Deposit Windfalls and Bank Reporting Quality: Evidence from Shale Booms*

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Abstract

This paper investigates how depositor information problems affect bank reporting quality. Using plausibly exogenous deposit windfalls coming from shale and oil leases, I find that banks exposed to shale booms provide higher reporting quality, measured as loan loss provision timeliness, compared to other banks. Improved loan provisioning timeliness is concentrated in banks with stronger incentives to attract deposits–smaller banks and banks with fewer uninsured deposits. Moreover, banks that improve the most experience a larger increase in their subsequent deposit levels, suggesting that depositors value timely information. Collectively, my results suggest that information asymmetry between depositors and banks is an important determinant of banks' reporting incentives.

Keywords: Banks, Financial reporting, Loan loss provision, Deposit shocks, Shale booms

JEL-Classification: G10, G21,G28, M41

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1 Introduction

Bank accounting plays an important role in addressing the asymmetric information problems between stakeholders and bank managers. Prior research shows that banks' financial reporting quality influences their liquidity provision and lending cyclicality, and thereby the stability of the financial industry.[1] An important determinant of banks' accounting practice is mandatory reporting requirements, which the current policy proposals aim at strengthening.[2] While accounting rules help shape bank reporting quality, it is essential to understand the economic determinants of banks' reporting incentives. To this end, existing research primarily focuses on the disciplinary effects of equity markets on bank accounting. However, as pointed out by the survey paper of Beatty and Liao (2014), despite the importance of debt funding for banks and the role of information asymmetry between bank managers and depositors in the microeconomic theory of banking, the literature largely ignores how depositor information problems affect bank reporting. Using plausibly exogenous deposit windfalls, this paper answers the call for research by investigating whether and how depositors' information demand affects banks' reporting practices.

It is unclear how deposit windfalls affect banks' financial reporting. Evidence suggests that depositors, especially uninsured depositors, monitor banks and act on banks' information, including but not limit to private regulatory audits (Iyer et al., 2016), credible reporting (Lo, 2015), and information on balance sheets (Anderson et al., 2017; Calomiris and Jaremski, 2018). If deposit windfalls affect depositors' demand for banks' information, such as the arrival of uninsured depositors that have strong incentives to act on banks' performance contained in banks' financial statements, banks may respond by changing their accounting practices. In particular, banks may improve their reporting quality to reduce the information

[1] See for example, Akins et al. (2017); Beatty and Liao (2011, 2014); Bhat et al. (2018); Bushman and Williams (2012); Ryan (2012).

[2] For example, SEC voted on March 1, 2017, to collect public feedback on whether to update its disclosure requirements for bank holding companies, see https://www.sec.gov/news/pressrelease/2017-54.html. Also see http://tabbforum.com/channels/regulatory/news/sec-opens-door-to-overhaul-of-bank-disclosure-rules for an article of "SEC Opens Door to Overhaul of Bank Disclosure Rules".

asymmetry between depositors and bank managers. On the other hand, banks with greater access to deposits are less concerned about liquidity constraints and external financing, and thus have lower incentives to provide high-quality financial reporting.

Identifying the impact of the local supply of deposits on bank reporting is challenging because local deposit supply is likely associated with local economic conditions. In other words, it is difficult to distinguish the impact of deposits from other factors that affect banks' reporting quality, such as unobservable economic conditions and reporting incentives. To overcome these challenges, I examine how exogenous deposit windfalls caused by oil and natural shale gas booms affect banks' reporting quality. More specifically, I examine the accounting practices of geographically proximate banks with and without exposure to deposit shocks.

An unexpected technological breakthrough made the development of vast shale oil and natural gas resources profitable. To develop and operate shale resources, oil and gas companies need to negotiate mineral royalty payments with landowners. These payments cause massive local deposit windfalls for banks with branches in shale boom counties. Compared to other banks, I find that exposed banks on average have an annual increase in deposits of more than five percent, consistent with recent studies examining the wealth shock (Gilje, 2017; Plosser, 2014).

Using shale booms as exogenous shocks to local deposits, I examine whether banks change their financial reporting to attract deposits. I compare changes in financial reporting quality between banks with branches located in the boom counties and banks with branches located in nearby non-boom counties. I control for bank fixed effects to examine within bank variation in financial reporting and for time fixed effects to capture country-wide changes that affect all banks. The variation in both the timing and location of shale booms reduces potential confounding effects.

Following the prior literature, I use loan loss provision timeliness to measure banks' financial reporting quality. Loan loss provisions indicate banks' expectation of future loan losses. For most banks, the provision is the largest accrual that requires significant managerial discretion in the estimation process. It is banks' most important means to manage earnings and regulatory capital (e.g., Beatty and Liao, 2014). This accrual has important implications for performance and is a leading indicator of credit quality (e.g., Beatty and Liao, 2014; Bushman and Williams, 2015; Liu and Ryan, 1995; Nichols et al., 2009). In the main tests, I find that after the deposit windfalls induced by shale booms, banks are more timely in recognizing their loan losses. The results are robust to additional controls, to examining treated banks only, and to using an alternative measure of reporting quality—the discretionary loan loss provision.

I conduct several cross-sectional analyses to explore the underlying mechanisms. There are two main mechanisms through which deposit shocks could positively affect banks' financial reporting quality. First, bank financial reporting quality reduces information asymmetry between depositors and banks, and therefore banks may improve their reporting quality to attract deposits. I call this mechanism the "Access to Deposits" channel. Second, existing investors are concerned about the increase in leverage and free cash flows of banks, and thus demand more timely information. I call this mechanism the "Shareholder Monitoring" channel. My results are in line with the Access to Deposits channel. In particular, improved loan loss provision timeliness is concentrated in banks with stronger incentives to obtain deposits–smaller banks and banks with fewer uninsured or large time deposits. Further tests suggest that depositors value improvements in banks' timeliness of loan loss recognition, providing easier access to deposits for exposed banks. Specifically, banks that improve the most tend to experience a larger increase in their deposit levels following deposit windfalls. Overall, my results suggest that depositors' demand for information affects banks' financial reporting quality. After the deposit windfalls induced by shale booms, banks improve their accounting quality to attract deposits. Banks with stronger incentives to attract the deposits—smaller banks and banks with fewer uninsured deposits—tend to increase their reporting quality more.

The results are unlikely to be driven by alternative mechanisms. First, the effects are similar for high and low profitability banks, suggesting that bank health is not an important factor. Second, exposed and unexposed banks have similar loan charge-offs, and thus the results are unlikely to be explained by banks having riskier loan portfolios. Third, falsification tests including a placebo indicator for the year prior to boom years indicate that banks did not expect the booms or change their reporting quality before the booms. Furthermore, exposed and unexposed banks had similar loan loss provision timeliness prior to the shale booms, suggesting a parallel trend in reporting quality of the treated and control banks.

This study makes three contributions to the literature. First, applying a unique approach, this study adds to the literature of bank accounting and depositors' information problems. Freixas and Rochet (2008) argue the importance of asymmetric information between banks and depositors in understanding banks' delegated monitoring and deposit-taking roles. Even though depositors' information problems are at the heart of the microeconomic theory of banks, most research focuses on shareholder monitoring and ignores the role of depositors (Beatty and Liao, 2014). This paper suggests that the information asymmetry between depositors and banks affects banks' reporting quality following deposit windfalls. Furthermore, this paper complements the literature showing that changes in the trade-offs of providing high-quality financial information can shift firms' accounting choices. Most of the literature examines non-financial firms. For example, Gormley et al. (2012) find that firms adapt their accounting policies to changes in the banking industry to access to finance. There is less research on financial firms. This paper shows that attracting deposits plays an important role in shaping banks' reporting, and improved loan loss provision timeliness positively relates to subsequent deposit increases.

Second, my findings extend our understanding of the role of bank accounting and how it interacts with different economic conditions. For example, Liu and Ryan (2006) find that profitable banks managed income downward by accelerating loss provisions for homogeneous loans during the 1990s boom, indicating income smoothing over a prolonged horizon. Beatty and Liao (2011) show that banks that record timely loan loss provisions have higher loan growth during recessions. That is, these banks exhibit lower loan origination procyclicality. Xie (2016) finds that fair value accounting did not have procyclical effects on bank lending over the past two business cycles. Lo (2015) finds that credible reporting enables small non-public banks to raise external funds during liquidity shortages. Rather than analyzing the effect of accounting information on banks' investments during adverse periods, I test whether banks change their reporting in response to deposit windfalls. This paper documents that banks provide timelier loan loss provisions during deposit windfalls. The positive relation between reporting quality and deposit windfalls appears to be driven by banks' incentives to attract deposits.

Third, this paper adds to the research on the interaction between deregulation induced competition in the banking industry and banks' financial reporting by providing a potential channel to explain how deregulation may affect banks' reporting incentives. Several studies show that increase in competition post-deregulation affects banks' reporting. For example, Jiang et al. (2016) show that the increased competition following the interstate deregulation improves the quality of governance and lowers incentives for banks to conceal suboptimal actions by manipulating financial statements, thereby reducing bank opacity. Dou et al. (2017) find that higher entry threat following deregulation induces incumbent banks to record lower loan loss provisions to convey better loan underwriting quality on average. This paper proposes a potential channel to explain the positive relation between banking deregulation and financial reporting quality. That is, competition induced by deregulation incentivizes banks to improve reporting quality in order to attract deposits.

The rest of the paper proceeds as follow. Section 2 provides the background on shale booms and discusses the related literature. Section 3 describes the sample selection and the research design. Section 4 presents the empirical results. Section 5 discusses the additional analyses and robustness checks. Section 6 concludes.

2 Background and Related Literature

2.1 Shale Boom and Deposit Windfalls

One of the biggest changes in the U.S. energy landscape in the last 20 years is the advent of natural shale gas development. In 2000, natural gas produced from shale comprised only 1% of natural gas production in the United States. While reports and assessments from the 1970s through the 1990s suggest that shale boundaries and characteristics were well known, the advent of large-scale shale gas production did not occur until early 2000s when shale gas production became a commercial reality in the Barnett Shale located in north-central Texas (EIA, 2013).

Shale gas and oil are fossil fuels trapped in shale formations. It is highly nonporous causing nature gas to be trapped in the rock and thus difficult to extract. In 2003, a technology that combines horizontal drilling with hydraulic fracturing of shale (informally referred to "fracking") was developed. Fracking allowed drill operators to penetrate shale oil and gas reserves that were previously difficult to access, and made fracking wells much more economically profitable to develop.[3] Several states began to experience more efficient production in natural gas shale, both quantitatively and economically (Yergin, 2011). After the continued development of the technology, shale wells have little risk of being unproductive today. According to the Energy Information Administration (EIA), shale gas represented approximately one-third of the United States' recoverable natural gas reservoirs in 2013. EIA also estimated that the United States had 223 billion barrels of shale oil and 2,431 trillion cubic feet of shale natural gas, over one-third of the world's recoverable shale resources (EIA, 2013). The United States transitioned from being a modest net importer of natural gas to a net exporter by 2017 (EIA, 2015).

To exploit shale oil and gas, firms must sign contracts with local landowners to lease

[3]After 20 years of experimentation, Mitchell Energy found that the hydraulic fracturing could break apart shale and free natural gas for collection at the surface. In 2003, Devon Energy with expertise in horizontal drilling acquired Mitchell Energy. Wang and Krupnick (2013) discuss several key events that led to the shale revolution starting in the mid-2000s.

mineral rights to drill on a parcel of land.[4] These landowners receive large upfront signing bonuses based on the number of acres leased and royalties based on the value of the oil or gas produced from their land over time. The upfront signing bonus can vary anywhere from a few hundred dollars an acre to $10,000 to $30,000 an acre, and the royalty percentage ranges from 10% to 25%.[5] For example, an individual with 100 acres of land who leases his access to minerals at $10,000/acre would receive an upfront signing bonus of $1 million. In addition, the landowner would receive 20% of the value of gas produced monthly. Because the amount of gas resources was massive and the risk of unproductive wells was relatively low, there was a high demand for mineral leases. Communities have experienced significant fast-paced mineral booms that result in large wealth windfalls for local landowners. For example, Plosser (2014) estimates that some counties can receive as much as one billion dollars per year. Feyrer et al. (2017) estimate that each million dollars of new oil and gas production produces $80,000 in wage income and $132,000 in royalty and business income within a county.

