), yet employment gaps between high and low O&G bank presence counties remained nearly as large as at the trough. This persistence—consistent with findings by Autor, Dorn, and Hanson (2013) documenting slow regional adjustment to economic shocks—suggests that credit supply disruptions transformed a temporary commodity price shock into lasting regional economic damage. Businesses that failed due to credit constraints during the downturn did not automatically restart when conditions improved. Workers who exited the labor force experienced human capital depreciation or migrated to other regions. Investment delayed during the credit crunch represented permanently lost productivity growth. These dynamics underscore the importance of policies that preserve credit access during downturns, particularly in regions with concentrated banking systems.

This contrast between high and low O&G bank presence counties—both experiencing the same oil price shock but different credit supply responses—provides compelling within-shock variation supporting the banking structure hypothesis. Morgan, Rime, and Strahan (2004) find that states with more bank holding company integration experienced less volatile employment growth. Our findings provide complementary micro-level evidence: counties with more concentrated banking systems experienced more severe downturns, while those with more diversified systems were partially insulated. The ability of diversified banks to maintain credit supply when concentrated banks were not capable of demonstrates that banking structure is a first-order determinant of regional economic resilience.

8 Robustness Tests

This section examines robustness of our main findings to alternative definitions, specifications, and outcome measures. Core results remain statistically significant and economically meaningful across all tests, with effects often strengthening under more stringent definitions.

8.1 Alternative Definitions of Treatment and Control Groups

Table 11 examines robustness to alternative definitions of O&G counties and O&G banks across our main specifications. For regional impacts (Panel A), using location quotient-based (LQ-based) county classification (upstream oil and gas employment concentration exceeding national average) yields stronger effects: 4.07% employment decline and 6.75% wage declines (both $p<0.01$) versus 2.26% and 3.93% baseline. Using shale-reserve counties produces 2.05% employment decline and 2.19% wage decline (both $p<0.01$). Bankruptcy increases remain significant across all definitions.

For bank performance (Panel B), LQ-based bank classification yields 10.3 basis point ROA decline and 45.1 basis point noncurrent loan increase (both $p<0.01$) versus 7.2 and 34 baseline. Using only

100% O&G banks produces similar results: 8.1 basis point ROA decline and 38.7 basis point noncurrent loan increases.

For credit supply (Panel C), revenue-based small business loans show 27.1% reduction in loan counts and 22.5% in loan amounts (both $p<0.01$), stronger than baseline 22.6% and 13.1%.

[Table 11: Robustness to Alternative Definitions]

Table 12 tests alternative definitions of High O&G Bank Presence for amplification results. Using the 75th percentile threshold (81.8% branch share) yields dramatically stronger effects: employment amplification increases from 3.2% to 8.7% ($p<0.01$), and the direct effect becomes negative (-1.48%) and significant at the 5% level. Wage amplification becomes strongly significant (-3.4%, $p<0.01$). Using O&G bank share (number of banks rather than branches) confirms results: 4.2% employment amplification, 3.4% wage amplification, and 13.0% bankruptcy amplification. The dose-response relationship—stronger effects with higher concentration—provides compelling evidence that banking system structure causally affects regional outcomes.

[Table 12: Robustness of Amplification Results to Alternative Definitions]

8.2 Alternative Specifications

Table 13 examines deposit stability robustness. Using commuting zones rather than county fixed effects yields a slightly larger coefficient estimate of -0.0184, yet statistically insignificant as well. Using additive rather than interactive fixed effects still produces statistically insignificant estimate of -0.0071. Alternative O&G county definitions (shale reserves: -0.0353; location quotient: -0.0065) also yield insignificant coefficients. Across all specifications, deposits remained stable in O&G regions, confirming that asset quality deterioration—not funding stress—drove credit supply responses.

[Table 13: Robustness of Deposit Stability Results]

Table 14 tests robustness to continuous rather than binary treatment for geographic concentration results. Using actual percentage of O&G bank branches yields consistent and often stronger effects: total loan counts decline by 28.2% (versus 18.5% baseline), and large loans decline by 23.0% (versus 11.2%). This dose-response relationship demonstrates results strengthen with degree of O&G exposure.

[Table 14: Geographic Concentration of Credit Supply Reductions:

Binary vs. Continuous Treatment]

8.3 Alternative Outcome Measures

Table 15 decomposes bankruptcy effects into business and non-business (consumer) bankruptcies.[21] Panel A reports direct regional impact estimates from Table 3, and Panel B reports amplification estimates from Table 10.

Both categories increased significantly in O&G counties, with business bankruptcies showing substantially larger effects. For direct effects (Panel A), business bankruptcies increased by 9.2% compared to 4.9% for non-business. Regarding amplification effects (Panel B), business bankruptcies increased by 23.0%--nearly double the 12.8% total effect—compared to 13.1% for non-business.

The larger amplification for business bankruptcies provides direct evidence that the credit channel operated primarily through business credit constraints. This is consistent with evidence that businesses, particularly small businesses, are more dependent on bank credit and have fewer alternative financing sources than households (Petersen and Rajan 1994; Berger and Udell 2006; Chodorow-Reich 2014). The differential amplification across bankruptcy types—with business effects nearly double those for consumers—indicates that credit supply reductions, rather than general economic conditions alone, drove the additional financial distress in high O&G bank presence counties.

[Table 15: Business vs. Non-Business Bankruptcies: Direct and Amplification Effects]

9 Conclusion

The 2014-2016 oil price collapse imposed severe economic hardship on oil-producing regions of the United States. This paper demonstrates that the banking system amplified rather than absorbed this regional shock. Banks with concentrated exposure to oil-dependent regions experienced credit quality deterioration, reduced lending disproportionately in already-distressed areas, and contributed to deeper and more persistent regional downturns.

Our analysis traces the transmission of the shock from regional economies through the banking system and back to regional outcomes, documenting a destabilizing feedback loop. The oil price shock directly harmed regional economies, which deteriorated bank asset quality. Banks with concentrated geographic exposure then reduced credit supply in affected regions, which deepened and prolonged the regional downturn. Rather than serving as shock absorbers that redistribute and smooth regional distress—as geographically diversified banks might (Cortes and Strahan 2017)—banks with geographically concentrated exposures acted as shock amplifiers.

[21] Business bankruptcies include Chapter 7 and Chapter 11 commercial filings. Non-business bankruptcies include Chapter 7, Chapter 11, and Chapter 13 consumer filings.

We document this transmission mechanism through four sets of findings. First, the oil price shock caused substantial economic distress in oil and gas counties. Following the mid-2014 price collapse, counties with oil and gas reserves experienced 2.26% slower employment growth, 3.93% slower wage growth, and 5.67% higher bankruptcy filings compared to counties without such reserves. These effects emerged immediately after the shock and persisted through 2019, representing approximately 1.04 million jobs lost directly from falling oil prices and 20,000 additional bankruptcies annually.

Second, banks with concentrated exposure to oil-producing regions—those with more than 50% of branches in O&G counties—experienced significant performance deterioration. Return on assets declined by 7.2 basis points for O&G banks relative to other banks. This performance decline was driven by credit quality deterioration: noncurrent loans rose by 34 basis points and net charge-offs increased by 8.5 basis points. Critically, we find no evidence of funding pressures: net interest margins remained stable (1.2 basis points, statistically insignificant) and deposits in O&G regions did not decline (1.8%, statistically insignificant). These findings indicate O&G banks faced asset-side problems stemming from borrower distress, not liability-side disruptions.

Third, banks facing asset quality deterioration reduced credit supply, and concentrated these reductions geographically in oil-dependent counties. O&G banks reduced small business lending by 22.6% in terms of loan counts and 13.1% in dollar amounts, with cuts concentrated among the smallest loans (24.8% for loans under $100K). Most importantly, using high-dimensional fixed effects that control for both local credit demand and bank-wide lending capacity (through bank and county-year fixed effects), we show that O&G banks reduced lending by an additional 18.5% in loan counts and 31.7% in loan amounts in O&G counties compared to their lending in non-O&G counties. This geographic pattern reveals that banks reduced credit supply most sharply in the very regions where they faced the greatest losses and where credit was most needed.

Fourth, this geographic pattern of credit contraction had significant real economic consequences. Among oil and gas counties experiencing the same direct oil price shock, those with high O&G bank presence—where more than 25% of bank branches were operated by O&G banks—experienced substantially worse outcomes. Because 96% of oil-producing counties (representing 97% of oil county employment) are dominated by geographically concentrated banks, these amplification effects characterize the typical oil county experience. High O&G bank presence counties (1,333 counties with 44.5 million workers) suffered employment declines of 2.3% (1.03 million jobs), with credit supply disruptions accounting for 1.44 million jobs lost (3.2% amplification effect). This amplification exceeded net employment losses because the direct effect, absent credit disruptions, would have been positive (+0.9%, or +410K jobs). The credit channel accounts for 140% of net employment losses in high-concentration counties—equivalently, credit supply disruptions were responsible for essentially all employment losses, as diversified banks would have largely insulated these counties from the oil shock.

In contrast, the 55 low O&G bank presence counties (representing 1.4 million workers, 3.1% of O&G county employment) experienced employment gains of 0.9% (+13,000 jobs), demonstrating that diversified banking systems can effectively buffer regional economies from sector-specific shocks.

Event study analysis confirms that high and low O&G bank presence counties followed parallel trends before the shock and diverged only afterward, supporting causal interpretation. The effects persist through 2019 even as oil prices partially recovered, suggesting that credit supply disruptions transformed a temporary commodity price shock into persistent regional economic damage.

These findings carry important lessons for financial stability policy and banking regulation. Geographic concentration risk deserves greater attention from banking supervisors. Banks with geographically concentrated operations face correlated credit losses when regional economies suffer shocks, which can erode capital cushions and force lending reductions that transmit shocks back to regional economies. Banking supervisors could enhance monitoring through standardized concentration metrics, incorporate regional economic scenarios into stress testing frameworks, and consider whether banks with high geographic concentration should face higher capital requirements or enhanced supervisory attention. Our results suggest that banking regulators should track not only sectoral concentrations (such as commercial real estate or energy lending) but also geographic concentration combined with regional economic correlation.

