Essays on Financial Regulations, Bank Opacity, and Bank Risks

By

Arisyi Fariza Raz

Department of Finance
Birmingham Business School
University of Birmingham

A thesis submitted to the University of Birmingham in accordance with the requirements of the degree of Doctor of Philosophy in the Birmingham Business School, School of Social Science.

July 2022

Abstract

We evaluate how various policies and financial regulations, namely why the liquidity coverage rule (LCR), state corporate tax, and the 1990s deregulation, affect US banks' opacity. First, we find that banks subject to the LCR become significantly more opaque. A separate study also shows that a tax rise provokes more discretionary earnings smoothing and increases earnings opacity. Greater opacity caused by the LCR and higher tax rates lead to higher liquidity risk as investors confidence diminishes and more likely to withdraw their money where a liquidity shock happens. Bank opacity does not only increase liquidity risk but also overall risk appetite and insolvency. The final part of our study finds that the 1990s deregulation creates complex and more opaque banks. These banks use opacity to obfuscate risk-taking activities and hide vulnerabilities arising from low levels of capitalization. Our findings contribute to the literature regarding the unintended consequences of various policies and regulations on bank opacity.

Dedication and acknowledgements

I express my sincere gratitude to Danny McGowan who is not only my primary supervisor but also a mentor and a friend.

I thank Nicola Cetorelli from the Federal Reserve Bank of New York for his generosity in providing us with his organizational structure data.

I am grateful for helpful suggestions from my second supervisor, Tianshu Zhao, Murillo Campello, three anonymous referees, Nicolo Bandera, Tobias Berg, Victoria Böhnke, Tatiana Damjanovic, Piotr Danisewicz, Hans Degryse, Declan French, Malika Hamadi, Florian Hoffman, Vasso Ioannidou, Victoria Ivashina, Santosh Koirala, Mike Mariathasan, Stephen Millard, Enrico Onali, Amiyatosh Purnanandam, Tarik Roukny, Seyit Gokmen, Alessandro Scopelliti, Aniruddha Rajan, John Turner, Iman van Lelyveld, and seminar and conference participants at the Bank of England, University of Birmingham, University of Durham, KU Leuven, Queen's University Belfast, University of Zürich, the European Economic Association (EEA) Conference, the European Financial Management Association (EFMA) Conference, the Essex Finance Centre (EFiC) Conference, the International Finance and Banking Society (IFABS) Conference, and the Money, Macro and Finance (MMF) Conference.

Finally, I thank my parents for their motivation and support.

Table of Contents

List of Tables

List of Figures

Figure **Page**

Chapter 1

Introduction

Information asymmetry between insiders and managers exists in all firms. While in non-financial firms, agency problems can be minimized through market discipline (Fama and Jensen, 1983), this mechanism may not work in banks due to their inherently opaque nature (Flannery, 1996; Flannery et al., 2004). Theory shows the relationship between bank opacity and risk is complex and depends on various factors (Moreno and Takalo, 2016). Banks avoid transparency if market participants are not skilled at information processing because transparency can generate asymmetric information among agents (Pagano and Volpin, 2012). On the contrary, too much opacity can undermine investor confidence and make refinance more difficult, leading to higher rollover risk (Ratnovski, 2013). Due to this complex theoretical relationship, examining the nexus between bank opacity and risk is an empirical matter. In this thesis, we empirically show three separate studies that investigate how bank opacity responds to various regulations and policies. Each study explains the mechanism behind the relationship between each regulation and opacity response. We further examine the consequences, either intended or unintended, faced by these opaque banks and the effect on overall financial stability.

The *first* study examines the effect of the Liquidity Coverage Ratio (LCR) rule on bank opacity and liquidity risk. Banking theory maintains that banks are exposed to liquidity mismatch because they invest in long-term assets using short-term deposits (Diamond and Dybvig, 1983). Outsiders - in this case, individual savers - cannot observe banks' actual liquidity mismatch and may randomly withdraw funds from banks due to unforeseen expenditures. Under normal circumstance, this activity does not pose any threats to banks. However, due to information asymmetry individual savers may incorrectly assess the internal condition of banks and trigger panics. If a panic happens, individual savers simultaneously withdraw their money from banks and prompt a bank run.

Basel III LCR was thus introduced to minimize this risk by mandating banks to hold High Quality Liquid Assets (HQLA) that serve as liquidity buffers. Theory shows that banks can manage liquidity risk by 1) accumulating liquidity buffers; or 2) becoming transparent (Ratnovski, 2013). A liquidity buffer allows the bank to refinance internally but is only effective in covering small funding withdrawals. Alternatively, the bank can reduce opacity to better communicate its solvency status to creditors and maintain access to any amount of external funding. Liquidity buffer is always effective but communication of solvency status may sometimes be ineffective (e.g. due to investor herding or irrationality), which prevents refinancing. Even though both of these strategies are complementary, bank managers consider them as strategic substitutes to avoid redundant and costly liquidity hedging. Therefore, a bank chooses the most effective liquidity hedging strategy given its internal business characteristics.[1] The introduction of liquidity requirements such as the LCR, however, coerces all banks to choose liquidity buffers instead. Under certain parameter values, there exists banks that prefer to be transparent but are coerced to abandon transparency by the LCR rule. This decision results in sub-optimal liquidity management, which increases funding liquidity risk of such banks and represents the unintended effect of liquidity requirements. Answering this question is an empirical matter.

Using difference-in-difference estimation applied to US Bank Holding Company (BHC) data, we find that the LCR provokes a significant 5.18 percentage points increase in HQLA and greater opacity, reflected by a 2.2% decrease in disclosure quality, and a 10.8% increase in asset opacity. The net effect of these changes is greater funding liquidity risk. Estimates show that funding liquidity risk increases by 3.63 basis points per thousand dollars of assets. This equates to a $245 million increase in the average bank's funding liquidity risk each quarter, and reflects the LCR triggering an increase in liabilities' liquidity risk that is not offset by decreasing asset liquidity risk.

Our *second* study extends the conceptual framework of Ratnovski (2013) by incorporating taxation. Firms, including banks, avoid tax authorities by becoming more opaque or less transparent (Ellul et al., 2015). Banks respond to a tax increase by accelerating the recognition of provisions for expected future and current loan losses because this behavior deducts tax (Andries et al., 2017). This acceleration of loan loss recognition enables banks to pursue opportunistic earnings smoothing that obscures fundamentals and transparency (Bushman and Williams, 2012). While this reduces transparency by obscuring the release of accurate information to outsiders, a benefit to the bank is that it accumulates a provisions buffer that it can deploy to cover future loan losses. However, as shown by Ratnovski (2013), a bank's decision to become more opaque may have negative consequences.

To identify the effect of taxes on bank earnings opacity and liquidity risk, we use variation in state corporate taxes. Unlike federal taxes that change infrequently and affect all banks equally, changes to state taxes occur often, are plausibly exogenous, and apply only to banks doing business

[1] For instance, whether a bank can accumulate liquidity buffers easily or whether it is exposed to small funding withdrawals or large funding withdrawals.

in the state (Heider and Ljungqvist, 2015). We estimate staggered difference-in-difference model to evaluate the effect of tax changes on opacity and liquidity risk. We further complement our baseline model with a novel interaction-weighted difference-in-difference estimator to alleviate potential biases arising in staggered difference-in-difference environments (Sun and Abraham, 2021; Baker et al., 2022).

Our estimates show that a tax increase raises earnings opacity by 32.7% and liquidity risk by 9.2%. However, tax cuts have no impacts on earnings opacity or liquidity risk. Our results also report that banks with weaker performance tend to become more opaque after a tax increase, thus more exposed to higher liquidity risk. Banks with greater reliance on wholesale funding are also more exposed to liquidity risk because they are more prone to large funding withdrawals.

Bank opacity is not only related to liquidity risk but also a bank's risk-taking activities and capitalization. Our *third* study empirically tests these linkages by exploiting a series of financial deregulation throughout the 1990s in the US. The deregulation phase started in 1996 with the eliminations "firewall" that cushioned bank subsidiaries from risky non-bank subsidiaries and ended in 1999 with the enactment of the Gramm-Leach-Bliley Act (GBLA) that enabled the creation of "universal banks". This deregulation encouraged some banks to diversify their business into non-traditional off-balance sheet transactions, while other banks remained non-diversified. Diversified banks are less transparent relative to focused banks because of their complex structures, resulting in a higher level of information asymmetry between managers and investors (Thomas, 2002; Bushman et al., 2004).

Using a difference-in-difference estimator, we study the differential effect of the deregulation episode on opacity levels of diversified banks versus non-diversified banks. We find the opacity of diversified banks increased by 43.1% after the deregulation. Section 20 banks, which engaged in more complex investment banking activities, became more opaque relative to other diversified banks. Our findings also show that, while each deregulation phase, namely "firewall" eliminations and the enactment of the GLBA, significantly increased the opacity within section 20 banks, the effect of the GLBA was economically more sizeable. Different from the 1996 deregulation that only eliminated some of the restrictions, the GLBA completely abolished the restrictions related to investment banking activities and enabled the creation of universal banks, which explains the results.

We find that complex banks are more opaque because they want to obfuscate risk taking activities. This study also examines how levels of capital interact with this dynamics. Our findings show that banks with lower equity are more likely to take more risk to increase their capital levels. Simultaneously, these banks have greater opacity because they want to hide their internal vulnerabilities to the outsider.

We validate our main empirical findings by employing novel econometric techniques and a battery of robustness checks. In our first study, we complement our baseline results with synthetic control method (SCM) outlined by Cavallo et al. (2013) to construct a representative counterfactual to test the robustness of the baseline findings. SCM improves the reliability of the results where it provides a better pre-treatment fit of the trends in the outcome variables between LCR and exempt banks. Our second study uses interaction-weighted difference-in-difference (IW-DID) estimator outlined by Sun and Abraham (2021) to remove potential biases that can arise in staggered difference-in-difference environments (Baker et al., 2022). Our robustness checks also rule out concerns related to shock endogeneity, reverse causality, anticipation effects, and other potential confounding effects.

Our thesis relates to several strands of literature. First, a strand of literature studies the relationship between information disclosure and bank risk. Chen and Hasan (2006) show the effect of transparency on increasing the probability of bank run among fundamentally weaker banks. They further show how this effect diminishes if a bank manager can control the timing of information disclosure. Huang and Ratnovski (2011) show the benefits of wholesale funding in "traditional banks" that mostly hold conventional assets and loans. However, it can increase the risk of bank run in "modern banks" with more complex and opaque balance sheet structure that can be influenced by noisy public signal. Other studies examine the relationship between informational networks and bank runs (Iyer and Peydró, 2011; Kelly and O Grada, 2000). Our paper shows how a bank's decision to abandon transparency may expose it to higher liquidity shock and give it incentives to take more risk.

A parallel strand of literature establishes theoretical relationships between bank opacity and regulation. Previous theoretical work show the unintended consequence of financial regulations on bank opacity (Ratnovski, 2013; Landier and Thesmar, 2014). Existing theory also shows the complex relationship between disclosure requirement and opaqueness (Moreno and Takalo, 2016; Pagano and Volpin, 2012). A novel contribution of our paper is to empirically show how bank opacity responds to these various regulatory shocks.

The thesis proceeds as follows. Chapter 2 analyses the unintended consequences of the LCR rule on bank opacity and liquidity risk. Chapter 3 extends the conceptual framework from Chapter 2 by incorporating taxation and empirically investigates the effects of tax changes on bank opacity and liquidity risk. Chapter 4 evaluates the effects of bank deregulation on business complexity, bank risk taking and vulnerability avoidance. Section 5 concludes.

CHAPTER 2

The dark side of liquidity regulation: Bank opacity and funding liquidity risk

[1]

Using short-term liabilities to invest in long-term assets exposes banks to funding liquidity risk (Diamond and Dybvig, 1983). As banks increasingly rely on wholesale funding that can be withdrawn at short notice, funding liquidity risk has become a greater threat to bank failure (Huang and Ratnovski, 2011). To mitigate this concern, regulators have mandated that banks hold liquidity buffers. Notably, the Basel III Accord contains the liquidity coverage ratio (LCR) that requires banks to hold sufficient high quality liquid assets (HQLA) to cover 30 days of estimated net cash outflows (BCBS, 2010, 2013).

Theory shows that under certain conditions accumulating liquidity reserves provokes the unintended consequence that bank transparency and funding liquidity risk deteriorate. Ratnovski (2013) develops a model where a bank invests in long-term assets using short-term liabilities. When the bank refinances a fraction of its liabilities, information asymmetries prevent creditors precisely observing its solvency status. If creditors receive an uncertain negative signal about the bank's condition they may cease lending to the bank, preventing it from rolling over its liabilities, creating funding liquidity risk. A liquidity buffer allows the bank to refinance internally but is only effective in covering small funding withdrawals. Alternatively, the bank can reduce opacity to better communicate its solvency status to creditors and maintain access to any amount of external funding. While liquidity buffers and opacity are complementary funding liquidity risk management devices, they are also strategic substitutes because with some probability a liquidity

[1] Previous versions of this chapter appeared at 2021 EFMA conference, 2021 EEA conference, 2021 MMF conference, 2021 EFiC conference, and 2021 Day-ahead workshop University of Zurich. A version of this chapter has been accepted at the Journal of Financial Intermediation: Raz, A.F., McGowan, D., and Zhao, T. (2022) The dark side of liquidity regulation: Bank opacity and funding liquidity risk. *Journal of Financial Intermediation*, accepted proof.

buffer makes reducing opacity redundant in addressing a liquidity crisis, and vice versa. Under certain parameter configurations, the LCR creates a trade-off between liquidity buffers and bank opacity that may lead to greater bank opacity and funding liquidity risk. Answering this question is an empirical matter.

Using difference-in-difference estimation applied to US Bank Holding Company (BHC) data, we find that the LCR significantly increases HQLA by 5.18 percentage points. Banks also become more opaque, reflected by a 2.2% decrease in disclosure quality, and a 10.8% increase in asset opacity. The net effect of these changes is greater funding liquidity risk. Estimates show that funding liquidity risk increases by 3.63 basis points per thousand dollars of assets. This equates to a $245 million increase in the average bank's funding liquidity risk each quarter, and reflects the LCR triggering an increase in liabilities' liquidity risk that is not offset by decreasing asset liquidity risk. The effects are larger for banks that are exposed to the most stringent LCR requirements, and systemically risker banks.

Rising opacity reflects LCR banks increasing their holdings of complex assets that are difficult for outsiders to value (Jones et al., 2012; Bratten et al., 2019). Managers reach for yield by holding more (high yielding) opaque assets to mitigate the costs of holding more (low yielding) HQLA. The opacity increasing effects of holding more opaque assets dominates the reduction in opacity from holding additional HQLA.

Our paper relates to two strands of literature. A small but rapidly evolving body of research documents the effects of the LCR on the banking industry. Roberts et al. (2018) study the effects of the LCR on bank credit supply, liquidity creation, and fire sale risk. They show that LCR banks cut lending and liquidity creation, and that these activities migrate to non-LCR banks. Furthermore, they report that the increase in liquid assets on LCR banks' balance sheets reduces fire-sale risk. In contrast, our paper illustrates how the LCR can, paradoxically, increase banks' funding liquidity risk: the degree of duration mismatch between assets and liabilities. In addition, we document that the LCR triggers an increase in bank opaqueness that is due to the policy creating incentives for managers to reach for yield by investing in opaque assets to offset the low return on HQLA.

Bruno et al. (2018) show the Basel Committee's liquidity regulation announcements between 2008 and 2013 triggered negative abnormal market returns in European banks' stock prices. Hartlage (2012) develops a model in which the LCR undermines bank stability because satisfying the rule's HQLA requirements leads to 'snowballing' leverage in cases where banks have little flexibility to adjust the maturity profile of liabilities. Unlike these articles, our work speaks to the effects of the LCR on US banks' internal funding liquidity risk management and asset reconstitution.

A parallel literature studies bank behavior during liquidity crises. Ivashina and Scharfstein (2010) and Cornett et al. (2011) show the liquidity crunch during the financial crisis reduced banks' flexibility in making balance sheet adjustments, resulting in lower credit supply. The crisis also demonstrates how systemic liquidity risk has become a major contributor to bank failures (Hong et al., 2014). A novel contribution of our paper is to show how the LCR potentially magnifies funding liquidity risk, raising concerns surrounding duration mismatch and the withdrawal of wholesale market funding.

Our findings contribute to a lively policy debate surrounding the efficacy and trade-offs of liquidity regulation. Quantitative liquidity buffers are now a key pillar in the regulatory framework across many countries including the US, European Union, and the United Kingdom. An advantage of the LCR is that it lowers banks' reliance on a lender of last resort, thereby reducing the distortions of public liquidity backstops. Moreover, the LCR makes it difficult for a bank to bear more risk through excessive liquidity and maturity transformation. However, the usefulness of the LCR also depends on its effectiveness in alleviating liquidity stress. We show an unintended consequence of the LCR is to raise funding liquidity risk, the issue it looks to address. This suggests the LCR is not a panacea to liquidity problems, and that policymakers must evaluate a complex set of trade-offs when designing liquidity policy instruments.

The paper proceeds as follows. Section 2 summarizes the theory that underpins the empirical analysis. Section 3 describes the LCR and liquidity regulation in the US. In Section 4 we provide an overview of the data sources, descriptive statistics, and outline the empirical model. We report econometric results in Section 5, and present robustness tests in Section 6. Section 7 draws conclusions.

2.1 Conceptual model

The theoretical apparatus underlying our empirical tests is Ratnovski's (2013) model of bank funding liquidity risk management. At time 0 a bank invests in a profitable project that produces a return at time 2 using funds raised from investors. Two independent events happen simultaneously at time 1. First, an exogenous quantity of the initial funding is withdrawn. Second, an independent noisy signal on the bank's solvency emerges. If the signal on solvency status is positive, conditional on the bank being solvent, it can refinance through new borrowing. All insolvent banks receive a negative signal and are unable to refinance, leading them to fail. Owing to information asymmetries, a solvent bank may also receive a negative signal with some probability.

Faced by the noisy signal on a (solvent) bank's solvency status, investors at time 1 must decide whether to continue funding it or withdraw funds. With a high probability the signal is positive, allowing the bank to refinance at the risk free rate. However, a negative signal induces doubts about the bank's solvency, leading investors to withhold funding to avoid potential losses.

Where a solvent bank receives a negative signal, it can manage funding liquidity risk through two channels. At time 0 it can attract additional funds and invest them in a liquidity buffer comprising HQLA that may be sold at any time. During a liquidity crisis, the bank can use these assets to cover its refinancing needs internally. However, maintaining a liquidity buffer incurs managerial effort costs that are not offset by liquid assets' low rate of return. The bank's owner-manager incurs a per dollar cost of managing a liquidity buffer through administrative expenses and opportunity costs from diverting their attention from core business functions. A limitation of liquidity buffers is that they can only cover refinancing in proportion to their size.

Alternatively, at time 0 a bank can decide whether to be opaque or transparent. Opacity is an ex-ante decision (a bank-level state variable), and the reduction thereof allows the bank to communicate more accurate information about its solvency status to investors. Where a less opaque bank receives a negative signal at time 1, with a high probability it can communicate the value of bank assets to outsiders to prove it is solvent and obtain funding. However, there is also a low probability that a transparent solvent bank is unable to communicate that it is solvent, leading investors to withhold funding. The imperfect probabilistic nature of transparency in overcoming an episode of liquidity stress reflects that despite putting in place the necessary preconditions, communication of solvency status may sometimes be ineffective (e.g. due to investor herding or irrationality) which prevents refinancing. The advantage of reducing opacity is that a bank can refinance liabilities of any size providing it is successful in communicating that it is solvent to investors. The downside of transparency is that the bank's owner-manager loses private control benefits (Ratnovski, 2013; Dang et al., 2017).

A key outcome of the model is that liquidity buffers and reducing opacity are complements: both mitigate funding liquidity risk albeit with different costs. Yet they are also strategic substitutes: using one lever diminishes the additional value of the other because with some probability the other is redundant in addressing a liquidity crisis. For example, a bank with large liquid asset holdings has little incentive to reduce opacity because it has ample reserves to withstand funding withdrawals. Ratnovski (2013) shows that when the costs of liquidity buffers and reducing opacity are sufficiently low, the optimal decision is for banks to use both to manage liquidity risk. However, when the cost of using each hedge is more substantial, a trade-off emerges depending upon the probability of success of each conditional on its hedging cost.

Owing to the model's stylized nature, and the unknown parameter values determining the costs of liquidity buffers and reducing opacity, it is an empirical question whether the LCR provokes an increase in bank opacity and funding liquidity risk. Ratnovski (2013) shows that if the cost of reducing opacity is low, a bank chooses to manage funding liquidity risk by being transparent. Introducing a LCR in this context ensures it also holds a liquidity buffer to manage funding liquidity risk. However, where the cost of reducing opacity is sufficiently high, while the social optimum would be to use both strategies, a bank responds to the LCR by shifting from transparency to liquidity buffers. This condition is sub-optimal because the imposed liquidity buffer only protects it against small refinancing shocks, while transparency can respond to both large and small refinancing needs under effective communication. Moreover, this implies an increase in funding liquidity risk where the probability that a bank can effectively communicate its solvency to investors is greater than the probability that the bank's refinancing need is small.

Ratnovski (2013) shows using a quantitative example calibrated using parameter values that approximate conditions in the US banking industry that the range of parameters for which a LCR induces a switch from transparency to liquidity buffers is wider than the range of parameters for which it does not. Introducing the LCR may trigger strategic substitution in banks' liquidity risk management strategies leading to higher levels of opacity, rather than the complementary effect. Ultimately, whether this is the case is an empirical issue.

2.2 Liquidity regulation in the US

The LCR's objective is to strengthen banks' short-term liquidity risk profile by maintaining an adequate level of HQLA (BCBS, 2010, 2013). The LCR formally defines the minimum ratio requirement as

$$LCR = \frac{HQLA}{TENCO} \geq 100\%, \tag{2.1}$$

where $HQLA$ denotes high quality liquid assets, and $TENCO$ is total expected net cash outflows over the next 30 days.

The numerator in equation (2.1) contains a variety of liquid assets divided into two categories based on their liquidity level. "Level 1" assets are the most liquid, comprising excess reserves, US treasury securities, Government National Mortgage Association (GNMA) mortgage backed securities (MBS), and non-government sponsored enterprise (non-GSE) agency debt (e.g. the FDIC, and the Small Business Administration). As these assets can be easily converted to cash, they are not subject to haircuts or compositional caps. Less liquid "Level 2" assets cannot account for more than 40% of HQLA and contain two sub-categories: i) "Level 2A" assets, comprising GSE debt securities, MBS, and commercial MBS (CMBS), and ii) "Level 2B" assets, comprising corporate debt securities. Level 2A assets are subject to a 15% haircut, and account for the majority of Level 2 assets, whereas Level 2B assets are subject to a 50% haircut and must not exceed 15% of HQLA.

2.2.1 Timeline

On October 24, 2013, the Federal Reserve Board (FRB) announced it would introduce a LCR. The rule is consistent with establishing an enhanced prudential liquidity standard under section 165 of the Dodd-Frank Act and complies with the Basel III LCR, but sets more stringent standards on the range of assets that qualify as high quality. It also imposes a shorter implementation period.