Landowners deposit a meaningful share of these proceeds in their local banks. These deposit shocks are plausibly exogenous to banks and are often well in excess of the economic activity in the area. Kelsey et al. (2011) find that among survey respondents about 10% of natural gas royalty payments to landowners was spent, leaving millions to be saved. Plosser (2014) finds that shale booms generate deposit windfalls for local banks and establishes that energy payments are positively correlated with county-level deposit growth. Annual payments for mineral leases can exceed $1 billion a year, and typically 13% of these payments are deposited in local banks. Gilje et al. (2016) show that banks with branches in counties with fracking wells have higher deposit growth and lower interest expense than a group of control banks. Analyst reports from FBR Capital Markets say that "many banks are

[4] Land and mineral rights may be held separately in some states. All references to landowners in the paper should be interpreted as owners of the mineral rights.

[5] For example, Thakor (2016) estimates that the average upfront payment typically ranges from $500 to $10,000 per acre in Oklahoma. With an average farm size in Oklahoma of roughly 450 acres, these payments can range from tens of thousands of dollars to a few million dollars. Andrews (2010) reports that the average upfront payment in Texas can reach up to $10,000 to $20,000 per acre.

telling anecdotal stories of landowners walking into branches with checks for several hundred thousand dollars" (Post-Gazette, 2011).

Since the technological breakthroughs were unexpected and their applicability to a given location was uncertain, the wealth shocks to landowners and the deposit shocks to banks at boom counties are plausibly exogenous. The economic viability of the wells was unrelated to local economic conditions as it was determined by broad macroeconomic forces, such as demand for natural gas and natural gas prices (Lake et al., 2013). Fedaseyeu et al. (2016) find that before 2003 there was virtually no mention of shale in media. After 2003, however, there was a sharp increase in media attention. By 2012, there were more than five times as many articles per paper mentioning shale or fracking in boom areas than in non-boom areas. Thakor (2016) illustrates the exogeneity of the shale boom using another example. Although there was fracking activity in Oklahoma during the early 2000s, it was not until 2005 when a large influx of fracking operators flooded the state. One reason is that the new technology was not developed until 2003. Another reason is that the Energy Policy Act of 2005 exempted fluids used in fracking from federal clean water laws, and thereby greatly reduced regulatory uncertainty for well operators. Therefore, even though Oklahoma was known to be an oil-rich state, the exact timing of its shale boom was unknown ex ante. Overall, it is unlikely that the banks could strategically alter branch structures to gain greater exposure to shale booms (Gilje et al., 2016). The exogeneity of the shale booms and their effects on local deposit supply allow me to examine banks' reporting changes in response to the deposit inflows.

2.2 Related Literature and Hypothesis Development

The quality of banks' accounting systems is important to both investors and regulators. Primary roles of banks' accounting information include mitigating information asymmetry between banks and investors and addressing agency problems that arise from banks' delegated monitoring role. Acharya and Ryan (2016) and Beatty and Liao (2014) provide thorough reviews of the existing studies regarding the role of bank accounting in addressing frictions in the financial markets.

Prior studies show that depositors monitor banks and act on banks' information. Iyer et al. (2016) examine micro-level depositor data for a bank and find that depositors respond to bank fundamentals. Specifically, they find that uninsured depositors withdraw funds in response to a private regulatory audit that found the bank insolvent. Moreover, uninsured depositors are far more likely to run than insured depositors following the public news of a high-solvency-risk shock of the bank. Calomiris and Jaremski (2018) use bank data from 1990 to 1920 and find that loans to assets and real estate to assets negatively predict deposit growth while capital to assets positively predicts deposits. Anderson et al. (2017) find that depositors react to news about banks' balance sheets and economic aggregates, and the reaction is more pronounced before deposit insurance. Lo (2015) finds that the growth of uninsured liabilities during periods of monetary policy tightening is higher for audited banks than for unaudited banks. In addition, audited small banks exhibit more timely recognition of loan losses in earnings than other small banks. Lo (2015) also notes that investors of large uninsured liabilities routinely use bank accounting information to assess the quality of the issuers. Because the deposits following shale booms can easily range from hundreds of thousands to millions of dollars, banks' uninsured deposits are most likely to increase. The investors may not be depositors. In fact, many landowners hire professionals and wealth management companies to take care of their money. Those with high balances may have strong incentives to act on banks' performance contained in banks' financial statements, since their financial well-being is tied up with their banks', and thus banks may respond to deposit windfalls by changing their accounting practices.

Deposit shocks may positively affect banks' information quality through two mechanisms. The first mechanism relies on the role of bank accounting in reducing information asymmetry between depositors and banks. Freixas and Rochet (2008) argue the importance of asymmetric information between banks and depositors in understanding banks' delegated monitoring and deposit-taking roles. Because the incentives of bank managers and depositors are not aligned, banks may engage in suboptimal risk-taking behavior from depositors' perspectives.

Bank accounting can address the information asymmetry between banks and depositors by informing depositors about bank fundamental and performance. When banks are exposed to deposit windfalls, they may improve their accounting quality to attract deposits. Holod and Peek (2007) show that the degree of information asymmetry between a bank and a potential depositor affects banks' access to deposits during periods of monetary policy tightening. A similar phenomenon is documented in studies examining nonfinancial firms. Gormley et al. (2012) show that foreign bank entry is associated with more timely loss recognition of local nonfinancial firms, suggesting that local firms improve reporting quality in order to borrow from these foreign banks. I call this the Access to Deposits channel.

The second mechanism, which I call the Shareholder Monitoring channel, relies on bank managers' concern over market reactions for their stocks and bonds. Bliss and Flannery (2002) argue that effective market monitoring of banks occurs when their investors can accurately assess changes in banks' condition, and promptly impound those changes into their stock and bond prices. This relatively large literature indicates that bank investors identify risky banks and increase their cost of capital (e.g., Bouther and Francis, 2017; Maechler and McDill, 2006). Since the stock market is more information sensitive than the bond market, in this paper, I focus primarily on shareholder monitoring of banks. The effectiveness of shareholder monitoring depends on the extent to which a bank is financed by uninsured liabilities and the transparency of its risk-taking. Moreover, Tirole (2006) argues that either demandable debt or equity can be used as plausible alternative mechanisms to control bank agency problems. Flannery and Nikolova (2004) find that banks' uninsured subordinated notes and debentures, uninsured CDs, and federal funds reflect differences in credit risk across banks. They conclude that banks with more uninsured deposits have more exposure to market monitoring. Following the shale booms, investors may be concerned about agency issues (e.g., overinvestment) induced by the unexpected cash inflows. Banks may record timelier provisions to mitigate the increased shareholder concern.

Alternatively, deposit shocks may not positively affect banks' information quality. Banks with more deposits may become less concerned about liquidity constraints, and thus exert less effort in monitoring loan performance, leading to delays in recognizing loan loss provisions. Furthermore, information on banks' financial health may not matter to depositors with only modest checking accounts, and thus banks do not have incentives to change reporting. Monnet and Quintin (2017) show that depositors would not monitor banks even in the absence of deposit insurance because they would lose the "liquidity services that the bank provides". In addition, timely loss recognition can be costly for banks. High provision for loan losses reduces stated earnings, which may negatively affect managerial compensation and outsiders' valuation of the bank. Changes in the trade-offs of providing high-quality financial information can shift banks' accounting choices. Overall, whether and how the deposit windfalls affect banks' accounting or provision quality remain to be determined.

3 Data and Research Design

3.1 Sample Selection

Nine states experienced major shale discoveries between 2003 and 2010 based on Plosser (2014). I supplement his list with drilling productivity reports from EIA. Appendix B presents the major energy fields and their years of shale gas or oil discoveries in the sample. Some formations can have multiple years of shale booms because of differential timing of the development of the formation. Figure 1 shows that each of the nine states contains multiple boom counties as well as many non-boom counties.[6] Some boom counties specialized in natural resource production at the start of the boom period. I choose the non-boom counties

[6] Some of those non-boom counties may also have drilling activities, but they are treated as non-boom because the estimated impact of shale boom on deposits is insignificant relative to that of the county. Plosser (2014) uses drilling and production data from various state agencies to identify major shale oil and gas discoveries. He constructs an estimate of the payments paid to local landowners using the drilling permit and production data. Specifically, he measures royalties based on press reports and communications among landowners, and measures bonus payments by formation based on self-reported bonuses from http://www.mineralrightsforum.com. Counties are excluded from his treatment sample if the annual payments are small (maximum annual payment less than $30 million) and the relative impact is low (cumulative payments after four years are less than 20% of the deposit base). The treatment sample is relatively insensitive to changes in the estimation of payments or the screening criteria. On average, treatment county payments exceed $70 million a year or 39% of the local deposit base.

in the same state as the control sample because neighboring counties should share similar production level prior to the boom. My final sample consists of 123 counties that experienced booms and 709 counties that did not across the nine states. The sample includes all bank-quarters for banks with branches operating in any of these nine states from 2001 to 2012 with the required data.[7]

[Figure 1 About Here]

To identify treatment banks, I use the Summary of Deposits (SOD) from the Federal Insurance Deposit Corporation (FDIC). SOD provides deposits at the bank branch level as of June 30th of each year. The data allows me to identify banks whose branches are exposed to the shale boom and measure the impact of the shale boom on deposits at both the county and bank level. A bank is defined as a treated bank if it has branches located in one or more boom counties. A bank is defined as a control bank if it has branches in any of the nine states but is not in the treatment group. I create an indicator variable ***Boom*** that equals one for banks with branches in boom counties after the onset of shale booms and zero otherwise. The ***Boom*** variable equals zero for all bank-quarters prior to 2003, the first year of the shale booms. Because shale booms happened at different times during boom years and SOD only provides data as of June of each year, I omit observations of treatment counties and banks in the year of shale booms. Therefore, ***Boom*** is one for years after the boom year and zero for years before the boom year for treatment banks and counties. Some banks may have branches in multiple boom counties that experienced booms at different times. Those banks are treatment banks with ***Boom*** equal to one after the first boom they experienced. Although the treatment period (from the first year of boom exposure to the end of the sample period) sometimes is long, the average increase in deposits is persistent and not subject to reversals for treatment banks (Plosser, 2014). Moreover, some banks are exposed to multiple booms at different times, mitigating the concern.[8] In robustness tests, the results are qualitatively

[7] My findings are robust to restricting or extending the sample period.

[8] Gilje (2017) and Plosser (2014) report that the average cumulative impact of shale discoveries results in

similar when I set the treatment period to be four or five years. Another concern is that banks may strategically open branches in boom counties following a boom. To alleviate this concern, I require bank branches to exist in boom counties before booms.[9]

Chartered commercial banks must provide detailed financials to the FDIC on a quarterly basis in Call Report of Income and Condition (Call Report). I use quarterly data from Call Reports to construct the bank financial measures used in the empirical models.[10] All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers. The main sample consists of 96,103 bank-quarter observations for 2,560 unique banks over the period of 2001-2012. The sample is smaller in some tests due to test specifications and lack of data availability.

3.2 Impact of Shale Booms on Deposits

In this section, I first identify the impact of shale booms on local deposit supply and establish that the deposit windfalls led to increases in bank deposits. I show that there is a substantial increase in deposits for treatment counties and banks following shale booms, consistent with recent studies (Gilje et al., 2016; Gilje, 2017; Plosser, 2014).

To examine the effect of the booms on deposits, I first calculate the fraction of branches and deposits held by each treatment bank in boom counties of the nine states each quarter. The measure ranges from zero (for banks without branches in boom counties during the quarter prior to a boom) to one (for banks with all of their branches in boom counties after the onset of the booms). Panel A in Table 1 shows that the average fraction of an exposed bank's branches (deposits) located in boom counties is about 34% (36%).

To test the statistical significance of deposit growth, I estimate the following pooled

20% higher deposits after five years and almost 40% after six years in boom counties. In their tests, a bank remains treated after the onset of the first boom, same as in this study.

[9] Other studies show that banks do not strategically open branches in boom counties (Gilje et al., 2016; Plosser, 2014).