Our results also reinforce the importance of strong capital and liquidity buffers for maintaining credit supply during downturns (Bernanke and Lown 1991; Peek and Rosengren 1995). Banks entering regional downturns with robust capital positions have greater capacity to absorb credit losses without drastically curtailing lending. Counter-cyclical capital buffers—built during boom periods and released during downturns—could provide banks with concentrated regional exposures the capacity to maintain lending when shocks occur. Our findings suggest that such buffers could be calibrated to regional economic conditions rather than only national business cycles, requiring banks operating in boom regions to build capital specifically for release when regional conditions deteriorate.

More broadly, our results demonstrate that financial system structure materially affects regional economic outcomes. The organization of banking markets—the geographic footprint of individual institutions, the diversification of local banking systems, the concentration of credit provision—shapes how regional economies respond to adverse shocks (Morgan, Rime, and Strahan 2004; Loutskina and Strahan 2015). Regions served by geographically diversified banks experienced less severe downturns than regions dominated by locally concentrated banks. Among oil-producing counties experiencing identical commodity price shocks, those with access to diversified banks maintaining credit supply experienced modest employment gains (+0.9%, or +13,000 jobs), while those dependent on geographically concentrated banks experienced combined employment losses of 2.3% (1.03 million jobs), with the credit channel accounting for essentially all losses (140%

of net effects). This variation demonstrates that banking system structure is a first-order determinant of regional economic resilience.

The persistence of amplified effects through 2019 is particularly striking. By 2019, oil prices had recovered to approximately 60% of pre-shock levels, yet employment gaps between high and low O&G bank presence counties remained nearly as large as at the trough. This persistence suggests that credit supply disruptions can have lasting impacts on regional economic capacity. Businesses that fail due to credit constraints during downturns do not automatically restart when conditions improve. Workers who exit the labor force may experience human capital depreciation or migrate to other regions (Autor, Dorn, and Hanson 2013). Investment delayed during credit crunches may represent permanently lost productivity growth. These dynamics underscore the importance of policies that preserve credit access during downturns, particularly in regions with concentrated banking systems.

The policy implications extend beyond banking regulation to regional economic development. Regional economic development policy should consider banking system structure alongside traditional factors like infrastructure, workforce development, and industry diversification. Our findings indicate that regions served by geographically diversified banking systems demonstrated greater resilience during the oil price shock. Policies that encourage bank entry and competition—particularly from institutions with geographic diversification—could enhance regional resilience. This does not necessarily require large national banks; regional banks operating across multiple economically distinct areas can provide diversification benefits. State-level policymakers should monitor local banking system concentration and consider policies to attract diverse financial institutions, particularly in regions with concentrated economic bases vulnerable to sector-specific shocks.

Our findings also inform debates about banking industry consolidation and structure. The U.S. banking industry has experienced substantial consolidation, with the number of FDIC-insured institutions declining from over 18,000 in 1985 to fewer than 5,000 today. While much attention focuses on systemic risks posed by the largest institutions, our findings highlight that regional concentration also matters for local economic stability. The question of whether financial intermediaries amplify or stabilize economic fluctuations depends critically on the alignment between banks' exposures and economic shocks (Bernanke, Gertler, and Gilchrist 1996). When banks' fortunes are tightly tied to the regions they serve, feedback loops emerge. When banks' portfolios span multiple economically distinct regions, cross-subsidization can occur (Cortes and Strahan 2017). This insight extends beyond oil price shocks to any situation where regional economic fortunes diverge—natural disasters, technological disruption of regional industries, shifts in trade patterns, or climate change impacts.

As policymakers consider banking industry structure, the regional stability implications we document deserve consideration alongside more commonly emphasized factors such as competition, efficiency, and access to credit. Building resilient regional economies requires attention not only to economic diversification but also to financial system structure and the concentration of credit provision. Policies to monitor, manage, and potentially limit geographic concentration risk—or to ensure that regions have access to geographically diversified financial institutions—could enhance both financial stability and regional economic resilience, reducing the likelihood that temporary regional shocks are transformed into persistent economic damage through destabilizing feedback loops in the banking sector.

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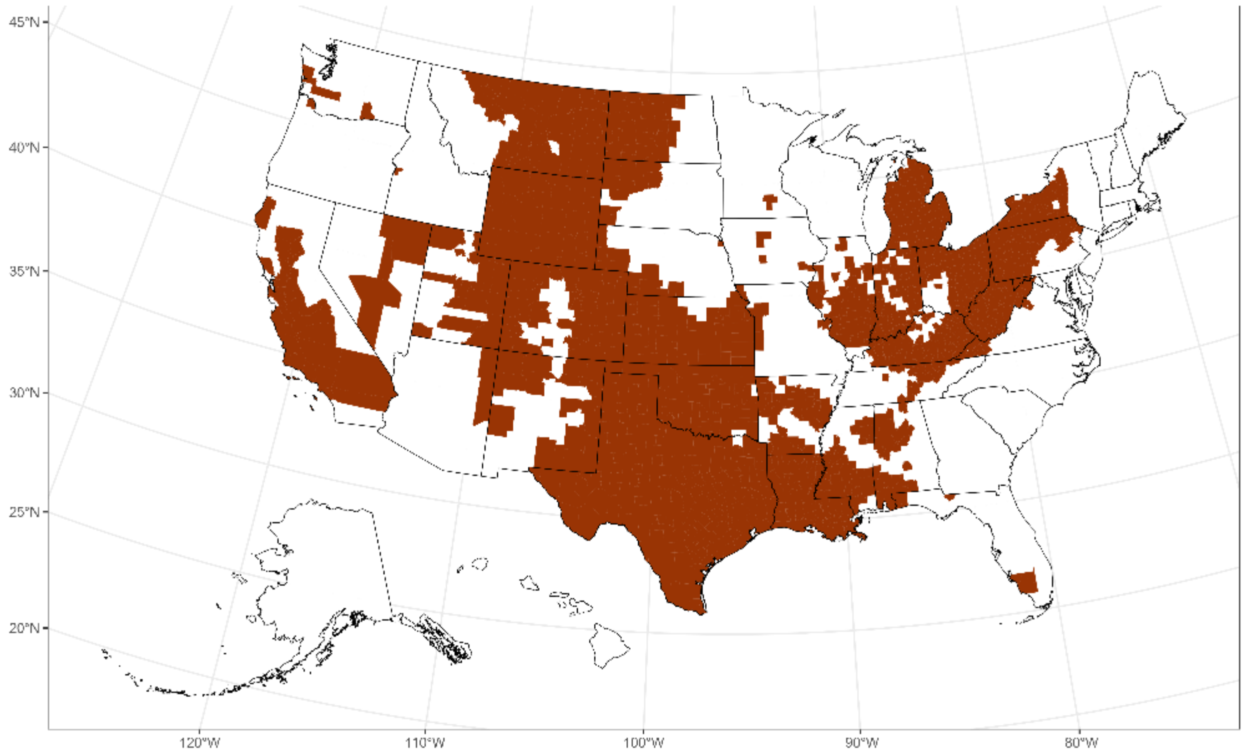
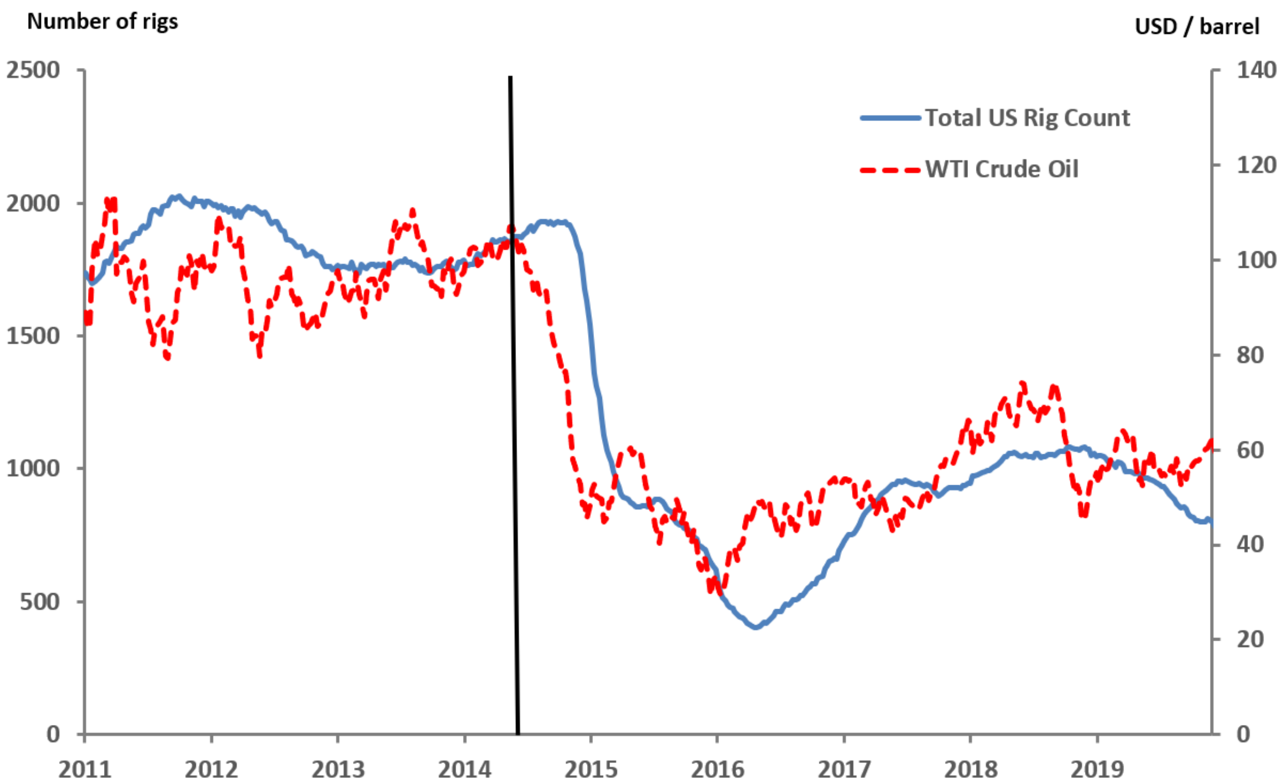
Figures

Figure 1: Geographic Distribution of Oil and Gas Producing Counties



Note: Figure 1 presents a map of the United States showing counties with oil and gas reserves (shaded). The map highlights major producing regions including the Permian Basin (West Texas and southeastern New Mexico), Bakken Formation (North Dakota and Montana), Eagle Ford Shale (South Texas), Marcellus Shale (Pennsylvania, West Virginia, Ohio), Anadarko Basin (Oklahoma and Texas Panhandle), and conventional production areas (Wyoming, Louisiana, Alaska).

