Liquidity Windfalls and Bank Reporting Quality: Evidence from Shale Booms

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Abstract

Do banks lower their reporting quality during good times? I find that banks exposed to plausibly exogenous liquidity windfalls provide higher reporting quality, measured as loan loss provision timeliness, compared to non-exposed banks. Improved loan provisioning timeliness is concentrated among banks with strong incentives to attract liquidity, suggesting that access to liquidity plays a key role in shaping banks' reporting. Moreover, improved timeliness positively relates to a subsequent increase in deposits. Contrary to the belief that banks lower their reporting standards during expansionary periods, evidence suggests that they improve their reporting quality during good times with deposit windfalls.

JEL-Classification: G10, G21,G28, M41

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

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1 Introduction

Following the Great Recession, both bank regulators and researchers blamed banks for triggering the global economic meltdown and for not providing sufficient information about the risky assets they held prior to the crisis.[1] For instance, Governor Sarah Bloom Raskin from the Federal Reserve argued that the reduced transparency of risk in banks' balance sheets before 2008 contributed to the financial crisis.[2] The underlying assumption is that banks did not have incentives to provide sufficient information or be transparent during expansionary periods. These claims are anecdotal, yet they raise an important question that rarely has been investigated: do banks lower their reporting quality during good times?

Banks' financial reporting plays an important role in liquidity provision, lending cyclicality, and the stability of the financial industry.[3] Current policy discussions are oriented toward more requirements on bank reporting.[4] This study examines whether and how banks change their financial reporting during good times, defined as "liquidity windfalls." Contrary to the assumption that banks tend to lower their reporting standards during boom periods, I find that banks improve their reporting quality, measured as loan loss provision timeliness, to attract more liquidity during good times with liquidity windfalls.

It is unclear how deposit windfalls could affect banks' financial reporting. On one hand, banks with greater access to liquidity may be less concerned about liquidity constraints and external financing. Therefore, these banks may have lower incentives to provide high-quality financial reporting. On the other hand, because of the information asymmetry between depositors and bank managers, banks may improve their reporting quality anticipating to attract more liquidity.

[1] An article discussing this issue can be found here.

[2] Full speech of Governor Sarah Bloom Raskin can be found here.

[3] See for example, Beatty and Liao (2011); Bushman and Williams (2012); Ryan (2012); Beatty and Liao (2014); Akins, Dou, and Ng (2017); Bhat, Ryan, and Vyas (2017).

[4] For example, SEC voted to collect public feedback on whether to update itsădisclosureărequirements for bank holding companies, see here. Also see here for articles on "SEC Opens Door to Overhaul of Bank Disclosure Rules".

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

An unexpected technological breakthrough made vast shale oil and natural gas resources economically profitable to develop. To develop and operate shale resources, oil and gas companies need to negotiate mineral royalty payments with landowners. Doing so causes a wealth shock resulting in massive liquidity windfalls for banks with branches in shale boom counties. Compared to unexposed banks, I find that exposed banks could have an annual increase in deposits of more than five percent, consistent with recent studies examining the wealth shock (Plosser (2014); Gilje (2017)).

Using shale booms as exogenous shocks, I examine whether banks change their financial reporting in response to local liquidity windfalls. In particular, 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 variations in financial reporting and time fixed effects to address country-wide changes that affect all banks. The variation both in the timing of shale booms and in their location reduces potential confounding effects that might arise from other changes in banks' reporting incentives.

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 the most important channel through which banks 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., Liu and Ryan (1995); Nichols, Wahlen, and Wieland (2009); Beatty and Liao (2014); Bushman and Williams (2015)). In the main tests, I find that banks improve their standards for recognizing expected loan losses after shale booms. Following liquidity windfalls, banks are more timely in recognizing loan losses. The results are robust to adding more controls and to using only banks with branches in boom counties. My tests include bank fixed effects and therefore estimate average within-bank changes in loan loss provision timeliness. Controlling for time fixed effects accounts for concomitant national trends. Additionally, using an alternative measure of reporting quality—the discretionary loan loss provision—leads to the same conclusions.