[10] The use of annual data does not affect my inferences.

regressions for deposit growth at both the county and bank level:

$$\triangle DepositCounty_{i,t} = \alpha + \beta_1 BoomCounty_i + controls + \delta_t + \gamma_i + \epsilon, \tag{1}$$

$$\triangle DepositBank_{i,t} = \alpha + \beta_2 Boom_i + controls + \delta_t + \gamma_i + \epsilon \tag{2}$$

where $\boldsymbol{BoomCounty}$ ($\boldsymbol{Boom}$) equals one for treatment counties (banks) after the onset of shale booms. Since SOD only provides data as of June of each year, I measure $\triangle \boldsymbol{DepositCounty}$ and $\triangle \boldsymbol{DepositBank}$ as the county-level and bank-level deposit growth from June to June, respectively. I also control for county and bank characteristics in the two tests, respectively. In Model (1), I control for county-level deposits. In Model (2), the controls include $\boldsymbol{Size}$, $\boldsymbol{Deposit}$, $\boldsymbol{Liquidasset}$ and $\boldsymbol{Hete}$. $\boldsymbol{Hete}$ represents heterogeneous loans and is the sum of commercial and industrial loans and commercial real estate loans divided by total assets. County (Bank) fixed effects are included to control for time invariant county (bank) effects. Year fixed effects are included to account for time-varying effects. Standard errors are clustered by county in Model (1) to account for arbitrary serial correlation of county-level errors, and are clustered by bank in Model (2) for a similar reason. If shale booms increase deposit supply at both the county and bank level, both β_1 and β_2 should be significantly positive. In particular, β_1 is an estimate of the annual deposit growth rate in treatment counties, compared to control counties in the same states and neighboring states. Since some control counties also have shale development, the point estimates are likely biased downward.

To further establish the deposit-inflow effect, I examine the impact of shale booms on the price of deposits, measured as the interest expense on deposits divided by total deposits. Specifically, I regress the deposit price on $\boldsymbol{Boom}$, along with other controls. If shale booms increase deposit supply, there should be a reduction in deposit price following shale booms.

Panel A in Table 2 shows the estimates of deposit growth at the county level. On average, deposits grow four percentage points faster annually in treatment counties after shale booms and are statistically significant at the 1% level. The estimated effect holds after controlling for contemporaneous macroeconomic effects and county characteristics. Using two-year deposit growth generates similar conclusions. Panel B in Table 2 shows the results at the bank level. Compared to unexposed banks, the exposed banks' deposits grow about 2 - 5.6 percentage points faster, depending on the model specification. Moreover, the interest expense on deposits is significantly lower for exposed banks than for unexposed banks. These results are consistent with a positive deposit supply shock, and the economic magnitudes are in line with the summary statistics in Table 1. In the robustness tests, I substitute ***Boom*** dummy with a continuous measure of boom exposure: the fraction of branches held by each bank in boom counties. A higher fraction indicates more exposure to shale booms. The results are similar to those in Panel B both quantitatively and qualitatively.

[Table 1 About Here]

[Table 2 About Here]

3.3 Measuring Provision Quality

To evaluate whether and how deposit windfalls affect banks' financial reporting quality, I use the timeliness in loan loss provision to measure banks' reporting quality. Loan loss provisions are accrued expenses that reflect managers' estimation of changes in expected future losses from credit risk in the loan portfolio. These provisions determine the timeliness with which banks recognize loan loss expectations in income. A critical aspect of the incurred loss model is determining when a loan is impaired and should be provided for in the loan loss reserve. Prior studies often use the timeliness in loan loss provisioning to capture the quality of the accounting system, considering provisions more timely if they are recorded concurrently with or in advance of loans becoming non-performing (e.g., Beatty and Liao, 2011; Bushman and Williams, 2012, 2015; Nichols et al., 2009). These studies show that banks differ in their loan loss provisioning policies, with some banks more aggressively delaying expected losses to future periods. Such delays boost banks' current accounting profitability but lower expected future profitability.

Since most of my tests involve cross-sectional comparisons of banks' treatment status and characteristics, I estimate a pooled model to allow for cross-sectional differences. Built on the literature, I use the recognition of concurrent (quarter t) and future (quarter $t+1$) non-performing loans in the loan loss provision to capture timeliness. Beatty and Liao (2014) compare nine different loan loss provision determinant models proposed by the banking literature, and find that the residual term of their Model (a) performs particularly well in predicting future earnings restatements and SEC comment letters. I use their proposed residual model to build my base model and confirm that my results are robust to using alternative loan loss provision models. Specifically, the base model is an ordinary least square (OLS) model of the following format:

$$\begin{aligned} LLP_{i,t} = \ & \beta_0 + \beta_1 \triangle NPL_{i,t+1} + \beta_2 \triangle NPL_{i,t} + \beta_3 \triangle NPL_{i,t-1} + \beta_4 \triangle NPL_{i,t-2} \\ & + \beta_5 Ebllp_{i,t} + \beta_6 Tier1_{i,t-1} + \beta_7 Size_{i,t-1} + \beta_8 \triangle LOAN_{i,t} \\ & + \beta_9 ALLL_{i,t-1} + \sum \beta LoanType_{i,t-1} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where subscript i indexes the bank and t indexes the quarter; LLP is loan loss provision scaled by lagged total loans; $\triangle NPL$ is the change in non-performing loans over the quarter scaled by lagged total loans, which represents the exogenous and relatively nondiscretionary indicators of possible future credit losses; $Ebllp$ is earnings before loan loss provisions for quarter t scaled by lagged total loans; $Size$ is the logarithm of total assets at the beginning of the quarter and is included to account for different levels of regulatory scrutiny or monitoring; $\triangle Loan$ is the change in loans scaled by lagged loans and controls for changes in the size of a bank's loan portfolio; $Tier1$ is the Tier 1 risk-based capital ratio and is included to capture capital management (e.g., Beatty et al., 1995; Collins et al., 1995); $ALLL$ is the allowance for loan losses at the beginning of the quarter. I control for past allowance because high past provisions may indicate low current provisions. However, lagged allowance and provision could also be positively correlated if past allowance reflects the overall credit quality of the bank's clients. I also control for different loan types and loan composition because they are likely to be affected by the deposit shock, leading to a change in the recognition of loan loss provisions. Specifically, $shrRE$ is the real estate loans scaled by total loans; $shrCI$ is the commercial and industrial loans scaled by total loans; $shrCONS$ is the share of consumer loans; $shrAGRI$ is agricultural loans scaled by total loans.

To capture the timeliness of expected loan loss recognition, I include $\triangle NPL$ measured in four different time periods, $t+1$, t, $t-1$, and $t-2$. $\triangle NPL_{t-1}$ and $\triangle NPL_{t-2}$ capture the fact that some banks use past non-performing loan information to estimate loan loss provisions. $\triangle NPL_{t+1}$ and $\triangle NPL_t$ reflect the fact that some banks may use forward-looking information on non-performing loans in estimating loan loss provisions. For more timely banks, current loan loss provisions are more sensitive to current and future changes in nonperforming loans, and therefore the level of timely recognition of loan loss provision is increasing in the coefficients on future and contemporaneous $\triangle NPL$.

3.4 Research Design

To test the effect of deposit windfalls on provision timeliness, I examine differences in β_1 and β_2 across exposed and non-exposed banks.[11] Specifically, I expand Model (1) by interacting $Boom$ with the main explanatory variables $\triangle NPL_{t+1}$ and $\triangle NPL_t$. In addition, I interact $Boom$ with other explanatory variables to account for changes in the relation between loan loss provisions and the explanatory variables following the deposit shocks. The full model is specified as follows:

$$\begin{aligned} LLP_{i,t} = \; & \beta_0 + \alpha_1 Boom_t + \alpha_2 Boom_t \times \triangle NPL_{i,t+1} + \alpha_3 Boom_t \times \triangle NPL_{i,t} \\ & + \alpha_4 Boom_t \times \triangle NPL_{i,t-1} + \alpha_5 Boom_t \times \triangle NPL_{i,t-2} + \beta_1 \triangle NPL_{i,t+1} + \beta_2 \triangle NPL_{i,t} \\ & + \beta_3 \triangle NPL_{i,t-1} + \beta_4 \triangle NPL_{i,t-2} + \beta_5 Ebllp_{i,t} + \beta_6 Tier1_{i,t-1} + \beta_7 Size_{i,t-1} \\ & + \beta_8 \triangle LOAN_{i,t} + \beta_9 ALLL_{i,t-1} + \sum \beta LoanType_{i,t-1} + \mu_t + \gamma_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

[11] I also allow β_3 and β_4 to vary across treatment and control banks but do not explicitly examine them.

I include time fixed effects to control for time-series effects common to all banks and bank fixed effects to control for time-invariant differences across banks. I cluster standard errors by bank to account for the bank-specific, persistent nature of loan loss provisions and regulatory status (Petersen, 2009). In additional tests, I include $\triangle NPL_{t+1}$ and $\triangle NPL_t$ interactions with $TreatBank$, an indicator that equals one for exposed banks and zero otherwise. The interactions control for average differences in loan loss provision timeliness across the two types of banks. The main coefficients of interest, α_2 and α_3, capture the changes in loan loss provision timeliness for exposed banks relative to changes for unexposed banks. Positive α_2 and α_3 indicate that loan loss provisions are timelier for exposed banks than for other banks.

To estimate the effect of the deposit windfalls on banks' provision quality, it is essential to have a control sample to account for potential correlated omitted variables that vary in time simultaneously with the shale booms. The shale booms may trigger or be associated with other changes in the boom areas that influenced the quality of information disclosed by banks, and it could be these other changes that influenced the provision quality of banks. In the model specification, I include a control sample consisting of banks with branches in nearby counties that are not exposed to the shale booms but share the same economic market with the treatment banks. Furthermore, by construction, the indicator variable $Boom$ is one for treatment banks only after the onset of booms. These banks are in the control group prior to their treatment. The use of variation in both the location and timing of shale booms reduces potential confounding effects that might arise from other changes in banks' reporting incentives. Unless specified otherwise, I exclude observations of treatment banks in the year of booms.

This approach is analogous to a difference-in-differences estimation and relies on two identification assumptions. Firstly, the effect of the localized wealth shock on bank reporting must be observable at the bank level because accounting information is not available at the branch level. The use of bank-level data likely biases against finding any effect. In robustness tests, I restrict the sample to single-county banks and include county fixed effects to control for the average change in each county and reach similar conclusions. Secondly, shale booms did not selectively occur in areas where banks already had trends with respect to their loan loss provision timeliness for reasons unrelated to the wealth shock. I show later that there is no evidence of differential trends in loan loss provision timeliness prior to the shale boom. I discuss this issue further in section 4.

4 Empirical Results

4.1 Descriptive Statistics

Panel B in Table 1 reports summary statistics of the main variables of interest, separately by whether a bank has any exposure to a shale boom. Tier1 risk-based capital ratio is well above the 8% threshold. The mean of loan loss provision is 0.001 for both treatment and control banks. On average, both groups of banks are well capitalized and have similar characteristics, such as the level of loan loss provisions and changes in nonperforming assets. The similarities in both the means and standard deviations of the variables provide support for the identification strategy. Deposit growth is higher, and the cost of deposits is lower for exposed banks, consistent with the notion that exposure to the shale boom leads to increases in bank deposits. Given the skewed distribution of bank assets, I measure bank size as the logarithm of total assets. The table shows that treatment banks are slightly larger than control banks, which may be a concern because large banks differ in many ways from smaller ones. In robustness tests, I remove very large banks[12] and also estimate the model using only treatment banks.

Panel C displays the Pearson correlations of the bank characteristics. Consistent with prior studies, I find a positive correlation between the lagged Tier1 capital ratio and growth in loans. I also find a positive relation between loan growth and deposit growth. The table also

[12] Very large banks are defined as those in the top decile of the asset size distribution. After removing those banks, the magnitudes of main coefficient estimates become slightly smaller but remain significant.

shows a positive relation between loan loss provision and bank size, consistent with more solvent banks reserving more for loan losses. Moreover, loan loss provision is negatively correlated with Tier1 capital ratio and positively correlated with earnings ($Ebllp$). Finally, loan loss provision is positively associated with current and lagged changes in nonperforming loans, consistent with banks reserving more for loan losses when economic loan losses are higher.

4.2 Main Results

4.2.1 Loan Loss Provision Timeliness Following Deposit Windfalls

My main test examines the effect of deposit windfalls on loan loss provision timeliness. The main results are presented in Table 3. I include bank and time fixed effects in all tests and cluster robust standard errors at the bank level. Column (1) shows the results from Model (4) using the full sample. The coefficients on $\triangle NPL_t$ and $\triangle NPL_{t+1}$ are positive, and the coefficient on $\triangle NPL_t$ is significant. This indicates that in the absence of shale booms, banks incorporate forward-looking information of future non-performing loans in estimating loan loss provisions. The interactive terms, $\boldsymbol{Boom_t} \times \triangle NPL_t$ and $\boldsymbol{Boom_t} \times \triangle NPL_{t+1}$, are the main variables of interest and test whether deposit windfalls affect banks' timeliness in loan loss provisioning. Specifically, the coefficients on $\boldsymbol{Boom_t} \times \triangle NPL_t$ and $\boldsymbol{Boom_t} \times \triangle NPL_{t+1}$ are both positive and statistically significant, indicating that exposed banks record timelier loan loss provisions than other banks. Improved loan loss provision timeliness is economically significant: the point estimates suggest that the timeliness of loan loss recognition increases by about four times from 0.22% to 1.15%. The results are robust to controlling for $size$, $Tier1$ capital ratio, earnings before provisions, loan growth, allowance for loan losses, and different loan types.