The FRB's standard LCR rule mandates a minimum ratio requirement of 100% and applies to BHCs with either at least \$250 billion in total consolidated assets, or at least \$10 billion in on-balance sheet foreign exposure. We refer to these banks as 'standard LCR banks'. The FRB also finalized a modified version of the LCR that sets a minimum ratio requirement of 70% and applies to BHCs with total consolidated assets between $50 billion and $250 billion. We refer to these banks as 'modified LCR banks'. Banks with total consolidated assets less than $50 billion, and BHCs and savings and loan holding companies with substantial insurance operations are exempt from both versions of the LCR.

Recognizing that it would take time for banks to accumulate HQLA, the FRB staggered the intensity of the LCR's introduction through time. In its October 24 announcement, the FRB states, 'covered companies would be required to comply with a minimum LCR of 80% as of January 1, 2015. From January 1, 2016, through December 31, 2016, the minimum LCR would be 90%, and 100% from January 1, 2017, and thereafter.' Ihrig et al. (2019) highlight that following announcement of the LCR, banks started increasing their HQLA to meet the 80% compliance threshold by January 2015.

2.3 Data description and econometric model

2.3.1 Outcome variables

The key dependent variables in the empirical analysis measure banks' opacity, funding liquidity risk, and liquidity buffers. We discuss the construction of each in turn.

2.3.1.1 Bank opacity

Measuring bank opaqueness presents an empirical challenge. A bank's opacity stems from the composition of its assets which determine outsiders' ability to evaluate its solvency status. Following Jones et al. (2012), we measure asset opacity (AOP) as the ratio of opaque assets (comprising trading assets, fixed assets, intangible assets, other assets, investments in unconsolidated subsidiaries, other real estate owned, and opaque available-for-sale and held-to-maturity securities) to total assets. A higher opaque asset ratio increases information asymmetries and reduces bank transparency.

In addition, we follow Chen et al. (2015) who outline a disclosure quality (DQ) measure of bank opaqueness. Regulatory bodies require a minimum standard of mandatory filings for most financial disclosures. However, managers have considerable discretion about whether to report more financial information (Chen et al., 2015). Disclosure quality therefore captures how much information firms disclose in their reports and is computed as the quarterly ratio of nonmissing to total Compustat items. Bank opacity is thus high when managers use discretion to limit public information release by reporting fewer items. Chen et al. (2015) further show that this variable correlates strongly with other opacity measures used in the literature.

2.3.1.2 Funding liquidity risk

Calculating funding liquidity risk relies upon the liquidity mismatch index (LMI) outlined by Bai et al. (2018). The LMI captures the extent of liquidity mismatch between the market liquidity of a bank's assets and the funding liquidity of its liabilities. The LMI is defined as:

$$\begin{aligned} LMI_{i,t} &= \sum_k \lambda_{t,a_k} a_{i,t,k} + \sum_{k'} \lambda_{t,l_{k'}} l_{i,t,k'} \\ &= LMIA_{i,t} + LMIL_{i,t}, \end{aligned} \tag{2.2}$$

where $LMIA_{i,t}$ and $LMIL_{i,t}$ are the asset and liability mismatch indexes for bank i at time t, respectively. The asset-side weights are $\lambda_{t,a_k} = 1 - m_{t,k}$ and the liability-side weights are $\lambda_{t,l_{k'}} = -e^{-\mu_t T_{k'}}$. $a_{i,t,k}$ and $l_{i,t,k'}$ are assets and liabilities for bank i at time t across classes k and k', respectively, and $\lambda_{t,a_k} > 0$ and $\lambda_{t,l_{k'}} < 0$. $T_{k'}$ is the remaining maturity of liability k'. $m_{t,k}$ is the repo market haircuts and μ_t is the OIS-T-bill spread as outlined in Appendix B of Bai et al. (2018). We divide $LMIA_{i,t}$ and $LMIL_{i,t}$ by total assets to give per dollar amounts. Higher values of $LMI_{i,t}$ indicate a sound liquidity position and low liquidity mismatch, whereas low or even negative values imply liquidity stress. Online Appendix A.1 describes the calculation methods behind the liquidity weights and details of the asset and liability classes.

Following Bai et al. (2018), we calculate funding liquidity risk by shifting the vector of repo market haircuts, $m_{t,k}$, and the OIS-T-bill spread, μ_t, which captures the liquidity state of the economy, by one standard deviation

$$\lambda_{t,a_k,1\sigma} = 1 - (m_{t,k})(1 + \sigma_{m_k}), \tag{2.3}$$

and

$$\lambda_{t,l_{k'},1\sigma} = -e^{(-\mu_t T_{k'})(1+\sigma_\mu)}. \tag{2.4}$$

Given equations (2.3) and (2.4), funding liquidity risk ($LRISK$) is the difference between LMI and LMI with a 1σ change in market ($\lambda_{t,a_k,1\sigma}$) and funding ($\lambda_{t,l_{k'},1\sigma}$) liquidty conditions, that is

$$LRISK_{i,t} = LMI_{i,t} - LMI_{i,t,1\sigma}. \tag{2.5}$$

We extend Bai et al. (2018)'s $LRISK_{i,t}$ variable by separating it into asset and liability components. The objective is to investigate which side of the balance sheet is most affected by the LCR rule from a funding liquidity risk perspective. We substitute equations (2.2), (2.3), and (2.4) into equation (2.5), as follows

$$LRISK_{i,t} = \sum_k (\lambda_{t,a_k} a_{i,t,k} - \lambda_{t,a_k,1\sigma} a_{i,t,k}) + \sum_{k'} (\lambda_{t,l_{k'}} l_{i,t,k'} - \lambda_{t,l_{k'},1\sigma} l_{i,t,k'}). \tag{2.6}$$

Equation (2.6) shows a bank's funding liquidity risk comprises its asset-side liquidity risk ($LRISKA_{i,t}$) and liability-side liquidity risk ($LRISKL_{i,t}$). These are defined as

$$LRISKA_{i,t} = \sum_k \triangle\lambda_{t,a_k,1\sigma} a_{i,t,k}, \tag{2.7}$$

and

$$LRISKL_{i,t} = \sum_k \triangle\lambda_{t,l_{k'},1\sigma} l_{i,t,k'}, \tag{2.8}$$

where $\triangle\lambda_{t,a_k,1\sigma}$ is equal to $\sigma_{m_k} m_{t,k}$, or the volatility of the assets' haircuts. $\triangle\lambda_{t,l_{k'},1\sigma}$ is equal to $-e^{-\mu_t T_{k'}} + e^{-\mu_t T_{k'}(1+\sigma_\mu)}$, or the change in liquidity cost given a 1σ higher liquidity premium. We weight $LRISK_{i,t}$, $LRISKA_{i,t}$, and $LRISKL_{i,t}$ by total assets to obtain ratios. In the rest of the paper we refer to these variables without subscripts.

2.3.1.3 Liquidity buffers

We measure liquidity buffers following the LCR's definitions of which assets constitute HQLA. To capture overall HQLA, we compute HQR (the ratio of HQLA to total assets). $HQ1$ (the ratio of Level 1 HQLA to total assets), and $HQ2$ (the ratio of Level 2 HQLA to total assets) denote Level 1 and Level 2 HQLA holdings, respectively. Online Appendix A.2 describes the data sources and calculation method for each asset class.

2.3.2 Data and descriptive statistics

We construct a balanced quarterly panel of US BHCs from 2010Q1 to 2017Q4. Starting the sample in 2010Q1 avoids the confounding effects of banks increasing liquid asset holdings following the financial crisis. Setting 2017Q4 as the end date ensures consistency in the sample as the modified LCR threshold increased to $100 billion in May 2018. We retrieve quarterly BHC-level panel data from the FR Y-9C Consolidated Financial Statements for Holding Companies provided by the FRB. For each BHC, this provides quarterly information on total assets, liquid assets, loans, deposits, equity capital, undrawn loan commitments, and other variables. Constructing HQLA and the liquidity risk variables requires data that are not available through the FR Y-9C form. We collect these items from quarterly FFIEC 031 Condition and Income Reports for BHCs' subsidiary banks and aggregate the FFIEC 031 variables to the BHC level.

Table 2.1: Variable descriptions

Variable	Description
Dummy variables for difference-in-difference estimation	
T_i	A dummy variable equal to 1 if bank i is a standard or modified LCR bank, 0 for exempt banks
T_i^S	A dummy variable equal to 1 if bank i is a standard LCR bank, 0 otherwise
T_i^M	A dummy variable equal to 1 if bank i is a modified LCR bank, 0 otherwise
LCR	A dummy variable equal to 1 for 2013Q4 onward, 0 otherwise
Initial	A dummy variable equal to 1 for 2013Q4 to 2014Q3, 0 otherwise
Interim	A dummy variable equal to 1 for 2014Q4 to 2016Q4, 0 otherwise
Full	A dummy variable equal to 1 for 2017Q1 onward, 0 otherwise
Dependent variables	
Bank opacity variables	
$DQ_{i,t}$	Disclosure quality for bank i at time t, calculated following Chen et al. (2015) as the share of nonmissing items to total Compustat items. Higher values reflect better disclosure quality/less opacity.
$AOP_{i,t}$	Opaque assets to total assets for bank i at time t. Opaque assets are defined following Jones et al. (2012).
Liquidity risk variables[a]	
$LRISKA_{i,t}$	Asset-side liquidity risk per thousand dollars of assets for bank i at time t.
$LRISKL_{i,t}$	Liability-side liquidity risk per thousand dollars of assets for bank i at time t.
$LRISK_{i,t}$	Funding liquidity risk per thousand dollars of assets for bank i at time t.
Liquidity buffers variables[b]	
$HQR_{i,t}$	High quality liquid assets (HQLA) divided by total assets for bank i at time t.
$HQ1_{i,t}$	HQLA Level 1 assets divided by total assets for bank i at time t.
$HQ2_{i,t}$	HQLA Level 2 assets divided by total assets for bank i at time t.
Bank complexity variables	
$CIL_{i,t}$	The ratio of commercial and industrial loans to total loans for bank i at time t.
$HGN_{i,t}$	The ratio of heterogeneous loans to total loans for bank i at time t. The definition of heterogeneous follows Liu and Ryan (2006).
$COUNT_{i,t}$	The number of 50+% owned affiliates under bank i at time t.
$NBTB_{i,t}$	The ratio of the number of 50+% owned non-bank affiliates to the number of 50+% owned bank affiliates for bank i at time t.
$BUSCOM_{i,t}$	A normalized Herfindahl index based on affiliate types for bank i at time t. $BUSCOM_{i,t} = \frac{T}{T-1}(1-\sum_{k=1}^{T}(\frac{count^k}{totalcount^k})^2)$ where T is the number of affiliate types. There are five different affiliate types: 1) banks, 2) insurance companies, 3) mutual and pension funds, 4) other financial subsidiaries, and 5) nonfinancial subsidiaries. $BUSCOM_{i,t}$ values range from 0 (least complex) to 1 (most complex).
Independent variables	
$SIZE_{i,t}$	The natural logarithm of total assets for bank i at time t.
$ILA_{i,t}$	The ratio of illiquid assets to total assets for bank i at time t.
$NBL_{i,t}$	The ratio of non-bank loans to total assets for bank i at time t.
$OBS_{i,t}$	The ratio of off-balance sheet commitments to total assets for bank i at time t.
$DOM_{i,t}$	The ratio of domestic deposits to total assets for bank i at time t.
$CAP_{i,t}$	The ratio of equity capital to total assets for bank i at time t.
CBA_t	FRB's total assets at time t.
$\triangle NPL_{i,t}$	Credit risk, represented by the change in the non-performing loans ratio for bank i at time t.
$ZSC_{i,t}$	Distance to default of bank i at time t. $ZSC_{i,t} = \frac{ROA_{i,t}+CAR_{i,t}}{\sigma ROA_{i,t}}$ where ROA is return on assets, CAR is the capital ratio, and $sigma$ denotes the standard deviation.
$GSP_{i,j,t}$	The natural logarithm Gross State Product in state j where bank i is headquartered at time t.
$UNEMP_{i,j,t}$	Unemployment rate in state j where bank i is headquartered at time t.
$CDIFF_{i,t}$	Capital difference of bank i at time t. Computed as the gap between capital adequacy ratio and regulatory minimum capital.

Notes: This table provides a definition of each variable used in the empirical analysis. For brevity we suppress the variables' subscripts in the manuscript. [a] indicates the variable is derived from the LMI index as shown by equations (2.5)-(2.8). Online Appendix A.1 provides details of the calculation method. [b] Online Appendix A.2 provides data sources and details of the calculation method.

Table 2.2: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Full sample					All banks before LCR announcement					LCR banks after LCR announcement				
Variables	Mean	Std. dev.	p25	p50	p75	Mean	Std. dev.	p25	p50	p75	Mean	Std. dev.	p25	p50	p75
Bank opacity															
$DQ_{i,t}$	0.6578	0.0603	0.6229	0.6441	0.7153	0.6603	0.0560	0.6229	0.6449	0.7186	0.6516	0.0475	0.6212	0.6407	0.6627
$AOP_{i,t}$	0.2771	0.1243	0.1849	0.2565	0.3485	0.2768	0.1216	0.1927	0.2593	0.3319	0.2673	0.1230	0.1795	0.2464	0.3201
Liquidity risk															
$LRISKA_{i,t}$	0.1678	0.0422	0.1393	0.1748	0.2007	0.1455	0.0352	0.1271	0.1455	0.1705	0.1503	0.0310	0.1315	0.1490	0.1727
$LRISKL_{i,t}$	0.0579	0.0901	0.0103	0.0306	0.0720	0.0321	0.0571	0.0053	0.0149	0.0322	0.0178	0.0209	0.0042	0.0102	0.0232
$LRISK_{i,t}$	0.2257	0.0923	0.1667	0.2106	0.2639	0.1776	0.0552	0.1461	0.1683	0.1985	0.1681	0.0383	0.1422	0.1629	0.1914
Liquidity buffers															
$HQR_{i,t}$	0.1446	0.0773	0.0926	0.1262	0.1735	0.1467	0.0790	0.0968	0.1301	0.1754	0.1501	0.0844	0.0944	0.1333	0.1842
$HQ1_{i,t}$	0.0515	0.0518	0.0151	0.0346	0.0706	0.0527	0.0499	0.0178	0.0395	0.0714	0.0505	0.0516	0.0154	0.0356	0.0659
$HQ2_{i,t}$	0.0931	0.0654	0.0521	0.0824	0.1190	0.0939	0.0698	0.0480	0.0844	0.1198	0.0995	0.0740	0.0483	0.0891	0.1271
Bank complexity	0.1862	0.1224	0.0946	0.1643	0.2427	0.1758	0.1206	0.0875	0.1617	0.2232	0.1695	0.1195	0.0841	0.1507	0.2175
$CIL_{i,t}$															
$HGN_{i,t}$	0.2080	0.1212	0.1170	0.1885	0.2718	0.1989	0.1196	0.1157	0.1878	0.2482	0.1938	0.1189	0.1128	0.1740	0.2411
$COUNT_{i,t}$	2.9237	6.6292	1.0000	2.0000	2.0000	2.9246	7.2890	1.0000	2.0000	2.0000	1.8850	1.5239	1.0000	1.0000	2.0000
$NBTB_{i,t}$	6.8322	8.2882	2.1000	4.0000	8.0000	6.6083	7.8528	2.0000	4.0000	8.0000	6.0925	6.9594	2.2000	4.0000	7.0000
$BUSCOM_{i,t}$	0.1736	0.3620	0.0000	0.0000	0.0000	0.1695	0.3607	0.0000	0.0000	0.0000	0.1804	0.3719	0.0000	0.0000	0.0000
Control variables	16.5211	1.6821	15.3247	15.9556	17.0207	16.3364	1.7238	15.1079	15.7397	16.8683	15.6323	0.7485	15.0200	15.5163	16.1768
$SIZE_{i,t}$															
$ILA_{i,t}$	0.0161	0.0112	0.0085	0.0127	0.0210	0.0187	0.0127	0.0099	0.0146	0.0248	0.0203	0.0133	0.0109	0.0157	0.0288
$NBL_{i,t}$	0.6305	0.1553	0.5848	0.6666	0.7299	0.6148	0.1523	0.5783	0.6477	0.7110	0.6387	0.1205	0.5863	0.6538	0.7173
$OBS_{i,t}$	0.2071	0.1880	0.1107	0.1765	0.2550	0.1714	0.1777	0.0747	0.1370	0.2150	0.1415	0.0986	0.0694	0.1303	0.1894
$DOM_{i,t}$	0.7288	0.1514	0.7080	0.7753	0.8147	0.7200	0.1608	0.6974	0.7708	0.8124	0.7666	0.0810	0.7295	0.7832	0.8201
$CAP_{i,t}$	0.1128	0.0246	0.0986	0.1114	0.1246	0.1116	0.0269	0.0960	0.1094	0.1231	0.1130	0.0286	0.0961	0.1108	0.1246
CBA_t	0.0220	0.0359	-0.0032	0.0032	0.0482	0.0359	0.0435	-0.0051	0.0315	0.0834	0.0359	0.0435	-0.0051	0.0315	0.0834
$SHADOW_t$	-0.0086	0.0115	-0.0145	-0.0105	0.0034	-0.0114	0.0035	-0.0143	-0.0112	-0.0088	-0.0114	0.0035	-0.0143	-0.0112	-0.0088
$\triangle NPL_{i,t}$	-0.0009	0.0037	-0.0019	-0.0007	0.0001	-0.0013	0.0050	-0.0030	-0.0011	0.0002	-0.0012	0.0053	-0.0030	-0.0011	0.0004
$ZSC_{i,t}$	63.9991	19.0745	51.7372	64.1302	76.1477	56.2962	20.2288	40.4848	54.0927	69.9056	55.9964	20.4231	40.1026	53.8548	69.7963
$GSP_{i,j,t}$	0.0676	0.0185	0.0500	0.0670	0.0835	0.0853	0.0082	0.0780	0.0850	0.0930	0.0853	0.0082	0.0780	0.0850	0.0930
$UNEMP_{i,j,t}$	9.7267	0.0507	9.6845	9.7196	9.7707	9.6796	0.0205	9.6622	9.6806	9.6952	9.6796	0.0205	9.6622	9.6806	9.6952
$CDIFF_{i,t}$	0.0665	0.0337	0.0482	0.0621	0.0784	0.0769	0.0334	0.0556	0.0692	0.0885	0.0806	0.0346	0.0593	0.0717	0.0933

Notes: This table presents summary statistics for all variables. Columns (1) to (5) present summary statistics using all observations in the data set. Columns (6) to (10) present summary statistics for LCR banks for the period 2010Q1 to 2013Q3. Columns (11) to (15) present summary statistics for exempt banks for the period 2013Q4 to 2017Q4. Table 2.1 provides a description of each variable.

To create a balanced sample, we drop acquired banks and new entrants. We also exclude BHCs with consolidated assets less than \$3 billion since they have different characteristics from LCR banks. We therefore define exempt banks as those with assets between \$3 billion and \$50 billion. This provides a sample of 2,697 observations for 87 BHCs.

The data set contains several variables including the log of total assets ($SIZE$), the sum of fixed and other illiquid assets to total assets (ILA), the ratio of non-bank loans to total assets (NBL), off-balance sheet commitments to total assets (OBS), domestic deposits to total assets (DOM), and equity capital to total assets (CAP). Table 2.1 provides the source and a description of each variable in the data set. Table 2.2 reports summary statistics.

2.3.3 Empirical specification

We use a difference-in-difference estimation strategy to quantify the LCR's effects. We exploit cross-sectional variation in BHCs' exposure to the LCR based on their asset holdings, and time series variation in the FRB's announcement of the rule. In the most basic setup, we estimate

$$y_{i,t} = \alpha_i + \gamma_t + \theta(T_i \times \text{LCR}_t) + X_{i,t-1} + \varepsilon_{i,t} \tag{2.9}$$

where $y_{i,t}$ is the outcome of interest (opacity, funding liquidity risk) for BHC i in quarter t; α_i and γ_t are BHC and quarter-year fixed effects, respectively; T_i is a dummy variable equal to 1 if a BHC has total assets of at least \$50 billion (referred to as a LCR bank), 0 otherwise; LCR_t is a dummy variable equal to 1 for 2013Q4 and all subsequent quarters, 0 otherwise; $X_{i,t-1}$ is a vector of lagged BHC covariates; $\varepsilon_{i,t}$ is the error term. Following Bertrand et al. (2004) we block bootstrap the standard errors using 50 bootstrap samples, where a block is defined based on treatment status (e.g. LCR and exempt banks constitute two blocks).

To separately isolate the effect of the LCR rule on standard and modified LCR banks we estimate

$$y_{i,t} = \alpha_i + \gamma_t + \theta_1(T_i^S \times \text{LCR}_t) + \theta_2(T_i^M \times \text{LCR}_t) + X_{i,t-1} + \varepsilon_{i,t} \tag{2.10}$$

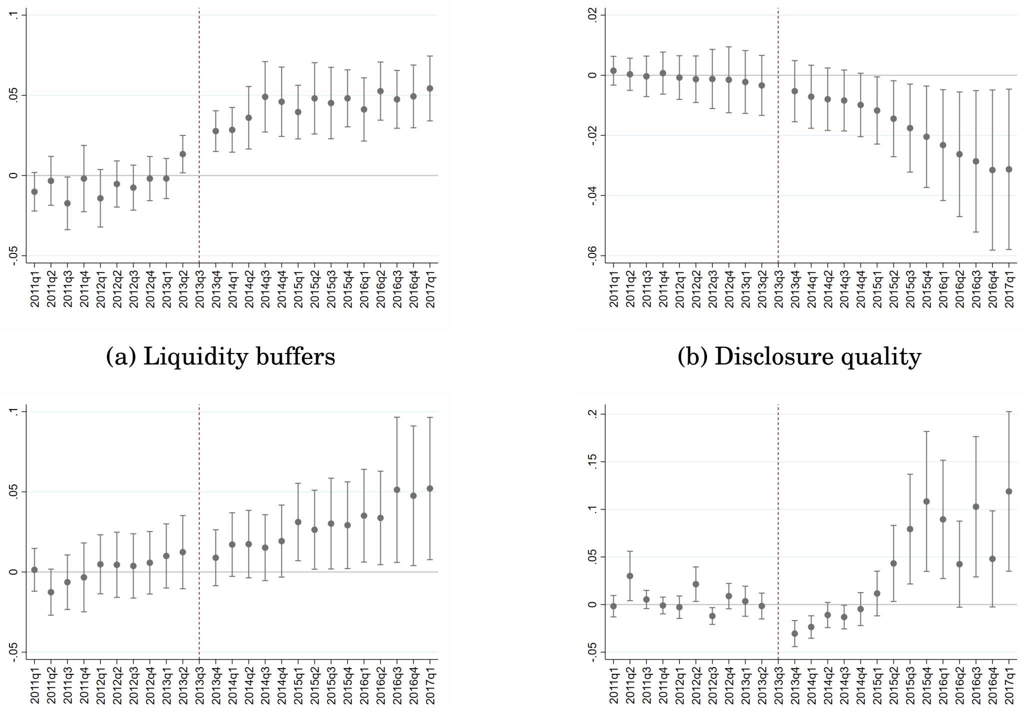
where all variables are defined as before except T_i^S and T_i^M denote the standard and modified LCR bank dummy variable, respectively. This is our preferred specification because it provides insights into differing LCR intensities across banks.