To explore the underlying mechanisms, I conduct several cross-sectional analyses. There are two main mechanisms through which liquidity shocks could potentially positively affect banks' financial reporting quality. The first mechanism relies on the role of bank accounting in reducing information asymmetry between depositors and banks, and therefore banks may choose to improve their reporting quality to attract deposits. I call this mechanism the "Access to Liquidity" channel. The second mechanism, which I call the "Shareholder Monitoring" channel, relies on managers' concerns about equity market reactions. My results are in line with the Access to Liquidity channel. In particular, improved loan loss provision timeliness is concentrated among banks with strong incentives to obtain deposits: smaller banks, banks with fewer uninsured deposits, and banks with fewer large time deposits. Further tests suggest that depositors value changes in banks' provisioning behavior: improvements in timeliness of loan loss recognition are accompanied by easier access to liquidity for exposed banks.

The results are unlikely to be driven by alternative mechanisms and are robust to different research design choices. First, the effects are similar for high and low profitability banks, suggesting 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, to address concerns about reverse causality and endogeneity, I use falsification tests and include a placebo indicator for the year prior to the boom year. I show that banks did not have preempted expectations of the booms and did not change their reporting quality before the boom. Furthermore, prior to the shale boom, banks that later experienced liquidity windfalls had similar loan loss provision timeliness relative to banks that did not.

This study makes three contributions to the literature. First, 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 does not have procyclical effects on bank lending over the past two business cycles. This paper documents that banks provide timelier loan loss provisions during good times, in particular, those with deposit windfalls. The positive relation between reporting quality and liquidity windfalls appears to be driven by banks' incentives to attract liquidity.

Second, applying a unique approach, this study adds to the literature of microbanking and bank accounting. 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 information asymmetry between depositors and banks affects banks' reporting quality following liquidity windfalls. Furthermore, this paper complements the literature that studies the role of accounting information in firms' access to financing. Most of the literature looks at the role of the accounting information of non-financial firms in their access to debt (e.g., Bharath, Sunder, and Sunder (2008); Gormley, Kim, and Martin (2012)), but 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.

Third, this paper adds to the research on the interaction between financial integration of U.S. markets 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, Levine, and Lin (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, Ryan, and Zou (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 compete for deposits.

The rest of the paper proceeds as follow. Section 2 provides a 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. With an important development in technology that combines horizontal drilling with hydraulic fracturing (informally referred to "fracking") in the shale industry in 2003, several states began to experience more efficient production in natural gas shale, both quantitatively and economically (Yergin (2011)). According to the Energy Information Administration (EIA), the United States would transition from being a modest net importer of natural gas to a net exporter by 2017 (EIA (2015)).

Shale gas and oil refer to fossil fuels trapped in shale formations. The natural gas shale is highly nonporous that causes the gas to be trapped in the rock and thus difficult to extract. 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)).

A new technique developed by oil operators in Texas in 2003 combined horizontal drilling with hydraulic fracturing, together with the high natural gas prices, 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.[5] The technology was first applied to natural gas and then was adapted for oil. After the continued development of the technology, shale wells have little risk of being unproductive today. Shale development has resulted in rapid increases in both natural gas and oil production. According to EIA, Shale gas now represents approximately one-third of the United States' recoverable natural gas reservoirs. EIA estimates that the United States has 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)).

To exploit the shale oil and gas, firms must sign contracts with local landowners to lease mineral rights to drill on a parcel of land.[6] These landowners receive large upfront signing

[5]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 culminating events that lead to the shale revolution starting in the mid-2000s.

[6]Land rights 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.

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%.[7] For example, an individual with 100 acres of land who leases out his 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 resource 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 a year. Feyrer, Mansur, and Sacerdote (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, Shields, Ladlee, and Ward (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 liquidity 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, Loutskina, and Strahan (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 telling anecdotal stories of landowners walking

[7] 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.

into branches with checks for several hundred thousand dollars."[8]

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, Martin, Ramsey, and Titman (2013)). Fedaseyeu, Gilje, and Strahan (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 the shale areas than in non-shale areas. Thakor (2016) illustrates the exogeneity of the shale boom through 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 windfalls (Gilje, Loutskina, and Strahan (2016)). The exogeneity of the shale boom and its effect on local deposit supply allow me to examine banks' reporting changes in response to the liquidity inflows.