Consistent with prior research,[13] I find the coefficient on $Ebllp$ positive and significant,

[13] E.g., Bushman and Williams (2012); Collins et al. (1995); Laeven and Majnoni (2003).

indicating that on average banks smooth earnings via loan loss provisions. The coefficient on loan growth ($\triangle Loan$) is negative and significant, indicating that banks do not extend credit to more clients with lower credit. The coefficient on past loan loss allowance ($ALLL$) is significantly positive, consistent with past allowance reflecting the overall credit quality of the bank's clients. The coefficient on $Tier1$ capital ratio is negative but insignificant, and thus does not suggest capital management of the banks on average. This is in line with the discussion in Beatty and Liao (2014) that the use of the loan loss provision for Tier1 capital management attenuated in the post-BASEL regime.

One concern might be that treatment and control banks are inherently different from each other in affecting the relation between loan loss provision and changes in non-performing loans. Column (2) includes two additional variables to address the concern. Specifically, I include the interaction terms of $\triangle NPL_t$ and $\triangle NPL_{t+1}$ with $TreatBank$, an indicator that equals one for exposed banks. These interactions control for average differences in timely loan loss recognition across the exposed and non-exposed banks, and the results are qualitatively similar.

Another concern might be that the main results are driven by the control banks because of economic spillovers from shale to non-shale areas located nearby. To eliminate the possibility that the results from columns (1) and (2) are affected by control banks or by spillovers to adjacent areas that did not experience booms, I estimate the main model using only treatment banks that experience a shale boom at some point during the sample period. In this specification, treatment banks are compared to themselves prior to the treatment. The results are presented in column (3). All results continue to hold. In particular, the coefficients estimate of $Boom_t \times \triangle NPL_t$ and $Boom_t \times \triangle NPL_{t+1}$ are similar to those in the other two columns, suggesting that the effect of deposit windfalls on loan loss provision timeliness is not driven by control banks.

Overall, the results suggest a positive effect of the deposit windfalls on banks' provision quality. That is, banks with exposure to shale booms increase the timeliness of loan loss recognition after the onset of shale booms.

[Table 3 About Here]

4.2.2 Addressing Endogeneity

The main tests show that shale booms lead to changes in the timeliness of loan loss provisioning. However, the concerns arise that banks expect the booms and change their reporting in advance of the booms, or that an omitted variable differentially affects the treatment and control banks. In these cases, changes in loan loss provision timeliness may not be driven by the effect of deposit windfalls. To address these concerns, I conduct a falsification test to show that the changes in loan loss provision timeliness of treatment and control banks would have been the same in the absence of shale booms. Specifically, I re-estimate Model (4) and include a placebo event indicator variable $Boom_{t-1}$ that equals one for the year prior to the boom year, and zero otherwise. The coefficients on the interactions between $Boom_{t-1}$ and $\triangle NPL$ estimate changes in provisioning timeliness for treatment banks relative to control banks one year before the actual shale boom, relative to earlier years.

Panel A in Table 4 presents the placebo test results. The coefficient estimates on $Boom_{t-1}$ and its interactions with $\triangle NPL$ are statistically insignificant, which suggest that there were no pre-existing, differential trends in loan loss provision timeliness prior to the shale boom. Moreover, I find that adding these terms has almost no impact on the point estimates of $Boom_t \times \triangle NPL_t$ and $Boom_t \times \triangle NPL_{t+1}$. The timing of improvements in timeliness coincides with the onset of the shale booms. Thus, shale booms lead to increased loan loss provision timeliness, but the reverse does not hold. Collectively, the change in provision quality is unlikely to be caused by omitted firm characteristics. In order for an omitted variable rather than the shale boom to drive the change in provision quality, it has to differentially affect exposed and non-exposed banks, and at various points in time coinciding with the staggered boom years from 2003 to 2010. Such an omitted variable is unlikely to exist.

To further validate the identification strategy, I examine whether there is differential loan loss provision timeliness between treatment and control banks prior to the first shale boom in 2003. Specifically, I estimate Model (4) for the period of 1999-2002 and include the interaction terms of $TreatBank$ with all $\triangle NPL$. The results are presented in Panel B in Table 4. All of the coefficients on the interactions between $TreatBank$ and $\triangle NPL$ are insignificant, suggesting that prior to the first boom, the provision timeliness was similar between treatment and control banks. The results further validate the identification.

[Table 4 About Here]

4.3 Identifying Mechanism

The main results show that banks with exposure to the deposit windfalls improve their provision quality after the onset of the booms. Based on the literature on bank accounting, the role of banks' accounting information lies primarily in mitigating information asymmetry between banks and investors and in addressing agency problems that arise from banks' delegated monitoring role (e.g., Beatty and Liao, 2014). There are two potential mechanisms through which the deposit shocks can positively affect banks' information quality. The first mechanism relies on the role of bank accounting in reducing information asymmetry between depositors and banks. Timely recognition of loan loss provisions can improve bank transparency and therefore exposed banks may improve their provision quality expecting to attract more deposits. If this is the primary mechanism, then improved loan loss provision timeliness after shale booms would be concentrated in banks with stronger incentives to obtain deposits. I call this the Access to Deposits channel.

The second mechanism, which I call Shareholder Monitoring channel, relies on shareholder monitoring and bank managers' concern over market reactions. Following the shale booms, investors may be concerned about agency issues (e.g., overinvestment) induced by the unexpected cash inflows. Banks that care about their relationship with shareholders may signal with high-quality accounting information to mitigate their concern. If this is the mechanism, then I expect to see more pronounced positive effects of the shale booms on provision quality in banks subject to more shareholder monitoring.

4.3.1 Loan Loss Provision Timeliness and Access to Deposits

I first investigate the Access to Deposits channel by examining whether loan loss provision timeliness differs when banks' perceived benefits of improving provision quality are high. Since timely loan loss provision could reduce information asymmetry between banks and depositors, which increases banks' expected access to deposits, banks that are more dependent on deposit financing and that are more constrained in liquidity are more likely to increase timely loan loss recognition. Because the deposits following shale booms can easily range from hundreds of thousands to millions of dollars, banks' uninsured deposits are most likely to increase. The investors may not be depositors. In fact, many landowners hire professionals and wealth management companies to take care of their money. No matter who eventually deposits the money, bank managers improve their provision quality expecting to attract more uninsured deposits, and banks with fewer uninsured deposits ex-ante have more incentives to improve provision quality. Prior studies also suggest bank size as a proxy for banks' liquidity dependence. I re-estimate Model (4) based on subsamples of banks split by ex-ante uninsured deposits and size.

Table 5 reports the results by splitting the sample into two groups based on the median of uninsured deposits. Uninsured deposits are accounts of $100,000 or more until the first quarter of 2006 and accounts of $250,000 or more starting from the second quarter of 2006. Thus, I separately report my analyses using the full sample period as well as sub-periods before and after the second quarter of 2006. Columns (1) and (2) report the results for the full sample. The increase in loan loss provision timeliness is greater, on average, among banks with below median uninsured deposits scaled by total assets. The coefficients on $Boom_t \times \triangle NPL_t$ and $Boom_t \times \triangle NPL_{t+1}$ are positive and significant for banks with uninsured deposits below the median. I further test the differences in the coefficients between the two samples and find the differences to be statistically significant at 1% level. To address concerns regarding the rule change of the uninsured deposits, I re-estimate the same tests for the periods before and after the second quarter of 2006. The results are reported in columns (3) to (6). The coefficient on $Boom_t \times \triangle NPL_{t+1}$ remains positive and significant for banks with fewer uninsured deposits. The coefficient on $Boom_t \times \triangle NPL_t$ is positive and significant in the pre-2006 period, but is insignificant in the post-2006 period. This may imply that with an increased coverage of insured deposits, depositors are less concerned about bank solvency and thus reduce their demand for timely information.[14] Taken together, the results show that banks with a lower level of uninsured deposits in the previous period become more timely in loan loss provisioning following shale booms.

[Table 5 About Here]

Another measure of uninsured liability that is used as the marginal source of funds for banks during times of liquidity constraint is large time deposits, which are time deposits in denominations of more than $100,000. I find consistent results where the increase in timely loan loss recognition appears larger, on average, in banks with lower than the median large time deposit. The results are shown in Table 6. Collectively, the results are consistent with constrained banks having more incentives to attract the deposit inflows. In addition, the evidence suggests that it is not driven by existing uninsured depositors' monitoring because the effects concentrate more among banks with fewer uninsured deposits.

[Table 6 About Here]

Prior studies also use size to proxy for a bank's access to external finance and being liquidity constrained (e.g., Kashyap and Stein, 2000). Splitting the full sample into two groups based on the median of bank size, I find that provisioning timeliness increases more for smaller banks. Table 7 presents the results. The coefficients on $Boom_t \times \triangle NPL_t$ and

[14]The results are consistent with the notion in Holod and Peek (2007) that deposit insurance alters the importance of accounting for insured depositors.

$Boom_t \times \triangle NPL_{t+1}$ are positive and significant for smaller banks, suggesting that smaller banks have more incentives to improve provision quality after the deposit windfalls.

[Table 7 About Here]

To further investigate the Access to Deposits channel, I test if timely loan loss provision is indeed beneficial for banks to get more deposits. Specifically, I examine whether improved timeliness is accompanied by an increase in deposit levels for exposed banks. Firstly, I re-estimate Model (4) for treatment banks only and the results are in column (3) of Table 3. As discussed before, all results still hold, and treatment banks become more timely in loan loss provisioning following exposure to deposit windfalls. Next, I divide the treatment sample into banks that experience an increase in deposit level after shale booms and those that do not. A bank has an increase in deposit level if its overall deposits increase over the year following a shale boom. This bank is included in the "deposit increase" group. The other banks are included in the "no deposit increase" group. If improved loan loss provision timeliness is associated with better access to deposits, then I expect the improvements to be more pronounced for banks in the "deposit increase" group. As shown in Table 8, only banks that increase their provision timeliness have an increase in deposit level after shale booms. In particular, the coefficients on $Boom_t \times \triangle NPL_t$ and $Boom_t \times \triangle NPL_{t+1}$ for the "deposit increase" group are positive and statistically significant, whereas the coefficients for the "no deposit increase" group are not significant.

Collectively, the results support the Access to Deposits channel and suggest that banks that are more liquidity constrained are more likely to increase their loan loss provision timeliness following the shale booms. The evidence also supports the role of bank accounting in mitigating information asymmetry between depositors and banks.

[Table 8 About Here]

4.3.2 Loan Loss Provision Timeliness and Shareholder Monitoring

Another mechanism that may positively affect banks' loan loss provisioning is through the Shareholder Monitoring channel. Although the evidence so far is in line with the Access to Deposits channel, the role of shareholder monitoring remains to be examined. The mechanism suggests that banks that care about their relationship with investors and markets' response would signal through timelier accounting information to alleviate market's concern. If this is the mechanism, then banks subject to greater market discipline and shareholder monitoring are more likely to increase the timeliness of loan loss recognition. Two proxies are commonly used in prior studies to capture the strength of market discipline and shareholder monitoring for banks: legal ownership and dependence on short-term uninsured funding (e.g., Diamond and Rajan, 2001; Nier and Baumann, 2006).

Prior studies show that public banks are more subject to market discipline and shareholder monitoring than private banks (e.g., Nichols et al., 2009). If the mechanism is through the Shareholder Monitoring channel, then I expect to see a bigger increase in provision timeliness for public banks than for private banks. Some studies also use legal ownership as a proxy for external financing availability for banks. Specifically, public banks are argued to be less financially constrained than private banks because public banks are more transparent and less informationally problematic (e.g., Holod and Peek, 2007). If private banks increase their provisioning timeliness more than public banks, then the mechanism is less likely to be market discipline and shareholder monitoring, but more likely to be Access to Deposits. I re-estimate Model (4) separately for public and private banks. Table 9 presents the results. The increased timeliness of loan loss recognition is concentrated in private banks. Public banks do not exhibit a significant increase in provision timeliness. However, the difference between public and private banks is not statistically significant. Although the evidence does not support the Shareholder Monitoring channel, the legal ownership subsample test does not provide conclusive evidence that private and public banks respond differentially to deposit windfalls.