Later we disaggregate the LCR_t dummy to capture how $y_{i,t}$ responds to the initial LCR period, the interim stage of the rule, and the full compliance stage. We estimate

$$\begin{aligned} y_{i,t} = {} & \alpha_i + \gamma_t + \theta_1(T_i^S \times \text{LCR}_t^{initial}) + \theta_2(T_i^M \times \text{LCR}_t^{initial}) + \theta_3(T_i^S \times \text{LCR}_t^{interim}) \\ & + \theta_4(T_i^M \times \text{LCR}_t^{interim}) + \theta_5(T_i^S \times \text{LCR}_t^{full}) + \theta_6(T_i^M \times \text{LCR}_t^{full}) + X_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{2.11}$$

where all variables are defined as in equation (2.10) except $\text{LCR}_t^{initial}$ is a dummy variable equal to 1 for 2013Q4 to 2014Q4, 0 otherwise; $\text{LCR}_t^{interim}$ is a dummy variable equal to 1 for 2015Q1 to 2016Q4, 0 otherwise; LCR_t^{full} is a dummy variable equal to 1 from 2017Q1 onward, 0 otherwise.

Figure 2.1: Evolution of liquidity buffers, opacity, and liquidity risk



(a) Liquidity buffers

(b) Disclosure quality

(c) Asset opacity

(d) Liquidity risk

Notes: This figure reports coefficient estimates and 95% confidence intervals of equation (2.12), using HQR (2.1a) , DQ (2.1b), AOP (2.1c), and $LRISK$ (2.1d) as the outcome variables. The coefficients θ_t show the quarterly average difference in the outcome variable between LCR (standard and modified LCR banks) and exempt banks. The standard errors are block bootstrapped (there are two blocks: LCR and exempt banks) drawing 50 samples.

Constructing the implied counterfactual in our tests relies on the assumption that exempt banks provide an accurate depiction of the behavior of opacity, funding liquidity risk, and liquidity buffers among LCR banks in the absence of the LCR. To inspect the parallel trends assumption we estimate

$$y_{i,t} = \alpha_i + \gamma_t + \theta_t(T_i \times \gamma_t) + X_{i,t-1} + \varepsilon_{i,t}, \tag{2.12}$$

where all variables are defined as in equation (2.9). Figure 2.1 illustrates the evolution of the main dependent variables between LCR and exempt banks during the sample period by plotting estimates of θ_t. Prior to the LCR announcement, LCR and exempt banks' liquidity buffers, opacity, and funding liquidity risk evolve similarly within the two groups. Almost all the pre-

LCR coefficient estimates of θ_t are insignificant, suggesting that the parallel trends identifying assumption holds.[2]

2.4 Empirical results

We begin by inspecting the patterns in the underlying data. Figure 2.1a shows that following implementation of the LCR, banks subject to the rule increase their HQLA holdings relative to exempt banks. The dynamic coefficient estimates are positive and significant during each post-2013Q4 quarter. Figures 2.1b, 2.1c, and 2.1d show that LCR banks become significantly more opaque and experience higher funding liquidity risk relative to exempt banks once the LCR is in force, respectively.

Table 2.3: Baseline opacity and funding liquidity risk results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Net effects					Standard and modified banks		
	Bank opacity		Liquidity risk			Bank opacity		Liquidity risk		
Dependent variable:	DQ	AOP	LRISKA	LRISKL	LRISK	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i \cdot$ LCR	-0.0147***	0.0300**	-0.0113***	0.0477**	0.0363**					
	(-2.66)	(2.55)	(-4.31)	(2.47)	(2.01)					
$T_i^S \cdot$ LCR						-0.0204*	0.0341**	-0.0183***	0.0589***	0.0407**
						(-1.87)	(2.23)	(-5.26)	(3.30)	(2.48)
$T_i^M \cdot$ LCR						-0.0092	0.0260**	-0.0047**	0.0369	0.0322
						(-1.09)	(2.04)	(-2.15)	(1.17)	(1.08)
$SIZE_{i,t-1}$	0.0082	-0.0257	-0.0017	-0.0237**	-0.0254**	0.0080	-0.0256	-0.0019	-0.0233**	-0.0252**
	(1.19)	(-1.50)	(-0.80)	(-2.29)	(-2.47)	(1.22)	(-1.50)	(-0.96)	(-2.25)	(-2.42)
$ILA_{i,t-1}$	-0.0897	0.1223	-0.1444***	0.9264**	0.7820**	-0.0843	0.1184	-0.1379**	0.9158**	0.7779**
	(-0.50)	(0.21)	(-2.75)	(2.44)	(2.04)	(-0.47)	(0.20)	(-2.49)	(2.39)	(2.03)
$NBL_{i,t-1}$	-0.0073	-0.0261	0.1693***	-0.0002	0.1691***	-0.0073	-0.0261	0.1693***	-0.0001	0.1691***
	(-0.37)	(-0.49)	(23.70)	(-0.00)	(3.30)	(-0.36)	(-0.49)	(24.81)	(-0.00)	(3.37)
$OBS_{i,t-1}$	-0.0265*	0.0430	0.0011	0.0457**	0.0468**	-0.0281*	0.0442	-0.0008	0.0488**	0.0480**
	(-1.70)	(1.40)	(0.32)	(2.13)	(2.39)	(-1.81)	(1.46)	(-0.29)	(2.24)	(2.37)
$DOM_{i,t-1}$	-0.0433	-0.0291	-0.0434***	-0.1712*	-0.2147**	-0.0375	-0.0332	-0.0365***	-0.1825**	-0.2190***
	(-1.30)	(-0.31)	(-4.09)	(-1.69)	(-2.28)	(-1.07)	(-0.34)	(-3.86)	(-2.04)	(-2.59)
$CAP_{i,t-1}$	0.0423	-0.0511	0.0016	-0.3161**	-0.3145***	0.0499	-0.0566	0.0108	-0.3310***	-0.3202***
	(0.43)	(-0.30)	(0.06)	(-2.50)	(-2.70)	(0.57)	(-0.34)	(0.43)	(-3.05)	(-3.17)
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.2314	0.1009	0.9605	0.5812	0.7641	0.2373	0.1016	0.9633	0.5832	0.7643
Number of BHCs	87	87	87	87	87	87	87	87	87	87

Notes: Columns 1-5 report estimates of equation (2.9). Columns 6-10 report estimates of equation (2.10). Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The standard errors are block bootstrapped drawing 50 samples: in columns 1-5 there are two blocks (LCR and exempt banks), and in columns 6-10 there are three blocks (standard LCR, modified LCR, and exempt banks). The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

In view of the significant increase in LCR banks' HQLA holdings, we next test the hypothesis that the LCR erodes transparency. Column 1 of Table 2.3 reports estimates of equation (2.9) using disclosure quality as the dependent variable. The interaction coefficient is negative and significant at the 1% level. Economically, the estimates show LCR banks' disclosure quality

[2]Our unreported tests show that connections between bank directors and the Federal Reserve do not explain the modest increase in LCR banks' HQLA holdings relative to exempt banks in 2013Q3. It is therefore unlikely this reflects information leakage and peremptory accumulation of HQLA ahead of the LCR's announcement. The most likely explanation is that the reversal of the Federal Reserve's previous decision to scale back the third quantitative easing episode during this quarter differentially increased LCR banks' HQLA holdings.

declined by 1.47 percentage points or 2.2% relative to the pre-LCR mean of 66% following the LCR's introduction. The findings in columns 2 of Table 2.3 corroborate this result. Specifically, the LCR triggered a significant 3 percentage points (or 10.8%) increase in LCR banks' opaque assets ratio. Together the findings indicate that banks subject to the LCR become more opaque.

In columns 3-5 of Table 2.3 we study the equilibrium effects of the increase in liquidity buffers and opacity on funding liquidity risk. On the asset side of the balance sheet the LCR has a risk-reducing effect. The interaction coefficient estimate in column 3 shows asset liquidity risk falls by 1.13 basis points and this is significant at 1%.[3]

However, the reduction in asset liquidity risk is offset by a significant increase in liability liquidity risk. The estimates in column 4 show liability liquidity risk increases by 4.77 basis points within LCR banks after the rule. This result is consistent with investors responding to greater opacity by becoming reluctant to lend to banks and providing funds that can be withdrawn at shorter notice. The net effect of these changes in column 5 of the table is a significant 3.63 basis points per thousand dollars of assets increase in funding liquidity risk. This is a substantial effect, equivalent to a $245 million increase in funding liquidity risk per quarter for the average LCR bank.

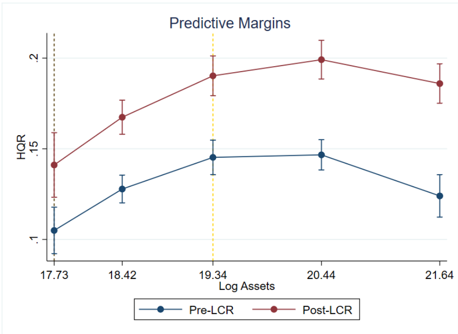
Among the control variables, the results show that larger banks tend to have significantly lower funding liquidity risk. Illiquid assets are positively correlated with liability liquidity risk and funding liquidity risk, and negatively correlated with asset liquidity risk. There is a positive association between non-bank loans, asset liquidity risk, and funding liquidity risk. We find a positive link between off balance sheet commitments and liability liquidity risk and funding liquidity risk, and a negative association with disclosure quality. Deposit liabilities are significantly negatively correlated with all liquidity risk variables. Better capitalization is also associated with lower liability and funding liquidity risk.

2.4.1 Size heterogeneity

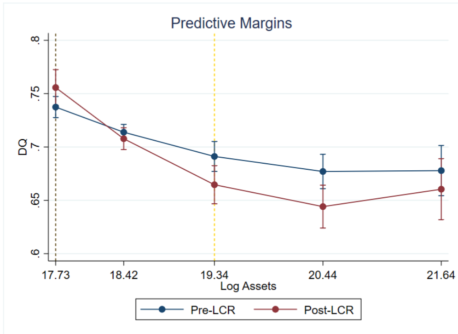
While it is challenging to map the Ratnovski model parameters to empirical values due to the model's stylized nature, both the probability of solvency risk (s), and the probability of a negative signal (q) likely correlate with bank size. To establish whether there exist heterogeneous relationships between size and the outcome variables we perform nonparametric estimation using polynomial splines.

[3] Asset liquidity risk falls because banks' assets become more liquid. While the HQLA share of assets increases by 5.18 percentage points, later we show opaque asset holdings increase by 4.84 percentage points. The net effect of these changes is to reduce asset liquidity risk: holding approximately 5 percentage points more HQLA reduces asset liquidity risk by more than holding 5 percentage points more opaque assets increases asset liquidity risk.

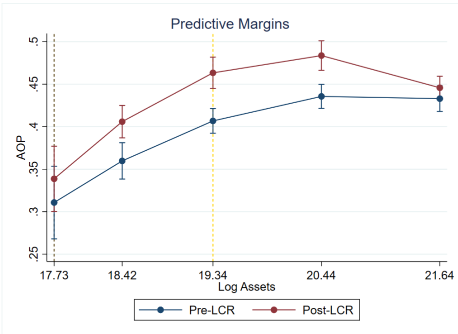
Figure 2.2: Marginal effects of bank size using polynomial splines



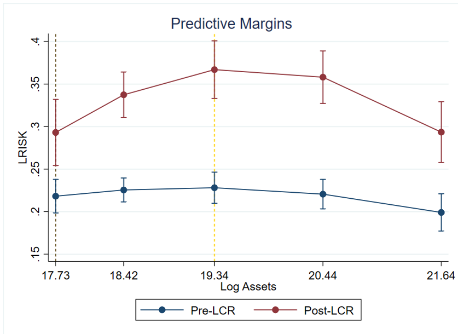
(a) Liquidity buffers



(b) Disclosure quality



(c) Asset opacity



(d) Liquidity risk

Notes: This figure illustrates nonparametric estimates using a polynomial spline of order 2. $y = f_1(SIZE) + f_2(T_i \cdot SIZE) + f_3(T_i \cdot LCR \cdot SIZE) + \varepsilon$, where y denotes an outcome variable: HQR (2.2a), DQ (2.2b), AOP (2.2c), and $LRISK$ (2.2d). Each panel shows the pre- and post-LCR marginal effects at five knots across the bank size distribution. The knots are 17.73 (the modified LCR threshold of $50 billion), 18.42 (the midpoint between the modified and standard LCR thresholds), 19.34 (the standard LCR threshold of $250 billion), 20.44 (the midpoint between the standard LCR threshold and the maximum value), and 21.64 (the highest size value in the sample). Marginal effects are indicated by circles while the vertical bars indicate 95% confidence intervals.

Figure 2.2 presents the econometric results of this test graphically. It shows the coefficient estimates for the two size splines: $f_2(T_i \times Size_{i,t})$ and $f_3(T_i \times LCR_t \times Size_{i,t})$ and the 95% confidence intervals denoted by the vertical lines around each coefficient. The $f_2(T_i \times Size_{i,t})$ and $f_3(T_i \times LCR_t \times Size_{i,t})$ splines illustrate the relationship between bank size and the outcome variables for LCR banks during the pre- and post-LCR periods, respectively. In all cases the coefficients are statistically significant.

We can draw two inferences from Figure 2.2. First, following the LCR, the marginal effect size for liquidity buffers (Panel A), disclosure quality (Panel B), asset opacity (Panel C), and liquidity risk (Panel D) become larger irrespective of bank size. For disclosure quality all but one of the marginal effects during the post-LCR period lie below the pre-LCR period effects. This is consistent with an increase in bank opacity because lower disclosure quality implies greater bank opacity. These findings are consistent with the earlier evidence that the LCR provokes an increase in liquidity buffers, bank opacity, and liquidity risk. Second, Figure 2.2 shows heterogeneous effects across the bank size distribution during the post-LCR period. The effect sizes tend to be greater for larger banks. However, the largest marginal effects across each panel in Figure 3 are for banks with assets between 19.34 ($250 billion) and 20.44 ($750 billion). For these banks we observe the largest increases in liquidity buffers, opacity (more asset opacity and lower disclosure quality), and liquidity risk.

Strategic substitution between liquidity buffers and opacity therefore occurs across all LCR banks regardless of their size because the post-LCR coefficient estimates are significantly different from zero. However, strategic substitution is most pronounced among smaller standard-LCR banks. A potential explanation for this result is that smaller standard LCR banks face the most severe refinancing needs due to their greater reliance on wholesale funding. Online Appendix Figure A.3 shows that wholesale funding accounts for approximately 85% of small standard LCR banks' funding during the sample period compared to 77% for large standard LCR banks and 57% among modified LCR banks. Owing to their greater reliance on wholesale funding, smaller LCR banks are potentially exposed to a higher probability of funding withdrawals. In the Ratnovski (2013) model this characteristic implies that small standard LCR banks face a high probability of a large funding withdrawal, and consequently face a higher cost of maintaining a liquidity buffer. Smaller LCR banks therefore potentially have the largest strategic substitution incentives because managers incur greater costs of managing HQLA.

2.4.2 Standard and modified bank effects

Next, we study how the LCR affects standard and modified banks separately. Using equation (2.10), we obtain similar results to before. In columns 6 and 7 of Table 2.3 we find the increase in opaqueness due to the rule tends to be larger for standard relative to modified LCR banks. Disclosure quality significantly declines following the LCR only for standard LCR banks. While asset opacity significantly increases for both standard and modified LCR banks, the economic magnitude of the interaction coefficient is larger for standard LCR banks.

In the remainder of Table 2.3 we find the LCR leads to a significant reduction in asset liquidity risk irrespective of a bank's type. However, the increase in liability liquidity risk and funding liquidity risk is only statistically significant for standard LCR banks. Hence, differences in the minimum reserve requirement create heterogeneity in the opacity and funding liquidity risk responses of modified and standard banks to the LCR.[4]

[4] Online Appendix Table A.3 presents validation checks of the main results. Panel A of the table reports estimates of equation (2.10) without control variables. The interaction coefficients are similar in economic magnitude and statistical significance to the baseline findings. This affirms that the findings are not due to a 'bad controls' phenomenon. We provide estimates from a propensity score matched sample in Panel B of Online Appendix Table A.3 to ensure differences in the characteristics of LCR and exempt banks do not drive the inferences. We match LCR banks to their nearest neighbor based on the Z-score, ROA, capital ratio, loan-to-assets ratio, and the off-balance-sheet commitments to assets ratio using a 2.5% caliper without replacement. This results in a sample of 76 banks. The interaction coefficients remain qualitatively and quantitatively similar to before. Online Appendix Table A.4 shows significant increases in LCR banks' HQLA holdings following enactment of the LCR.

2.4.3 Synthetic control methods

The counterfactual in our tests are exempt banks that are smaller than modified and standard LCR banks. The time-invariant size difference is removed by the bank fixed effects in the regression equations such that conditional on covariates, exempt and LCR banks are randomly different. However, exempt banks may differ from LCR banks in other ways over time that make it difficult to compute the implied counterfactual. We therefore use a synthetic control method (SCM) to construct a representative counterfactual to test the robustness of the baseline findings. SCM may also improve the reliability of the results where it provides a better pre-treatment fit of the trends in the outcome variables between LCR and exempt banks. As the sample contains several banks subject to the LCR, we follow Cavallo et al. (2013) who outline a multiple unit extension of the original SCM (Abadie and Gardeazabal, 2003; Abadie et al., 2010).

Consistent with the difference-in-difference estimations, we set 2013Q4 as the start of the treatment date. The outcome variables are HQLA, disclosure quality, asset opacity, and funding liquidity risk. To construct the synthetic control we use several bank characteristics: size, the ratio of non-bank loans to total assets, the sum of fixed and other illiquid assets to total assets, off-balance sheet commitments to total assets, domestic deposits to total assets, equity capital to total assets, and the log of stock trading volume.

Table 2.4: Average quarterly effects

	(1)	(2)	(3)	(4)
Dependent variable:	HQLA	DQ	AOP	LRISK
Average-quarterly effects	0.0393*	-0.0137***	0.0321***	0.0613***
p-value	0.0773	0.0000	0.0027	0.0000

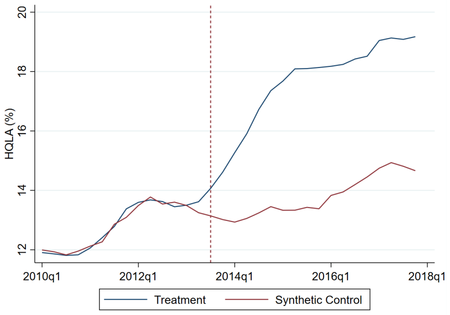
Notes: This table reports estimates of the average quarterly effects for the outcome variables, and their corresponding p-value from the placebo tests. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Figure 2.3 presents the evolution of the outcome variables within the treated (modified and standard LCR banks) and the synthetic control banks. We find a good fit between the outcome variables and their synthetic controls prior to 2013Q4. The high degree of overlap during the pre-2013Q4 period suggests the SCM is able to produce an accurate depiction of treated banks. Figure 2.3 shows that following 2013Q4 there is an increase in liquidity buffers, opacity, and funding liquidity risk within treated relative to synthetic control banks.

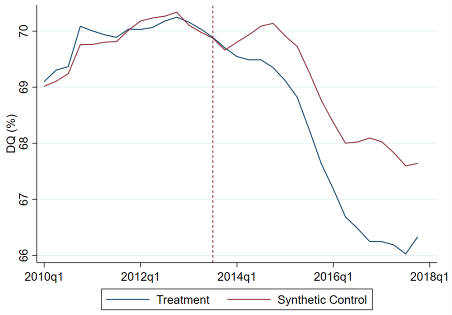
To pin down econometric estimates of the magnitudes, we calculate the post 2013Q4 average quarterly effect for each outcome variable and the corresponding p-value.[5] Estimates in Table 2.4 confirm the graphical patterns and support the earlier difference-in-difference results. Column 1

[5] To derive valid p-values for the outcome variables, we construct a distribution of average placebo effects by computing the placebo effects using the available controls, then ranking the placebo effects and the actual estimated effect in descending order. Finally, we compute the p-value by dividing the rank of the actual estimated effect in the distribution of average placebo averages by the number of possible placebo averages. Let $\overline{\alpha}^{PL(i)}$ represent the average placebo selection and $N_{\overline{PL}}$ represents the number of possible placebo averages. The p-value is then formally given as $p = \frac{\sum_{i=1}^{N_{\overline{PL}}} I(|\overline{\alpha}^{PL(i)}| \geq |\overline{\alpha}|)}{N_{\overline{PL}}}$.

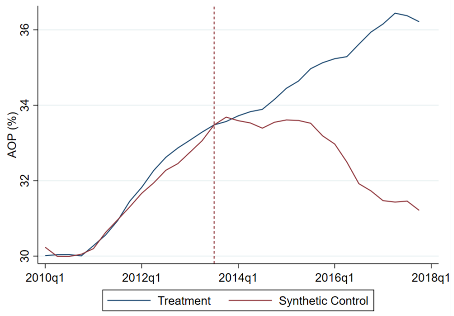
Figure 2.3: Synthetic control estimates



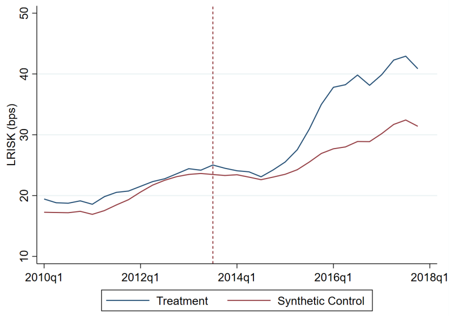
(a) Liquidity buffers



(b) Disclosure quality



(c) Asset opacity



(d) Liquidity risk

Notes: These figures illustrate the trends of each outcome variable for LCR banks (Treatment) and their synthetic control (Synthetic Control). Treatment begins in 2013Q4, denoted by the vertical dashed line. We follow the approach outlined by Cavallo et al. (2013) by estimating the average effect $\overline{\alpha} = (\overline{\alpha}_{T_0+1}, ..., \overline{\alpha}_T) = G^{-1}\sum_g^G \widehat{\alpha}_g$, given the index treatment units, $g \in \{1...G\}$, and the first post-treatment period effect, $\widehat{\alpha}_g$.

in Table 2.4 shows that following announcement of the LCR, the HQLA share of assets is 3.93 percentage points significantly higher within treated relative to synthetic control banks post LCR. In column 2, the treatment coefficient estimate is negative and significant, indicating disclosure quality is 2.1% lower after the announcement. Column 3 shows a positive and significant increase in asset opacity. The coefficient estimate (0.0321) implies asset opacity increases by 11.6% relative to the synthetic control. Finally, in column 4 the treatment effect for funding liquidity risk is 6.13 basis points and statistically significant. Despite using an alternative methodology, the magnitude of the treatment effects are remarkably similar to those obtained using difference-in-difference analysis.

2.4.4 Disaggregating the effects across stages

A key feature of the LCR is the staggered intensity of its introduction. The increase in opacity evolves in tandem with banks' liquidity risk. In columns 1 and 3 of Table 2.5 we find during the initial phase LCR banks become more opaque but the coefficient estimates are insignificant at conventional levels. However, during the interim and full compliance phases, standard LCR banks are significantly more opaque relative to exempt banks indicating for this group that the LCR provokes greater increases in opacity through time. During the interim period, modified LCR banks also significantly increase asset opacity.