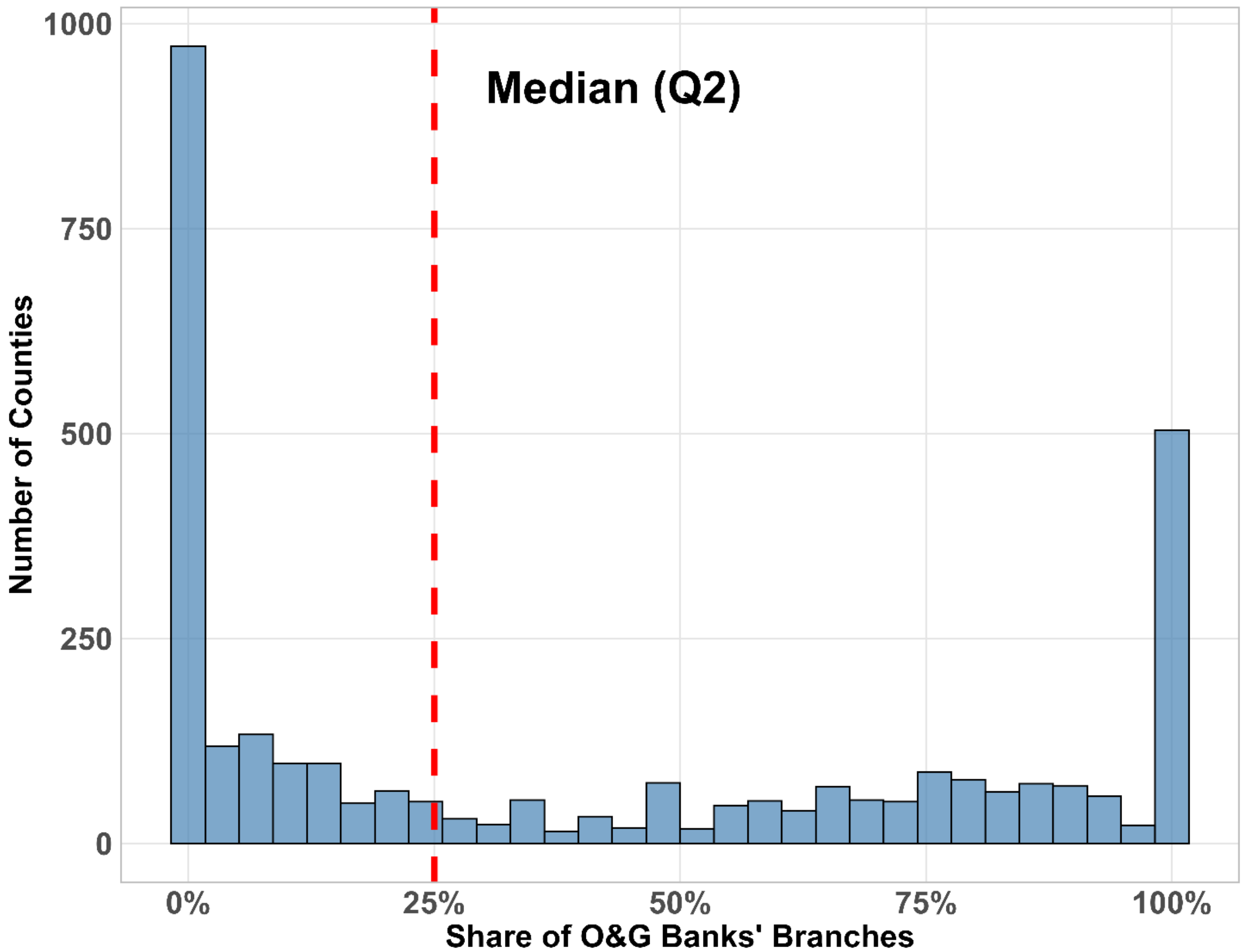
Figure 2: Oil Price and Drilling Activity, 2010-2019



Notes: Monthly WTI crude oil spot prices ($/barrel, red dotted line) and U.S. rotary rig counts (blue solid line), January 2010 – December 2019. Vertical line marks June 2014 (start of price collapse). Oil prices fell 75% from $107/barrel (June 2014) to $26/barrel (February 2016). Rig count fell 80% from 1,930 rigs (October 2014) to 404 rigs (May 2016). The two series exhibit strong co-movement, demonstrating the tight linkage between oil prices and drilling activity throughout the period.

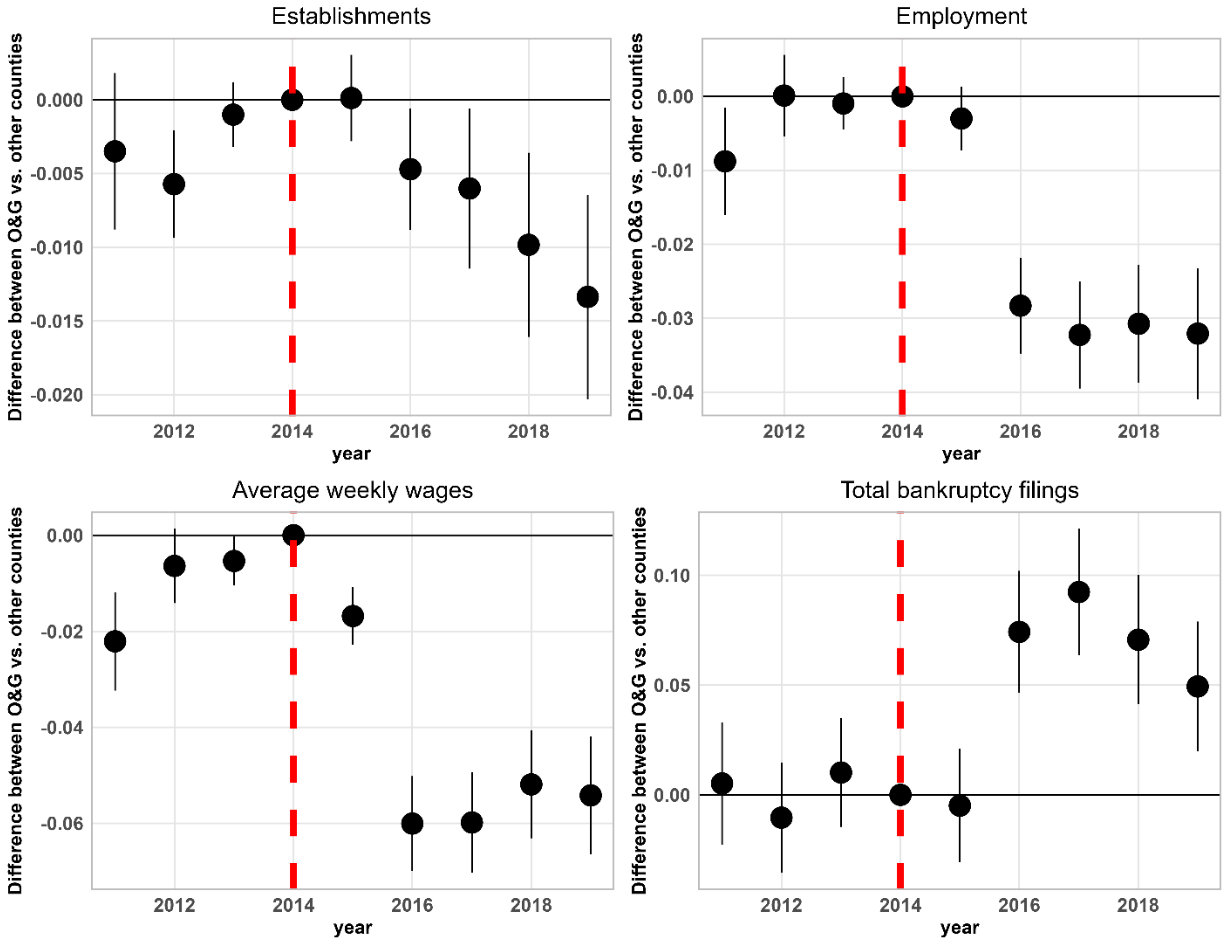
Sources: Bloomberg (WTI crude oil prices), Baker Hughes (rig count)