[Table 9 About Here]

Next, I split the full sample into two groups based on the median of short-term uninsured liability in the previous quarter, where short-term uninsured liability is measured as either "other borrowed money" or "subordinated notes and debentures." If shareholder monitoring plays a role, then I expect banks with more short-term liability to increase more in provision timeliness. Table 10 presents the results. Columns (1) and (2) show the results using "other borrowed money," which is borrowing primarily from government and government-sponsored agencies. The results indicate that both groups of banks increase loan loss provision timeliness after exposure to shale booms. The difference in the timeliness of provisioning between banks with more versus less short-term uninsured liabilities is not statistically significant. Columns (3) and (4) present the results using "subordinated notes and debentures" and show that only banks with less subordinated notes and debentures display a significant increase in provision timeliness following shale booms. However, the two groups do not have a statistically significant difference in provision timeliness following deposit windfalls. Taken together, the results do not support the Shareholder Monitoring channel.

[Table 10 About Here]

5 Additional Analyses

5.1 Alternative Explanations

The evidence is consistent with the Access to Deposits channel, where banks increase timely loss recognition following shale booms to attract more deposits. However, it is also possible that the deposit windfalls induce changes in banks' profitability and poorly managed banks become well managed afterward, leading to the change in the relation between loan loss provision and changes in non-performing loans. In other words, the results may be driven by less profitable and poorly managed banks. While I control for time-varying profitability in all regressions, I conduct an additional test to address this concern. I follow Beatty and Liao (2011) and use bank profitability to measure the quality of bank management. Well (poorly) managed banks are banks having higher (lower) than the median profitability calculated at the beginning of the quarter. Table 11 presents the results of the effect of deposit windfalls on provision timeliness separately for well versus poorly managed banks. I find that the coefficient on $Boom_t \times \triangle NPL_t$ is positive and significant for both sets of banks, and the difference between the two subsamples is not statistically significantly. Therefore, both groups exhibit an increase in provision timeliness following the deposit windfalls and there is no difference in the increase between the groups. The results suggest that the findings are not driven by banks' profitability and management quality.

[Table 11 About Here]

Another concern is that the main results are driven by differences in banks' ex-ante credit risk. Although I include bank fixed effects in all tests to control for any time-invariant bank characteristics, and include the interaction terms of $\triangle NPL_t$ and $\triangle NPL_{t+1}$ with $TreatBank$ to control for any systematic differences between treatment and control banks, I conduct an additional test to address this concern. I split the sample into two groups based on the median of loan charge-offs of past period. In untabulated results, I find no significant difference in timely loss recognition between the two sets of banks, suggesting that differences in credit risk do not drive the results. Another related concern is that banks may make riskier investments following the deposit shocks, leading to higher non-performing loans reflected in loan loss provisions for reasons unrelated to a change in reporting quality. Although I cannot completely rule out this explanation due to the lack of detailed information on banks' investments, existing evidence does not support this mechanism. Specifically, the coefficient on $Boom_t$ is negative and significant in most of the tests, indicating a decrease in the level of loan loss provisions for exposed banks following the deposit shocks. In addition, using the fraction of mortgage loans that were charged off or are delinquent at the bank-year level, Gilje et al. (2016) find that loan performance is better at banks with exposure to the shale booms.

5.2 Alternative Measure of Provision Quality

An extensive literature uses the absolute value of the residuals from variations of Model (3) as the discretionary portion of loan loss provisions (e.g., Beatty and Liao, 2014; Jiang et al., 2016). A higher value of the discretionary loan loss provisions (discretionary LLP) implies higher portion of the provisions unexplained by fundamental determinants, thus indicates lower disclosure and provision quality. To construct the measure of discretionary LLP, I use the absolute value of the residuals from estimating modified Model (3), where the model controls for size, profitability, loan growth, Tier1 capital ratio, as well as macroeconomic indicators as defined in Appendix A. I multiply the absolute residuals by 100 to better present the coefficient estimates.[15] I then use a difference-in-differences specification to examine the relation between the measure of provision quality and the shale booms. Specifically, the model I estimate is as follows:

$$\begin{aligned} DisLLP_{i,t} = \; & \beta_0 + \beta_1 Boom_{i,t} + \beta_2 Size_{i,t} + \beta_3 Ebllp_{i,t} + \beta_4 LLP_{i,t-1} \\ & + \beta_5 Loss_{i,t} + \mu_t + \gamma_i + \epsilon_{i,t} \end{aligned} \tag{5}$$

where $DisLLP$ is the measure of the discretionary component of loan loss provisions of bank i in quarter t. Following Jiang et al. (2016), I control for size, profitability, Tier1 capital ratio, one quarter-lag of loan loss provisions, and negative net income indicator variable ($LOSS$).[16]

[15] I also run Model (3) including the boom indicator and its intersections with the other controls to allow the shale booms to change the accuracy of the LLP model. This addresses the concern that the measure simply captures a change in the underlying model. All results still hold.

[16] The results are robust to controlling for the particular features of each bank's loan portfolio, such as the proportion of real estate, commercial and industrial and agriculture. Including these loan types does not alter the findings.

I also include time fixed effects and bank fixed effects that may explain the discretionary LLP. Robust standard errors are clustered by bank.

Table 12 presents the results. Different columns use different specifications of the ***Boom*** measure. Column (1) uses the ***Boom*** dummy as in other tests. Column (2) uses the share of branches located in boom counties, and column (3) uses the share of deposits in boom counties. The coefficients of all three measures of ***Boom*** are negative and significant, indicating that exposed banks reduce discretionary LLP following deposit windfalls. The control variables also have expected coefficients. Moreover, I conduct sub-sample analyses as in previous sections and obtain similar results and conclusions. Specifically, the reduction in discretionary LLP is more pronounced among smaller banks, banks with fewer uninsured deposits, and private banks. Furthermore, I substitute the ***Boom*** dummy in Model (5) with indicator variables for five quarters before and after the year of shale booms. I plot coefficient estimates of the indicators in Figure 2. There is a distinct drop in ***DisLLP*** starting from the first quarter following shale booms and there is no evidence of a trend in the measure before shale booms. The evidence suggests that the change in provision quality is induced by the deposit windfalls. Any omitted factors suggested to drive the results must differentially affect treatment and control banks, and do so at various points in time coinciding with the staggered boom years during the sample period.

[Figure 2 About Here]

In addition, several studies find that bank managers use discretion in the loan loss provision for earnings management and capital management. Those studies argue that a positive relation between ***LLP*** and ***Ebllp*** can indicate the smoothing of reported earnings that do not reflect underlying economic performance (e.g., Bushman and Williams, 2012; Collins et al., 1995; Liu and Ryan, 2006). After controlling for fundamental determinants of loan losses, the coefficient on ***Ebllp*** picks up the extent to which banks record loss provisions based solely on the level of earnings without reference to information about the loan portfolio. If banks reduce discretion in the loan loss provisions, then that also indicates an improvement in their provision quality. In the main test, I find consistent evidence of earnings management on average in my sample, where $Ebllp$ is positively associated with LLP. Thus I test if banks' earnings management behavior changes following the shale booms.[17] I include interactions of $Boom$ with $Ebllp$ in the main model but find the coefficient to be statistically insignificant, suggesting that the smoothing of earnings does not change after shale booms.

[Table 12 About Here]

6 Conclusion

In this paper, I find that banks improve accounting quality following deposit windfalls. Specifically, banks with exposure to shale booms increase timely loan loss recognition after the onset of shale booms. Moreover, improved loan loss provision timeliness is concentrated in liquidity-dependent banks that have stronger incentives to attract deposits by reducing information asymmetries. I find that improvements in timeliness are concentrated in smaller banks and banks with fewer uninsured deposits. Further tests suggest that depositors value changes in bank accounting information. Specifically, improvements in timeliness are accompanied by an easier access to deposits for exposed banks. Taken together, the evidence is consistent with the Access to Deposits channel but not with the Shareholder Monitoring channel. Banks' loan loss provision timeliness is of interest to regulators, auditors, investors, and researchers. Investigating how it is used by bank managers in response to different economic conditions helps us understand the role of bank accounting and its interaction with economics. The findings in this paper contribute to the literature by shedding lights on the effects of positive liquidity shocks on banks' reporting choices. The results suggest that banks improve accounting quality in order to attract the increased local deposits. Contrary

[17] Because Tier1 ratio is not significantly associated with LLP in the main test, I do not draw inferences regarding capital management.

to changes in regulations regarding disclosure rules, which directly affect banks' accounting policies, my findings suggest that local economic conditions are important determinants of banks' reporting incentives.

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Figure 1: Distribution of the Shale Booms

This figure maps the counties that experienced shale booms included in this study. Colored counties are shale-boom counties with corresponding boom year on the side.

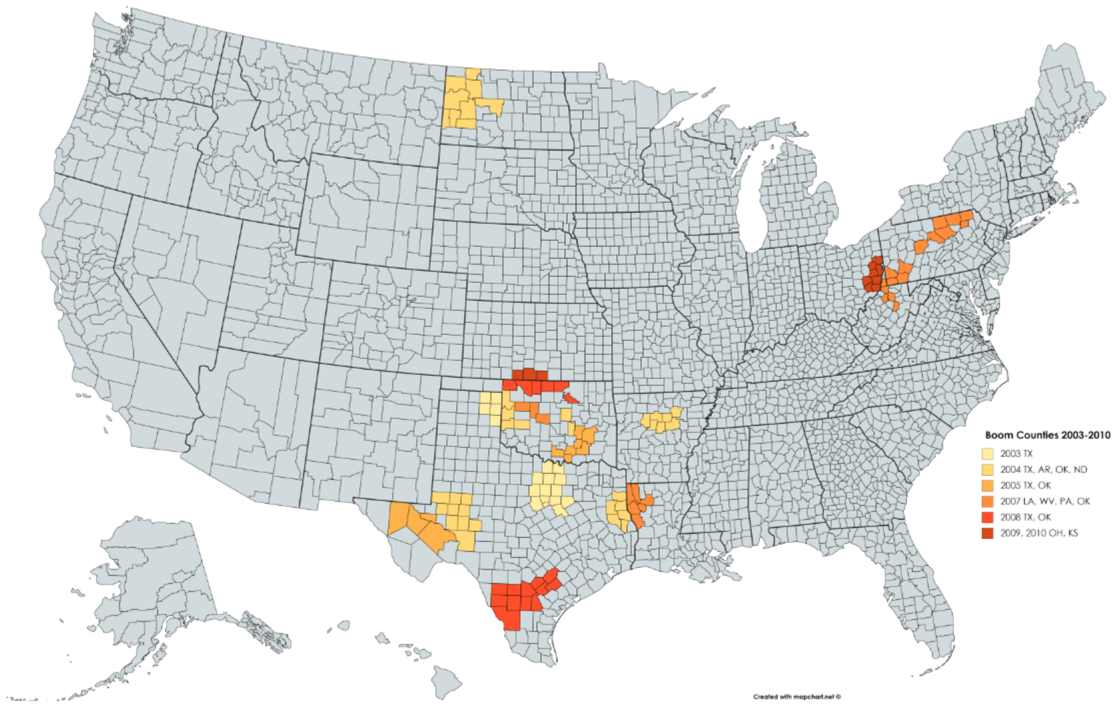

Figure 2: Discretion LLP around the Shale Booms

This figure reports the point estimates of $\boldsymbol{Boom_n}$ (n=-5,..., -1, 1,..., 5), indicators for five quarters before and five quarters after a boom year, in the regression of

$$\begin{aligned} DisLLP_{i,t} = \; & \beta_0 + \sum \alpha_n Boom_{i,t,n} + \beta_2 Size_{i,t} + \beta_3 Ebllp_{i,t} \\ & + \beta_4 LLP_{i,t-1} + \beta_5 Loss_{i,t} + \mu_t + \gamma_i + \epsilon_{i,t} \end{aligned}$$

where $DisLLP_{i,t}$ is the measure of the discretionary component of loan loss provisions of bank i in quarter t. μ_t and γ_i are time and bank fixed effects, respectively. The solid line denotes the estimated coefficients of $\boldsymbol{Boom_n}$(n=-5,..., -1, 1,..., 5), while the dashed lines represent 95% confidence intervals.