2.2 Related Literature and Hypothesis Development

The quality of banks' accounting system is important to both investors and regulators. The 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. Beatty and Liao (2014) and Acharya and Ryan (2016) provide

[8]The quote is from here.

thorough reviews of the existing studies regarding the role of bank accounting in addressing frictions in the financial markets.

The liquidity shock may positively affect banks' information quality through two potential mechanisms. The first mechanism relies on the role of bank accounting in reducing information asymmetry between depositors and banks. Because the incentives of bank managers and depositors may not be aligned, banks may engage in suboptimal risk taking behavior from depositors' perspectives. Bank accounting can potentially address the information asymmetry problem between banks and depositors by informing depositors about bank fundamental and performance. When banks are exposed to liquidity windfalls, they may improve their accounting quality to attract the liquidity. Holod and Peek (2007)show that the degree of information asymmetry between a bank and a potential depositor determines the extent of bank access to deposits during periods of monetary policy tightening. A similar phenomenon is also documented in studies examining nonfinancial firms. In particular, Gormley, Kim, and Martin (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 Liquidity channel.

The second mechanism, which I call the Shareholder Monitoring channel, relies on bank managers' concern over market reactions. Bliss and Flannery (2002) argue that effective market monitoring occurs when investors can accurately assess changes in a firm's condition, and promptly impound those changes into the firm's stock and bond prices. The relative large literature indicates that bank investors can identify risky banks and penalize them by increasing their cost of capital (e.g., Maechler and McDill (2006); Bouther and Francis (2017)). Since the stock market is more information sensitive than the bond market, in this paper, I focus primarily on shareholders monitoring. The effectiveness of shareholder monitoring depends on the extent to which the bank is financed by uninsured liabilities and the transparency of banks' risk taking. Flannery and Nikolova (2004) find that banks uninsured subordinated notes and debentures, uninsured CDs, and federal funds reflect differences in credit risk across borrowers. They conclude that banks with more uninsured deposits have more exposure to market monitoring. Following the shale boom, market and investors may be concerned about agency issues (e.g., overinvestment) induced by the unexpected cash inflows. Banks may signal with timelier accounting information to mitigate the increased shareholder concern.

Alternatively, the liquidity shock may negatively affect banks' information quality. On one hand, banks with more liquidity may become less concerned about capital constraint, thus exert less effort in monitoring their loan performance, leading to a delay in recognizing loan loss provision. On the other hand, although information asymmetry between bank managers and depositors is typically assumed undesirable, some theories argue that opacity is desirable. For example, Dang, Gorton, Holmström, and Ordonez (2017) argue that banks are optimally opaque to minimize information leakage because both investors and banks desire information insensitivity in debt. 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". Holmstrom (2009) argues that transparency may not lead to more market liquidity, and therefore depositors or creditors may not demand more or timelier information from banks. Overall, whether and how the liquidity windfalls would affect banks' accounting or provision quality remain to be examined.

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 the identification with drilling productivity report 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 different start years of shale booms because of different timing of energy development. Figure 1 shows that each of the nine states contains multiple boom counties as well as many nonboom counties.[9] Boom counties could have already specialized in natural resource production at the start of the boom period. Therefore, I choose the neighboring nonboom counties 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 is built at the bank-quarter level and includes all banks with branches operating in any of these nine states. After requiring available data for the banks and keeping a balanced sample period, the sample begins in 2001 and ends in 2012.[10]

[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 a dummy 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 to zero for all bank-quarters prior to 2003, the first year of the shale booms. Because shale booms happened at different times during different boom years and

[9]Some of those nonboom counties may also have drilling activities, but they are treated as nonboom because the estimated impact of shale boom on deposits was very little relative to that of the county. Plosser (2014) uses drilling and production data from various state agencies to identify major shale oil or 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 $30m) 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 $70m a year or 39% of the local deposit base.