Figure 3: Distribution of O&G Bank Branch Share Across Counties, 2014



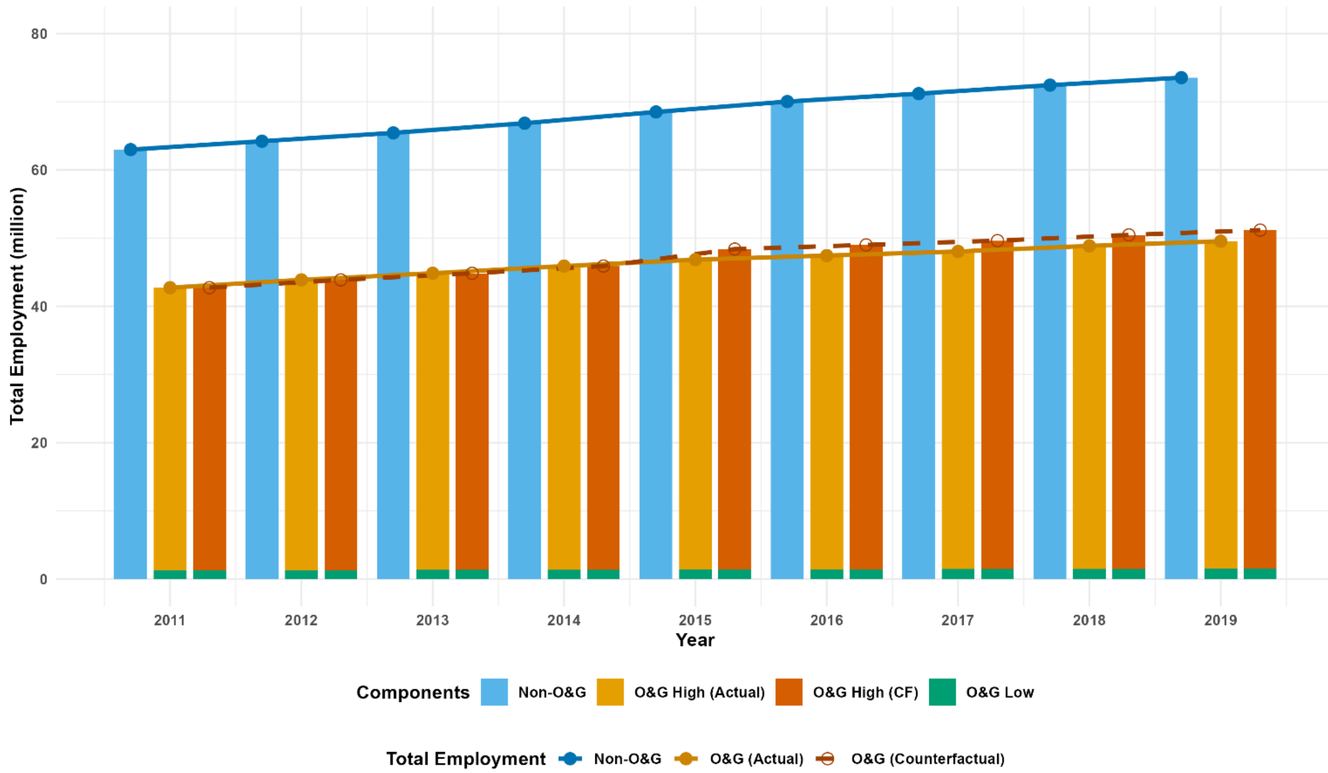
Notes: This histogram shows the distribution of the share of bank branches operated by O&G banks across all 3,132 counties as of 2014. O&G banks are defined as banks with more than 50% of branches in oil and gas counties as of June 2010. The distribution is highly bimodal, with 955 counties (30.5%) having zero O&G bank presence and 504 counties (16.1%) having exclusively O&G bank branches. The median share is 25% (vertical dashed line), which we use as the threshold to define High O&G Bank Presence counties. Quartiles: Q1= 0%, Q2= 25%, Q3= 81.8%.

Figure 4: Dynamic Effects of Oil Price Shock on Regional Economic Outcomes



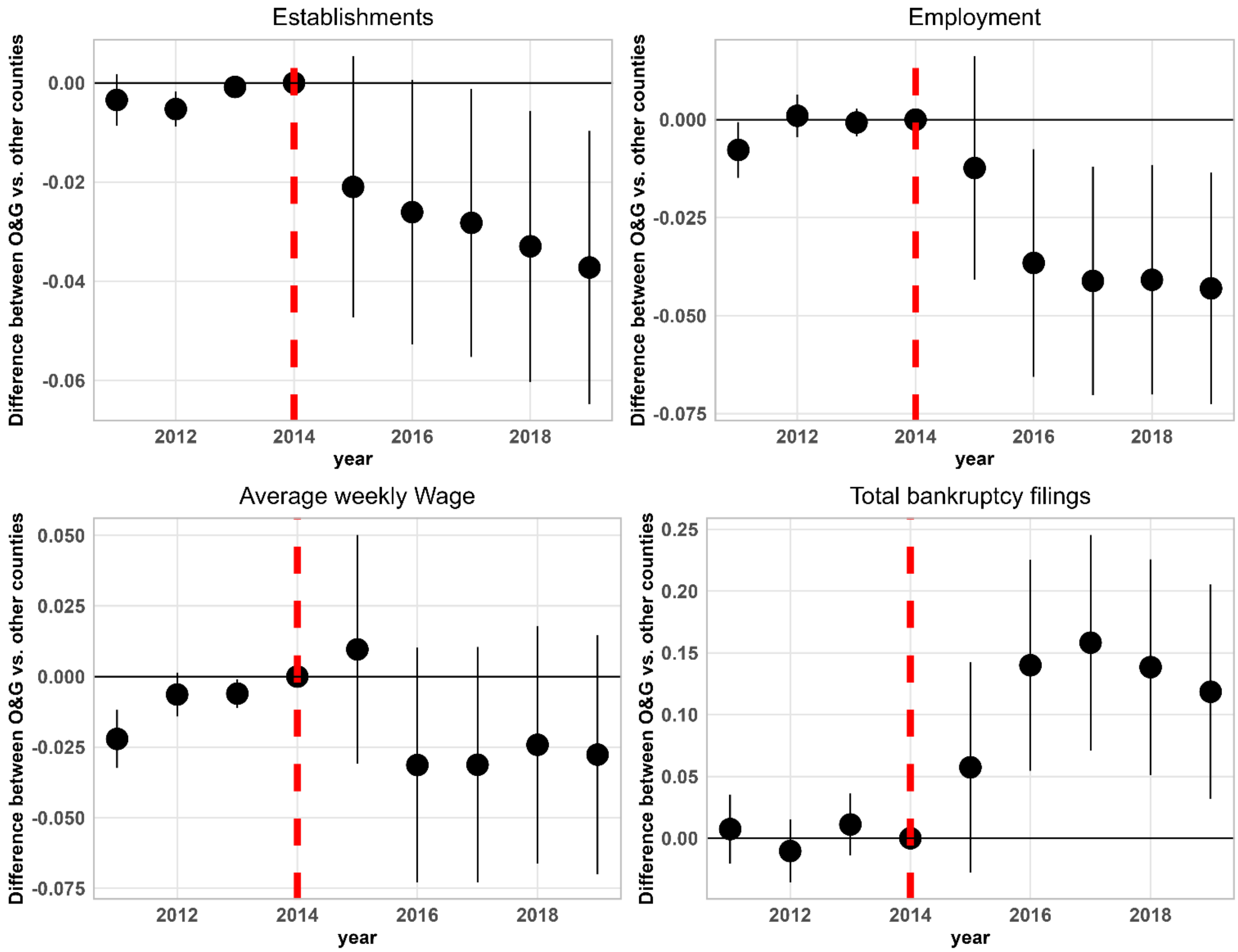
Notes: Event study estimates of θ_τ from Equation (2). Panel A shows log establishments, Panel B shows log employment, Panel C shows log average weekly wages, and Panel D shows log total bankruptcy filings as dependent variables. Dots show point estimates; bars show 90% confidence intervals with standard errors clustered at the county level. Base year is 2014 (vertical dashed line). All specifications include county fixed effects, year fixed effects, and Post x county characteristics controls. Pre-shock coefficients are statistically insignificant, supporting parallel trends. Post-shock effects emerge in 2015 and persist through 2019.

Figure 5: Employment Dynamics and the Credit Channel: Actual vs. Counterfactual Outcomes



Notes: This figure displays aggregate employment trends from 2011 to 2019 for non-O&G counties (blue line) and O&G counties (orange and red lines). The blue line represents total employment across all non-O&G counties, which increased from 63.0 million in 2011 to 73.5 million in 2019. The orange line shows actual total employment across all O&G counties, which increased from 42.7 million in 2011 to 49.5 million in 2019. The red line represents the counterfactual employment trajectory for O&G counties, calculated by removing the amplification effect attributable to credit supply disruptions. The counterfactual is constructed by removing the amplification effects (-0.0329 from Table 10, Column 2) from high O&G bank presence counties, showing the employment path that would have occurred if these counties had experienced only the direct effect comparable to low O&G bank presence counties. The red line tracks the orange line through 2014, then diverges starting in 2015 as the amplification effect is applied, reaching 51.2 million by 2019. The green segment at the base of both the orange and red bars represents employment in low O&G bank presence counties (approximately 1.4 million workers), which experienced modest employment gains and remained stable throughout the period. The gap between actual (orange, 49.5 million) and counterfactual (red, 51.2 million) employment in 2019—approximately 1.7 million jobs—quantifies the cumulative employment losses attributable to credit supply disruptions in high O&G bank presence counties. The vertical dashed line marks mid-2014, when the oil price collapse began. All employment figures represent total workers across counties in each category. The counterfactual demonstrates that O&G counties would have maintained employment growth trajectories similar to the broader economic recovery had credit access been preserved through diversified banking system.

Figure 6: Dynamic Amplification Effects on Regional Economic Outcomes



Notes: Event study estimates of θ_τ from a dynamic version of Equation (7), where the triple interaction term $Post_t \times High\ O\&G\ Bank\ Presence_c \times O\&G\ County_c$ is replaced with year-specific triple interactions $High\ O\&G\ Bank\ Presence_c \times O\&G\ County_c \times 1[\mathrm{t} = \tau]$. Panel A shows log establishments, Panel B shows log employment, Panel C shows log average weekly wages, and Panel D shows log total bankruptcy filings as dependent variables. Dots show point estimates; bars show 90% confidence intervals with standard errors clustered at the county level. Base year is 2014 (omitted category, marked by vertical dashed line). All specifications include county fixed effects, year fixed effects, and Post x county characteristics controls. Pre-shock coefficients are statistically indistinguishable from zero across all outcomes, supporting parallel trends. Post-shock coefficients show that O&G counties with high O&G bank presence experienced additional declines in establishments, employment, and wages, and additional increases in bankruptcy filings starting in 2015. Effects persist through 2019 despite partial oil price recovery.

Tables

Table 1: Summary Statistics: O&G vs. Non-O&G Counties, 2011-2019

	2011-2014		2015-2019		
	O&G	Non-O&G	O&G	Non-O&G	Change
Panel A: Economic Outcomes					
Number of establishments	2,415	2,874	2,609	3,042	26
Total employment	31,815	37,396	34,531	41,017	(906)
Average wages	36,819	34,932	40,561	39,228	(555)
Annual bankruptcy filings per million population	2,741	3,130	2,099	2,301	187
Business bankruptcy filings per 1,000 establishments	3.575	4.055	2.885	2.614	0.751
Non-Business bankruptcy filings per million population	2,661	3,036	2,032	2,239	168
Panel B: Industry Composition					
Employment Share (%)- Upstream O&G	7.372	1.092	6.025	1.138	(1.392)
Employment Share (%) - Manufacturing	4.108	4.007	4.025	3.779	0.146
Panel C: Demographics					
Population	92,734	104,167	95,788	107,788	(567)
Housing units per capita	0.473	0.486	0.480	0.492	0.001
Panel D: Banking Presence					
Number of branches per thousand population	0.485	0.473	0.464	0.446	0.007
Deposits per capita	18,630	20,439	20,700	23,616	(1,108)
Small Business Loan amounts per capita	436	490	484	538	(1.803)

Notes: This table compares county characteristics for O&G counties (N=1,424) and non-O&G counties (N=1,718) during pre-shock (2011-2014) and post-shock (2015-2019) periods. O&G counties are defined as counties with oil and gas reserves (EIA classification). All values are unweighted county averages. Column 5 (Change) reports the difference-in-differences: $(O\&G_{Post} - O\&G_{Pre}) - (Non\ O\&G_{Post} - Non\ O\&G_{Pre})$. Negative values in parentheses indicate relative decline in O&G counties.