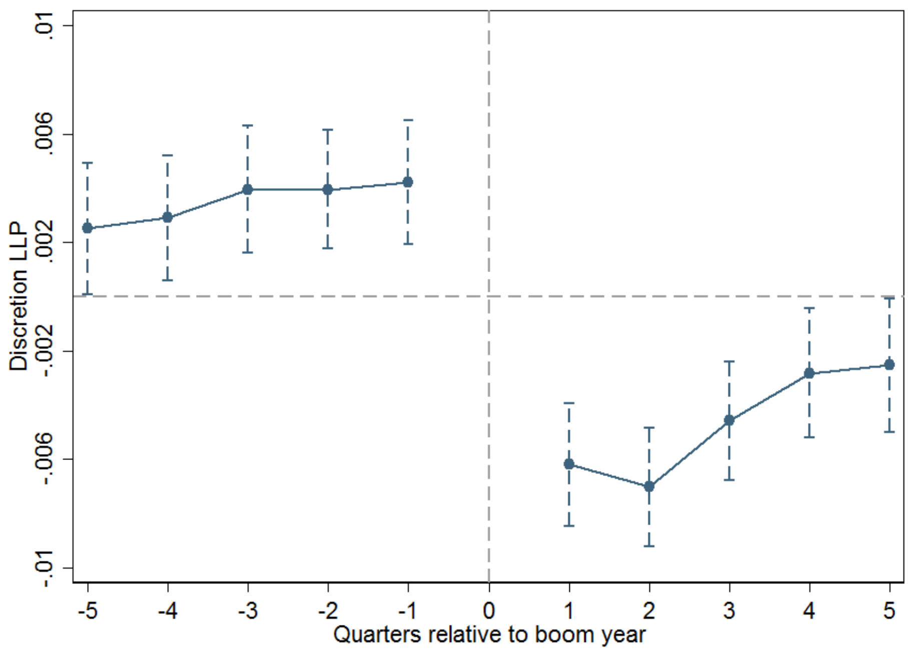

Table 1: Summary Statistics

This table provides summary statistics for the pooled sample of banks in Panel A and separate samples in Panel B between 2001 and 2012. All variables are defined in Appendix A. Continuous variables are winsorized at the 1st and 99th percentiles.

	Exposed Banks			Nonexposed Banks		
	Mean	Median	SD	Mean	Median	SD
Panel A: Exposure to Shale Boom						
Share of branches	0.343	0.125	0.402	0	0	0
Share of deposit	0.362	0.084	0.426	0	0	0
Number of banks		416			2,144	
Number of bank-quarters		16,952			79,151	
Panel B: Bank Characteristics						
Size	12.263	11.959	1.707	11.598	11.479	1.251
Loans	0.573	0.592	0.165	0.599	0.616	0.165
ΔLoans	0.019	0.013	0.055	0.016	0.011	0.060
LLP	0.001	0.001	0.002	0.001	0.000	0.002
ΔNPL	0.000	0.000	0.007	0.000	0.000	0.008
Tier1	0.161	0.135	0.080	0.172	0.148	0.082
Ebllp	0.007	0.006	0.004	0.006	0.005	0.004
NCO	0.001	0.000	0.002	0.001	0.000	0.002
COD	0.438	0.407	0.246	0.479	0.444	0.254
ALLL	0.015	0.013	0.007	0.015	0.013	0.008
Liquidasset	0.384	0.361	0.179	0.366	0.345	0.174
Deposit	0.836	0.859	0.077	0.835	0.854	0.073
ΔDeposit	0.021	0.014	0.054	0.018	0.011	0.058
Hete	0.224	0.214	0.118	0.210	0.187	0.126
shrRE	0.593	0.609	0.181	0.622	0.644	0.197
shrAGRI	0.085	0.022	0.129	0.093	0.024	0.137
shrCI	0.173	0.151	0.101	0.152	0.136	0.097
shrCONS	0.126	0.104	0.091	0.113	0.087	0.097
Uninsured deposits	0.288	0.278	0.117	0.266	0.254	0.115
Sub	0.001	0.000	0.003	0.000	0.000	0.002
Otherborrow	0.035	0.004	0.054	0.037	0.005	0.057
Largetimedeposit	0.150	0.138	0.076	0.148	0.136	0.077

Panel C. Pearson and Spearman Correlation Matrix

Pearson's correlation coefficients are in the lower triangle and Spearman's rank correlations appear above the diagonal.

	$Boom$	LLP	$\triangle NPL_t$	$\triangle NPL_{t-1}$	$\triangle NPL_{t-2}$	$\triangle NPL_{t+1}$	$Size$	$\triangle Loans$	$Tier1_{t-1}$	$Ebllp$	NCO	$ALLL$	$\triangle Deposit$
$Boom$		0.037	-0.001	-0.001	0.001	-0.001	0.156	0.006	-0.070	0.086	0.039	0.018	0.038
LLP	0.015		0.026	0.060	0.057	0.004	0.253	0.039	-0.263	0.042	0.484	0.082	0.057
$\triangle NPL_t$	0.001	0.038		-0.141	-0.039	-0.139	0.023	0.065	-0.031	-0.007	-0.101	-0.012	0.018
$\triangle NPL_{t-1}$	0.000	0.087	-0.157		-0.144	-0.038	0.027	0.014	-0.037	-0.006	0.071	-0.022	0.009
$\triangle NPL_{t-2}$	0.002	0.071	-0.056	-0.162		-0.016	0.028	-0.016	-0.041	-0.003	0.047	-0.022	0.009
$\triangle NPL_{t+1}$	0.002	0.010	-0.155	-0.055	-0.030		0.020	0.028	-0.027	0.001	-0.010	-0.058	0.034
$Size$	0.180	0.121	0.020	0.023	0.024	0.017		0.036	-0.375	0.054	0.224	-0.072	0.065
$\triangle Loans$	0.000	-0.012	0.067	0.006	-0.018	0.013	0.016		-0.049	0.032	-0.095	-0.084	0.142
$Tier1_{t-1}$	-0.059	-0.092	-0.019	-0.022	-0.024	-0.016	-0.311	0.010		0.219	-0.186	0.146	-0.055
$Ebllp$	0.066	0.026	-0.003	-0.003	-0.004	0.004	0.048	0.010	0.275		0.007	0.131	-0.043
NCO	0.012	0.654	-0.114	0.083	0.069	-0.019	0.100	-0.122	-0.073	-0.002		0.034	-0.021
$ALLL$	0.007	0.215	0.007	-0.004	-0.004	-0.055	-0.072	-0.048	0.219	0.101	0.170		-0.073
$\triangle Deposit$	0.025	0.026	0.027	0.004	0.002	0.030	0.048	0.259	-0.012	-0.046	-0.040	-0.057	

Table 2: Shale-Boom Exposure and Deposit Growth

This table contains estimates of the pooled cross-sectional regressions of one-year deposit growth at the county (bank) level on $BoomCounty(Boom)$ that equals one for boom counties (banks) after the onset of shale booms over 2001-2012. All variables are measured as of June of each year. $\triangle Deposit$ is the deposit growth in a county or bank, respectively. $Deposit\,Price$ is the interest expense on deposits divided by total deposits. Constant in Model (1) Panel A is suppressed for brevity. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by county in Panel A and by bank in Panel B. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A. Regression of Deposit Growth on Treatment Counties					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\triangle Deposit$	$\triangle Deposit$	$\triangle Deposit$	$\triangle Deposit$	$\triangle Deposit$
$BoomCounty_i$	0.039***	0.037***	0.039***	0.036***	0.016***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
$Log(countydep)$					0.204***
					(0.010)
Year fixed effects		Yes		Yes	Yes
County fixed effects			Yes	Yes	Yes
Observations	9,853	9,853	9,853	9,853	9,853
Adj. R-squared	0.027	0.062	0.065	0.102	0.216

Panel B. Regression of Deposit Growth on Treatment Banks					
	(1)	(2)	(3)	(4)	(5)
VARIABLES	$\triangle Deposit$	$\triangle Deposit$	$\triangle Deposit$	$\triangle Deposit$	$Deposit\,Price$
$Boom_i$	0.022***	0.057***	0.026***	0.036***	-0.042**
	(0.004)	(0.006)	(0.004)	(0.006)	(0.018)
$Size_{t-1}$	-0.011***	-0.136***	-0.011***	-0.191***	0.441***
	(0.001)	(0.007)	(0.001)	(0.010)	(0.027)
$Deposit_{t-1}$	-0.326***	-0.827***	-0.327***	-0.858***	0.547***
	(0.025)	(0.043)	(0.025)	(0.044)	(0.108)
$Liquidassets_{t-1}$	-0.031***	-0.098***	-0.027***	-0.094***	-0.298***
	(0.009)	(0.022)	(0.009)	(0.023)	(0.060)
$Hete_{t-1}$	0.205***	0.239***	0.210***	0.205***	-0.149
	(0.016)	(0.040)	(0.016)	(0.043)	(0.110)
Bank fixed effects		Yes		Yes	Yes
Year fixed effects			Yes	Yes	Yes
Observations	23,899	23,790	23,899	23,790	23,790
Adj. R-squared	0.052	0.250	0.062	0.277	0.907

Table 3: Loan Loss Provision Timeliness Following Deposit Windfalls

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness. The dependent variable is current loan loss provisions. Column (1) presents results of Model (4) using the full sample. Column (2) includes additional variables. Column (3) reports estimates for treatment banks. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t								
	(1)			(2)			(3)		
	Whole Sample			Whole Sample			Treatment Banks only		
VARIABLES	Coeff		SE	Coeff		SE	Coeff		SE
$Boom_t$	-0.0001	**	(0.000)	-0.0001	**	(0.000)	-0.0001		(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0093	**	(0.005)	0.0127	**	(0.006)	0.0127	**	(0.006)
$Boom_t \times \Delta NPL_t$	0.0178	***	(0.005)	0.0204	***	(0.007)	0.0205	***	(0.007)
$Boom_t \times \Delta NPL_{t-1}$	0.0162	***	(0.005)	0.0163	***	(0.005)	0.0181	***	(0.006)
$Boom_t \times \Delta NPL_{t-2}$	0.0126	***	(0.004)	0.0126	***	(0.004)	0.0187	***	(0.005)
$\triangle NPL_{t+1}$	0.0022		(0.001)	0.0024	*	(0.001)	-0.0017		(0.005)
$\triangle NPL_t$	0.0110	***	(0.002)	0.0111	***	(0.002)	0.0076		(0.006)
$\triangle NPL_{t-1}$	0.0208	***	(0.002)	0.0208	***	(0.002)	0.0186	***	(0.005)
$\triangle NPL_{t-2}$	0.0162	***	(0.001)	0.0162	***	(0.001)	0.0098	**	(0.004)
$Size_{t-1}$	0.0003	***	(0.000)	0.0003	***	(0.000)	0.0001		(0.000)
$Ebllp_t$	0.0578	***	(0.006)	0.0578	***	(0.006)	0.0769	***	(0.012)
$\Delta Loans_t$	-0.0006	***	(0.000)	-0.0006	***	(0.000)	-0.0007		(0.000)
$Tier1_{t-1}$	-0.0004		(0.000)	-0.0004		(0.000)	-0.0014	*	(0.001)
$ALLL_{t-1}$	0.0150	***	(0.003)	0.0150	***	(0.003)	0.0167	**	(0.007)
$shrRE_{t-1}$	-0.0012	**	(0.001)	-0.0012	**	(0.001)	0.0008		(0.001)
$shrCI_{t-1}$	0.0002		(0.001)	0.0002		(0.001)	0.0020	*	(0.001)
$shrCONS_{t-1}$	0.0014	**	(0.001)	0.0014	**	(0.001)	0.0029	**	(0.001)
$shrAGRI_{t-1}$	-0.0012	**	(0.001)	-0.0012	**	(0.001)	0.0007		(0.001)
$Treatbank \times \Delta NPL_t$				-0.0028		(0.006)			
$Treatbank \times \Delta NPL_{t+1}$				-0.0037		(0.005)			
Bank fixed effects	Yes			Yes			Yes		
Time fixed effects	Yes			Yes			Yes		
Observations	96,103			96,103			16,952		
Adj. R-squared	0.227			0.227			0.253		