[10]My findings are also robust to restricting or extending the sample to different sample periods.

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 different 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 may be long (from the first year of boom exposure to the end of the sample period), the average increase in deposits is persistent and not subject to reversals for treatment banks Plosser (2014) and banks may be exposed to multiple booms at different times, mitigating the concern.[11] In the robustness tests, I set the treatment period to be four or five years and the results are qualitatively similar. Another concern is that banks may strategically open branches in boom counties. To alleviate this concern, I require bank branches to exist in boom counties before booms.[12]

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 bank financial measures used in the empirical models.[13] 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 2001-2012. The sample may be different in some tests due to sample construction and 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

[11] Based on Plosser (2014) and Gilje (2017), the average cumulative impact of shale discoveries results in 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.

[12] Other studies also show evidence that banks do not strategically open branches in boom counties (Gilje, Loutskina, and Strahan (2016); Plosser (2014)).

[13] The use of annual values does not affect my inferences.

establish that the liquidity 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 that document the impact of shale booms on liquidity inflows (Plosser (2014); Gilje, Loutskina, and Strahan (2016); Gilje (2017)).

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 across the nine states every quarter. The measure ranges from zero (for banks with 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 regressions for deposit growth at both the county and bank level:

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

and

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

where Boomcounty (Boombank) 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 $\triangle DepositCounty$ and $\triangle DepositBank$ 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 (2), the controls include $Size$, $Deposit$, $Liquidasset$ and $Hete$, which 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 and 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 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 measures 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, my estimates are likely biased downward.

To further establish the liquidity-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 Boombank, 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 4 percentage points faster annually in treatment counties after the shale boom 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 liquidity 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. It determines 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. The timeliness in loan loss provisioning is considered to capture the quality of the accounting system. Prior studies consider provisions as more timely if they are recorded concurrently with or in advance of loans becoming non-performing (e.g., Nichols, Wahlen, and Wieland (2009); Beatty and Liao (2011); Bushman and Williams (2012, 2015)). 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 the current accounting profitability of the banks at the expense of 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 earning restatements and SEC comment letters. I use their proposed residual model to build my base model and confirm that the 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. Collins, Shackelford, and Wahlen (1995); Beatty, Chamberlain, and Magliolo (1995)); $ALLL$ is the allowance for loan losses at the beginning of the quarter. I control for past allowance because high provisions recognized in the past may be correlated with 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 liquidity 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 liquidity windfalls on provision timeliness, I examine differences in β_1 and β_2 across exposed and non-exposed banks.[14] Specifically, I expand Model (1) by

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

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 boom. The full model is specified as follows:

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

I include time fixed effects to control for times-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 banks that eventually experience a shale boom 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 nearby unexposed banks. Positive α_2 and α_3 indicate that loan loss provisions are timelier for exposed banks relative to other unexposed banks.

To estimate the effect of the liquidity 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 boom. The shale boom may trigger or be associated with other changes in the boom area 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 neighboring counties that are not exposed to the shale boom 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 the boom, thus the treatment banks are in either treatment or control group depending on the timing of the 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.

The intuition of this approach is analogous to a difference-in-difference estimation, which relies on two identification assumptions. Firstly, it implicitly assumes that the effect of the localized wealth shock on bank reporting is realized at the bank level, rather than limiting to the branch level. I would obtain more precise estimation using branch level bank reporting, but the accounting information is not available at the branch level. This restriction likely biases my results against finding any effect, suggesting that the point estimates are the lower-bound of the real effect. In robustness tests, I restrict the sample to single county banks and include county fixed effects to control for the average change in an area and reach similar conclusions. The second identification assumption is that shale booms did not select into 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 differences in loan loss provision timeliness prior to the shale boom. I discuss more on this issue 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 the 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. The 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 take the logarithm of total assets to measure bank size. The table shows that treatment banks are slightly larger than control banks, which may be a potential concern because large banks differ in many ways from smaller ones. In robustness tests, I filter out larger banks and also estimate the model using only treatment banks.