Table 2.5: Disaggregated results by bank type and LCR stages

	(1)	(2)	(3)	(4)	(5)
	Bank opacity		Liquidity risk		
Dependent variable:	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ Initial	-0.0056	0.0142	-0.0136***	-0.0170***	-0.0306***
	(-1.00)	(1.46)	(-4.64)	(-2.75)	(-3.98)
$T_i^M \cdot$ Initial	-0.0015	0.0126	-0.0030	-0.0144***	-0.0175***
	(-0.41)	(1.62)	(-1.26)	(-2.68)	(-3.11)
$T_i^S \cdot$ Interim	-0.0217*	0.0399**	-0.0195***	0.0788***	0.0594***
	(-1.85)	(2.19)	(-5.22)	(3.33)	(2.68)
$T_i^M \cdot$ Interim	-0.0105	0.0246**	-0.0049**	0.0516	0.0467
	(-1.31)	(2.38)	(-2.41)	(1.34)	(1.26)
$T_i^S \cdot$ Full	-0.0384*	0.0488***	-0.0218***	0.1177***	0.0959***
	(-1.92)	(2.87)	(-5.85)	(3.45)	(2.96)
$T_i^M \cdot$ Full	-0.0182	0.0481	-0.0070***	0.0747	0.0677
	(-1.11)	(1.45)	(-2.84)	(1.43)	(1.34)
Control variables	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697
R^2	0.2640	0.1137	0.9638	0.6328	0.7903
Number of BHCs	87	87	87	87	87

Notes: This table reports estimates of equation (2.11). Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The dynamics of the funding liquidity risk variables evolve similarly. After the initial announcement funding liquidity risk falls for both types of LCR banks as asset and liability liquidity risk decrease. However, this pattern reverses during the interim and full compliance periods. Standard and modified LCR banks exhibit increasing funding liquidity risk during these periods as the rise in liability liquidity risk is not offset by reductions in asset liquidity risk, even though we observe significant effects only within standard banks. Economically, the magnitude of the effect is large for standard LCR banks. Funding liquidity risk increases by 5.94 and 9.59 basis points within standard LCR banks during the interim and full compliance periods, respectively.

2.4.5 Why does opacity Increase?

Why does the LCR provoke an increase in bank opacity? Ratnovski (2013) defines opacity as decisions that inhibit effective communication of bank asset values to outsiders. We test two potential channels: balance sheet and organizational complexity.

Prior research highlights the relative opaqueness of different types of assets. Bratten et al. (2019) show that C&I loans are difficult for outsiders to value because they are typically collateralized, syndicated, and large. Outsiders must therefore exert effort and attention to, 1) verify the collateral exists and value it, 2) disentangle syndicated loan issues and ascertain which parts of the loan a bank owns, and 3) review large C&I loans on a case-by-case basis. Liu and Ryan (2006) report that a bank is more opaque when its balance sheet contains a larger share of heterogeneous loans that comprise C&I loans, direct lease financing, other real estate loans, agricultural loans, and foreign loans. Unlike homogeneous loans, statistical methods applied to the loan portfolio cannot be used to value heterogeneous loans that often require managerial judgment.

Table 2.6: Opacity and complexity

	(1)	(2)	(3)	(4)	(5)
Type of complexity:	Balance sheet		Organizational		
Dependent variable:	CIL	HGN	COUNT	NBTB	BUSCOM
$T_i^S \cdot$ LCR	0.0484***	0.0436***	-2.5302	-1.0320	0.0806
	(3.12)	(3.07)	(-0.63)	(-0.33)	(1.43)
$T_i^M \cdot$ LCR	0.0298**	0.0325**	-3.0305	1.7465	-0.0737
	(2.32)	(2.45)	(-0.63)	(0.59)	(-0.39)
Control variables	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,604	2,604	2,604
R^2	0.2251	0.1934	0.0269	0.0365	0.0208
Number of BHCs	87	87	84	84	84

Notes: This table reports estimates of equation (2.10). Columns 1 and 2 (3 to 5) report estimates using dependent variables that capture balance sheet (organizational) complexity. Data availability constraints prevent observation of organizational complexity for 3 BHCs. The number of observations in columns 3 to 5 is therefore smaller than in columns 1 and 2. Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

We therefore evaluate how the composition of assets evolves in response to the LCR. In column 1 of Table 2.6, we estimate the LCR significantly increased the ratio of C&I loans to total loans (CIL) by 4.84 and 2.98 percentage points within standard and modified LCR banks, respectively. We obtain similar inferences in column 2 when using the ratio of heterogeneous loans to total loans (HGN) as the dependent variable in equation (2.10). Following the LCR, standard and modified LCR banks significantly increase the heterogeneous loans ratio by 4.36 and 3.25 percentage points, respectively.

Alternatively, banks may become opaque by concealing information through organizational complexity (Berger et al., 2000; Cetorelli and Goldberg, 2016; Goldberg and Meehl, 2020), because outsiders find it more difficult to accurately value banks with operations in diverse sectors (Thomas, 2002). To examine this dimension we follow Cetorelli and Goldberg (2016) to calculate three bank organizational complexity variables: $COUNT$ (the number of 50+% owned affiliates under a parent organization), $NBTB$ (the ratio of the number of 50+% owned nonbank affiliates to the number of 50+% owned bank affiliates), and $BUSCOM$ (a normalized Herfindahl index based on affiliate types).

Columns 3 to 5 of Table 2.6 report estimates of equation (2.10) using the organizational complexity measures as the dependent variable. Throughout all cells of these columns the interaction coefficients are statistically insignificant. Organizational complexity appears invariant to the LCR.

The key message emanating from Table 2.6 is that the opacity increasing effects of the LCR are due to changes in the composition of banks' balance sheets rather than banks becoming organizationally more complex. Specifically, banks hold more complex assets whose value is difficult to communicate to outsiders. This finding is consistent with the argument in Ratnovski (2013) that, 'establishing transparency can involve other corporate actions, such as avoiding complexity.' The results also align with theoretical models where managers face a trade-off between transparency and the private benefits of control (Ratnovski, 2013; Dang et al., 2017). In this context, the primary benefit of opaque assets to managers is that they earn a higher return on C&I and heterogeneous loans compared to liquid assets. Such incentives are likely strong as the mandated increase in HQLA by the LCR reduces bank profitability. Hence, the LCR has two countervailing effects. While it induces an increase in HQLA whose values are relatively easy for outsiders to value, it also leads banks to hold more opaque assets. The net effect of these changes is increased opacity.

A related question is, why do banks increase their holdings of opaque assets when this incurs capital requirement costs, especially as these are more irreversible capital structure decisions compared to LCR-imposed HQLA? In managing its balance sheet, a bank faces a joint optimization problem under the Basel III equity capital and liquidity constraints. Recent theoretical work shows that while capital and liquidity regulation may be complements (Calomiris et al., 2015; Carletti et al., 2020), their interaction is complex with potential trade-offs. This literature also shows that when the liquidity constraint binds, satisfying it may lead banks to choose sub-optimal levels of capital adequacy. For example, Carletti et al. (2020) note that when liquidity constraints are binding increasing liquidity buffers reduces a bank's portfolio return due to the low yield on HQLA. This provokes a decrease in retained earnings leading to a lower Tier 1 capital ratio, although this effect may be partially offset by lower risk weighted assets from holding safer HQLA. Using a general equilibrium framework, Boissay and Collard (2016) show that in response to tightening liquidity requirements banks accumulate Treasuries to increase HQLA. As Treasury yields decrease, investors rebalance their asset portfolio towards deposits which are a close substitute for Treasuries. By issuing more deposits, banks' capital ratios deteriorate. Cecchetti and Kashyap (2018) and Carletti et al. (2020) highlight that banks may respond differently to liquidity regulation depending on their business model, their ex ante liquid asset holdings and capitalization, and the state of the macroeconomy.

Carletti et al. (2020) report two benefits to a bank of reducing capital adequacy levels to satisfy their liquidity constraints. First, because bank capital is a more expensive form of financing than debt, reducing capital adequacy lowers capital costs. Second, a bank can increase profits by investing in risky assets to offset the reduction in profitability associated with holding more HQLA. However, this increases risk weighted assets and may lead to a lower risk weighted capital ratio depending on each asset's return, holdings, and risk weight (Cecchetti and Kashyap, 2018). A potential explanation for why banks accumulate opaque assets and sacrifice equity capital in response to the LCR is that this offsets the reduction in profitability due to increased HQLA holdings.

2.4.6 Bank risk

Studies show positive correlations between funding liquidity risk and systemic risk (Pierret, 2015; Adrian and Boyarchenko, 2018). As a validation check, we examine whether the degree of a bank's systemic risk influences the effect of the LCR on its funding liquidity risk. We approximate systemic risk using the Acharya et al. (2017) marginal expected shortfall (MES) variable. We then divide the sample into high- and low-risk banks depending on whether a bank's MES lies above or below the sample median.

Table 2.7: Systemic risk and liquidity risk

	(1)	(2)	(3)	(4)	(5)	(6)
	MES ≤ median (low risk)			MES > median (high risk)		
Dependent variable:	LRISKA	LRISKL	LRISK	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	-0.0140***	0.0342***	0.0202***	-0.0188***	0.0593***	0.0406**
	(-7.81)	(4.98)	(2.59)	(-4.01)	(3.08)	(2.49)
$T_i^M \cdot$ LCR	-0.0032*	-0.0054	-0.0086	-0.0077*	0.1096*	0.1019
	(-1.93)	(-0.88)	(-1.44)	(-1.76)	(1.65)	(1.61)
Control variables	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES
Observations	1,209	1,209	1,209	1,488	1,488	1,488
R^2	0.9664	0.7834	0.9071	0.9619	0.5875	0.7361
Number of BHC	39	39	39	48	48	48

Notes: This table reports estimates of equation (2.10) using samples split at the median level of MES which is calculated following Acharya et al. (2017). Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.7 presents the sub-sample estimates. Columns 1-3 show the regression results for banks with MES less than or equal to the industry median (low-risk), while columns 4-6 report those with MES above the industry median (high-risk). A consistent pattern emerges. The LCR triggers a significant reduction in asset liquidity risk within standard and modified LCR banks regardless of a bank's systemic risk level. However, the magnitude of this effect is larger among systemically riskier banks and standard LCR banks. Estimates in columns 2 and 5 show the LCR provokes a significant increase in liability liquidity risk for standard LCR banks but the effect size is again larger for systemically riskier banks. Among modified banks, the LCR only significantly increases liability liquidity risk for banks with MES above the median.

Ultimately, we find that funding liquidity risk only significantly increases within standard LCR banks. Column 3 shows that for less systemically risky banks the LCR provokes a 2.02 basis points increase in funding liquidity risk. In contrast, column 6 indicates that for systemically riskier banks, the LCR increases funding liquidity risk by 4.06 basis points. The effect of the LCR on funding liquidity risk is thus more pronounced within systemically riskier, and standard LCR banks. This finding is consistent with investors taking steps to increase the liquidity of their claims in more vulnerable banks to enable rapid withdrawal of funding should negative news emerge.

2.5 Robustness checks

In this section we conduct sensitivity checks to rule out potential threats to identification and alternative explanations. Prior research documents how banks manipulate their asset holdings to remain exempt from regulation (Ben-David et al., 2020). In principle, banks could hold less than $50 billion of assets to avoid the LCR. However, Online Appendix Figure A.1 shows that no bank in the sample crosses this threshold. Online Appendix Table A.5 shows our findings are also robust to instrumenting banks' LCR status using their 2005 asset holdings. A related concern is that because assignment to LCR status depends on a bank's asset holdings, the results may reflect differential trends across bank size post-2013. We therefore estimate a triple-difference version of equation (2.10). Online Appendix Table A.6 demonstrates the results are robust.

During the sample period policymakers introduce macroprudential reforms that aim to stabilize banks. Basel III initiated capital surcharges for Global-Systemically Important Banks (GSIBs) in 2011 (BCBS, 2011), the Dodd-Frank Act mandated new capital requirements for BHCs, and the FRB instituted the "Comprehensive Capital Analysis and Review" (CCAR) and Resolution Plans, popularly known as "living wills", in 2011. While these measures may influence the outcomes of interest in our study, they are unlikely confounds because they were introduced before the LCR. Online Appendix Tables A.7 and A.8 document that our findings are robust to controlling for these factors, as well as bank stress tests using the Acharya et al. (2018) methodology.

A potential unintended consequence of the LCR is its spillover effects on exempt banks. The LCR may trigger a flight-to-quality response as LCR banks increase their HQLA and deposits at the expense of exempt banks. To investigate whether such effects are present in the data, we restrict the sample to exempt banks and run Monte Carlo simulations by using the ratio of of a bank's HQLA (deposits) to total industry HQLA (deposits) as the dependent variable in equation (2.10). The rejection rates in Online Appendix Table A.9 are in line with type-1 errors, indicating that spillover effects are not present.

We also rule out a series of potential omitted variables. During the sample period, the FRB used quantitative easing (QE) to stimulate the US economy by buying Treasuries, agency MBS, bank debt, and other financial assets. These asset purchases may mechanically increase banks' holdings of reserves, a key component underlying the increase in HQLA. It appears implausible that QE drives our results as the three QE episodes predate announcement of the LCR. The first (second) QE episode ran from 2009Q1 to 2010Q2 (2010Q4 to 2011Q2) while the third QE intervention was announced in 2012Q3 and ran through 2015. We address this issue from four angles: 1) by including interactions between the treatment interactions and the period when each QE episode was in force (Panel A of Online Appendix Table A.10); 2) by interacting the treatment indicators with central bank assets, a measure of the size of the Federal Reserve's asset holdings (Panel B of Online Appendix Table A.10); ; and 3) following the Oster (2019) approach to test for omited variables (Online Appendix Table A.11). In each case the findings are robust.

Solvency concerns are central to liquidity runs. We therefore test whether the effects of the LCR are robust to controlling for credit risk and banks' distance to default. Panels A and B of Online Appendix Table A.12 shows this is the case. Liu and Ryan (2006) show that bank opacity changes over the business cycle. The estimates are robust to controlling for macroeconomic conditions in Panel C of Online Appendix Table A.12. Online Appendix Table A.13 Panel A shows that implementation of the LCR disclosure rule in 2017Q2 does not confound the estimates (Lu, 2021). In Online Appendix Table A.13 Panel B we control for the potential effects of Basel III capital regulation on asset composition and opacity. The results are robust to this change.

2.6 Conclusions

The prudential regulation of banks has changed dramatically since the financial crisis. While reforms to capital regulation have attracted most attention, policymakers now pursue liquidity regulation with the objectives of avoiding episodes of liquidity stress and promoting stability in the banking sector. Part of this agenda relies on quantitative liquidity buffers. Regulators have therefore designed LCR rules that mandate banks hold a minimum quantity of liquid assets to protect against funding liquidity risk.

We empirically document how the LCR influences bank opacity, and funding liquidity risk in US banks. Surprisingly, we find the LCR provokes an increase in funding liquidity risk. The magnitude of this effect equates to a $245 million per quarter increase in funding liquidity risk for the average bank subject to the rule. While the idea that the LCR may undermine a regulator's goal to reduce funding liquidity risk, the results are consistent with theoretical predictions outlined by Ratnovski (2013). By accumulating a liquidity buffer banks may have fewer incentives to provide transparency to market participants about their solvency status. This reflects the substitutability of liquidity buffers and transparency in addressing liquidity crises such that by increasing liquid asset holdings, during a crisis with some probability transparency is redundant. We show tests that demonstrate these mechanisms are operative and economically important. The LCR-induced increase in opacity reflects banks investing in more opaque assets whose value is difficult to communicate to investors. This behavior is consistent with managers offsetting the reduction in profits arising from greater HQLA holdings under the LCR by investing in high yielding opaque assets. Ultimately, the equilibrium effect of the increase in liquidity buffers and opacity is greater funding liquidity risk.

Our findings provide novel insights into the unintended consequences of liquidity regulation. So far, only a few studies empirically address the LCR despite the potentially widespread ramifications of liquidity regulation, and the adoption of liquidity policy instruments in several countries. As banks increasingly rely on short-term wholesale funding that may evaporate at short notice, the LCR may destabilize banks and exacerbate liquidity shortages during crisis episodes.

Chapter 3

Taxation and bank earnings opacity: The liquidity strategy dilemma

Tax avoidance is one of the highlighted issues in finance and accounting literature. Firms can become less visible to tax authorities by becoming less transparent or, conversely, more opaque (Ellul et al., 2015). For banks, however, the decision to become more opaque may have negative consequences. Banks' reliance on short-term liabilities to invest in long-term assets exposes them to liquidity risk (Diamond and Dybvig, 1983). Opacity due to information asymmetries and limited public disclosure may escalate the situation and transform liquidity risk into bank runs and financial crises (Bouvard et al., 2015; Danisewicz et al., 2021; Huang and Ratnovski, 2011; Iyer and Peydró, 2011; Iyer and Puri, 2012; Kelly and O Grada, 2000). Transparency, on the other hand, enhances investor confidence (Ellul et al., 2015), which enables banks to attract funding easily, minimizes liquidity risk, and reduces the probability of experiencing runs (Raz et al., 2022; Ratnovski, 2013). In this article, we show (1) how banks adjust their transparency in response to a tax change and (2) the effect of this apparatus on liquidity risk.

To identify the effect of taxes on bank earnings opacity and liquidity risk, we use variation in state corporate taxes. Unlike federal taxes that change infrequently and affect all banks equally, changes to state taxes occur often, are plausibly exogenous, and apply only to banks doing business in the state (Heider and Ljungqvist, 2015). Using data centered on the time of a tax change, we compare the evolution of the dependent variables among treated banks versus controls that have not yet experienced a tax change in a three year window either side of a tax change. We further complement our baseline model with a novel interaction-weighted difference-in-difference estimator. This setup ensures the estimates are not contaminated by the biases that can arise in staggered difference-in-difference environments (Sun and Abraham, 2021; Baker et al., 2022).

Estimates show that tax rates have asymmetric effects depending on the nature of the tax change. A tax increase raises earnings opacity by 32.7%. It also elevates liquidity risk by 9.2% as creditors increase the liquidity of their claims leading to duration mismatches between banks' assets and liabilities. In contrast, tax cuts exert no bearing on earnings opacity or liquidity risk.

Why do higher tax rates increase opacity? When banks can deduct loan loss provisions for tax purposes, higher tax rates give incentives for banks to exploit discretionary earnings by accelerating the recognition of provisions for expected future and current loan losses to pay smaller taxes (Andries et al., 2017). This acceleration of loan loss recognition enables banks to pursue opportunistic earnings smoothing that obscures fundamentals and transparency (Bushman and Williams, 2012). We test this mechanism by evaluating the effects of tax changes on earnings management. The data show that following a tax increase banks systematically understate their earnings, leading to the build up of provision reserves. While this reduces transparency by obscuring the release of accurate information to outsiders, a benefit to the bank is that it accumulates a provisions buffer that it can deploy to cover future loan losses. In essence, in the face of rising taxes, discretionary provisions allow bank managers to accrue resources that would otherwise flow to tax authorities (Bushman and Williams, 2012; Ratnovski, 2013).

Further tests show that a tax increase only provokes higher opacity and liquidity risk in banks with high transparency cost or low performance. Banks with lower performance have high transparency cost because they tend to have weaker corporate governance (Aebi et al., 2012; Klapper and Love, 2004) and more likely to extract private benefits of control by becoming more opaque (Verrecchia, 1983; Ahmed et al., 2010; Ratnovski, 2013; Raz et al., 2022). Opaque banks with high reliance on wholesale funding are also more exposed to liquidity risk because they are more prone to large funding withdrawals.

Our paper contributes to two broad literature strands. First, we discuss the effect of corporate taxation on transparency in the banking sector. While the relationship between transparency and corporate tax in non-financial firms is extensively discussed (Chen and Lin, 2017; Ellul et al., 2015; Huseynov and Klamm, 2012), the coverage in banking literature is still relatively limited. One existing study is that of Andries et al. (2017), which shows evidence of tax system's encouragement of timelier loan loss recognition. While we find similar evidence, our study further extends the analysis and shows that this forward-looking orientation is motivated by earnings smoothing objective that increases opacity and liquidity risk.

Second, a number of studies examine the relationship between information disclosure and liquidity risk. Chen and Hasan (2006) show the effect of transparency on the probability of bank run among fundamentally weaker banks. They further show how this effect diminishes if a bank manager can control the timing of information disclosure. Huang and Ratnovski (2011) show the benefits of wholesale funding in "traditional banks" that mostly hold conventional assets and loans. However, it can increase the risk of bank run in "modern banks" with more complex and opaque balance sheet structure that can be influenced by noisy public signal. Other studies examine the relationship between informational networks and bank runs (Iyer and Peydró, 2011; Kelly and O Grada, 2000). A novel contribution of our paper is to show how a bank's decision to abandon transparency may expose it to higher liquidity risk.

The paper proceeds as follows. Section 3.1 outlines our conceptual mode that underpins the empirical analysis. In Sections 3.2 and 3.3 we provide an overview of the data sources, descriptive statistics, and outline the empirical model. We report econometric results in Section 3.4, and present robustness tests in Section 3.5. Section 3.6 draws conclusions.

3.1 Conceptual model

Our conceptual model builds on Ratnovski's (2013) model of bank liquidity risk management. Banks use short-term liabilities to invest in long-term assets, which expose them to funding liquidity risk. To mitigate this risk, a bank can become more transparent or accumulate additional liquidity buffers. Transparency is an ex-ante decision, and more transparency thereof allows the bank to communicate more accurate information about its solvency status to investors. Where this communication is successful, a bank can acquire the funding. Alternatively, a bank can attract additional funds and invest them in a liquidity buffer comprising cash and liquid assets that may be sold at any time. During a liquidity crisis, a bank can use these assets to cover its refinancing needs internally.

Each strategy has its own strengths and weaknesses. Liquidity buffer is always effective but can only cover small funding withdrawals. Transparency, on the other hand, may not always be effective (e.g. due to investor herding or irrationality) but enables a bank to maintain access to any amount of external funding. Each strategy also incurs some costs. Liquidity buffer requires additional operational costs to maintain the liquid assets, while transparency relinquishes a bank's private benefits. Where the costs of both strategies are cheap, a bank can implement both strategies as complementary hedging. Yet a bank may consider both strategies as strategic substitutes where the costs are high because using one lever diminishes the additional value of the other and with some probability the other is redundant in addressing a liquidity crisis. For example, a bank with large liquid asset holdings that still wants to extract private benefits of control has little incentive to reduce opacity because it has ample reserves to withstand funding withdrawals.

Another important feature of this model is the difference between social payoffs and a bank manager's payoffs. A bank manager's payoffs are always lower than the social payoffs since her payoffs are reduced by the bank's cost of funding. This additional cost prevents a bank manager from fully internalizing the maximum benefit of liquidity strategy hedging. As a consequence, under certain parameter values, a bank manager only chooses one strategy whereas it is socially optimal to have both strategies, leading to insufficient hedging.