Table 4: Falsification Tests

This table reports bank-quarter regressions of falsification tests. The dependent variable is current loan loss provisions. Panel A shows results of estimating model (4) and includes a placebo event indicator variable $Boom_{t-1}$ that equals one for the year prior to a boom year, and zero otherwise. Panel B shows estimates of loan loss provision timeliness between treatment and control banks for the period of 1999-2002. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A. Placebo Test			
	Dep Var = LLP_t		
VARIABLES	Coeff		SE
$Boom_t$	-0.0001	**	(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0094	**	(0.005)
$Boom_t \times \Delta NPL_t$	0.0180	***	(0.005)
$Boom_t \times \Delta NPL_{t-1}$	0.0161	***	(0.005)
$Boom_t \times \Delta NPL_{t-2}$	0.0126	***	(0.004)
$Boom_{t-1}$	0.0000		(0.000)
$Boom_{t-1} \times \Delta NPL_{t+1}$	0.0140		(0.010)
$Boom_{t-1} \times \Delta NPL_t$	0.0152		(0.012)
$Boom_{t-1} \times \Delta NPL_{t-1}$	-0.0067		(0.007)
$Boom_{t-1} \times \Delta NPL_{t-2}$	0.0002		(0.007)
$\triangle NPL_{t+1}$	0.0020		(0.001)
$\triangle NPL_t$	0.0108	***	(0.002)
$\triangle NPL_{t-1}$	0.0209	***	(0.002)
$\triangle NPL_{t-2}$	0.0162	***	(0.001)
$Size_{t-1}$	0.0003	***	(0.000)
$Ebllp_t$	0.0578	***	(0.006)
$\Delta Loans_t$	-0.0006	***	(0.000)
$Tier1_{t-1}$	-0.0004		(0.000)
$ALLL_{t-1}$	0.0150	***	(0.003)
$shrRE_{t-1}$	-0.0012	**	(0.001)
$shrCI_{t-1}$	0.0002		(0.001)
$shrCONS_{t-1}$	0.0014	**	(0.001)
$shrAGRI_{t-1}$	-0.0012	**	(0.001)
Bank fixed effects		Yes	
Time fixed effects		Yes	
Observations		96,103	
Adj. R-squared		0.227	

Panel B. Loan Loss Provision Timeliness before the Shale Booms			
	Dep Var = LLP_t		
VARIABLES	Coeff		SE
$\triangle NPL_{t+1}$	-0.0011		(0.002)
$\triangle NPL_t$	0.0034		(0.003)
$\triangle NPL_{t-1}$	0.0187	***	(0.002)
$\triangle NPL_{t-2}$	0.0159	***	(0.002)
$Size_{t-1}$	-0.0001		(0.000)
$Ebllp_t$	0.0926	***	(0.010)
$\Delta Loans_t$	0.0002		(0.000)
$Tier1_{t-1}$	0.0015	*	(0.001)
$ALLL_{t-1}$	-0.0506	***	(0.008)
$shrRE_{t-1}$	-0.0011		(0.001)
$shrCI_{t-1}$	0.0014		(0.001)
$shrCONS_{t-1}$	0.0022	**	(0.001)
$shrAGRI_{t-1}$	0.0001		(0.001)
$Treatbank \times \Delta NPL_t$	0.0062		(0.006)
$Treatbank \times \Delta NPL_{t+1}$	-0.0062		(0.005)
$Treatbank \times \Delta NPL_{t-1}$	0.0102		(0.007)
$Treatbank \times \Delta NPL_{t-2}$	-0.0020		(0.006)
Bank fixed effects	Yes		
Time fixed effects	Yes		
Observations	34,481		
Adj. R-squared	0.292		

Table 5: Uninsured Deposits and Difference in Loan Loss Provision Timeliness

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness for subsamples based on the median of uninsured deposits. The dependent variable is current loan loss provisions. All tests include bank and time fixed effects. Loan portfolio controls are included but are suppressed for brevity. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t					
	(1)	(2)	(3)	(4)	(5)	(6)
	Whole Sample		2001-2006Q1		2006Q2-2012	
	>median	<median	>median	<median	>median	<median
$Boom_t$	-0.0001	-0.0002*	-0.0002*	-0.0001	-0.0001	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Boom_t \times \Delta NPL_{t+1}$	-0.0012	0.0213***	-0.0070	0.0518*	-0.0029	0.0143**
	(0.006)	(0.007)	(0.009)	(0.028)	(0.006)	(0.007)
$Boom_t \times \Delta NPL_t$	0.0129*	0.0213***	-0.0040	0.0355**	0.0105	0.0131
	(0.007)	(0.008)	(0.015)	(0.016)	(0.007)	(0.008)
$Boom_t \times \Delta NPL_{t-1}$	0.0101*	0.0218***	-0.0007	0.0117	0.0085	0.0197***
	(0.006)	(0.007)	(0.011)	(0.015)	(0.006)	(0.007)
$Boom_t \times \Delta NPL_{t-2}$	0.0094*	0.0140**	0.0053	0.0144	0.0068	0.0122*
	(0.006)	(0.006)	(0.007)	(0.017)	(0.006)	(0.007)
$\triangle NPL_{t+1}$	0.0053***	-0.0016	-0.0001	-0.0031	0.0068**	-0.0029
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$\triangle NPL_t$	0.0154***	0.0062***	0.0059*	-0.0020	0.0184***	0.0097***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\triangle NPL_{t-1}$	0.0239***	0.0177***	0.0202***	0.0149***	0.0248***	0.0195***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
$\triangle NPL_{t-2}$	0.0179***	0.0136***	0.0135***	0.0109***	0.0198***	0.0144***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
$Size_{t-1}$	0.0001	0.0005***	0.0002	0.0003*	-0.0002	0.0004**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ebllp_t$	0.0738***	0.0542***	0.0779***	0.0715***	0.0910***	0.0540***
	(0.007)	(0.008)	(0.010)	(0.012)	(0.010)	(0.010)
$\Delta Loans_t$	-0.0004	-0.0007**	-0.0000	0.0002	-0.0006*	-0.0009**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Tier1_{t-1}$	-0.0003	0.0002	-0.0011	0.0013	0.0015*	0.0028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$ALLL_{t-1}$	0.0155***	0.0001	-0.0273***	-0.0583***	0.0147**	-0.0081
	(0.005)	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47,945	47,961	22,199	22,219	25,596	25,617
Adj. R-squared	0.241	0.248	0.262	0.292	0.299	0.290

Table 6: Large Time Deposits and Difference in Loan Loss Provision Timeliness

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness for subsamples based on the median of Large time deposits. The dependent variable is current loan loss provisions. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t					
	(1)			(2)		
	Above median			Below median		
VARIABLES	Coeff		SE	Coeff		SE
$Boom_t$	-0.0002	**	(0.000)	-0.0000		(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0046		(0.007)	0.0159	***	(0.006)
$Boom_t \times \Delta NPL_t$	0.0113		(0.007)	0.0271	***	(0.008)
$Boom_t \times \Delta NPL_{t-1}$	0.0144	**	(0.007)	0.0189	***	(0.007)
$Boom_t \times \Delta NPL_{t-2}$	0.0108		(0.007)	0.0156	***	(0.006)
$\triangle NPL_{t+1}$	0.0045	**	(0.002)	-0.0010		(0.002)
$\triangle NPL_t$	0.0135	***	(0.002)	0.0065	***	(0.003)
$\triangle NPL_{t-1}$	0.0219	***	(0.002)	0.0183	***	(0.002)
$\triangle NPL_{t-2}$	0.0174	***	(0.002)	0.0131	***	(0.002)
$Size_{t-1}$	0.0003	***	(0.000)	0.0002	***	(0.000)
$Ebllp_t$	0.0608	***	(0.008)	0.0636	***	(0.007)
$\Delta Loans_t$	-0.0009	***	(0.000)	-0.0004		(0.000)
$Tier1_{t-1}$	-0.0010	*	(0.001)	0.0007		(0.001)
$ALLL_{t-1}$	0.0130	***	(0.005)	0.0050		(0.004)
$shrRE_{t-1}$	-0.0015		(0.001)	-0.0007		(0.001)
$shrCI_{t-1}$	-0.0006		(0.001)	0.0012		(0.001)
$shrCONS_{t-1}$	0.0021	*	(0.001)	0.0009		(0.001)
$shrAGRI_{t-1}$	-0.0008		(0.001)	-0.0012		(0.001)
Bank fixed effects	Yes			Yes		
Time fixed effects	Yes			Yes		
Observations	47,975			47,974		
Adj. R-squared	0.227			0.264		

Table 7: Bank Size and Difference in Loan Loss Provision Timeliness

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness for subsamples based on the median of bank size. The dependent variable is current loan loss provisions. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t					
	(1)			(2)		
	Above median			Below median		
VARIABLES	Coeff		SE	Coeff		SE
$Boom_t$	-0.0002	**	(0.000)	-0.0003	***	(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0029		(0.007)	0.0122	**	(0.006)
$Boom_t \times \Delta NPL_t$	0.0084		(0.008)	0.0152	**	(0.007)
$Boom_t \times \Delta NPL_{t-1}$	0.0180	**	(0.007)	0.0039		(0.005)
$Boom_t \times \Delta NPL_{t-2}$	0.0187	***	(0.006)	-0.0019		(0.005)
$\triangle NPL_{t+1}$	0.0066	***	(0.002)	-0.0025		(0.002)
$\triangle NPL_t$	0.0255	***	(0.003)	0.0006		(0.002)
$\triangle NPL_{t-1}$	0.0287	***	(0.003)	0.0138	***	(0.002)
$\triangle NPL_{t-2}$	0.0217	***	(0.002)	0.0112	***	(0.002)
$Size_{t-1}$	0.0000		(0.000)	0.0006	***	(0.000)
$Ebllp_t$	0.1167	***	(0.011)	0.0274	***	(0.006)
$\Delta Loans_t$	-0.0017	***	(0.000)	-0.0001		(0.000)
$Tier1_{t-1}$	-0.0024	***	(0.001)	0.0002		(0.001)
$ALLL_{t-1}$	0.0410	***	(0.006)	-0.0103	***	(0.004)
$shrRE_{t-1}$	-0.0008		(0.001)	-0.0018	**	(0.001)
$shrCI_{t-1}$	0.0008		(0.001)	-0.0004		(0.001)
$shrCONS_{t-1}$	0.0017	**	(0.001)	0.0011		(0.001)
$shrAGRI_{t-1}$	-0.0006		(0.001)	-0.0019	**	(0.001)
Bank fixed effects	Yes			Yes		
Time fixed effects	Yes			Yes		
Observations	48,023			48,030		
Adj. R-squared	0.320			0.173		

Table 8: Loan Loss Provision Timeliness and Access to Deposits

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness for treatment banks based on their deposit growth over the year following a shale boom. A bank has an increase in deposit level if its overall deposits increase over the year following a shale boom. The dependent variable is current loan loss provisions. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t					
	(1)			(2)		
	Deposit increase			No deposit increase		
VARIABLES	Coeff		SE	Coeff		SE
$Boom_t$	-0.0002	*	(0.000)	0.0004		(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0155	**	(0.007)	0.0006		(0.012)
$Boom_t \times \Delta NPL_t$	0.0206	**	(0.008)	0.0199		(0.017)
$Boom_t \times \Delta NPL_{t-1}$	0.0164	**	(0.007)	0.0136		(0.010)
$Boom_t \times \Delta NPL_{t-2}$	0.0145	**	(0.006)	0.0307	***	(0.011)
$\triangle NPL_{t+1}$	-0.0046		(0.005)	0.0094		(0.010)
$\triangle NPL_t$	0.0071		(0.006)	0.0066		(0.014)
$\triangle NPL_{t-1}$	0.0218	***	(0.005)	0.0150	*	(0.009)
$\triangle NPL_{t-2}$	0.0153	***	(0.004)	-0.0083		(0.010)
$Size_{t-1}$	0.0001		(0.000)	0.0006	**	(0.000)
$Ebllp_t$	0.0789	***	(0.014)	0.0745	***	(0.022)
$\Delta Loans_t$	-0.0005		(0.000)	-0.0010		(0.001)
$Tier1_{t-1}$	-0.0015	*	(0.001)	-0.0005		(0.002)
$ALLL_{t-1}$	0.0157	**	(0.008)	0.0135		(0.018)
$shrRE_{t-1}$	0.0004		(0.001)	0.0026		(0.002)
$shrCI_{t-1}$	0.0017		(0.001)	0.0028		(0.003)
$shrCONS_{t-1}$	0.0021	*	(0.001)	0.0059	**	(0.002)
$shrAGRI_{t-1}$	0.0004		(0.001)	0.0015		(0.004)
Bank fixed effects	Yes			Yes		
Time fixed effects	Yes			Yes		
Observations	14,523			2,092		
Adj. R-squared	0.262			0.205		