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

My main test examines the effect of liquidity 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 take forward-looking information of future non-performing loans into account in estimating loan loss provisions. The interactive terms, $Boom_t \times \triangle NPL_t$ and $Boom_t \times \triangle NPL_{t+1}$, are the main variables of interest and test whether the liquidity windfalls affect banks' timeliness in loan loss provisioning. Specifically, the coefficients on $Boom_t \times \triangle NPL_t$ and $Boom_t \times \triangle NPL_{t+1}$ are both positive and statistically significant, indicating that compared to unexposed banks, exposed banks are timelier in recording loan loss provisions. 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 $size$, Tier 1 capital ratio, earnings before provisions, loan growth, allowance for loan losses, and different loan types.

Consistent with prior research,[15] I find the coefficient on $Ebllp$ positive and significant, 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, 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 Tier 1 capital management appears to have 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 change 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

[15] e.g., Collins, Shackelford, and Wahlen (1995); Laeven and Majnoni (2003); Bushman and Williams (2012).

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 Column (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 - banks that eventually experience a shale boom. In this specification, treatment banks are compared to themselves. 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 liquidity windfalls on loan loss provision timeliness is not driven by control banks.

Overall, the results suggest a positive effect of the liquidity 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, one may concern that banks may have pre-empted expectations of the boom and change their reporting even before the boom. Another concern is that a third variable during the sample period differentially affects the treatment and control banks. In such case, changes in loan loss provision timeliness may not be driven by the effect of liquidity windfalls. To draw valid inferences from the main tests, I 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. Because of the staggered nature of shale booms, the pre-boom indicator $Boom_{t-1}$

is set corresponding to the timing of the shale discoveries. 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.

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 was no pre-existing, differential trend 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. Collectively, the change in provision quality is unlikely to be caused by any omitted firm characteristics. In order for a third missing factor 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 different boom years between 2003 and 2010. Such third 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 liquidity windfalls improve their provision quality after the onset of the boom. 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 liquidity shock 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 recognitions of loan loss provisions can improve bank transparency and therefore exposed banks may improve their provision quality expecting to attract more liquidity. If this is the primary mechanism, then improved loan loss provision timeliness after shale boom would be concentrated among banks with strong incentives to obtain liquidity. I call this the Access to Liquidity channel.

The second mechanism, which I call Shareholder Monitoring channel, relies on shareholder monitoring and bank managers' concern over market reactions. Following the shale boom, market and 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 market concern. If this is the mechanism, then I expect to see more pronounced positive effects of the shale boom on provision quality among banks subject to more shareholder monitoring.

4.3.1 Loan Loss Provision Timeliness and Access to Liquidity

I first investigate the Access to Liquidity channel by examining whether loan loss provision timeliness differs when banks' perceived benefits of improving provision quality are expected to be greatest. Since timely loan loss provision could reduce information asymmetry between banks and depositors, which increases banks' expected access to liquidity, 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 land owners hire professionals and wealth management companies to take care of their money. No matter who eventually decides where to put the money, bank managers improve their provision quality in expectation of attracting 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, after which they increased to $250,000. Thus I conduct the analyses using the full sample period as well as sub-periods before and after the second quarter of 2006. Column (1) - (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 $\boldsymbol{Boom_t} \times \triangle NPL_t$ and $\boldsymbol{Boom_t} \times \triangle NPL_{t+1}$ 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 statistically significant at 1% level. To address concerns regarding the rule change of the uninsured deposit in 2006, I re-estimate the same tests for the periods before and after and find consistent results. The results are reported in Column (3) – (6). Together, the results show that banks with 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 time of liquidity constraint is large time deposits. I find consistent results where the increase in timely loan loss recognition appears larger, on average, among banks with lower than 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 liquidity inflows. In addition, the evidence also suggests that it's not driven by 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 smaller banks have more increase in provisioning timeliness. Table 7 presents the results. The coefficients on $Boom_t \times \triangle NPL_t$ and $Boom_t \times \triangle NPL_{t+1}$ are positive and significant for smaller banks, suggesting that smaller banks have more incentives to improve provision quality after the liquidity windfalls.