We then extend the original model by incorporating taxation. Higher tax rate reduces a bank's return on investment. To avoid this, a bank may choose to increase the extraction of private benefits by becoming less transparent or more opaque (Ellul et al., 2015).[1] This implies that a tax raise increases the cost of maintaining transparency strategy and the likelihood of a bank's decision to switch to the lest costly liquidity buffer.[2]

Figure 3.1 illustrates the possible effects of these tax changes. The y-axis represents private benefits B or the cost of transparency. The x-axis represents additional expenses associated with holding more liquidity buffer $\alpha\gamma$. Where both strategies are too costly, a bank does not implement any strategy. This condition is represented by area N. Where the costs of both strategies are extremely low, a bank chooses both hedges (area LT). In between, there are banks that only choose liquidity buffers only (area L) or transparency only (area T). In Figure 3.1a we assume three different banks with different hedging costs. Bank A has low transparency and liquidity buffer costs, therefore choose both hedges. Bank B has high transparency cost but low liquidity buffer cost and chooses liquidity buffer. Bank C, on the other hand, opts for transparency due to its low transparency cost.

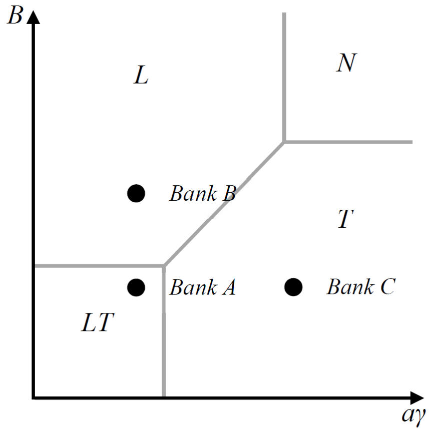
Where a tax rise happens, the transparency costs of these banks simultaneously raise. One possible scenario is where a bank manager may change its hedging policy if the effect of a tax raise sufficiently increases the cost of transparency and makes liquidity buffer more desirable. This scenario is represented by Bank A in Figure 3.1b, where it initially chooses both hedging policies but abandons transparency after a tax raise. Because a bank manager's payoffs are always lower than the socially optimal payoffs, a tax raise may prompt a condition where a bank manager decides to privately abandon transparency, while it is socially optimal to adopt both liquidity buffer and transparency. If the probability of effective communication is high and Bank A primarily relies on wholesale funding (with high probability of large funding withdrawal), abandoning transparency exposes it to refinancing (or liquidity) risk. This is because liquidity buffer only protects against small refinancing shocks, while transparency can respond to both large and small refinancing needs under effective communication.

On a contrary to a tax raise, a tax cut reduces the cost of transparency and increases the likelihood of a bank manager adopting transparency. As shown in Figure 3.1c, Bank A maintain both hedging strategies since, assuming the cost of liquidity buffer remains constant, the combined hedging costs decrease. Due to this reason, a tax cut may not have a symmetrical effect on banks since it reduces hedging cost and only reinforces the manager's decision that

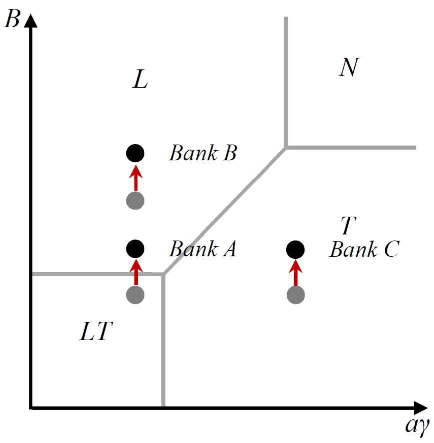
[1] Ellul et al. (2015) theoretically highlight the importance of the extraction of private benefits of control to tax evasion. By extracting more private benefits, a manager can curtail the cash flow verifiable by external parties such as investors and tax authorities. In practice, firms can extract more private benefits of control by exploiting audit quality or discretionary reporting (Chen et al., 2015). In the banking sector, banks can also extract private benefits by smoothing their earnings through discretionary loan loss recognition (Bushman et al., 2004; Bushman and Williams, 2012).

[2] Owing to the model's stylized nature, the parameter values determining the costs of liquidity buffers and reducing opacity are unknown (Ratnovski, 2013). In reality, this may be represented by several factors, such as profitability, operational efficiency, good corporate governance, etc. Nevertheless, defining a threshold remains empirically challenging if not impossible.

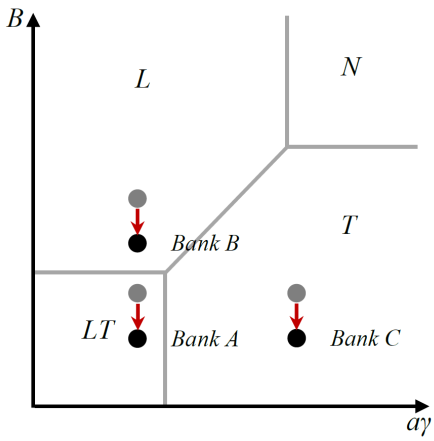
Figure 3.1: The effects of a tax change on the choice of liquidity management strategy



(a) Initial position



(b) The effect of a tax increase



(c) The effect of a tax cut

Notes: The cost of holding a liquidity buffer $a\gamma$ and becoming transparent B determine whether a bank pursues no strategy (N), liquidity buffer strategy (L), transparency strategy (T), or both liquidity buffer and transparency strategies (LT). Panel 3.1a shows the condition before a tax increase, while Panel 3.1b (Panel 3.1c) shows how a tax increase (cut) can affect a bank manager's choice of liquidity management strategy. A bank manager that chooses both hedging policies (bank A), may abandon transparency after a tax raise. This results in insufficient hedging and is socially sub-optimal. On the other hand, Panel 3.1c shows that such condition is unlikely after a tax cut because it reduces the cost of transparency and increase a manager's likelihood to choose transparency strategy.

already adopts both strategies.

Ultimately, due to the unknown parameter values determining the costs of liquidity buffer and transparency, answering the question whether banks realistically behave in such manner is an empirical issue.

3.2 Data and variable descriptions

3.2.1 State corporate income taxes

To examine the effect of taxation, we exploit the variation in state corporate income tax changes in different U.S. states. Owing to their geographically diversified branch network and income sources, it can be difficult to determine where a financial institution is required to pay state corporate income tax.[3] The location where a bank is taxed is referred to as its economic 'nexus', which most states determine as the states where a financial institution is doing business or deriving income (Serether et al., 2011; Schandlbauer, 2017). We therefore follow Schandlbauer (2017) who defines nexus as the state in which a financial institution has at least 75% of its branches in a given year.[4] Schandlbauer (2017) notes this approach provides a more accurate depiction of the corporate tax rate a bank is subject to compared to simply using a bank's headquarter state.

3.2.2 Outcome variables

The key dependent variables in the empirical analysis measure banks' opacity and funding liquidity risk. We discuss the construction of each in turn.

3.2.2.1 Earnings opacity

Following a large literature in accounting, banking, and finance, we measure bank opacity using variables that reflect discretion in loan loss provisioning (Yu, 2008; Hutton et al., 2009; Cornett et al., 2009; Beatty and Liao, 2014; Jiang et al., 2016; Danisewicz et al., 2021). Loan loss provisions are the principal discretionary financial reporting choice a bank manager can use to impede the release of information to the public about bank profitability, estimated losses on opaque assets (Beatty and Liao, 2014; Jiang et al., 2016; Andries et al., 2017), and to optimize managers' private benefits of control (Verrecchia, 1983; Leuz et al., 2003; Doidge et al., 2009). With this discretion, a bank manager can under-report (over-report) loan loss provisions to overstate (understate) earnings and obscure the actual performance of the bank (Bushman et al., 2004). Beatty and

[3]A further complicating factor is the apportionment rules of different tax rates of a financial institution.

[4]For example, if 80% of a bank's branches are in New York and 20% in Florida, the bank is subject to the New York state corporate tax rate. By using this approach, we exclude observations of banks that have less than 75% of branches in one state. Later, we show that using different thresholds have no bearing on the findings.

Liao (2014) identify different models to measure discretionary provisions. Following their main specification, we estimate

$$LLP_{i,s,t} = \gamma ST_s + \overbrace{\underbrace{\delta \cdot X_{i,s,t}}_{\text{bank-level}} + \underbrace{\theta \cdot Y_{s,t}}_{\text{state-level}}}^{\text{non-discretionary component}} + \overbrace{\epsilon_{i,s,t}}^{\text{discretionary component}} \tag{3.1}$$

where i, s, and t denote banks, states, and years; $LLP_{i,s,t}$ is loan loss provisions; $X_{i,s,t}$ is a vector of bank-specific fundamentals outlined by Beatty and Liao (2014) including the change in non-performing assets ratio (including its lag and lead values), the log of total assets at $t-1$, and the change in the ratio of total loans at t divided by total loans at $t-1$); $Y_{s,t}$ is a vector of state-level variables in the state where bank i is headquartered (the change in Gross State Product, unemployment rate, and the Case-Shiller house price index); $ST_{s,t}$ are state-year fixed effects; and $\epsilon_{i,s,t}$ is the residual.

Following prior research (Wahlen, 1994; Cornett et al., 2009; Hutton et al., 2009; Jiang et al., 2016; Danisewicz et al., 2021), we compute bank opacity as the logarithmic form of the absolute amount of the residuals from equation (3.1) to avoid positive and negative residuals offsetting each other. That is, $Opacity_{i,s,t} = \log\left|\epsilon_{i,s,t}\right|$. Larger values of $Opacity_{i,s,t}$ imply greater earnings opacity due to more discretionary loan loss provisioning. Following Jiang et al. (2016), we also estimate positive residuals only ($Resid^{+}_{i,s,t}$) and negative residuals only ($Resid^{-}_{i,s,t}$) as proxies for earnings understatement and earnings overstatement, respectively.

3.2.2.2 Liquidity risk

Liquidity risk stems from refinancing frictions that arise due to either insufficient liquidity stock (Diamond and Rajan, 2001; Kahn and Wagner, 2021; Paravisini, 2008) or informational asymmetries (Flannery, 1996; Huang and Ratnovski, 2011). We follow Bai et al. (2018) who outline a liquidity risk measure that incorporates concurrent interactions of asset and liability components. The liquidity mismatch index ($LMI_{i,s,t}$) captures the extent of liquidity mismatch between the market liquidity of a bank's assets and the funding liquidity of its liabilities.

$$LMI_{i,s,t} = \sum_{k} \lambda_{t,a_k} a_{i,t,k} + \sum_{k'} \lambda_{t,l_{k'}} l_{i,t,k'}, \tag{3.2}$$

where $LMI_{i,s,t}$ is the liquidity mismatch index bank i in state s at time t; the asset-side weights, $\lambda_{t,a_k} = 1 - m_{t,k}$, comprise the product of asset components and their respective asset haircuts (asset-side weights); the liability-side weights, $\lambda_{t,l_{k'}} = -e^{-\mu_t T_{k'}}$, measure the product of the liability components and their respective funding liquidity conditions (liability-side weights).

Liquidity risk ($LR_{i,s,t}$) is then calculated as the difference between the baseline liquidity mismatch index and a one standard deviation shock to the liquidity mismatch index. Liquidity risk therefore reflects a bank's exposure to a 1σ change in asset haircuts and funding liquidity conditions, computed as

$$LR_{i,s,t} = LMI_{i,s,t} - LMI^{1\sigma}_{i,s,t}, \tag{3.3}$$

where $LMI^{1\sigma}_{i,s,t}$ is liquidity mismatch index after shifting the asset-side and liability-side weights by 1σ. Online Appendix B.1 describes our calculation details and information about assets and liabilities classes.

The first advantages of this approach is that it incorporates all of a bank's balance sheet and off-balance sheet components. Second, the liquidity risk variable includes dynamic asset-side and liability-side weights that reflect the actual market and funding liquidity conditions a bank faces. Finally, the measure computes a single, quarterly bank-level value for liquidity risk in dollar terms that is easy to interpret and accurately reflects market conditions (Bai et al., 2018).

3.2.3 Data sources and independent variables

We retrieve annual balance sheet and income statement data for banks that are part of a bank holding company (BHC) between 2005 and 2018 from the Federal Financial Institutions Examination Council (FFIEC) 031 and 041 Report Forms. This source provides the information we use to construct the Bai et al. (2018) liquidity risk variable, bank opacity following (3.1), and bank-level control variables including the asset growth rate ($Size_{i,s,t}$), Bai's et al. (2018) liquidity mismatch ratio ($LMI_{i,s,t}$), return on assets ($ROA_{i,s,t}$), loans to assets ratio ($Loans_{i,s,t}$), non-performing assets ratio ($NPA_{i,s,t}$), and net interest income to assets ratio ($NIM_{i,s,t}$).

To calculate bank opacity following Beatty and Liao (2014), we merge in state-level data on GDP per capita (Bureau of Economic Analysis), house prices (Federal Housing Finance Agency), and the unemployment rate (Bureau of Labor Statistics). We then estimate equation (3.1) and compute the absolute values of the regression residuals to obtain $Opacity_{i,s,t}$. In subsequent tests, we examine how taxation affects the signed residuals from equation (3.1).

The key independent variable in the tests is the annual state corporate income tax rate. As no single source provides data continuously throughout the sample, we retrieve this information from the Tax Policy Center, the Tax Foundation, and Appendix A of Heider and Ljungqvist (2015). The US Census Bureau's State & Local Finances database provides state budget surplus information. Information on the political affiliation of each state's Govenor is taken from the Princeton Data Library. Table 3.1 provides a definition of each variable in the data set and its source.

Following the previous studies in the literature (Beltratti and Stulz, 2012; Schandlbauer, 2017), we invoke sample screens to ensure that sample includes only banks with a substantial intermediary function in the domestic economy. We therefore drop observations of banks with negative equity, deposit-to-asset and net loan-to-asset ratios less than 20%, and foreign deposits to total deposits above 5%. We omit banks with annual total assets growth above 100% to remove

Table 3.1: Variable descriptions

Variable	Description	Source
Outcome variables		
$Opacity$	Natural logarithm of earnings opacity as outlined by Beatty and Liao (2014).	FFIEC 031/041, BEA, FHFA, BLS
LR	Natural logarithm of liquidity risk as outlined by Bai et al. (2018).	FFIEC 031/041, Bloomberg, EDGAR
LLP	Loan loss provisions to total assets.	FFIEC 031/041
$Resid^{+}$	Earnings understatement, represented by the natural logarithm of positive residuals of 3.1.	FFIEC 031/041
$Resid^{-}$	Earnings overstatement, represented by the natural logarithm of negative residuals of 3.1.	FFIEC 031/041
$Cash$	Cash and cash equivalents to total assets.	FFIEC 031/041
LA	Cash, excess reserves, cash equivalents, repos, securities to total assets.	FFIEC 031/041
Bank-level control variables		
$Size$	Natural logarithm of total assets.	FFIEC 031/041
LMI	Liquidity mismatch to total assets as outlined by Bai et al. (2018).	FFIEC 031/041
ROA	Return on assets.	FFIEC 031/041
$Loans$	Loans to total assets.	FFIEC 031/041
NPA	Non-performing assets to assets ratio.	FFIEC 031/041
NIM	Net interest income to assets ratio.	FFIEC 031/041

Notes: This table provides a definition of each variable and its corresponding data source used in the empirical analysis. For brevity we suppress the variables' subscripts in the manuscript.

mergers and acquisitions. As S corporations are not subject to state corporate income taxes, we remove them from the database. Finally, we exclude banks with total assets above $500 million to ensure a homogeneous unit of observation as banks larger than this threshold may benefit from too-big-to-fail guarantees and loan loss provisions are subject to different treatment by the tax code (Andries et al., 2017).

3.3 Empirical design

Our econometric setup exploits state-level variation in corporate income tax rates. Whereas federal tax rates rarely change and apply to all firms equally, changes to state corporate income taxes occur often and apply only to banks doing business in the state. This provides a set of counterfactuals of banks in states where tax rates do not change which allows us to disentangle the effect of taxes on opacity and liquidity risk from other forces shaping the outcome variables.

Using difference-in-difference estimation, we estimate

$$\triangle y_{i,s,t} = \alpha + \beta \triangle Tax_{s,t} + \gamma \triangle X_{i,s,t-1} + \varphi_s + \varphi_t + \epsilon_{i,s,t}, \tag{3.4}$$

where i, s, and t denote banks, states, and years, respectively; $\triangle y_{i,s,t}$ denotes the change in the outcome variable of interest; $\triangle Tax_{s,t}$ is an indicator variable, which is equal to one if the state corporate income tax rate increases or decreases in state s during year t, 0 otherwise; $\triangle X_{i,s,t-1}$ are one period lagged changes of bank-level control variables to account for unobservable heterogeneity and linear regional trends; φ_s and φ_t are state and time fixed effects, respectively; $\epsilon_{i,s,t}$ is the error term. The first difference terms in equation (3.4) remove time-invariant bank-level heterogeneity in the same way bank fixed effects do in regressions where the dependent variable is measured in levels. Following Bertrand et al. (2004), we cluster the standard errors at the state level.

Recent econometric innovations highlight potential biases that may arise in difference-in-difference settings featuring staggered treatments and treatment effect heterogeneity (Sun and Abraham, 2021). We therefore follow Baker et al. (2022) and construct the sample using observations of banks three years either side of a tax change (time 0) in state s. The control banks are those from states that have yet to change the state corporate income tax rate. For example, if New York increases the corporate tax rate in 2015, the treatment group comprise banks with nexus in New York between 2012 and 2018 while the controls are observations of banks between 2012 and 2018 from states that have not previously changed their tax rate. This approach ensures the average treatment on the treated effect is not contaminated by the causal effects of other relative-time periods in the estimation sample.

3.3.1 Exogeneity of state corporate income tax rate changes

Central to obtaining consistent estimates of β in equation (3.4) is the exogeneity of changes to state corporate income tax rates. Revisions to the tax code often involve lobbying activity that could lead to simultaneity bias. However, prior research on US state corporate income taxes highlights that individual firms and banks are unlikely to lobby for tax increases (Heider and Ljungqvist, 2015; Schandlbauer, 2017). For example, in 2018 Illinois raised the state corporate income tax rate from 4.8% to 7%. The tax change is plausibly exogenous from the perspective of an individual bank that operates in Illinois. Moreover, policymakers are unlikely to adjust state corporate income tax rates due to bank opaqueness or liquidity risk. Indeed in their review of the motivations behind each state corporate income tax change between 1989 and 2011, Heider and Ljungqvist (2015) find no evidence that tax changes are due to transparency or liquidity risk in the banking sector.

To formally establish which factors provoke changes to state corporate income tax rates we follow Danisewicz et al. (2018) and estimate

$$\triangle T_{s,t} = \alpha + \beta X_{s,t-1} + \varphi_s + \varphi_t + \varepsilon_{s,t}, \tag{3.5}$$

where $\triangle T_{s,t}$ is a dummy variable denoting either a tax increase, tax decrease, or tax change (that is, either an increase or decrease) in state s during year t, 0 otherwise; $X_{s,t-1}$ is a vector of explanatory variables containing state budget variables, macroeconomic conditions, and characteristics of the banking industry; φ_s and φ_t denote state and year fixed effects, respectively; $\varepsilon_{s,t}$ is the error term. We cluster the standard errors at the state level.

Table 3.2: Determinants of state corporate income tax changes

	State budget only			Inc. political and economic factors			Inc. bank factors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable:	Tax increase	Tax cut	Tax change	Tax increase	Tax cut	Tax change	Tax increase	Tax cut	Tax change
State-budget (year t-1)									
Budget surplus	-0.0269	0.0972**	0.0703*	-0.0269	0.0931**	0.0662	-0.0258	0.0938**	0.0679
	(-1.16)	(2.56)	(1.68)	(-1.14)	(2.49)	(1.61)	(-1.11)	(2.47)	(1.63)
Political factor (year t-1)									
Party (=1 if Democrat)				0.0000	-0.0419	-0.0418	0.0006	-0.0400	-0.0394
				(0.00)	(-1.35)	(-1.25)	(0.07)	(-1.30)	(-1.18)
Economic factors (year t-1)									
State GDP growth				0.0002	-0.0297***	-0.0294***	-0.0001	-0.0287***	-0.0288***
				(0.16)	(-4.19)	(-4.16)	(-0.10)	(-3.76)	(-3.79)
Unemployment rate				0.0011	0.0479***	0.0491***	0.0001	0.0467***	0.0468***
				(1.27)	(6.15)	(6.34)	(0.04)	(5.11)	(5.20)
House property index				0.0011	-0.0108	-0.0097	-0.0036	-0.0155	-0.0191
				(1.54)	(-1.26)	(-1.11)	(-0.77)	(-0.97)	(-1.21)
Banking-industry factors (year t-1)									
Assets growth							-0.0012	-0.0079	-0.0092
							(-0.58)	(-0.74)	(-0.92)
Loan to deposits							0.0161	0.0064	0.0225
							(0.76)	(0.09)	(0.32)
provisions to assets							0.1201	-1.1977	-1.0776
							(0.48)	(-0.93)	(-0.90)
Equity ratio							0.0955	0.6121	0.7076
							(0.51)	(1.29)	(1.43)
Opacity							0.0122	0.0146	0.0269
							(0.95)	(0.38)	(0.65)
Liquidity risk							0.0021	-0.0313	-0.0293
							(0.40)	(-1.31)	(-1.28)
R^2	0.0312	0.0575	0.0343	0.0312	0.0649	0.0406	0.0338	0.0726	0.0466
Number of states	50	50	50	50	50	50	50	50	50
Observations	650	650	650	650	650	650	650	650	650

Notes: This table reports the probability that a state increases, cuts, or changes taxes using linear probability models using (3.5). Columns 1–3 reports the effect of state-budget balance on a tax change, columns 4-6 report the effects of state-budget balance and political economic factors on a tax change, and columns 7-9 report the effects of state-budget balance, political economic factors, and banking-industry factors on a tax change. The sample covers 50 U.S. states (District of Columbia is excluded because it does not have a state budget) between 2005-2018, resulting in a total of 650 observations. Variable definitions are provided in Table 3.1. All regressions include year and state fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

We report estimates of equation (3.5) in Table 3.2. While we find no significant relationship between a state budget surplus and tax increases in column 1 of Table 3.2, column 2 shows a state budget surplus increases the probability of a tax cut by 9.72 percentage points. The coefficient estimate is statistically significant at the 5% level. Consistent with this finding, column 3 of the table shows a budget surplus is positively related to the probability of a tax change. In columns 4 to 6 of Table 3.2 we report estimates of equation (3.5) that include a political party variable to capture different political parties' propensity to change fiscal policy, and a vector of state-level macroeconomic characteristics that may provoke tax policy changes. Across all specifications we find no significant relationships between political factor and the tax increase, tax cut, and tax change variables. We find, however, a negative and significant relationship between economic growth and the likelihood of a tax cut.

In the remainder of Table 3.2 we investigate whether conditions in the banking industry influence tax policy within the state. We find no significant correlations between the mean rate of asset growth, the loan to deposits ratio, the loan loss provisions to assets ratio, or the capital equity ratio and the corporate taxation variables. Moreover, neither the level of earnings opacity or liquidity risk among banks operating in the state provoke increases or cuts to the state corporate income tax rate. These findings support the view that changes in state corporate income tax rates are not due to bank transparency, liquidity risk, or banking issues more generally, making it unlikely that that estimates of β in equation (3.4) are driven by simultaneity bias.