Sources: BLS QCEW (employment, wages, establishments); U.S. Courts (bankruptcies); Census ACS (demographics); FDIC Summary of Deposits (branches, deposits); FFIEC CRA disclosures (small business loans).

Table 2: Summary Statistics: O&G vs. Non-O&G Banks, 2011-2019

	2011-2014		2015-2019		
	O&G	Non-O&G	O&G	Non-O&G	Change
Panel A: Size and Structures					
Total assets ($000s)	337,977	399,122	491,874	582,910	(29,891)
Number of branches	9.215	17.216	10.622	19.489	(0.866)
Number of counties with branches	8.838	16.627	10.202	18.911	(0.921)
Geographic concentration:					
Branch share in O&G counties (%)	95.3	2.8	94.4	3.7	(1.8)
Deposit share in O&G counties (%)	96.1	2.4	95.4	3.1	(1.4)
Panel B: Profitability					
Return on assets (%)	0.849	0.684	1.012	0.960	(0.113)
Return on equity (%)	7.872	6.109	9.116	8.533	(1.181)
Net interest margin (%)	3.751	3.686	3.752	3.667	0.019
Yield on earning assets (%)	4.399	4.423	4.279	4.255	0.048
Cost of funding earning assets (%)	0.646	0.735	0.522	0.582	0.030
Panel C: Asset Quality					
Net charge-offs / total loans (%)	0.344	0.475	0.136	0.121	0.146
Noncurrent loans / total loans (%)	1.626	2.141	0.948	0.942	0.522
Loss allowance / loans (%)	1.627	1.704	1.318	1.295	0.101
Panel D: Balance Sheet Composition					
Loans to total assets ratio	57.752	61.741	62.530	66.134	0.385
Deposits to total assets ratio	84.717	83.664	84.170	83.218	(0.102)
Panel E: Capital Adequacy					
Tier 1 risk-based capital ratio (%)	17.663	16.826	17.756	17.052	(0.133)
Total risk-based capital ratio (%)	18.791	17.983	18.930	18.251	(0.129)
Leverage ratio (Tier 1 / avg. assets) (%)	10.567	10.627	11.283	11.356	(0.013)
Equity / total assets (%)	11.032	11.047	11.536	11.616	(0.065)
Panel F: Small Business Lending					
Total loan amounts ($000s)	187,707	307,291	226,938	426,412	(79,891)
Number of loans originated	1,493	9,314	1,778	14,404	(4,804)
Average loan size ($000s)	178.577	202.139	187.961	215.093	(3.569)
Share of loans below $100K (%)	17.506	16.364	16.367	15.985	(0.760)

Notes: This table compares characteristics of O&G banks (banks with >50% of deposits in oil and gas counties as of 2010) and non-O&G banks. Values are unweighted bank-level averages of pre-shock (2011-2014) and post-shock (2015-2019) periods. Column (5) reports difference-in-differences: $(O\&G_{Post} - O\&G_{Pre}) - (Non\ O\&G_{Post} - Non\ O\&G_{Pre})$. Negative values indicate relative deterioration for O&G banks.

Sources: FFIEC Call Reports (Panels A-E), FDIC Summary of Deposits (geographic concentration), FFIEC CRA disclosures (Panel F).

Table 3: Impact of Oil Price Shock on Regional Economic Outcomes

	Log Establishments	Log Employment	Log Wages	Log Bankruptcy Filings (Total)
Post × O&G County	-0.0042	**-0.0229*** **	**-0.0401*** **	**0.0551*** **
	(0.0028)	(0.0037)	(0.0051)	(0.0092)
Post × County Characteristics:				
Log Population	**0.0259** **	-0.0014	0.0022	**0.2577*** **
	(0.0084)	(0.0108)	(0.0158)	(0.0315)
Log Median Income	**0.0597*** **	**0.0539*** **	**0.0614*** **	**-0.2145*** **
	(0.0081)	(0.0118)	(0.0169)	(0.0266)
Log Housing Units	**-0.0240** **	0.0122	0.0056	**-0.2811*** **
	(0.0086)	(0.0112)	(0.016)	(0.032)
Log Deposits	**0.0047*** **	**0.0088*** **	**0.0087*** **	-0.0036
	(0.0013)	(0.0017)	(0.0023)	(0.004)
HHI	**0.0674*** **	**0.0678** **	**0.0647** **	**-0.1281** **
	(0.0153)	(0.0213)	(0.0262)	(0.064)
County fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	28134	28134	28134	27544
R-squared	0.999	0.998	0.997	0.98
Pre-shock mean (O&G counties):				
In logs	7.789	10.367	10.514	4.11
In levels	2415 estab	31815 jobs	36819	347 filings
Implied % effect	-0.0042	-0.0226	-0.0393	0.0567
Implied absolute effect	-10 estab	-719 jobs	-$1,447	+20 filings

Notes: This table reports difference-in-difference estimates of the oil price shock's impact on county-level economic outcomes. The dependent variables are log establishments (Colum 1), log employment (Column 2), log average annual wages (Column 3), and log total bankruptcy filings (Column 4). The main independent variable is Post x O&G County, where Post equals one for years 2015-2019 and zero for years 2011-2014, and O&G County equals one for counties with oil and gas reserves (EIA classification). All specifications include county and year fixed effects. Post x County Characteristics include interactions between the Post indicator and 2010 county characteristics: log population, log median household income, log housing units, log total deposits in the county, and HHI (Herfindahl-Hirschman Index of bank deposit concentration). All county characteristics are measured as of 2010 (pre-shock). The sample includes 3,142 counties in the U.S. annually from 2011-2019. Standard errors (in parentheses) are clustered at the county level. Pre-shock mean in logs reports the average log outcome for O&G counties during 2011-2014. Pre-shock mean in levels reports the average outcome in levels (not log-transformed) for O&G counties during 2011-2014. For Column 4, bankruptcy filings measured as total annual filings in the county. Implied % effect calculated as 100 x beta for small coefficients (or more precisely, 100 x $[\exp(beta_1) - 1]$). For Columns 1-3, implied absolute effects calculated by applying the percentage change to pre-shock means in levels. For Column 4, implied absolute effect calculated as 5.67% x 347 = 20 additional bankruptcy filings per county. The sample for Column 4 contains 590 fewer observations due to missing bankruptcy data for some county-years. *** p<0.01, ** p<0.05, * p<0.10.

Source: Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW); U.S. Courts Table F-5A; U.S. Census Bureau American Community Survey; FDIC Summary of Deposits.

Table 4: Impact of Oil Price Shock on Bank Performance

	Net Interest Margin (%)	Yield on Earning Assets (%)	Cost of Funding Earning Assets (%)	Return on Assets (%)
Post × O&G Bank	0.0124	**0.0345*** **	**0.0217*** **	**-0.0717*** **
	(0.008)	(0.0077)	(0.0044)	(0.0096)
Post × Bank Characteristics:				
Log Assets	**-0.0282*** **	**-0.0232*** **	**0.0075*** **	0.0041
	(0.004)	(0.0039)	(0.0022)	(0.0044)
HHI	0.0975	0.1182	0.0053	0.1691*
	(0.0773)	(0.0813)	(0.0343)	(0.0873)
Lagged Bank Controls (t-1):				
Deposit Ratio	**0.0083*** **	-0.0006	**-0.0093*** **	**0.0041*** **
	(0.0009)	(0.0008)	(0.0005)	(0.001)
Core Capital Ratio	**0.0402*** **	**0.0089*** **	**-0.0328*** **	**0.0155*** **
	(0.0022)	(0.0021)	(0.0013)	(0.0029)
Loss Allowance Ratio	**-0.0377*** **	**-0.0408*** **	**-0.0079** **	**-0.1334*** **
	(0.0066)	(0.0063)	(0.0033)	(0.0088)
Liquid Asset Ratio	**-1.9480*** **	**-2.329*** **	**-0.3501*** **	**-0.1158** **
	(0.0443)	(0.0430)	(0.0218)	(0.0529)
Bank fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	55504	55230	55234	55507
R-squared	0.857	0.897	0.0848	0.712
Pre-shock mean (O&G banks)	3.751	4.399	0.646	0.849
Pre-shock mean (Non-O&G banks)	3.686	4.423	0.735	0.684
Implied effect (O&G banks)	+1.2bp	+3.5bp	+2.2bp	-7.2bp

Note: This table reports difference-in-differences estimates of the oil price shock's impact on bank performance. The dependent variables are net interest margin (Column 1), yield on earning assets (Column 2), cost of funding earning assets (Column 3), and return on assets (Column 4), all expressed in percentage points. The main independent variable is Post x O&G Bank, where Post equals one for years 2015-2019 and zero for years 2011-2014, and O&G Bank equals one for banks with more than 50% of branches in oil and gas counties as of June 2010. All specifications include bank and year fixed effects. Post x Bank Characteristics include interactions between the Post indicator and 2010 bank characteristics: log total assets and HHI (Herfindahl-Hirschman Index of the bank's deposit concentration across commuting zones, measuring geographic diversification). Lagged bank controls (t-1) include deposit ratio (deposits/assets), core capital ratio (Tier 1 capital/average assets), loss allowance ratio (loan loss allowance/total loans), and liquid asset ratio (liquid assets/total assets). All bank-level ratios are winsorized at the 5^{th} and 95^{th} percentiles. The sample includes commercial banks and savings institutions observed annually from 2011-2019. Standard errors (in parentheses) are clustered at the bank level. Pre-shock means are from Table 2 (2011-2014 average). Implied effect represents the differential change for O&G banks (in basis points, where 100bp = 1 percentage point). *** p<0.01, ** p<0.05, * p<0.10.