[Table 7 About Here]

To further investigate the Access to Liquidity channel, I test if timely loan loss provision is indeed beneficial for banks to get more liquidity. 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 deposit increases 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 liquidity, then I expect the improvements to be more pronounced for banks in the "deposit increase" group. As shown in Table 8, only banks with an increase in deposit level after shale booms increase their provision timeliness. In particular, the coefficient on $Boom_t \times \triangle NPL_{t+1}$ for the "deposit increase" group is positive and statistically significant, whereas the coefficient for the "no deposit increase" group is not significant.

Collectively, the results support the Access to Liquidity 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 Liquidity channel, whether shareholder monitoring plays a role remains to be thoroughly examined. The mechanism suggests that banks that care about their relationship with investors and markets' response would signal with timelier accounting information to alleviate market's concern. If this is the mechanism, then banks subject to more market discipline and shareholder monitoring are more likely to increase timeliness in loan loss recognition. There are two proxies commonly used in prior studies to capture the strength of market discipline and shareholder monitoring for banks – legal ownership and dependence onăshort-term uninsured funding (e.g., Diamond and Rajan (2001); Nier and Baumann (2006)).

Public banks are argued to have more exposure to market discipline and shareholder monitoring. If the mechanism is through the Shareholder Monitoring channel, then I expect to see more increase in provision timeliness among public banks. However, legal ownership is also used as a proxy for external financing dependence for banks in some studies. Specifically, public banks are assumed to be less financially constrained than private banks because they are more transparent and less informationally problematic (e.g., Holod and Peek (2007)). If private banks turn out to have more incentives to improve their provision quality to access the liquidity, then the mechanism is less likely to be market discipline and shareholder monitoring. I re-estimate Model (4) separately for public and private banks. Table 9 presents the results. The increase in timely loan loss recognition appears to be concentrated among private banks. Public banks do not have a significant increase in provision timeliness, but the difference between public and private banks is not statistically significant. Although the evidence suggests that private banks are more affected, there is no conclusive evidence on which mechanism dominates based on the legal ownership subsample tests.

[Table 9 About Here]

Next, I split the full sample into two groups based on the median of short-term uninsured liabilities in the previous quarter, and use "other borrowed money" and subordinated notes and debentures as the measurements. 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. Column (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 and the difference in timely provisioning between banks with more short-term uninsured liabilities and banks with less is not statistically significant. Column (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. Moreover, the two groups do not have a statistically significant difference in provision timeliness following liquidity windfalls. Taken together, the results do not support the Shareholder Monitoring channel.

[Table 10 About Here]

5 Additional Analyses

5.1 Alternative Possible Channels

The evidence is consistent with Access to Liquidity channel, where banks increase timely loss recognition following shale booms to attract more liquidity. However, it is also possible that the liquidity 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. While I control for time-varying profitability in all regressions, I conduct an additional test to address this possible concern. I split the sample into two groups based on the median of profitability of last period. Table 11 presents the results. 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 liquidity 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 change in management quality.

[Table 11 About Here]

Another concern may be that the main results are driven by the difference in banks' ex-ante credit risk. Although I include bank fixed effects in all tests to control for any banks time-invariant characteristics, and include an indicator for treatment banks to control for any systemic differences between treatment and control banks, I conduct an additional test to examine the potential issue. Specifically, 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. This suggests that differences in credit risk do not drive the results.

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 provision (e.g., Beatty and Liao (2014); Jiang, Levine, and Lin (2016)). A higher value of the discretionary loan loss provision (discretionary LLP) implies higher portion of the provision unexplained by fundamental determinates, thus indicates lower disclosure and provision quality. To construct the measure of discretionary LLP, I use the natural logarithm of the absolute value of the residues from estimating modified Model (3), where the model controls for size, profitability, loan growth, Tier 1 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.[16] I then use a difference-in-differences specification to examine the relation between the measure of provision quality and the liquidity boom. Specifically, the model I estimate is as follows:

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

where $DisLLP$ is the measure of the discretionary component of loan loss provisions of bank i in quarter t. Following Jiang, Levine, and Lin (2016), I control for size, profitability, Tier 1 capital ratio, one quarter-lag of loan loss provisions, and negative net income indicator variable ($LOSS$).[17] I also include time fixed effects and bank fixed effect 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

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

[17] 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.

counties. The coefficients of all three measures of Boom are negative and significant, indicating that exposed banks reduce discretionary LLP following liquidity 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 in Figure 2. There is a distinct drop in discretionary LLP starting from the first quarter (q_0) 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 liquidity 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 shale booms in different counties 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., Collins, Shackelford, and Wahlen (1995); Liu and Ryan (2006); Bushman and Williams (2012)). 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 provision, then that's also indicative of an improvement in their provision quality. In the main test, I find consistent evidence of earnings management on average in my sample, where $Ebllp$ has positive and significant relation with LLP on average. Thus I test if banks' earnings management behavior change following the boom.[18] 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 evidence that banks attempt to improve accounting quality following liquidity 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 among liquidity-dependent banks that have strong incentives to attract deposits by reducing information asymmetries. I find that improvements in timeliness are concentrated among smaller banks and banks with fewer uninsured deposits. Further tests suggest that bank depositors value changes in bank accounting information. Improvements in timeliness are accompanied by easier access to liquidity for exposed banks. Taken together, the evidence is consistent with the Access to Liquidity channel but not 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 bank accounting choices during good times defined as local liquidity windfalls. The results suggest that banks improve accounting quality in order to attract the increased local liquidity. Contrary to changes in regulations regarding disclosure rules, which directly affect

[18]Because Tier 1 ratio is not significantly associated with LLP in the main test, I do not draw inferences regarding capital management.

banks' accounting policies, my findings suggest that local economic conditions are important determinants of bank reporting incentives.

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Figure 1: Distribution of the Shale Boom