3.4 Results

3.4.1 Taxation, bank opacity, and liquidity risk

Table 3.3 reports estimates of equation (3.4). Column 1 of the table reports the effect of a tax increase on bank opacity. Our coefficient of interest is positive and statistically significant. The overall magnitude of the rise in opacity is 0.2832, which corresponds to an increase of 32.7% relative to the implied counterfactual. Next, we test the hypothesis that a tax raise increases liquidity risk. Column 2 of Table 3.3 shows estimates of equation (3.4) using liquidity risk as the outcome variable. The result reports a magnitude of 0.0876 and is statistically significant at the 1% level. This effect is equivalent to a 9.2% or $2.86 million (given average pre-tax liquidity risk of $31.11 million) increase in bank liquidity risk. Overall, these findings confirm the positive and significant effect of a tax increase on bank opacity and liquidity risk.

Next, we evaluate the effects of tax cuts on bank opacity and liquidity risk. To test this effect, we regress equation (3.4) on bank opacity and liquidity risk using the state corporate income tax cut dummy as the key explanatory variable. Columns 3 and 4 of Table 3.3 report the effects of tax cut on bank opacity and funding liquidity risk, respectively. In contrast to the previous findings, we find tax cuts have economically small and statistically insignificant effects on both bank opacity and liquidity risk. These findings indicate the asymmetrical effect of tax changes.

What explains the asymmetries between tax increases and cuts? As discussed in Section 3.1, a tax change primarily affects the cost of transparency yet has little effect on the cost of liquidity buffers. A tax raise increases the cost of transparency and may coerce a bank that initially pursue both hedging strategies to abandon transparency. Conversely, the cost of transparency declines following a tax cut. If the majority of banks in our sample behave similarly to Bank A shown in Figure 3.1, a tax cut only reduces the combined hedging costs further and does not affect its initial hedging decision.

Among the control variables, our results show larger banks are more transparent and have lower liquidity risk. Return on assets have positive correlations with opacity and transparency. We also find positive links between loans and both opacity and liquidity risk. Finally we find a negative relationship between non-performing assets and liquidity risk, and a positive relationship between non-performing assets and opacity.

Table 3.3: Effects of tax changes on bank opacity and liquidity risk

	Tax Increase		Tax Cut	
	(1)	(2)	(3)	(4)
Dependent variable:	$Opacity$	LR	$Opacity$	LR
$\triangle Tax_t$	0.2832*	0.0876***	0.0180	0.0146
	(2.77)	(8.66)	(0.43)	(0.98)
$\triangle Size_{t-1}$	-0.0153*	-0.0123***	-0.0800***	-0.0092***
	(-2.72)	(-9.80)	(-5.69)	(-3.90)
$\triangle LMI_{t-1}$	-0.0157	-0.0499	-0.1253	0.0817
	(-0.34)	(-2.06)	(-1.33)	(1.52)
$\triangle ROA_{t-1}$	13.1440***	1.4484**	12.3262***	1.0506***
	(10.61)	(4.63)	(6.19)	(3.57)
$\triangle Loans_{t-1}$	0.5680***	0.4239	-0.4876	0.4321***
	(8.17)	(2.04)	(-0.91)	(4.15)
$\triangle NPA_{t-1}$	4.6039	-0.8332**	4.5262**	-1.1791***
	(2.34)	(-3.26)	(2.27)	(-4.11)
$\triangle NIM_{t-1}$	0.7560	-0.7931	-0.1998	-1.8766
	(0.56)	(-1.28)	(-0.04)	(-1.27)
State FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	3,115	3,115	5,435	5,435
R^2	0.0322	0.9634	0.0344	0.9294

Notes: This table reports estimates of equation (3.4). $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

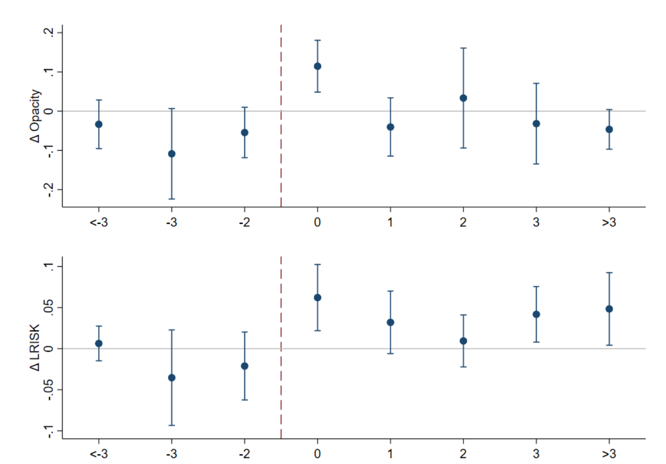
3.4.2 Interaction-weighted difference-in-difference estimator

Our identification strategy exploits the staggered implementation of state corporate income taxes across US states using two-way fixed effects (FE) difference-in-difference estimator. This strategy relies on the identifying assumptions of random exogenous shocks conditional on time and group fixed effects. However, recent econometric literature suggests that this strict exogeneity assumption may be violated under the FE design since the heterogeneity and differential timing causes the composite error term to be correlated with the treatment variable and group fixed effects (Baker et al., 2022; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021).

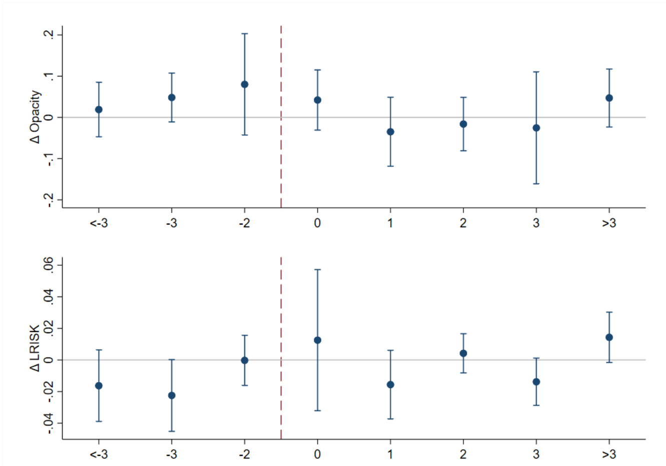
To solve this issue, Sun and Abraham (2021) proposes an alternative estimation called an interaction-weighted (IW) difference-in-difference estimator. The estimator focuses on the weighted average of "cohort-specific average treatment effects on the treated" (*CATT*) for a particular event group e and their relative time periods l, and is robust to heterogeneous treatment effects across cohorts. To complement our baseline results, we reestimate the effect of tax change on bank opacity and liquidity risk using IW estimator.

Figure 3.2 plots the estimated dynamic effect of state corporate tax increase and cut, res-

Figure 3.2: Non-parametric event study: Interaction-Weighted estimator



(a) Tax increase



(b) Tax cut

Notes: The graph illustrates the estimated dynamic coefficients and 95% confidence intervals for the effects of tax changes on bank opacity and liquidity risk using interaction-weigthed (IW) estimator. The dynamic coefficients show the yearly average difference in the outcome variable between banks subject to a tax change and banks that do not. Panel (a) reports the effects of a tax increase on the outcome variables, while Panel (b) shows the effects of a tax cut. A tax increase or cut occurs at $t = 1$. To create a more balanced panel, following Sun and Abraham (2021), we bin time periods $t < -3$ and $t > 3$.

pectively, on bank opacity and liquidity risk using IW estimator. The upper figure of Panel 3.2a shows the dynamic effects of a tax increase on bank opacity. Prior to the tax increase ($t < 0$), all dynamic coefficients are statistically insignificant. This confirms the absence of anticipation effects prior to tax raises. The coefficient becomes positive and statistically significant at $t = 0$, where the tax increase occurs. The effect of the tax increase, however, does not increase further at $t \geq 1$. Because the outcome variable is in its first-difference, this evidence implies bank opacity does not increase further in the subsequent years following a tax increase. At the same time, this also suggests no reversal effect of a tax raise on bank opacity. We also observe similar patterns in the lower figure of 3.2a. The dynamic coefficients are insignificant prior to the tax increase and become positive and significant at $t = 0$. The insignificant coefficients at $t \geq 1$ also confirm the absence of reversal effect on liquidity risk. Next, we turn our discussion to the effect of a tax cut on bank opacity and liquidity risk. The upper (lower) figure of Panel 3.2b illustrates the dynamic effects of a tax cut on bank opacity (liquidity risk). Our findings show statistically insignificant effects of a tax cut on both outcome variables across all time periods.

Overall, our FE and IW estimates happen to be similar in their magnitude. Hence, the results of our baseline FE estimates still hold: a tax increase has positive effects on bank opacity and liquidity risk, while a tax cut has muted effects on both outcome variables. This auxiliary test also corrects potential contamination arising from our heterogeneous treatment effects.

3.4.3 Taxation and opacity: The earnings smoothing channel

Our baseline results in Table 3.3 show how higher corporate taxation provokes banks to extract more private benefits, which reduces opacity. Now, our discussion turns to the mechanism behind this relationship.

Firms can extract more private benefits by smoothing their earnings (Bushman and Williams, 2012; Ellul et al., 2015). For banks, earnings smoothing can be managed using loan loss recognition (Bushman et al., 2004; Beatty and Liao, 2014). Higher corporate tax rate therefore may lead to greater loan loss provisioning because it gives incentives to banks to have timelier loan loss recognition and smooth earnings (Andries et al., 2017). Since loan loss provisioning has discretionary and non-discretionary components, banks may exploit the discretionary component to recognize more than necessary provisioning and build up reserves when earnings are high, which can be utilized when earnings are low. This implicit forward-looking orientation enables opportunistic earnings smoothing that conceals fundamentals and increases opacity (Bushman and Williams, 2012).[5]

To test this mechanism, we first evaluate how loan loss provisions evolve in response to a tax change. In column 1 of Table 3.4, we estimate a tax increase has a positive and significant

[5]Bushman et al. (2004) also suggest another potential channel through discipline over risk-taking. Timelier loan loss recognition may signal the public about the bank's future expected losses, inciting market discipline behavior. We test this mechanism using the approach outlined by Andries et al. (2017). Online Appendix Table B.5, however, shows that this is not the case.

Table 3.4: Earnings smoothing channel

	Tax Increase			Tax Cut		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	LLP	$Resid^+$	$Resid^-$	LLP	$Resid^+$	$Resid^-$
$\triangle Tax_t$	0.0025**	0.8305***	0.0217	-0.0001	-0.0415	0.1042
	(3.36)	(6.89)	(0.20)	(-0.57)	(-0.64)	(1.72)
Control Variables	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Observations	3,115	1,596	1,519	5,435	2,468	2,967
R^2	0.1505	0.0836	0.1727	0.1328	0.0887	0.1186

Notes: This table reports estimates of equation (3.4) using loan loss provisions, earnings understatement ($Resid^+$), and earnings overstatement ($Resid^-$) as the outcome variables. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

correlation with loan loss provisions to assets ratio ($LLP_{i,s,t}$). Economically, a tax raise increases loan loss provisions by 0.25 percentage point, which translates to 75.8% increase given the pre-tax amount of loan loss provisions of 0.33% of total assets. This evidence confirms the banks' incentives to have a timelier loan loss recognition after a tax increase.

Next, we examine whether the opportunity to recognize timelier loan loss provisioning motivates earnings smoothing by exploiting discretionary provisions. Equation (3.1) shows that loan loss provisions comprise of discretionary and non-discretionary components. If banks build up reserves to smooth earnings, the contribution of discretionary component, particularly earnings understatement will increase. Hence, we estimate equation (3.4) using earnings understatement ($Resid^+_{i,s,t}$) and overstatement ($Resid^-_{i,s,t}$) as the outcome variables. Columns 2 and 3 of Table 3.4 present the estimates. Column 2 reports the estimate of equation (3.4) using earnings understatement as the outcome variable. The result shows positive effect of tax increase on earnings understatement and is significant at the 1% levle. This evidence is consistent with the finding of Bushman and Williams (2012) that suggests the presence of earnings smoothing behavior due to the banks' implicit forward-looking orientation. Column 3 in Table 3.4 provides the result of equation (3.4) using earnings overstatement as the dependent variable and reports no evidence of significant impact of a tax increase on earnings overstatement.

The remainder of Table 3.4 reports estimates for tax cuts. Across columns 4 to 6, we find no evidence that a tax cut provokes a significant change in loan loss provisions, earnings understatement, or overstatement.

3.4.4 Liquidity strategy and hedging cost

A key feature of our conceptual model is the role of each hedging cost in influencing a bank manager's liquidity management decision. As shown by Figure 3.1, a bank with higher transparency cost is more likely to abandon transparency after a tax increase. This raises a follow-up question: Why some banks have higher transparency cost than the others?

Since banks contain complex information, increased transparency may generate information asymmetries among agents (Landier and Thesmar, 2014). This relationship is more pronounced in low performance banks where information asymmetries can easily provoke the inefficient emergence of adverse selection and increase the probability of liquidation risk (Pagano and Volpin, 2012). Lower banks performance is also often associated with weaker corporate governance (Aebi et al., 2012; Klapper and Love, 2004). Other studies also suggest that transparency erodes managers' private benefits of control of banks with lower profitability (Verrecchia, 1983; Ahmed et al., 2010; Ratnovski, 2013). This implies that, in the face of a tax increase, banks with worse performance have relatively higher cost of transparency compared to more profitable banks because a higher tax rate exposes them to greater information asymmetries and reduces managers' payoffs to a greater extent.

Table 3.5: Liquidity strategy and hedging cost

	Tax increase				Tax cut			
	Above median		Below median		Above median		Below median	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$Opacity$	LR	$Opacity$	LR	$Opacity$	LR	$Opacity$	LR
$\triangle Tax_t$	0.0915	0.0190	0.3685**	0.0972***	0.1655	0.0272	-0.0470	0.0067
	(0.65)	(1.19)	(3.46)	(13.87)	(1.58)	(1.66)	(-1.04)	(0.55)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	911	911	2,204	2,204	1,643	1,643	3,792	3,792
R^2	0.0619	0.9739	0.0379	0.9576	0.0574	0.9417	0.0361	0.9263

Notes: This table reports estimates of equation (3.4) using samples split at the median level of return on assets. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

We evaluate the role of transparency cost by splitting the sample according to whether a bank's performance, represented by return on assets, lies above or below the median. Sample with return on assets above the median value represents banks with low transparency cost and *vice versa*. Columns 1 and 2 of Table 3.5 presents estimates of equation (3.4) for banks with return on assets above the median or low transparency cost. For this set, a tax increase has no effect on either bank opacity or liquidity risk. These results imply that, where transparency cost is low, banks are less responsive to a tax increase, thus do not change their liquidity management strategy. In contrast, in columns 3 and 4 of Table 3.5 we find that a tax increase provokes significant increases in bank opacity and liquidity risk for banks with below median return on assets. Bank opacity increases by 44.6% following a tax increase for less profitable banks, while liquidity risk increases by 10.2%. Overall, these findings highlight the imperative role of transparency cost in influencing a bank manager's liquidity management decision in response to a tax increase.

Columns 5 to 8 of Table 3.5 provide the corresponding results for a tax cut. Irrespective of which sample or dependent variable we consider, the tax cut coefficient estimate is statistically insignificant and in line with the outcome of our baseline results

3.4.5 Wholesale funding and liquidity risk

Another central tenet of our model that explains the linkages between taxation, bank opacity, and liquidity risk is the banks' reliance on wholesale funding. From discussions in Section 3.1, we can infer that a bank relying more on wholesale funding is more likely to be exposed to a large fund withdrawal, hence liquidity risk. For these banks, transparency is the more optimal liquidity strategy since it enables bank to refinance large withdrawals. Where a tax increase occurs, a combination of greater reliance on wholesale funding and a decision to abandon transparency exposes these banks to higher liquidity risk. As a validation check, we therefore examine whether the level of wholesale funding influences the effect of the taxation on its liquidity risk. Following Ratnovski (2013), we compute uninsured deposits to total deposits as a measure of wholesale funding level. We then divide the sample into high-reliant banks, if the ratio is above 25%, and low-reliant banks, if the ratio is equal or below 25%, and re-estimate equation (3.4).

Table 3.6: Wholesale funding and liquidity risk

	Tax increase				Tax cut			
	High reliance		Low reliance		High reliance		Low reliance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$Opacity$	LR	$Opacity$	LR	$Opacity$	LR	$Opacity$	LR
$\triangle Tax_t$	0.1572***	0.0796*	0.4065	0.0519**	-0.0950	0.0157	0.0924	-0.0048
	(5.90)	(3.04)	(1.55)	(4.38)	(-1.23)	(0.67)	(1.45)	(-0.71)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,218	1,218	1,897	1,897	2,378	2,378	3,057	3,057
R^2	0.0400	0.9771	0.0381	0.9669	0.0414	0.9618	0.0404	0.8486

Notes: This table reports estimates of equation (3.4) using sample split whether a bank relies on wholesale funding, represented by uninsured deposit to deposit ratio above 25% (high reliance) or below 25% (low reliance). $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.6 highlights the results of this split sample estimates. Columns 1-4 show the tax increase regressions. Column 1 of Table 3.6 shows a positive and statistically significant effect of a tax increase on the opacity of banks with greater reliance on wholesale funding. Similarly, a tax raise also significantly increases the liquidity risk of these banks (column 2). In terms of economic magnitude, the coefficients of these regressions are consistent with our baseline results in Table 3.3. Meanwhile, columns 3 reports an insignificant effect of a tax increase on bank opacity for banks that rely less on wholesale funding. Further, column 4 shows the effect of a tax rise on liquidity risk in wholesale funding less reliant banks. The result shows positive and significant effect of a tax increase on banks that rely less on wholesale funding even though the magnitude is much smaller than the wholesale funding reliant banks. In summary, this evidence supports the premise that the higher reliance on wholesale funding exposes banks to more liquidity risk.

Columns 5-8 of Table 3.6 report the results of the tax cut regressions. Similar to our baseline results, the regression estimates are statistically insignificant across all columns.

3.4.6 Taxation and liquidity buffers

Our model predicts that a tax increase provokes an increase in liquidity risk if a bank manager imposes insufficient (socially suboptimal) hedging by abandoning transparency. Therefore, liquidity risk solely increases in banks that are supposed to have two hedges but privately choose liquidity buffers only. This implies that a tax raise increases opacity but has no effect on liquidity buffers. To test this, we regress equation 3.4 using $Cash$ (cash and cash equivalents to total assets) and LA (cash, excess reserves, cash equivalents, repos, and securities to total assets) as the outcome variables. Table 3.7 presents the estimates. Columns 1 and 2 show no evidence of significant effects of a tax increase on both cash equivalents and liquid assets. This evidence infers that most banks in our samples initially imposed two hedges and decided to become opaque after a tax increase due to the increasing cost of transparency, while maintaining their liquidity buffers.

Indeed, as discussed in Section 3.1, a bank considers both strategies as substitutes if the hedging costs are sufficiently high. In this case, a transparent bank may switch to liquidity buffers if the cost of transparency is higher than that of liquidity buffers, leading to an increase in liquid assets holdings. However, we can plausibly rule out this situation due to two factors. First, the banks in our sample had relatively ample liquid assets throughout the sample period, i.e. liquid assets ratio between 25% and 30%. Even after the global financial crisis, these banks still maintained liquid assets ratio above 20%.[6] Second, expenses on repos and interbank market, which can be considered as a proxy for the cost of liquidity buffer, show a declining trend throughout the same period. Online Appendix Figure B.2 illustrates the evolution of liquid assets ratio and expenses on repos and interbank market, respectively.

[6]Unlike large bank holding companies, our sample consists of small to medium bank subsidiaries with total assets below $500 million that were not significantly affected by the financial crisis (**citation**).

Table 3.7: Liquidity management strategy trade-off

	Tax Increase		Tax Cut	
	(1)	(2)	(3)	(4)
Dependent variable:	*Cash*	*LA*	*Cash*	*LA*
Tax change$_t$	0.0048	-0.0062	0.0003	-0.0001
	(0.81)	(-1.15)	(0.12)	(-0.05)
Control Variables	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	3,115	3,115	5,435	5,435
R^2	0.0650	0.0750	0.0571	0.0728

Notes: This table reports estimates of equation (3.4) using cash equivalents ($Cash$) and total liquid assets (LA) as the outcome variables. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax increase. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Columns 3 and 4 of Table 3.7 report the effect of a tax cut on the liquid asset variables. Consistent with our previous evidence, the effects of tax cuts remain statistically insignificant.

3.5 Robustness tests

In this section, we test the sensitivity of the findings to alternative explanations and rule out threats to identification.

3.5.1 Placebo tests

Placebo tests offer a window into whether the findings are due to changes in state corporate income tax rates or other observable and unobservable confounds. In samples where there are no revisions to tax rates, there should be no changes to bank opacity or liquidity risk. We therefore conduct a falsification exercise by randomly assigning placebo tax shocks to banks in states contiguous to state A (where the tax rate changes at time t) where the tax rate does not change at time t. For example, Illinois increases the state corporate income tax rate from 4.80% to 7.00% in 2011. We then constrain the sample to banks in states without a tax change in 2011 that are contiguous to Illinois (Indiana, Iowa, Kentucky, Missouri, and Wisconsin), and randomly assign one of the contiguous states to a placebo treated status ($Placebo_{s,t} = 1$), and the rest to placebo control status ($Placebo_{s,t} = 0$). Then we estimate

$$\triangle y_{i,s,t} = \alpha + \beta \triangle Placebo_{s,t} + \gamma \triangle X_{i,s,t-1} + \varphi_s + \varphi t + \epsilon_{i,s,t}, \tag{3.6}$$

where all variables are defined as in equation (3.4) except $\triangle Placebo_{s,t}$ that equals 1 if a state is randomly assigned to placebo treated status, and 0 for placebo control status. We know that the null hypothesis that $\beta = 0$ in equation (3.6) holds. If this is not the case, then our baseline findings are likely driven by industry-wide shocks or trends in the dependent variables, rather than changes to state corporate income tax rates.

Table 3.8: Placebo test: Neighboring states without tax changes

	Tax Increase		Tax Cut	
	(1)	(2)	(3)	(4)
Dependent variable:	$Opacity$	LR	$Opacity$	LR
$\triangle Placebo_t$	0.0118	-0.0231	-0.0290	-0.0049
	(0.13)	(-0.70)	(-0.79)	(-0.73)
Control Variables	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	7,590	7,590	9,829	9,829
R^2	0.0561	0.9652	0.0309	0.9104

Notes: This table reports estimates of equation (3.4) using the neighboring states without tax changes as the sample. $\triangle Placebo$ is a dummy variable that is equal to one in the year of a placebo tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Column 1 of Table 3.8 reports estimates of equation (3.6) using bank opacity as the dependent variable. The placebo tax increase coefficient estimate is economically close to zero and statistically insignificant. We obtain similar results in column 2 which reports estimates of equation (3.6) using liquidity risk as the dependent variable. Again, the placebo tax increase is insignificant. Hence, it is only actual tax rate increases that provoke significant rises in bank opacity and liquidity risk. It therefore seems unlikely that the results reflect omitted variable bias.

3.5.2 Other tax policies

Perhaps the most serious threat to identification during the sample period are revisions to other forms of taxation.

We first rule out that cuts to the federal corporate income tax rate drive the inferences. While changes to federal corporate taxes are relatively rare, the Tax Cuts and Jobs Act of 2017 dramatically lowered the federal corporate income tax rate from 39% to 21%.[7] This is unlikely to confound the estimates because the shock is aggregate in nature, affects all banks equally, and is captured by the year fixed effects in the estimating equation. To ensure the inferences reflect the effects of the state corporate tax changes rather than the Tax Cuts and Jobs Act of 2017, we drop observations from the year 2015 onward. Table 3.9 reports the estimates using the trimmed data set. Overall, we find that the baseline results are robust.