Table 9: Legal Ownership and Difference in Loan Loss Provision Timeliness

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness for subsamples based on legal ownership. The dependent variable is current loan loss provisions. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t					
	(1)			(2)		
	Public banks			Private banks		
VARIABLES	Coeff		SE	Coeff		SE
$Boom_t$	-0.0003	**	(0.000)	-0.0002	***	(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0161		(0.014)	0.0066		(0.005)
$Boom_t \times \Delta NPL_t$	0.0329		(0.021)	0.0115	**	(0.005)
$Boom_t \times \Delta NPL_{t-1}$	0.0393	**	(0.016)	0.0100	**	(0.005)
$Boom_t \times \Delta NPL_{t-2}$	0.0229		(0.014)	0.0076		(0.005)
$\triangle NPL_{t+1}$	-0.0017		(0.007)	0.0017		(0.001)
$\triangle NPL_t$	0.0364	***	(0.009)	0.0090	***	(0.002)
$\triangle NPL_{t-1}$	0.0323	***	(0.007)	0.0196	***	(0.002)
$\triangle NPL_{t-2}$	0.0297	***	(0.007)	0.0151	***	(0.001)
$Size_{t-1}$	0.0001		(0.000)	0.0003	***	(0.000)
$Ebllp_t$	0.1286	***	(0.027)	0.0514	***	(0.006)
$\Delta Loans_t$	-0.0015	**	(0.001)	-0.0006	***	(0.000)
$Tier1_{t-1}$	-0.0008		(0.002)	-0.0004		(0.000)
$ALLL_{t-1}$	0.0602	***	(0.011)	0.0076	**	(0.004)
$shrRE_{t-1}$	-0.0022		(0.001)	-0.0011	*	(0.001)
$shrCI_{t-1}$	-0.0000		(0.001)	0.0001		(0.001)
$shrCONS_{t-1}$	-0.0001		(0.001)	0.0016	**	(0.001)
$shrAGRI_{t-1}$	-0.0017		(0.003)	-0.0013	**	(0.001)
Bank fixed effects		Yes			Yes	
Time fixed effects		Yes			Yes	
Observations		9,731			86,360	
Adj. R-squared		0.442			0.207	

Table 10: Short-term Liability and Difference in Loan Loss Provision Timeliness

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness for subsamples based on the median of short-term liability. Columns (1) and (2) show the results using "other borrowed money". Columns (3) and (4) present the results using "subordinated notes and debentures". The dependent variable is current loan loss provisions. All tests include bank and time fixed effects. Loan portfolio controls are included but are suppressed for brevity. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t											
	(1)			(2)			(3)			(4)		
	Other borrowed money						Subordinated notes and debentures					
	Above median			Below median			Above median			Below median		
VARIABLES	Coeff		SE	Coeff		SE	Coeff		SE	Coeff		SE
$Boom_t$	-0.0002	**	(0.000)	-0.0002	**	(0.000)	-0.0002		(0.000)	-0.0002	***	(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0124	*	(0.007)	0.0066		(0.006)	0.0245		(0.022)	0.0067		(0.005)
$Boom_t \times \Delta NPL_t$	0.0157	*	(0.009)	0.0174	***	(0.006)	0.0181		(0.030)	0.0131	***	(0.005)
$Boom_t \times \Delta NPL_{t-1}$	0.0266	***	(0.008)	0.0089	*	(0.005)	0.0432	*	(0.025)	0.0103	**	(0.005)
$Boom_t \times \Delta NPL_{t-2}$	0.0280	***	(0.007)	0.0020		(0.005)	0.0487	**	(0.021)	0.0066		(0.004)
$\triangle NPL_{t+1}$	0.0026		(0.002)	-0.0003		(0.002)	-0.0132		(0.013)	0.0018		(0.001)
$\triangle NPL_t$	0.0182	***	(0.003)	0.0027		(0.002)	0.0414	***	(0.013)	0.0097	***	(0.002)
$\triangle NPL_{t-1}$	0.0244	***	(0.002)	0.0149	***	(0.002)	0.0343	**	(0.015)	0.0200	***	(0.002)
$\triangle NPL_{t-2}$	0.0156	***	(0.002)	0.0139	***	(0.002)	0.0255	*	(0.015)	0.0157	***	(0.001)
$Size_{t-1}$	0.0002	**	(0.000)	0.0004	***	(0.000)	-0.0006	**	(0.000)	0.0003	***	(0.000)
$Ebllp_t$	0.0937	***	(0.010)	0.0395	***	(0.006)	0.1746	***	(0.035)	0.0528	***	(0.006)
$\Delta Loans_t$	-0.0017	***	(0.000)	0.0002		(0.000)	-0.0026	**	(0.001)	-0.0005	***	(0.000)
$Tier1_{t-1}$	-0.0022	***	(0.001)	0.0002		(0.001)	0.0035		(0.004)	-0.0005		(0.000)
$ALLL_{t-1}$	0.0391	***	(0.005)	-0.0150	***	(0.004)	0.0420	**	(0.016)	0.0098	***	(0.004)
Bank fixed effects	Yes			Yes			Yes			Yes		
Time fixed effects	Yes			Yes			Yes			Yes		
Observations	47,732			48,205			3,497			92,599		
Adj. R-squared	0.271			0.217			0.495			0.211		

Table 11: Profitability and Difference in Loan Loss Provision Timeliness

This table reports bank-quarter regressions estimating the effect of shale boom exposure on loan loss provision timeliness for subsamples based on the median of profitability. The dependent variable is current loan loss provisions. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = LLP_t					
	(1)			(2)		
	Above median			Below median		
VARIABLES	Coeff		SE	Coeff		SE
$Boom_t$	-0.0000		(0.000)	-0.0003	***	(0.000)
$Boom_t \times \Delta NPL_{t+1}$	0.0085		(0.006)	0.0085		(0.007)
$Boom_t \times \Delta NPL_t$	0.0193	***	(0.007)	0.0173	**	(0.007)
$Boom_t \times \Delta NPL_{t-1}$	0.0157	***	(0.006)	0.0177	***	(0.007)
$Boom_t \times \Delta NPL_{t-2}$	0.0136	**	(0.006)	0.0121	*	(0.007)
$\triangle NPL_{t+1}$	0.0015		(0.002)	0.0021		(0.002)
$\triangle NPL_t$	0.0097	***	(0.002)	0.0111	***	(0.002)
$\triangle NPL_{t-1}$	0.0207	***	(0.002)	0.0207	***	(0.002)
$\triangle NPL_{t-2}$	0.0149	***	(0.002)	0.0170	***	(0.002)
$Size_{t-1}$	0.0004	***	(0.000)	0.0002	***	(0.000)
$Ebllp_t$	0.0638	***	(0.007)	0.0652	***	(0.008)
$\Delta Loans_t$	-0.0008	***	(0.000)	-0.0006	**	(0.000)
$Tier1_{t-1}$	-0.0019	***	(0.001)	0.0018	***	(0.001)
$ALLL_{t-1}$	0.0084	*	(0.005)	0.0134	***	(0.004)
$shrRE_{t-1}$	-0.0013	*	(0.001)	-0.0005		(0.001)
$shrCI_{t-1}$	0.0001		(0.001)	0.0010		(0.001)
$shrCONS_{t-1}$	0.0023	**	(0.001)	0.0010		(0.001)
$shrAGRI_{t-1}$	-0.0016	*	(0.001)	-0.0002		(0.001)
Bank fixed effects	Yes			Yes		
Time fixed effects	Yes			Yes		
Observations	47,880			47,953		
Adj. R-squared	0.293			0.203		

Table 12: Alternative Measure

This table reports bank-quarter regressions estimating the effect of shale boom exposure on discretionary loan loss provisions ($DisLLP$). $DisLLP$ is the measure of the discretionary component of loan loss provisions and is the absolute value of the residues from estimating modified Model (3). The dependent variable is $DisLLP$ multiplied by 100. Different columns use different specifications of the boom exposure measure. Column (1) uses the $Boom$ indicator. Column (2) uses the share of branches located in boom counties, and column (3) uses the share of deposits in boom counties. All tests include bank and time fixed effects. Variable definitions are in Appendix A and all continuous variables are winsorized at the 1st and 99th percentiles. Robust standard errors reported in parentheses are clustered by bank. ***, **, * indicate statistical significance at 1%, 5%, and 10%, respectively.

	Dep Var = $DisLLP$		
	(1)	(2)	(3)
Measure of Boom	Boom	Boomsharebr	Boomsharedep
$Boom_t$	-0.00259***	-0.0129***	-0.0135***
	(-4.788)	(-15.55)	(-17.48)
$Size_t$	0.0208***	0.0207***	0.0207***
	(29.57)	(29.51)	(29.50)
$Ebllp_t$	3.625***	3.702***	3.707***
	(40.82)	(41.61)	(41.67)
$Tier1_t$	-0.131***	-0.132***	-0.132***
	(-30.63)	(-30.61)	(-30.62)
LLP_{t-1}	0.739***	0.737***	0.737***
	(9.155)	(9.125)	(9.116)
$Loss_t$	0.00360***	0.00359***	0.00359***
	(7.307)	(7.278)	(7.273)
Bank fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	96,103	96,103	96,103
Adj. R-squared	0.6853	0.6866	0.6869

Appendix A. Variable Definitions

Variable	Description
Boom	An indicator variable that equals one for banks with branches in boom counties after the onset of the boom, and 0 otherwise
Treatbank	An indicator variable that equals one for banks that eventually experiences a shale boom, and 0 otherwise
Size	Natural logarithm of total assets (RCFD2170)
Loans	Total loans (RCFD2122) divided by total assets (RCFD2170)
ΔLoans	Change in total loans over the quarter, divided by total loans at the beginning of the quarter
LLP	loan loss provision divided by lagged total loans
ΔNPL	Change in non-performing loans over the quarter **(**RCFD1403 + RCFD1407**)**, divided by lagged total loans
NCO	Net charge off (RIAD4635-RIAD4605) divided by lagged total loans
Ebllp	The sum of income before extraordinary items and other adjustments (RIAD4300) and provision for loan and lease losses (RIAD4230) divided by lagged total loans
Tier1	Tier1 risk-based capital ratio, defined as the ratio of Tier 1 capital (RCFD8274t - RCFDC228t) to risk-weighted total assets (RCFDA223t - RCFDB504t)
Alll	allowance for loan and lease losses (RCFD3123) divided by lagged total loans
Deposit	Total deposits (RCFD2200) divided by total assets (RCFD2170).
ΔDeposit	Change in deposit scaled by lagged deposit
Largetimedeposit	Total time deposits of $100,000 or more scaled by total assets (RCON2604)
Otherborrow	Other borrowed money: short-term uninsured funding (RCFD3190) scaled by total assets
Sub	Subordinated notes and debentures (RCFD3200) divided by total assets
Uninsured deposit	Total uninsured deposit divided by total assets. Uninsured deposits are accounts of $100,000 or more (include retirement accounts of $250,000 or more after 2006Q2). Uninsured deposits: RCON2710 (before 2006Q2); RCONF047 + RCONF051 (from 2006Q2)
COD	Cost of deposits, measured as the interest expenses on deposits (RIAD4170) divided by total deposits, multiplied by 100
Liquidasset	(Acharya and Mora 2015) Liquid assets are cash, federal funds sold and reverse repos, and securities. It is measured as (RCFD0010+[RCFD1350 (before 2002Q1) and RCONB987 + RCFDB989 (from 2002Q1)]+ RCFD1754+RCFD1773), divided by lagged total assets
Hete	The sum of commercial and industrial loans (RCFD1766) and commercial real estate loans (RCON1480) divided by total assets,
shrRE	Real estate loans (RCFD1410) scaled by total loans
shrCI	Commercial and industrial loans (RCFD1766) scaled by total loans

shrCONS	Consumer loans (RCFD1975) scaled by total loans
shrAGRI	Agriculture loans (RCFD1590) scaled by total loans
Public	Indicator variable equal to 1 if the bank is identified as a public bank, and 0 otherwise. Stand-alone public banks are identified using the link file provided by the Federal Reserve of New York at http://www.newyorkfed.org/research/banking_research/datasets.html. Subsidiaries of public holding companies are identified as BHCs that file with the SEC (RSSD9056 = 1, 3 or 4).
ΔGDP	Change in GDP over the quarter
CSRET	The return on the Case-Shiller Real Estate Index over the quarter
ΔUNEMP	Change in unemployment rates over the quarter
Loss	A dummy variable that equals one if net income (RIAD4300) is negative, and zero otherwise

Appendix B: Summary of Unconventional Energy Formations

States	Formation	Boom Year	Number of Counties
TX	Barnett Shale, Granite Wash	2003	19
TX	Haynesville Shale, Wolfberry Trend	2004	16
TX	Wolfcamp Shale	2005	4
TX	Eagle Ford Shale	2008	12
AR	Fayetteville Shale	2004	7
OK	Misener-Hunton Sandstone, Granite Wash	2004	6
OK	Woodford Shale	2005	7
OK	Cana Woodford Shale	2007	3
OK	Mississippi Lime	2008	6
WV	Marcellus Shale	2007	5
ND	Bakken Shale	2004	10
OH	Utica Shale	2009	8
LA	Haynesville Shale	2007	6
PA	Marcellus Shale	2007	11
KS	Mississippi Lime	2010	3