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

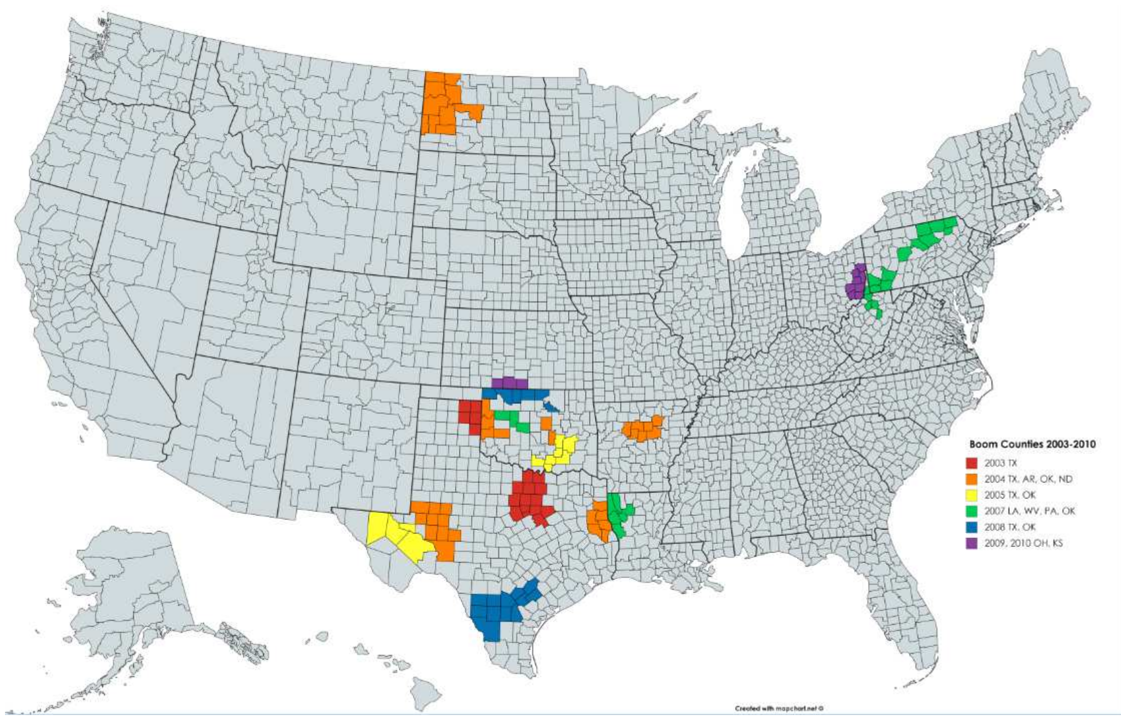

Figure 2: Discretion LLP around the Shale Boom

This figure reports the point estimates of $Boom_t$ (t=-5,-4,...,4,5), indicator for five quarters before and after boom year, in the regression of
$DisLLP_{i,t} = \beta_0 + \beta_1 Boom_{i,t} + \beta_2 Size_{i,t} + \beta_3 Ebllp_{i,t} + \beta_4 LLP_{i,t-1} + \beta_5 Loss_{i,t} + \mu_t + \gamma_i + \epsilon_{i,t}$.

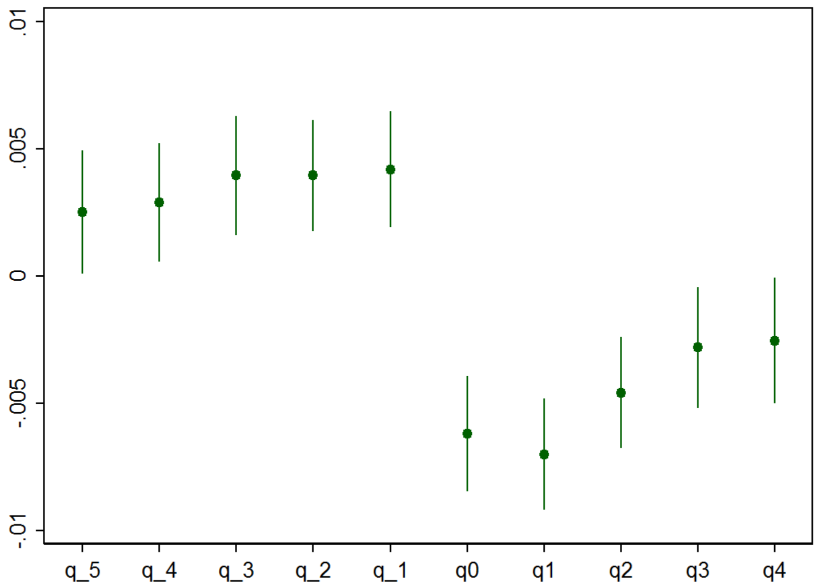

Table 1: Summary Statistics

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 shown 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) leven on Boomcounty(Boombank) 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. Variables 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	$\triangle Deposit$	$\triangle Deposit$	$\triangle Deposit$	$\triangle Deposit$	$Deposit\,Price$
$Boombank_i$	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 Liquidity 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 provision. 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 banks and time (quarter) fixed effects. Variables 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 provision. 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 the 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 banks and time fixed effects. Variables 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 Boom			
	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 provision. All tests include banks and time fixed effects. Loan portfolio controls are included but are suppressed for brevity. Variables 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 Deposit 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 deposit. The dependent variable is current loan loss provision. All tests include banks and time fixed effects. Variables 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 provision. All tests include banks and time fixed effects. Variables 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 Liquidity

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 if its overall deposit increases over the year following a shale boom. The dependent variable is current loan loss provision. All tests include banks and time fixed effects. Variables 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 provision. All tests include banks and time fixed effects. Variables 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. Column (1) and (2) show the results using "other borrowed money". Column (3) and (4) present the results using "subordinated notes and debentures". The dependent variable is current loan loss provision. All tests include banks and time fixed effects. Loan portfolio controls are included but are suppressed for brevity. Variables 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 provision. All tests include banks and time fixed effects. Variables 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 provision (LLP_Discretion). LLP_Discretion is the measure of the discretionary component of loan loss provisions and is the natural logarithm of the absolute values of the residues from estimating modified Model (3). The dependent variable is LLP_Discretion 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 banks and time fixed effects. Variables 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_Discretion		
	(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