Source: FFIEC Reports of Condition and Income (Call Reports).

Table 5: Impact of Oil Price Shock on Bank Asset Quality and Capital

	Noncurrent Loans Ratio (%)	Net Charge-offs Ratio (%)	Loss Allowance Ratio (%)	Equity Capital Ratio (%)
Post × O&G Bank	**0.3375*****	**0.0850*****	**0.0288*****	0.0082
	(0.0312)	(0.0077)	(0.0064)	(0.0242)
Post × Bank Characteristics:				
Log Assets	**-0.1634*****	**-0.0495*****	**-0.0324*****	**-0.0152**
	(0.0147)	(0.0037)	(0.0031)	(0.0126)
HHI	0.0142	-0.0156	**-0.0942***	-0.0442
	(0.2536)	(0.0674)	(0.0533)	(0.185)
Lagged Bank Controls (t-1):				
Deposit Ratio	-0.0024	**-0.0027****	**-0.0019****	**-0.0160*****
	(0.0031)	(0.0009)	(0.0007)	(0.0029)
Core Capital Ratio	**-0.0835*****	**-0.0312*****	**-0.0191*****	**0.5633*****
	(0.0081)	(0.0022)	(0.0019)	(0.0082)
Loss Allowance Ratio	**0.8414*****	**0.3341*****	**0.5714*****	**0.1026*****
	(0.0269)	(0.0081)	(0.0075)	(0.0187)
Liquid Asset Ratio	**-2.2960*****	**-0.9447*****	**-0.5325*****	**1.1220*****
	(0.1532)	(0.0424)	(0.034)	(0.1283)
Bank fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	55484	55507	55484	55505
R-squared	0.671	0.586	0.851	0.895
Pre-shock mean (O&G banks)	1.626	0.344	1.627	11.032
Pre-shock mean (Non-O&G banks)	2.141	0.475	1.704	11.047
Implied effect (O&G banks)	+34bp	+8.5bp	+2.9bp	+0.8bp

Notes: This table reports difference-in-differences estimates of the oil price shock's impact on bank asset quality and capital. The dependent variables are noncurrent loans to total loans (Column 1), net charge-offs to total loans (Column 2), loss allowance to total loans (Column 3), and equity capital to total assets (Column 4), all expressed in percentage points. Noncurrent loans include loans 90+ days past due and loans on nonaccrual status. The main independent variable is Post x O&G Bank, where Post equals one for years 2015-2019 and zero for years 2011-2014, and O&G Bank equals one for banks with more than 50% of branches in oil and gas counties as of June 2010. All specifications include bank and year fixed effects. Post x Bank Characteristics include interactions between the Post indicator and 2010 bank characteristics: log total assets and HHI (Herfindahl-Hirschman Index of the bank's deposit concentration across commuting zones). Lagged bank controls (t-1) include deposit ratio, core capital ratio, loss allowance ratio, and liquid asset ratio. All bank-level ratios are winsorized at the 5th and 95th percentiles. The sample includes commercial banks and savings institutions observed annually from 2011-2019. Standard errors (in parentheses) are clustered at the bank level. Pre-shock means are from Table 2 (2011-2014 average). DID reports the difference-in-differences from Table 2 for comparison. Implied effect represents the differential change for O&G banks from the regression coefficient (in basis point, where 100bp = 1 percentage point). *** p<0.01, ** p<0.05, * p<0.10.

Source: FFIEC Reports of Condition and Income (Call Reports).

Table 6: Impact of Oil Price Shock on Bank Deposits (Bank-County Level)

	Log Deposits	Log Deposits	Log Deposits
Post × O&G County	-0.0152	-0.0176	-0.0184
	(0.0178)	(0.017)	(0.0177)
Post × County Characteristics:			
Log Population		0.0935	0.1067
		(0.0655)	(0.0659)
Log Median Income		0.0659	0.0618
		(0.0673)	(0.073)
Log Housing Units		-0.0715	-0.084
		(0.0679)	(0.0713)
Log Deposits		-0.0342	-0.0332
		(0.0221)	(0.0266)
HHI		0.0371	0.043
		(0.1072)	(0.0956)
Bank × Year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	No
Commuting Zone fixed effects	No	No	Yes
Observations	239,611	239,611	239,611
R-squared	0.591	0.591	0.502
Implied % effect	-0.0152	-0.0176	-0.0184

Notes: This table reports difference-in-differences estimates of the oil price shock's impact on bank deposits at the bank-county level. The dependent variable is log total deposits for bank b in county c at year t. The main independent variable is Post x O&G County, where Post equals one for years 2015-2019 and zero for years 2011-2014, and O&G County equals one for counties with oil and gas reserves (EIA classification). All specifications include bank-year fixed effects, which absorb all bank-specific time-varying factors including overall deposit demand, funding strategies, and bank health, as well as the Post main effect. Column (1) includes county fixed effects. Column (2) adds interactions between Post and 2010 county characteristics: log population, log median household income, log housing units, log total county deposits, and HHI (Herfindahl-Hirschman Index of bank deposit concentration). Column (3) replaces county fixed effects with commuting zone fixed effects. With county fixed effects (Columns 1-2), the O&G County main effect is absorbed; with commuting zone fixed effects (Column 3), the O&G County indicator is included but not reported. Standard errors (in parentheses) are two-way clustered at the bank and county levels. Implied % effect calculated as 100 x beta. The sample includes 239,611 bank-county-year observations from the FDIC Summary of Deposits for 2011-2019. The coefficient on Post x O&G County is small in magnitude and statistically insignificant across all specifications, indicating that deposits in O&G counties did not decline differentially after controlling for bank-specific deposit strategies. *** p<0.01, ** p<0.05, * p<0.10.

Source: FDIC Summary of Deposits.

Table 7: Impact of Oil Price Shock on Small Business Credit Supply

	(1) All Loans	(2) ≤$100K	(3) $100K–$250K	(4) >$250K
Panel A: Log(Number of Small Business Loans)				
Post × O&G Bank	**-0.2262*** **	**-0.2481*** **	-0.0255	0.0368
	(0.0718)	(0.083)	(0.0347)	(0.0314)
Lagged Bank Controls (t-1):				
Deposit Ratio	0.0085	0.0078	0.0034	0.0014
	(0.0067)	(0.0073)	(0.0028)	(0.0021)
Core Capital Ratio	-0.0336	-0.0264	-0.0255	-0.0181
	(0.0517)	(0.049)	(0.0272)	(0.0178)
Loss Allowance Ratio	-0.0381	-0.0669	0.0252	0.0152
	(0.0686)	(0.0779)	(0.0299)	(0.0171)
Liquid Asset Ratio	-0.0959	0.0371	-0.2734	-0.1832
	(0.5638)	(0.5961)	(0.1923)	(0.1466)
Observations	833,231	730,161	241,162	241,879
R-squared	0.473	0.519	0.288	0.257
Implied effect (O&G banks)	-20.24%	-21.97%	-2.52%	3.75%
Panel B: Log(Dollar Amount of Small Business Loans)				
Post × O&G Bank	**-0.1308***	**-0.2132*** **	-0.0173	0.043
	(0.0727)	(0.0695)	(0.038)	(0.036)
Lagged Bank Controls (t-1):				
Deposit Ratio	-0.0004	0.0027	0.003	-0.0002
	(0.0057)	(0.0053)	(0.0029)	(0.0023)
Core Capital Ratio	-0.0186	-0.0162	-0.0268	-0.0218
	(0.0377)	(0.0399)	(0.027)	(0.0205)
Loss Allowance Ratio	0.0276	-0.0087	0.0237	0.0031
	(0.0635)	(0.062)	(0.0299)	(0.0192)
Liquid Asset Ratio	-0.3261	-0.0681	-0.2801	-0.1804
	(0.3905)	(0.4638)	(0.1968)	(0.162)
County x Year fixed effects	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Observations	832,401	729,309	241,162	241,879
R-squared	0.482	0.492	0.299	0.267
Implied effect (O&G banks)	-12.26%	-19.20%	-1.72%	4.39%

Notes: The table reports difference-in-differences estimates of the oil price shock's impact on small business lending at the bank-county level. Panel A examines the natural logarithm of the number of small business loans originated by bank *b* in county *c* in year *t*. Panel B examines the natural logarithm of total dollar amounts. Column (1) includes all small business loans (original amounts ≤$1 million). Columns (2)-(4) disaggregate by loan sizes: ≤$100K, $100K-$250K, and >$250K. Post equals one for years 2015-2019. O&G Bank indicates banks with more than 50% of branches in oil and gas counties as of June 2010. All specification include county x year fixed effects (which absorb all time-varying county-level factors, including local credit demand) and bank fixed effects (which absorb time-invariant bank characteristics). Lagged bank controls include the deposit ratio, core capital ratio (Tier 1 capital/average assets), loss allowance ratio, and liquid asset ratio, all measured at t-1. Standard errors (in parentheses) are two-way clustered at the bank and commuting zone levels. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively. Implied effects are calculated as ($\exp(\beta_1)$-1) times 100%.