[7] A major element of the bill was the reduction of federal tax rates for corporations. For example, the corporate tax rate was changed from a tiered system ranging between 15% and 39% to a flat 21%. This significant reduction rate affected both non-financial corporations and financial institutions. The Tax Cuts and Jobs Act of 2017 was introduced on 2 November 2017 and went into effect on 1 January 2018.

Table 3.9: Federal Tax Cuts and Jobs Act of 2017

	Tax Increase		Tax Cut	
	(1)	(2)	(3)	(4)
Dependent variable:	$Opacity$	LR	$Opacity$	LR
$\triangle Tax_t$	0.2844*	0.0877***	0.0562	0.0498
	(2.77)	(8.61)	(0.69)	(1.38)
Control Variables	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	2,739	2,739	3,399	3,399
R^2	0.0352	0.9644	0.0509	0.9488

Notes: This table reports estimates of equation (3.4) by dropping the observations from year 2015 onward. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

3.5.3 Sensitivity checks

The choice of control variables can have important repercussions for regression analyses. To ensure the results are not driven by the 'bad control' phenomenon, we remove the control variables from equation (3.4). The coefficient estimates in Panel A of Online Appendix Table B.2 are strongly similar to the baseline findings which indicates the results are not due to conditional correlations between the controls and the tax change variables. The high degree of comparability between the baseline coefficient estimates and those in Panel A of Online Appendix Table B.2 further strengthens the view that tax changes are exogenous with respect to bank bank opacity and liquidity risk (Roberts and Whited, 2013).

During financial crises banks use discretionary accounting to overstate the value of distressed assets and regulatory capital to conceal problems (Huizinga and Laeven, 2012). Policymakers may respond to the crisis using expansionary fiscal policy to alleviate the recession. To ensure the findings are not due to the crisis and concomitant changes to tax policy, we drop observations from before 2010. Despite this change, the estimates remain robust in Panel B of Online Appendix Table B.2.

Another potential threat to identification is that treated and control banks may differ along observable dimensions, and changes to these characteristics correlate with tax shocks. Importantly, Online Appendix Figure B.1 shows treated and control banks strongly resemble each other. Nevertheless, we use propensity score matching to ensure the two groups are comparable. We first compute propensity scores using banks' size, loans to assets, loans to deposits, net interest margin, share of C&I loans to total loans, and capital to assets as predictors of treatment status. Our matching algorithm then matches a treated bank to its five nearest neighbors with replacement and a 0.01 caliper.[8] This results in a sample size of 1,042 and 3,334 observations for

[8] Since our sample consists of multiple tax increases and cuts that occur at different points in time, we only match

tax increase and tax cut episodes, respectively. Panels A of Online Appendix Table B.3 report the characteristics of treated and control banks in cases of tax increases and tax cuts, respectively. Wilcoxson rank-sum test and the Kolmogorov-Smirnov test, and t-tests confirm that there are no significant differences between the size, loan-to-deposit ratio, deposit-to-asset ratio, loan-to-asset ratio, and net interest margins of treated and control banks.

Panel B of Online Appendix Table B.3 reports estimates of the average treatment on the treated effect using the matched sample. Despite a dramatic change in sample size, we continue to find that tax increases lead to significantly higher bank opacity and liquidity risk whereas tax cuts have insignificant effects on the outcome variables. Moreover, the coefficient estimates in columns 1 and 2 of the Panel are similar in economic magnitude compared to the baseline results.

Previously, we highlighted the difficulties researchers face in establishing a bank's nexus state. To ensure that defining nexus following the Schandlbauer (2017) approach provides reliable estimates, we conduct two sensitivity checks. First, we constrain the sample to banks that only operate branches within a single state. For this set of banks, tax nexus is most plausibly the state in which they exclusively operate. Second, rather than assigning nexus using the criteria that a bank has at least 75% of its branches within a state during each year, we use 85% as threshold instead. The estimates of Online Appendix Table B.4 show the results are robust to using only single-state banks and a 85% threshold, respectively.

3.6 Conclusions

The effect of corporate taxation on bank transparency has not been widely discussed. Our study outlines a model predicting how banks avoid higher tax rates by becoming less transparent or more opaque, provoking an increase in liquidity risk. Specifically we hypothesize that, where a bank relies on wholesale funding as its main source of funding and where the possibility of effective communication with investors is high, its decision to abandon transparency in response to a tax increase can lead to higher liquidity risk.

Our empirical findings confirm this prediction. First, we find evidence of 32.7% higher bank opacity following a tax increase, indicating a bank manager's decision to abandon transparency. This higher level of opacity is accompanied by 9.2% higher liquidity risk. Further investigation shows that greater opacity is due to the banks' exploitative behavior of discretionary earnings smoothing in response to a tax raise. Banks with higher transparency cost are more likely to abandon transparency in response to a tax increase. Additionally, banks that rely more on wholesale funding are also exposed more to liquidity risk, confirming the sub-optimal liquidity buffers hedging when the probability of experiencing a large withdrawal is high. Finally, we no significant effects of a tax raise on liquid assets, implying the muted effect of tax raise on liquidity buffers.

a bank from the treated group with five banks from the control groups in the same year for each tax increase or cut. Every bank is therefore either in the treated group or control group depending on the year of the tax change.

We also predict the insignificant effect of tax cuts on the banks' hedging strategy. On a contrary to a tax raise, a tax cut reduces the cost of transparency and has little effect on the cost of liquidity buffer. Lower tax rate therefore gives more incentives for banks to become more transparent. Our empirical tests further confirm this prediction.

This lack of symmetrical effect of taxation may be due to two possible reasons. First, most banks are more likely to have initial transparency strategy prior to a tax cut, which only reinforces their preexisting transparency strategy. Second, for banks with initial liquidity buffers, the average tax cuts are economically small to create any significant impact.

Our findings provide novel insights into the unintended consequences of corporate taxation. So far, only a few studies on banking and financial institutions empirically address this question despite the potentially widespread ramifications of tax regulation, particularly that related to tax deductible loan loss provisioning. In other words, the tax system can be used as a policy tool to influence bank managers liquidity management strategy to reduce liquidity risk in the banking system. Investigating whether this is the case is an interesting avenue for future research.

Chapter 4

Do complex banks deliberately hide their risks?

Regulators have become increasingly concerned about banks that operate multiple lines of business outside their core retail banking activities due to their opaqueness, which impedes monitoring and supervision (Morgan, 2002; Dam and Koetter, 2012; Duchin and Sosyura, 2014). This business model, which is known as "universal banking", was one of the major factors that increased bank risk and precipitated the Financial Crisis of 2007-2008 (Agarwal et al., 2012; Chernobai et al., 2020; Neuhann and Saidi, 2016). A common motivation for breaking up universal banks is that the resulting standalone institutions are more transparent and subject to less information asymmetry.[1] Owing to policymakers' concerns, recent changes to the regulatory framework create incentives for banks to become more transparent.[2] Despite these regulatory currents there is little evidence linking business diversification to bank opacity.

In this paper, we empirically study the link between bank business diversification and bank opacity. An econometric concern is reverse causality: a bank holding company may diversify its operations into non-banking activities due to rising opacity. To overcome this identification challenge, we exploit the staggered deregulation of non-banking activities between 1996 and 1999 when the Gramm-Leach-Bliley Act (GBLA) abolished these restrictions entirely.[3] We use a difference-in-difference estimator to study the differential effect of the deregulation episode on diversified banks versus non-diversified banks. During the 1980s the FRB allowed banks to

[1]Recent examples include Royal Bank of Scotland and Barclays which have scaled back their investment banking operations to focus on retail banking. Meanwhile, UBS closed parts of its investment bank to focus on wealth management.

[2]The 2010 Living Will provision of the Dodd-Frank Act increases the cost of operating a complex business model. Under the regulation organizationally complex banks must simplify their structures to assist in resolving the bank in the event of failure (Correa and Goldberg, 2020).Basel III contains capital surcharges that increase with bank peculiarities associated with complexity (Martynova and Vogel, 2022).

[3]Barth et al. (2000) provide several reasons for the exogeneity of the deregulation of non-banking activities, which is discussed in details in Sections 4.2 and 4.3 of this paper.

expand to non-banking activities by establishing section 20 investment banking subsidiaries. Section 20 banks were allowed to engage in securities underwriting with a cap of 5% of total revenue. As banks' pre-1996 diversification decisions were taken ahead of deregulation, these choices were not driven by omitted variables during the deregulation period. However, banks that dealt in securities through their section 20 subsidiaries before deregulation were able to expand into more non-banking activities after deregulation. This differential treatment effect allows us to isolate the effect of business diversification on opacity by comparing the evolution of opacity within section 20 and non-section 20 banks.

Following banking literature, we measure bank opacity using discretionary loan loss provision (Beatty and Liao, 2014; Jiang et al., 2016). Banks that use more discretion to manipulate their earnings are more likely to obscure fundamentals and less transparent. Using these variables as our main outcome variable, our estimates show the deregulation provoked a significant 43.1% increase in bank opacity. The effect on section 20 banks was economically more sizeable because these banks engaged more in complex banking activities. Because the deregulation was implemented gradually, from the "firewall" eliminations in 1996 until the enactment of the GLBA in 1999, we also evaluate the effect of each stage's deregulation phase. Our findings show that, while both phases significantly increased the opacity within section 20 banks, the effect of the GLBA was economically more sizeable. Different from the 1996 deregulation that only eliminated some of the restrictions, the GLBA completely abolished the restrictions related to investment banking activities and enabled the creation of universal banks, which explains the results.

Banks increased their opacity because more complex banking activities increased monitoring costs and reduced market discipline. Our tests show a positive and significant effect of bank complexity on opacity. We also find business complexity increased significantly after the deregulation, which explains the concomitant rise in bank opacity. Further examination shows that complex, diversified banks increased their opacity to obscure their risk taking activities and hide income volatility. This relationship is only significant within section 20 banks that were more invested in these complex non-commercial banking activities. Finally, we find that banks with higher insolvency risk are more likely to take more risk to raise capital and have greater opacity to hide internal vulnerabilities and avoid adverse selection.

Our findings contribute to the reemerging debate regarding complex diversified banks. Evidence from 2008 shows that complex banks played a prominent role in the financial crisis. Subsequent literature increasingly shows positive linkages between banks operating diversified business models and risk (Bonfim and Felix, 2020; Chernobai et al., 2020; Martynova and Vogel, 2022; Neuhann and Saidi, 2018). Central to this nascent literature is the assumption that diversified banks are more opaque than standalone institutions which exacerbates agency problems and risk taking (Correa and Goldberg, 2020; Landier and Thesmar, 2014; De Jonghe, 2010; Klein et al., 2021). We provide novel evidence that bank opacity, complexity, and risk taking are closely tied to each other because complex banks increase their opacity to obscure risk taking activities and avoid market discipline.

Our paper bridges two distinct streams of research. Prior theoretical work provides ambiguous predictions about the relationship between business diversification and opacity. Earlier literature suggests the negative effect of business diversification on transparency. Providing investors' earnings forecast errors not perfectly positively correlated across divisions, the error is in part diversified away across divisions leading to smaller absolute errors that reduce opacity (Thomas, 2002). In essence, diversification mitigates idiosyncratic shocks leading to more accurate earnings. However, more recent theoretical studies suggest the otherwise. Where banking business is more diversified, divisional managers have incentives to restrict transparency to increase their private benefits of control (Anderson et al., 2009; Pagano and Volpin, 2012; Dang et al., 2017; Hwang, 2021). Unlike these articles, our work shows the positive linkage between business diversification and opacity from an empirical point of view.

A parallel strand of literature links bank complexity and risk. Previous studies show the positive effects of geographic and organizational complexity on bank risk (Bonfim and Felix, 2020; Martynova and Vogel, 2022). Other studies provide the linkage between business complexity and bank volatility (Neuhann and Saidi, 2018) or operational risks (Chernobai et al., 2020). In contrast, our paper illustrates how banks increase their opacity to hide risks arising from greater business complexity as represented by the intensified complex non-commercial banking activities.

The paper proceeds as follows. Section 4.1 outlines our hypothesis statements. Section 4.2 describes the history of banking deregulation in the U.S. that preceded the increasing complexity of the U.S. banks. Section 4.3 provides the identification strategy and data sources. We report our empirical evidence in Section 4.4, and present robustness tests in Section 4.5. Finally, Section 4.6 concludes.

4.1 Hypotheses development

Our hypotheses build on prior research concerning the link between business diversification and opacity. Diversified banks are less transparent relative to focused banks because of their complex structures, resulting in a higher level of information asymmetry between managers and investors (Thomas, 2002; Bushman et al., 2004). Compared to standalone banks, a multidivisional, diversified bank typically gives managers informational advantage over outsiders on a bank's financial position and financial disclosure (Hwang, 2021). Outsiders may reduce their disadvantage by incurring monitoring costs. However, some firms may be relatively harder to monitor, particularly when they are engaged in more diverse lines of business (Rodriguez-Perez and van Hemmen, 2010).

From an investor's perspective, combining diverse operations obfuscates information because the earnings of each division within a diversified bank are reported at the bank rather than division level. Splitting a diversified firm's divisions into separately operated entities can mitigate the information asymmetries about each division's earnings (Thomas, 2002). In addition, banks that operate across industrial divisions force outsiders to expend greater resources to understand industries that lie outside their area of expertise (Landier and Thesmar, 2014). Indeed, evidence shows analysts specialize in industrial segments and monitoring firms outside their specialism imposes greater information collection costs (Gilson et al., 2001). Where banks diversify their business by increasing the proportion complex transactions, the outsiders' monitoring costs increase through information aggregation problems and by forcing them to exert additional monitoring effort. As the costs of monitoring increase, investors undertake less monitoring leading to a reduction in market discipline and a concomitant increase in bank opacity (Danisewicz et al., 2018, 2021). This leads to the hypothesis

H1: bank opacity is higher among diversified banks that engage in complex banking activities.

Why do complex, diversified banks want to increase their opacity? From the holding group's point of view, business diversification is often associated with risk diversification. While it is largely true for non-financial firms to have diversified revenue streams to maintain group performance, the relationship becomes less relevant in financial firms. Within financial firms, whether or not business diversification reduces risk largely depends on the type of diversifying activities undertaken by a bank holding company (De Jonghe, 2010). Traditional banking activities predominantly rely on stable and more transparent interest income (Landier and Thesmar, 2014). On the contrary, complex investment banking activities such as securitization tend to obscure risk and have greater return volatility (Klein et al., 2021). Evidence further shows that, despite the adverse effect on return volatility, these activities do not increase the average profitability and undermine banking stability (De Jonghe, 2010). Complex transactions such as securitization also reduces the incentives of banks to thoroughly screen their borrowers, leading to higher bank risk (Keys et al., 2010; Wang and Xia, 2014). Accordingly, higher opacity within diversified banks may be associated with the increasing proportion of complex activities within their business and the banks' attempt to conceal their risk appetite. In practice, this can be achieved by utilizing discretionary earnings smoothing that obscures fundamentals and transparency (Bushman and Williams, 2012). We hypothesize that

H2: diversified banks with complex business model become opaque to hide risk taking activities and obfuscate income volatility.

The dynamics between a bank's complexity, risk-taking and opacity may also be influenced by its solvency level. Undercapitalized banks face more incentives to reduce disclosure (Begley et al., 2017). If complex information from a bank is released to the public through disclosure, higher lever of transparency can generate information asymmetries among agents and lead to the inefficient emergence of adverse selection (Pagano and Volpin, 2012). Banks also have the propensity to take more risk to forcefully increase their capital levels (Acosta-Smith et al., 2020). This leads to the hypothesis

H3: diversified banks with lower capital levels are more likely to pursue more risk taking activities to increase capital and have greater opacity to hide their vulnerabilities.

Ultimately, whether this is the case is a matter of empirical question.

4.2 Institutional background

The enactment of the GSA of 1933 completely separated commercial and investment banking activities. Under section 20, the act prohibited banks from creating interlocks of managers and employees as well as affiliating with a financial institution "engaged principally" in securities underwriting or dealing (Lown et al., 2000). The aim of these more than 30 "firewalls" were to cushion bank subsidiaries from risky non-bank subsidiaries. Therefore, the GSA of 1933 limited the business scope of the banks to traditional "commercial banking" activities.

Throughout 1980s, however, the deterioration of the quality of credit in many banks and the declining competitiveness of the U.S. banks led to significant loan losses and the loss of market share of the U.S. banks domestically and abroad (Calomiris, 2000). These events pressured U.S. regulators to reform the banking system. According to the FRB's legal interpretation of the GSA in April 1987, commercial bank holding companies (BHCs) were allowed to establish separate section 20 subsidiaries with a 5% revenue limit on section 20 ineligible securities activities (Cornett et al., 2002). The FRB contended that the clause "engaged principally" allowed banks to engage in securities underwriting as long as the contribution was still negligible. After this reinterpretation, a number of banks, particularly primary dealers of government securities, immediately established section 20 subsidiaries to better manage their balance sheet (Kwan, 1998). In September 1989, The FRB raised the revenue cap of these section 20 subsidiaries from 5% to 10%.

Since its enactment, there were numerous attempts to repeal the GSA (Barth et al., 2000). The latest deregulation attempt began in the late 1980s when Alan Greenspan, the Chairman of The FRB, argued to eliminate the "firewalls" that separated bank subsidiaries from non-bank subsidiaries because it hampered banking competitiveness (Greenspan, 1988). This reignited the banking sector's attempt to formally propose the repeal of GSA. In 1990, Greenspan further argued that the affiliation restrictions undermine global competitiveness, financial innovation and assets growth of the U.S. banking sector (Greenspan, 1990). However, the proposal was rejected by the United States House Committee on Financial Services in 1991.[4]

Several factors that occurred in the late 1990s suddenly changed the view of regulators on this strict regulatory stance (Barth et al., 2000). The first factor was the growing contemporary empirical evidence supporting the deregulation (Kroszner and Rajan, 1997; Puri, 1999). These early studies endorsed deregulation to encourage U.S. banks to keep up with their Japanese

[4]Wilmart (2017) discusses in details the chronology of this failed deregulation attempt.

and European counterparts (Calomiris, 2000). The second factor was the few banking problems associated with the limited securities and insurance activities that had been allowed under the section 20 subsidiaries. This justified and advocated the allowance of wider range of investment banking activities. The third factor was the technological advancement that enabled banks to use data cheaply in engaging in these activities.

In response to these factors, The FRB initially eliminated many of the "firewalls" between bank and non-bank subsidiaries within banks and raised the cap on revenue from section 20 subsidiaries to 25% in August 1996. By the end of 1997, most of these firewalls had been removed. The continuous pressure from large financial such as Bankers Trust, Citicorp and J.P. Morgan to allow the creation of competitive "universal banks" finally resulted in the enactment of GLBA in November 1999 (Bhargava and Fraser, 1998).[5] The act fully repealed the GSA and eliminated the revenue cap. It also removed the barriers that separated commercial banking business from the insurance business. Concurrently, this repeal resulted in a significant increase in underwriting revenues and annuity sales immediately after the deregulation (Lown et al., 2000).

This deregulation transformed the landscape of banking system in the U.S. banks, which shifted their activities from balance sheet-based lending to off-balance sheet financing. They also implemented new strategies such as: 1) maximizing the use of complex financial transactions such as syndications, loan sales and securitizations; 2) exploiting customer niches; and 3) offering more innovative and flexible financial products (Calomiris, 2000). As a consequence, banks started imposing their new role as universal banks that provide one-stop financing services to firms, including various types of lending, underwriting, private equity financing, and asset management.

4.3 Data and methodology

We start this section by describing the variables and data sources. We then present our identification strategy. Finally, we describe the empirical implementation and econometric framework to test our hypotheses.

4.3.1 Data and variables descriptions

4.3.1.1 Bank opacity

In the banking literature, opacity can have various interpretations and the measurement thereof presents an empirical challenge. We follow mainstream bank literature by measuring opacity based on discretionary loan loss provision (Beatty and Liao, 2014; Jiang et al., 2016).[6] Loan loss

[5]The enactment of GLBA was motivated by the pressures from the banking sector to create a more competitive and innovative banking sector in the U.S. that can compete with their European counterparts (Barth et al., 2000; Cetorelli and Goldberg, 2014), which is unrelated to bank transparency, the main outcome variable of our study.

[6]Another strand of literature evaluates market microstructure properties of banks' stock prices in measuring bank opacity (Kyle, 1985; Flannery et al., 2004, 2013). We deem these opacity measures are less appropriate for our study

provisions are the principal discretionary financial reporting choice a bank manager can use to impede the release of information to the public about bank profitability (Beatty and Liao, 2014; Jiang et al., 2016). With this discretion, a bank manager can under-report (over-report) loan loss provisions to overstate (understate) earnings and obscure the actual performance of the bank (Bushman et al., 2004). We use the preferred loan loss provision model suggested by Beatty and Liao (2014) since it has the best prediction power at identifying discretionary loan loss provision. Specifically, we estimate

$$\begin{aligned} LLP_{b,s,t} = {} & \triangle_{s\times t} + \triangle_b + \triangle_t + \sum_{n=-2}^{1} \gamma_j \triangle NPA_{b,s,t+n} + \alpha_1 Size_{b,s,t-1} + \alpha_2 \triangle Loan_{b,s,t} \\ & + \alpha_3 \triangle GSP_{s,t} + \alpha_4 CSRET_{s,t} + \alpha_5 \triangle Unemp_{s,t} + \epsilon_{b,s,t} \end{aligned} \tag{4.1}$$

where b, s, and t denote banks, states, and quarters; $LLP_{b,s,t}$ is loan loss provisions; $\triangle NPA_{b,s,t+j}$ is the change in nonperforming assets; $Size_{b,s,t-1}$ is the lagged natural logarithm of total assets. $\triangle Loan_{b,s,t}$ the change in total loans; $\triangle GSP_{s,t}$ is the change in state gross domestic product; $CSRET_{s,t}$ is the Case-Shiller Real Estate Index; and $\triangle Unemp_{s,t}$ is the change in the state's unemployment rate. We also include state × quarter fixed effects to account for time-variant state characteristics that affect the estimation of loan loss provisions.

We compute earnings opacity by taking the logarithmic form of the absolute amount of the residuals from equation (4.1) to avoid positive and negative residuals offsetting each other (Cornett et al., 2009; Hutton et al., 2009; Jiang et al., 2016; Danisewicz et al., 2021). Higher $Opac$ implies more discretionary loan loss provisioning, that is greater opacity.

Since $Opac$ may be influenced by the revision accruals from previous periods (Yue et al., 2022; Hutton et al., 2009), we also estimate the four-quarter moving average of $Opac$ as our second opacity measure ($Opac_{ma}$), which is more likely to reflect bank policy on discretionary provisioning. We collect quarterly bank data from FR Y-9C form for Consolidated Financial Statements for Holding Companies. Variable descriptions are defined in Table C.1 of Online Appendix.