Table 8: Credit Supply Reduction by Bank Capital Position

	Below Median Capital Ratio	Above Median Capital Ratio	Difference (p-value)
Panel A: By Risk-Based Tier 1 Capital Ratio			
Post x O&GBank:	-0.2107**	-0.0173	-0.1934*
	(0.0828)	(0.1025)	(0.08)
N	547,408	252,246	
Pre-shock mean (%)	11.90%	18.30%	
N banks	421	344	
Panel B: By Leverage Ratio			
Post x O&GBank:	-0.1937**	-0.1370*	-0.0567
	(0.091)	(0.0801)	(0.48)
N	444,527	355,304	
Pre-shock mean (%)	8.82%	12.00%	
N banks	406	359	

Notes: The table examines whether credit supply reductions concentrated among banks with smaller capital cushions. The dependent variable is the log of the number of small business loans originated by bank b in county c in year t. The sample is split at the median capital ratio as of 2014 (pre-shock). Panel A splits by risk-based Tier 1 capital ratio. Panel B splits by leverage ratio (Tier 1 capital/average assets). Post equals one for years 2015-2019. O&G Bank indicates banks with more than 50% of branches in oil and gas counties as of June 2010. Lagged bank controls include deposit ratio (deposits/assets), core capital ratio (Tier 1 capital/average assets), loss allowance ratio (loan loss allowance/total loans), and liquid asset ratio (liquid assets/total assets), all measured at t-1. Column 3 reports the difference between coefficients with p-values in parentheses calculated from a pooled specification including Post x O&G Bank x Below Median Capital interaction. Standard errors (in parentheses under coefficients) are two-way clustered at bank and commuting zone levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Geographic Distribution of Credit Supply Reductions

	(1) All Loans	(2) ≤$100K	(3) $100K–$250K	(4) >$250K
Panel A: Log(Number of Small Business Loans)				
Post × O&G Bank × O&G County	**-0.2045*****	**-0.1801****	**-0.1913*****	**-0.1124*****
	(0.0775)	(0.0794)	(0.0493)	(0.0398)
Post × O&G Bank	-0.097	-0.1328	**0.1050****	**0.1160*****
	(0.0818)	(0.0938)	(0.0413)	(0.0377)
O&G Bank × O&G County	**0.9290*****	**0.7896*****	**0.8069*****	**0.9098*****
	(0.1346)	(0.1362)	(0.0803)	(0.0819)
Observations	*833,231*	*730,161*	*241,162*	*241,879*
R-squared	*0.481*	*0.524*	*0.3*	*0.275*
Implied DDD effect	*-18.5%*	*-16.5%*	*-17.4%*	*-10.6%*
Panel B: Log(Dollar Amount of Small Business Loans)				
Post × O&G Bank × O&G County	**-0.3191*****	**-0.2649*****	**-0.1935*****	**-0.0993****
	(0.0825)	(0.0821)	(0.0507)	(0.0418)
Post × O&G Bank	0.0626	-0.0498	**0.1148****	**0.1156*****
	(0.0764)	(0.0754)	(0.0446)	(0.043)
O&G Bank × O&G County	**1.1100*****	**0.9059*****	**0.8204*****	**0.9189*****
	(0.1388)	(0.1333)	(0.082)	(0.0829)
Observations	*832401*	*729309*	*241162*	*241879*
R-squared	*0.489*	*0.497*	*0.31*	*0.284*
Implied DDD effect	*-27.3%*	*-23.3%*	*-17.6%*	*-9.5%*

Notes: The table reports difference-in-difference-in-differences estimates of the geographic distribution of credit supply reductions by O&G banks following the oil price shock. Panel A examines the natural logarithm of the number of small business loans originated by bank *b* in county *c* in year *t*. Panel B examines the natural logarithm of total dollar amounts. Column (1) includes all small business loans (original amounts ≤$1 million). Columns (2)–(4) disaggregate by loan size: ≤$100K, $100K–$250K, and >$250K. Post equals one for years 2015–2019. O&G Bank indicates banks with more than 50% of branches in oil and gas counties as of June 2010. O&G County indicates counties with oil and gas reserves per EIA classification. The triple interaction coefficient captures the additional credit supply reduction by O&G banks specifically in O&G counties, relative to: (1) O&G banks' lending in non-O&G counties, (2) non-O&G banks' lending in O&G counties, and (3) non-O&G banks' lending in non-O&G counties. All specifications include county × year fixed effects (absorbing local credit demand) and bank fixed effects (absorbing time-invariant bank characteristics). The specifications also include lagged bank-level controls (deposit ratio, core capital ratio, loss allowance ratio, and liquid asset ratio measured at t-1), which are omitted from the table for brevity. Standard errors (in parentheses) are two-way clustered at the bank and commuting zone levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Implied DDD effects are calculated as $[\exp(beta_1) - 1]$ times 100%.

Table 10: Amplification Effects on Regional Economic Outcomes

	(1) Log Establishments	(2) Log Employment	(3) Log Wages	(4) Log Bankruptcy Filings
Post × High O&G Bank Presence	**-0.0267***	**-0.0329****	-0.0123	**0.1205*****
× O&G County	(0.0139)	(0.0148)	(0.0212)	(0.0427)
Post × High O&G Bank Presence	0.0035	-0.0006	-0.0113	-0.0359
	(0.0078)	(0.0068)	(0.0085)	(0.0221)
Post × O&G County	0.0182	0.0092	-0.0176	-0.0295
	(0.0114)	(0.013)	(0.019)	(0.0364)
Post × County Characteristics:				
Log Population	**0.0277*****	0.0047	-0.011	**0.2562*****
	(0.0078)	(0.0105)	(0.0144)	(0.0319)
Log Median Income	**0.0581*****	**0.0534*****	**0.0664*****	**-0.2133*****
	(0.0078)	(0.0117)	(0.0159)	(0.0269)
Log Housing Units	**-0.0249*****	0.0071	0.0188	**-0.2789*****
	(0.008)	(0.0108)	(0.0147)	(0.0323)
Log Deposits	**0.0045*****	**0.0080*****	**0.0091*****	-0.0037
	(0.0013)	(0.0017)	(0.0023)	(0.004)
HHI	**0.0687*****	**0.0618*****	**0.0702*****	**-0.1258****
	(0.0154)	(0.0213)	(0.0254)	(0.064)
County fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Observations	*27,911*	*27,911*	*27,911*	*27,418*
R-squared	*0.999*	*0.999*	*0.998*	*0.98*
Implied DDD effect	*-2.6%*	*-3.2%*	*-1.2%*	*12.8%*
Implied Total effect	*-0.8%*	*-2.3%*	*-3.0%*	*9.9%*

Notes: The table reports difference-in-differences estimates of the oil price shock's amplification effects on county-level economic outcomes. The dependent variables are the natural logarithm of the number of establishments (Column 1), employment (Column 2), average annual wages (Column 3), the total bankruptcy filings (Column 4). Post equals one for years 2015-2019. O&G County indicates counties with oil and gas reserves per EIA classification. High O&G Bank Presence indicates counties where more than 25% of bank branches were operated by O&G banks as of 2014 (pre-shock). The triple interaction coefficient captures the additional economic impact in O&G counties with high O&G bank presence, beyond the direct effect of the oil shock. This coefficient isolates the amplification effect attributable to the credit channel. All specifications include county fixed effects and year fixed effects. Post x County Characteristics includes interactions between Post and 2010 county-level characteristics: log population, log median household income, log housing units, log total deposits, and HHI of bank deposit concentration. Standard errors (in parentheses) are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Implied DDD effects are calculated as $[\exp(beta_1) - 1]$ times 100%. Implied total effect represents the total treatment effect for high O&G bank presence counties, calculated as $[\exp(beta_1 + beta_2) - 1]$ times 100%. The -2.3% employment effect closely matches the -2.29% baseline effect from Table 3, validating the DDD decomposition.

Table 11: Robustness to Alternative Definitions

	Baseline	LQ-Based	Other
Panel A: Regional Impact (Table 3)			
Post × O&G County:			
Log Establishments	-0.0042	-0.0035	0.0076
	(0.0028)	(0.0035)	(0.0047)
Log Employment	-0.0229***	-0.0415***	-0.0205**
	(0.0037)	(0.0055)	(0.0066)
Log Wages	-0.0401***	-0.0675***	-0.0218**
	(0.0051)	(0.0078)	(0.01)
Log Bankruptcies	0.0551***	0.0838***	0.0605***
	(0.0092)	(0.0121)	(0.0178)
Panel B: Bank Performance (Tables 4-5)			
Post × O&G Bank:			
ROA (%)	-0.0717***	-0.1026***	-0.0739***
	(0.0096)	(0.0119)	(0.0098)
Noncurrent Loans (%)	0.3375***	0.4510***	0.3448***
	(0.0312)	(0.0355)	(0.0318)
Net Charge-offs (%)	0.0850***	0.1199***	0.0844***
	(0.0077)	(0.0085)	(0.0077)
Panel C: Credit Supply (Table 7)			
Post × O&G Bank:			
Log # Loans (All)	-0.2262***	-0.1545**	-0.2710***
	(0.0718)	(0.0637)	(0.0793)
Log # Loans (≤$100K)	-0.2481***	-0.1962**	
	(0.083)	(0.0717)	
Log $ Amount (All)	-0.1308*	0.002	-0.2247**
	(0.0727)	(0.0553)	(0.0895)
Log $ Amount (≤$100K)	-0.2132***	-0.1245**	
	(0.0695)	(0.0553)	

Notes: The table reports robustness of main results to alternative definitions of treatment and control groups. Panel A shows regional impact results (Table 3) using alternative O&G County definitions: LQ-Based uses counties where upstream oil & gas employment concentration exceeds the national average (location quotient>1); Other uses only counties with shale reserves (narrower than EIA definition). Effects are robust and often stronger with alternative definitions. Panel B shows bank performance results (Tables 4-5) using alternative O&G Bank definitions; LQ-Based uses weighted average location quotient across commuting zones for bank branches; Other include only banks operating exclusively in O&G counties. Asset quality deterioration is consistent or stronger across all definitions. Panel C shows credit supply results (Table 7): LQ-Based uses alternative bank definition explained above; Other uses loans to firms with revenues ≤$1 million instead of loan amount thresholds as dependent variables. Credit supply reductions remain significant with revenue-based definition showing strongest effects (-27.1%). Standard errors in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Robustness of Amplification Results to Alternative Definitions

Outcome	Baseline (Median, 25%)	Q3 Threshold (75th pct, 81.8%)	O&G Bank Share (Median, 28.6%)
Post × O&G County × High O&G Bank Presence:			
Log Establishments	-0.0267*	-0.0484*	-0.0233*
	(0.0139)	(0.0294)	(0.014)
Log Employment	-0.0329**	-0.0914***	-0.0425***
	(0.0148)	(0.0238)	(0.0144)
Log Wages	-0.0123	-0.0933***	-0.0343*
	(0.0212)	(0.0242)	(0.0201)
Log Bankruptcies	0.1205***	0.0545	0.1300***
	(0.0427)	(0.088)	(0.0449)
Post × O&G County (Direct Effect):			
Log Establishments	0.0182	-0.0011	0.0117
	(0.0114)	(0.0032)	(0.0116)
Log Employment	0.0092	-0.0148***	0.015
	(0.013)	(0.0049)	(0.0126)
Log Wages	-0.0176	-0.0294***	-0.0036
	(0.019)	(0.0067)	(0.0179)
Log Bankruptcies	-0.0295	0.0408***	-0.0248
	(0.0364)	(0.0117)	(0.0392)
Implied Total Effect (High Presence Counties):			
Log Employment	-0.0237**	-0.1062***	-0.0275**

Notes: The table reports robustness of amplification results (Table 10) to alternative definitions of High O&G Bank Presence. Baseline uses median branch share (25%) to classify counties: those where more than 25% of branches were operated by O&G banks as of 2014 are classified as High O&G Bank Presence. Q3 Threshold uses the 75th percentile (81.8% branch share), identifying counties where the banking system is almost exclusively composed of O&G banks. O&G Bank Share uses the median share of O&G banks among all banks operating in a county (i.e., number of O&G banks / total number of banks) rather than branch share. This alternative measure accounts for the number of distinct banking institutions rather than their branch footprints, addressing the concern that branch share may overweight banks with multiple branches. The triple interaction coefficient (Post x O&G County x High O&G Bank Presence) captures the amplification effect—the additional economic impact in O&G counties with high O&G bank presence beyond the direct effect of the oil shock. The O&G Bank Share measure confirms results with all coefficients showing anticipated signs and stronger significance than baseline. Implied total effect represents the total treatment effect for high O&G bank presence counties, calculated as $[\exp(beta_1 + beta_2) - 1]$ times 100%. Standard errors in parentheses are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Robustness of Deposit Stability Results

	Post x O&G County	SE
Alternative Specification:		
Baseline (Bank x Year FE, County FE)	-0.0176	(0.0177)
Alternative 1 (Bank x Year FE, CZ FE)	-0.0184	(0.0177)
Alternative 2 (Bank FE, Year FE, CZ FE)	-0.0071	(0.0121)
Alternative O&G County Definition (Under Baseline Specification):		
With Shale O&G County	-0.0353	(0.0248)
With LQ O&G County	-0.0065	(0.0168)

Notes: The table reports robustness of deposit stability results (Table 6) to alternative specifications and O&G County definitions. The dependent variable is log deposits at the bank-county level. All specifications show no significant deposit decline in O&G counties following the oil price shock, confirming the absence of funding pressures or depositor flight. Baseline (Table 6, Column 2) includes bank x year fixed effects (absorbing bank-specific deposit demand) and county fixed effects. Alternative 1 replaces county FE with commuting zone FE to account for broader geographic deposit patterns. Alternative 2 uses additive fixed effects (Bank FE + Year FE + CZ FE) rather than interactive Bank x Year FE. Shale O&G County uses the narrower definition including only counties with shale reserves. LQ O&G County uses counties where upstream oil & gas employment concentration exceeds the national average (location quotient >1). Across all specifications and definitions, coefficients remain small in magnitude and statistically insignificant, indicating deposits remained stable in O&G regions even as banks reduced lending. This rules out liability-side explanations for credit supply reductions documented in Tables 7-8, confirming that asset quality deterioration—not funding stress—drove banks' credit supply responses. Standard errors in parentheses are two-way clustered at the bank and commuting zone levels (Alternative 1-2) or at the bank and county levels (baseline, shale, and LQ) specifications. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; no coefficients achieve statistical significance.

Table 14: Geographic Concentration of Credit Supply Reductions: Binary vs. Continuous Treatment

Outcome	Binary (O&G Bank Indicator)	Continuous (O&G Bank Branch Share)
Triple Interaction:	Post × O&G Bank × O&G County	Post × O&G Bank Branch Share × O&G County
Number of Loans:		
All Loans	-0.2045***	-0.2822**
	(0.0775)	(0.1238)
≤$100K	-0.1801**	-0.2844**
	(0.0794)	(0.1309)
$100K–$250K	-0.1913***	-0.2300**
	(0.0493)	(0.1092)
>$250K	-0.1124***	-0.2304***
	(0.0398)	(0.0778)
Loan Dollar Amounts:		
All Loans	-0.3191***	-0.3079***
	(0.0825)	(0.119)
≤$100K	-0.2649***	-0.3197***
	(0.0821)	(0.118)
$100K–$250K	-0.1935***	-0.2295**
	(0.0507)	(0.1133)
>$250K	-0.0993**	-0.2122***
	(0.0418)	(0.081)

Notes: The table reports robustness of geographic concentration results (Table 9) using continuous treatment instead of binary O&G Bank classification. Binary specification (baseline from Table 9) uses an indicator variable for O&G Bank (equals one if bank has >50% of branches in O&G counties as of 2010). Continuous specification replaces the binary indicator with the actual percentage of bank branches located in O&G counties, allowing for dose-response relationship between O&G exposure and lending behavior. The triple interaction coefficient captures the additional credit supply reduction by O&G banks (or banks with higher O&G branch shares) specifically in O&G counties, relative to their lending in non-O&G counties and relative to other banks' lending patterns. All specifications include bank-county fixed effects, county x year fixed effects, and bank x year fixed effects, with the same control variables as Table 9. Results show that geographic concentration of credit supply reductions is robust to using continuous treatment, with coefficients of similar or larger magnitude compared to the binary specification. The continuous specification reveals a dose-response pattern: banks with higher shares of branches in O&G counties reduced lending more severely in those counties. Notably, the continuous specification shows significant reductions even to large loans (>$250K) where the binary specification showed smaller effects, suggesting that the relationship between O&G exposure and lending reductions strengthens with the degree of exposure. Standard errors in parentheses are two-way clustered at the bank and commuting zone levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 15: Business vs. Non-Business Bankruptcies: Direct and Amplification Effects

	Estimates	SE	Implied Effect
Panel A: Direct Regional Impact (from Table 3)			
Post x O&G County:			
Total Bankruptcies	0.0551***	(0.0092)	+5.7%
Business Bankruptcies	0.0877***	(0.0182)	+9.2%
Non-Business Bankruptcies	0.0478***	(0.0091)	+4.9%
Panel B: Amplification Effect (from Table 9)			
Post x O&G County x High O&G Bank Presence:			
Total Bankruptcies	0.1205***	(0.0427)	+12.8%
Business Bankruptcies	0.2068***	(0.0857)	+23.0%
Non-Business Bankruptcies	0.1227***	(0.0422)	+13.1%

Notes: The table decomposes total bankruptcy effects into business and non-business (consumer) bankruptcies. Panel A reports direct regional impact estimates from Table 3, showing the differential change in bankruptcy filings in O&G counties relative to non-O&G counties following the oil price shock. Panel B reports amplification estimates from Table 10, showing the additional increase in bankruptcy filings in O&G counties with high O&G bank presence (where more than 25% of branches were operated by O&G banks) beyond the direct shock effects. Business bankruptcies include Chapter 7 and Chapter 11 commercial filings; non-business bankruptcies include Chapter 7, Chapter 11, and Chapter 13 consumer filings. Both business and non-business bankruptcies increased significantly in O&G counties following the shock, with business bankruptcies showing larger percentage increases in both panels. In Panel A (direct effects), business bankruptcies increased by 9.2% compared to 4.9% for non-business bankruptcies, suggesting that the oil price shock imposed particularly severe financial distress on businesses in affected regions. In Panel B (amplification effects), business bankruptcies increased by 23.0% in high O&G bank presence counties—nearly double the 12.8% increase in total bankruptcies—compared to 13.1% for non-business bankruptcies. This pattern indicates that credit supply disruptions affected businesses more severely than households, consistent with businesses being more dependent on bank credit for operations and having fewer alternative financing sources. The larger amplification effect for business bankruptcies provides direct evidence that the credit channel operated through constraints on business access to credit rather than consumer credit. Standard errors in parentheses are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Implied effects are calculated as $[\exp(beta_1) - 1]$ times 100%.

Table A1: Sample Composition by County Classification, 2014

County Classification	N	Establishments (thousands)	Employments (million)	Wages ($billion)	Bankruptcy filings (thousands)
Panel A: Total across counties					
ALL US counties	3132	8,491.9	112.8	5,718.4	924.5
O&G counties	1395	3,423.9	45.9	2,271.4	361.1
Low O&G bank presence	55	113.6	1.4	57.1	12.1
High O&G bank presence	1333	3,310.2	44.5	2,214.2	349.0
Non-O&G bank presence	1737	5,068.1	66.9	3,446.9	563.4
Low O&G bank presence	1520	4,666.2	61.7	3,212.8	514.8
High O&G bank presence	196	400.1	5.1	233.6	48.5
Panel B: Average					
ALL US counties		2,711.4	36,002.9	50,712.0	295.2
O&G counties		2,454.4	32,907.2	49,480.1	258.9
Low O&G bank presence		2,064.8	24,827.5	41,801.5	219.9
High O&G bank presence		2,483.2	33,412.2	49,715.4	261.8
Non-O&G bank presence		2,917.7	38,489.2	51,558.0	324.4
Low O&G bank presence		3,069.9	40,605.5	52,054.9	338.7
High O&G bank presence		2,041.1	26,123.3	45,616.1	247.6

Notes: This table reports the composition of our analysis sample as of 2014 (pre-shock). O&G counties are defined with oil and gas reserves per the U.S. Energy Information Administration county code master list. High O&G Bank Presence counties are those where more than 25% of bank branches were operated by O&G banks as of 2014. O&G banks are defined as banks with more than 50% of branches in O&G as of June 2010. Panel A reports totals aggregated across all counties within each classification. Panel B reports average per county, except for wages which represents average annual wage per employee. Employment figures are from the Bureau of Labor Statistics Quarterly Census of Employment and Wages (QCEW). Wage data represents total annual wages paid. Bankruptcy filings represent total annual filings in 2014 from U.S. Courts administrative data. The sample contains 3,132 counties with complete data as of 2014; regression sample sizes vary from 3,125 to 3,132 depending on specification and availability of time-varying control variables. Among O&G counties, 55 (3.9%) have low O&G bank presence while 1,333 (95.5%) have high O&G bank presence, with high-presence counties accounting for 96.9% of O&G county employment. Among non-O&G counties, 1,520 (87.5%) have low O&G bank presence while 196 (11.3%) have high O&G bank presence.