4.3.1.2 Control variables

For our control variables, we construct several variables using the FR Y-9C data. Similar to the existing literature (Chernobai et al., 2020; Danisewicz et al., 2021; Jiang et al., 2016; Neuhann and Saidi, 2018), our control variables include bank size ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), domestic deposits to assets ($Deposits$), equity to assets ($Equity$), allowances for loan losses ($Allowances$), net interest margin (NIM), and return-on-equity (ROE). Complete variable descriptions are defined in Table C.1 of Online Appendix. We retrieve quarterly

because they are primarily driven by the activity of stock market participants, thus other market factors apart from asset opacity also influence these market-derived measures. As a robustness check, however, we estimate equations (4.2) and (4.3) using these market measures, namely bid-ask spread (BAS) and stock volatility (STD). Table C.2 of Online Appendix show that the results remain consistent with our baseline findings.

data of 716 banks from 1988Q1 to 2006Q4 that translate into 22,590 observations. Table 4.1 exhibits summary statistics.

Table 4.1: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All sample				All banks before deregulation				Diversified banks after deregulation			
	Mean	Median	St. dev.	N	Mean	Median	St. dev.	N	Mean	Median	St. dev.	N
Opacity measures												
$Opac$	-6.692	-6.568	1.318	22590	-6.330	-6.200	1.323	8919	-6.728	-6.541	1.304	1373
$Opac_{ma}$	-6.683	-6.692	1.057	22590	-6.307	-6.293	1.056	8919	-6.731	-6.679	1.041	1373
BAS	2.502	2.208	1.394	15145	2.647	2.159	1.734	4221	2.504	2.304	1.113	1223
STD	0.021	0.018	0.014	15145	0.021	0.017	0.014	4221	0.019	0.017	0.013	1223
Independent variables												
$Size$	14.053	13.500	1.751	22590	13.981	13.315	1.816	8919	16.411	17.209	2.637	1373
$Cash$	0.086	0.073	0.057	22590	0.114	0.104	0.059	8919	0.070	0.058	0.039	1373
$Loans$	0.636	0.653	0.126	22590	0.608	0.628	0.114	8919	0.640	0.664	0.136	1373
$Deposits$	0.778	0.810	0.132	22590	0.816	0.856	0.123	8919	0.650	0.651	0.171	1373
$Equity$	0.085	0.082	0.032	22590	0.078	0.076	0.020	8919	0.084	0.082	0.017	1373
$Allowances$	0.015	0.013	0.008	22590	0.018	0.015	0.011	8919	0.015	0.014	0.006	1373
NIM	0.038	0.038	0.008	22590	0.039	0.039	0.007	8919	0.034	0.035	0.008	1373
ROE	0.121	0.127	0.895	22590	0.120	0.127	1.418	8919	0.141	0.148	0.078	1373
Org	-0.824	-1.000	0.232	22590	-0.889	-1.000	0.194	8919	-0.511	-0.500	0.140	1373
OBS	0.219	0.140	0.519	22590	0.162	0.103	0.336	8919	0.598	0.368	0.674	1373
NII	0.060	0.031	0.097	22590	0.004	0.000	0.024	8919	0.157	0.125	0.117	1373
ROA_{σ}	0.165	0.079	0.369	22590	0.186	0.086	0.364	8919	0.173	0.091	0.242	1373
$Return_{\sigma}^{nb}$	0.237	0.000	2.500	22590	0.154	0.000	0.747	8919	0.467	0.035	1.170	1373
$Return_{\sigma}^{bank}$	1.127	0.683	1.571	22590	0.863	0.568	0.949	8919	1.637	1.104	1.831	1373
$Access$	3.396	3.456	0.170	22590	3.372	3.419	0.168	8919	3.431	3.478	0.158	1373
$M\&A^{Assets}$	0.001	0.000	0.030	22590	0.002	0.000	0.037	8919	0.003	0.000	0.047	1373
$M\&A^{Count}$	0.364	0.000	1.144	22590	0.210	0.000	0.799	8919	1.142	0.000	2.297	1373
$Loans^{\%}$	0.126	0.020	0.223	22590	0.134	0.022	0.225	8919	0.298	0.232	0.282	1373
$Branch^{\%}$	0.128	0.029	0.215	22324	0.138	0.035	0.222	8665	0.269	0.209	0.252	1373
GSP	0.013	0.013	0.026	22590	0.014	0.013	0.029	8919	0.014	0.013	0.053	1373

The table shows descriptive statistics of the main variables employed in our analysis. The main sample covers the period 2Q1988-4Q2006 and contains 22,2590 observations from 716 US Bank Holding Companies. Pre-deregulation contains observations prior to 2Q1996 and post-deregulation contains observations from 1996Q3. For brevity we suppress the variables' subscripts in the manuscript.

4.3.2 Identification strategy

Our identification strategy exploits the variation of business diversification arising from the exogenous shock of the 1996 deregulation. Prior to the deregulation, commercial banking in the U.S. was primarily driven by an exogenous factor stemming from strict regulatory restrictions, rather than internal managerial decisions (endogenous factor). As shown in Section 4.2, this exogeneity argument is underpinned further by the fact that banks were very unlikely to anticipate the deregulation before 1996 considering their multiple failed requests to eliminate the "firewalls" between bank and non-bank subsidiaries from the late 1980s until early 1990s (Barth et al., 2000). In addition, the deregulation was aimed at objectives unrelated to the transparency (or opacity) of the banks, which alleviates the concerns of potential reverse causality problem.

The identification strategy of this paper is similar to that of Neuhann and Saidi (2016, 2018) and Chernobai et al. (2020). Neuhann and Saidi (2016, 2018) use the gradual repeal of the GSA to examine its effects on syndicated loans participation in the market and banks' idiosyncratic stock-return volatility. Meanwhile, Chernobai et al. (2020) investigate the effects of the same event on banks' operational risk.

In this paper, we identify banks with already diversified business before 1996 are more likely to be affected by the deregulation and thus have more probability to become more opaque after the 1996 deregulation. These diversified banks had more motivations to diversify to investment banking activities after the deregulation since they already made investments to diversify since the 1980s but were unable to do so due to the restrictions that existed until 1996 (Chernobai et al., 2020). This setting allows us to classify banks into two different groups. Our treated group consists of banks that had diversified their business by establishing non-bank subsidiaries prior to the 1996 deregulation, which we refer to as diversified banks. Our control group consists of banks that did not have diversified their business before the deregulation. We obtain the list of our diversified banks from Cetorelli and Goldberg (2014).

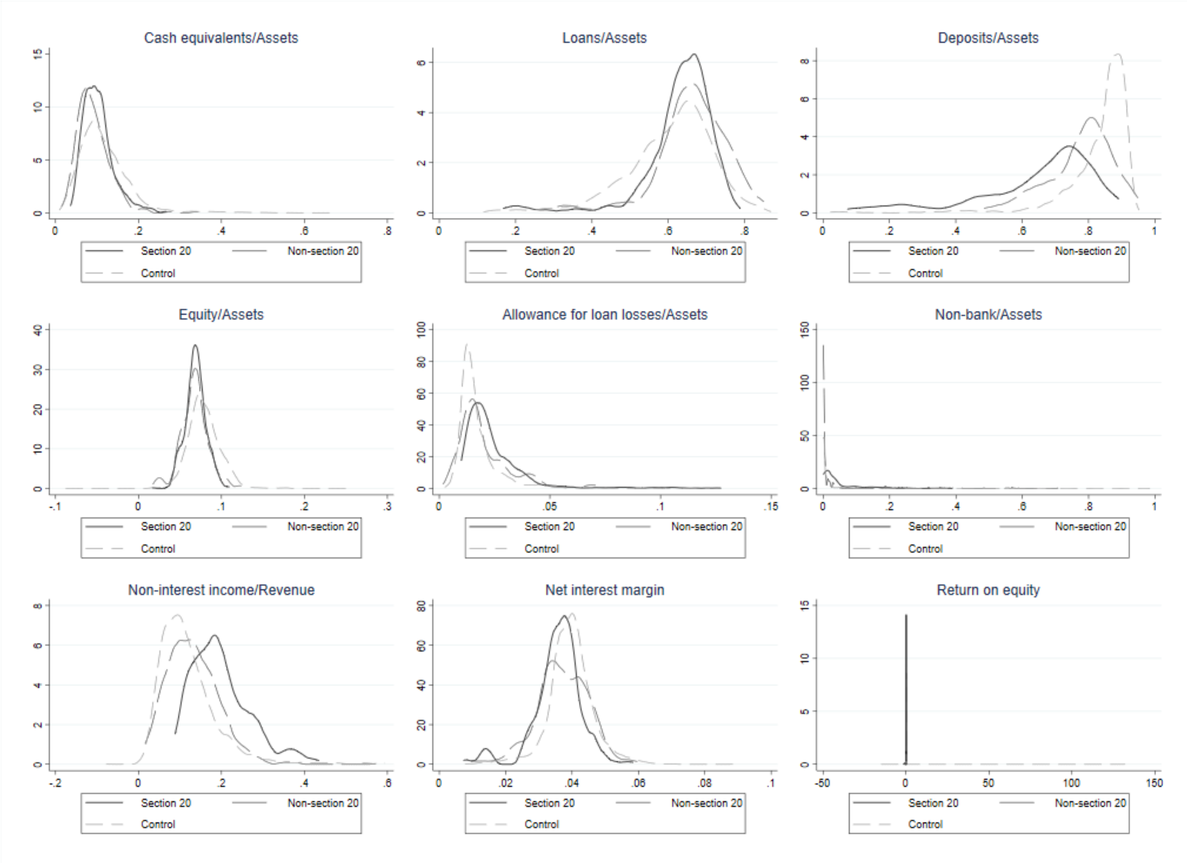
As outlined by Chernobai et al. (2020), this specification poses a potential problem since a bank can be considered as a part of the treated group only by having subsidiaries with business activities unaffected by the 1996 deregulation. In other words, we may falsely consider banks with subsidiaries as diversified banks even though the presence of these subsidiaries did not necessarily reflect business diversification. Hence, we further sort our diversified banks into two distinct groups. The first group is section 20 diversified banks, comprising of banks that owned section 20 subsidiary before the repeal of GSA. These banks already had subsidiaries that were allowed to engage in limited activities of securities underwriting prior to the 1996 deregulation. We refer to this group as T^{S20}. The second group, T^{NS20}, consists of banks that did not own section 20 subsidiary prior to the repeal of GSA but already diversified their business prior to the deregulation. We obtain the list of banks with section 20 subsidiary from Cornett et al. (2002).

To see the comparability between the treated groups and the control group, we compute kernel density estimates for various bank-level characteristics for section 20 banks, non-section 20 banks and non-diversified banks prior to the deregulation. Specifically, we compute kernel density estimates for cash equivalents to assets, loans to assets, domestic deposits to assets, equity to assets, allowance for loan losses to assets, non-bank assets to assets, non-interest income to revenue, net interest margin and return on equity. Figure 4.1 depicts the estimates and highlights the similarity of these groups across different bank characteristics.[7]

We also observe the evolution of our opacity variables. Figure 4.2 shows that prior to the 1996 deregulation, our opacity measures show that both the diversified banks and other banks evolved in a similar trend. The opacity of diversified banks started to increase relative to that of other banks after the deregulation was enacted in 1996. Figure 4.2b illustrates the diverging trend better, where the opacity of diversified banks started to increase relative to that of other banks in

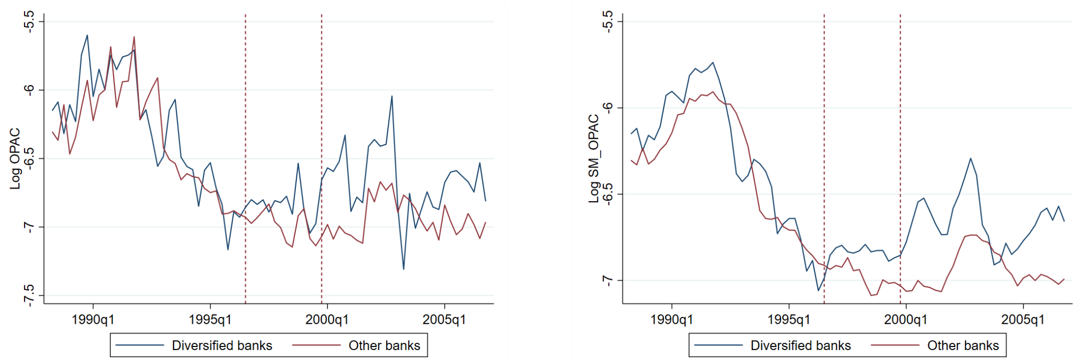
[7]We provide further validation check by estimating a propensity score matched sample in Table C.3 of Online Appendix to ensure differences in the characteristics of diversified and non-diversified banks do not drive the inferences. We match diversified banks to their nearest neighbor based on the size, cash equivalents, loans, domestic deposits, equity, and return-on-equity using a 2.5% caliper without replacement. This results in a sample of 295 banks. The interaction coefficients remain qualitatively and quantitatively similar to our main findings.

Figure 4.1: Kernel density estimates



Notes: The graphs illustrate the similarity between treated and control groups. The plots display the main kernel density estimates for the level of the different bank characteristics for the treated and control groups. The treated group refers to diversified banks prior to the deregulation, and the control group depicts the non-diversified banks. All variables are defined in Table C.1 of Online Appendix.

Figure 4.2: Evolution of bank opacity



(a) $Opac$

(b) $Opac_{ma}$

Notes: Dynamics of the effects of the 1996 firewall eliminations (red dashed line) and the 1999 GLBA (blue dashed line) on opacity measures ($Opac$ and $Opac_{ma}$) for diversified banks vs non-diversified banks.

1996 after the "firewalls" elimination and increased further after the 1999 enactment of GLBA. These trends justify the presence of parallel trends in the data.

4.3.3 Econometric framework

To investigate the effect of the 1996 deregulation on bank opacity, we use a difference-in-difference estimation strategy. We estimate:

$$y_{b,t} = \alpha_t + \theta_b + \beta_1 T_b \cdot Dereg_t + \sum_{j=1}^{4} \gamma_j \mathbf{X}_{j,b,t} + \varepsilon_{i,t}, \tag{4.2}$$

where, for each bank b and quarter t, $y_{b,t}$ is one of the opacity measures described previously, T_b is a dummy equal to 1 for diversified banks and 0 for non-diversified banks, $Dereg_t$ is a dummy equal to 1 for all quarters after the 1996 deregulation in 1996Q3, $\mathbf{X}_{j,b,t}$ is a vector of control variables, and $\varepsilon_{i,t}$ is the error term. As outlined by Bertrand et al. (2004), we block bootstrap the standard errors to prevent potential bias arising from serial correlations.

As mentioned above, we further breakdown our treated group into two categories, T_b^{S20} and T_b^{NS20}. Then, we estimate:

$$y_{b,t} = \alpha_t + \theta_b + \beta_1 T_b^{S20} \cdot Dereg_t + \beta_2 T_b^{NS20} \cdot Dereg_t + \sum_{j=1}^{4} \gamma_j \mathbf{X}_{j,b,t} + \varepsilon_{i,t}, \tag{4.3}$$

Equation (4.3) is the baseline model in our paper and most of our estimates are based on this equation model. Later in the paper, we expand the deregulation dummy variable to investigate the effects of different each deregulation episode by employing the firewall eliminations dummy ($Firewall$) that is equal to for 1996Q3 to 1999Q3, 0 otherwise; and the enactment of GLBA dummy ($GLBA$) that is equal to 1 from 1999Q4 onward, 0 otherwise.

4.4 Results

We begin our analysis with investigating the effect of the deregulation on bank opacity. Then, we test whether greater opacity of diversified banks was driven by the obfuscation of risk taking activities or the concealment of financial vulnerability.

4.4.1 Bank deregulation and opacity

We first examine how bank opacity responds to the deregulation. Columns 1 and 2 of Table 4.2 report estimates of equation (4.2). The interaction coefficient ($T \cdot Dereg$) of column 1 shows that $Opac$ increased by 43.1% after the deregulation with statistical significance at the 1% level. Column 2 presents the estimate using smoothed opacity measure ($Opac_{ma}$) as the outcome variable. Our interaction variable shows positive and statistically significant effect of the deregulation on $Opac_{ma}$. Specifically, $Opac_{ma}$ increased by 44.2% from 1996.

Table 4.2: Average effects on opacity

	(1)	(2)	(3)	(4)
	Net effects		Section 20 & non-section 20	
Dependent variable:	$Opac$	$Opac_{ma}$	$Opac$	$Opac_{ma}$
$T \cdot Dereg$	0.3584***	0.3658***		
	(3.15)	(3.53)		
$T^{S20} \cdot Dereg$			0.3718**	0.4067***
			(2.55)	(2.95)
$T^{NS20} \cdot Dereg$			0.3264**	0.2678*
			(2.09)	(1.74)
$Size$	0.0334	-0.0014	0.0334	-0.0014
	(0.67)	(-0.02)	(0.67)	(-0.02)
$Cash$	-0.0774	-0.0131	-0.0778	-0.0142
	(-0.29)	(-0.05)	(-0.29)	(-0.06)
$Loans$	0.0198	0.1385	0.0209	0.1418
	(0.07)	(0.55)	(0.08)	(0.57)
$Deposits$	0.0196	0.0235	0.0216	0.0296
	(0.04)	(0.06)	(0.05)	(0.07)
$Equity$	-0.0531	0.3758	-0.0509	0.3826
	(-0.06)	(0.41)	(-0.06)	(0.41)
$Allowances$	14.2113***	14.6650***	14.2643***	14.8274***
	(4.88)	(4.46)	(4.86)	(4.49)
NIM	-8.7605**	-11.1929***	-8.7216**	-11.0738***
	(-2.27)	(-3.29)	(-2.26)	(-3.24)
ROE	0.0030	0.0018	0.0030	0.0018
	(0.02)	(0.02)	(0.02)	(0.02)
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	22,590	22,590	22,590	22,590
R-squared	0.0614	0.1129	0.0614	0.1131
Number of Banks	716	716	716	716

Notes: This table reports estimates of equations (4.2) and (4.3). Outcome variables are $Opac$ and $Opac_{ma}$. T is equal to one if the bank is a diversified bank and zero otherwise. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. Control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Columns 3 and 4 depict the regression results of equation (4.3). Column 3 shows that the interaction variable between post-deregulation dummy and section 20 banks ($T^{S20} \cdot Dereg$) is significant at the 5% level. The result implies an increase of section 20 banks' opacity by 45.0% relative to the control group after the deregulation, which is higher than the coefficient of average diversified banks shown in column 1. Opacity of non-section 20 banks ($T^{NS20} \cdot Dereg$) increased by 38.6% and the result is significant at the 5% level. We also find similar evidence in the $Opac_{ma}$ regression (column 4), where bank opacity of section 20 and non-section 20 banks increased by 50.2% and 30.7% respectively after the deregulation.

Together these inferences indicate that diversified banks became more opaque following the deregulation. When we break diversified banks into section 20 and non-section 20 banks, we find that the effect of bank opacity on section 20 banks was significantly more sizeable relative to that of non-section 20 banks. Section 20 banks were more invested in diversifying their business after the deregulation because they already engaged in limited securitization and underwriting activities prior to the 1996 "firewalls" elimination. The absence of diversification prior to the 1996 deregulation was primarily driven by the exogenous factor of regulatory restrictions. When the restrictions were lifted, these banks continuously increased the intensity of their complex and diversified business activities. Non-section 20 banks, on the other hand, lacked the motivation to expand to investment banking activities despite having diversified early. Accordingly, the effect of the deregulation on their opacity was relatively milder. In summary, these findings support the hypothesis that diversified banks have higher opacity and the stage of bank diversification influences the degree of opacity.

4.4.2 The effects of staggered deregulation phase

Section 4.2 of this paper shows how the deregulation was implemented episodically from the elimination of the "firewalls" in 1996 until the final repeal of GSA in 1999. We therefore examine whether banks reacted differently to each deregulation episode.

Table 4.3: The effects of individual deregulation phase

	(1)	(2)	(3)	(4)
	Net effects		Section 20 & non-section 20	
Dependent variable:	$Opac$	$Opac_{ma}$	$Opac$	$Opac_{ma}$
$T \cdot GLBA$	0.4081***	0.4337***		
	(3.79)	(4.41)		
$T \cdot Firewall$	0.2895*	0.2715*		
	(1.85)	(1.93)		
$T^{S20} \cdot GLBA$			0.4104**	0.4599***
			(2.42)	(2.86)
$T^{S20} \cdot Firewall$			0.3178*	0.3325**
			(1.84)	(2.15)
$T^{NS20} \cdot GLBA$			0.3879***	0.3512**
			(2.70)	(2.41)
$T^{NS20} \cdot Firewall$			0.2434	0.1553
			(1.14)	(0.75)
Control variables	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	22,590	22,590	22,590	22,590
R-squared	0.0615	0.1134	0.0615	0.1136
Number of Banks	716	716	716	716

Notes: This table reports estimates of equations (4.2) and (4.3). Outcome variables are $Opac$ and $Opac_{ma}$. T is equal to one if the bank is a diversified bank and zero otherwise. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $GLBA$ is equal to 1 from 1999Q4 onward, 0 otherwise; $Firewall$ is equal to for 1996Q3 to 1999Q3, 0 otherwise. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.3 presents the estimates of these effects. Columns 1 and 2 report the individual effects of the interaction between diversified banks and 1996 "firewalls" elimination and the GLBA on our outcome variables. In column 1, we find the interactions between diversified banks and both the GLBA and the 1996 "firewalls" elimination have positive and significant impacts on $Opac$. The economic impact of the GLBA on $Opac$ of 50.4%, however, is almost twice larger than that of the 1996 "firewalls" elimination of 33.6%. We observe similar results in the $Opac_{ma}$ regression (column 2), where the effects of the GLBA and the 1996 "firewalls" elimination are 54.3% and 31.2%, respectively.

Next, we disaggregate diversified banks into section 20 banks and non-section 20 banks. Columns 3 and 4 of Table 4.3 present the effects of this disaggregation on our bank opacity measures. Consistent with our previous findings, the estimates show that within section 20 banks both the GLBA and the 1996 "firewalls" elimination have positive and significant effects on bank opacity even though the effect of the former is economically more sizeable. Within non-section 20 banks, we also find positive and significant effect of the GLBA on bank opacity. The magnitude, however, is relatively smaller compared to that of section 20 banks. Finally, we find positive but insignificant effect of the 1996 "firewalls" elimination on bank opacity within non-section 20 banks.

To conclude, our empirical investigation indicates that the effect of the GLBA was more pronounced relative to that the 1996 "firewalls" elimination. This may be explained by the more decisive nature of the GLBA. For instance, despite the lifting of various "firewalls", after the 1996 deregulation, banks were still subject to the 25% cap on revenue from non-commercial banking activities such as securitization and underwriting transactions. On the other hand, the GLBA fully repealed the GSA and completely eliminated the revenue cap, which resulted in the creation of universal banks with more complex and opaque activities. Our findings confirm the presence of differences in bank diversification characteristics, which create heterogeneity in the opacity responses of section 20 and non-section 20 banks to the deregulation. Due to this reason, our analysis from now focuses on equation (4.3) to enable separate evaluation of the effects of the deregulation on section 20 and non-seciton 20 banks.

4.4.3 Complexity channel

The deregulation of 1996 and the enactment of the GLBA of 1999 were compelled by the intention to promote the competitiveness of the U.S. banking industry through the introduction of universal banking business model. This includes the expansion into complex investment banking activities such as securities underwriting and dealing (Calomiris, 2000). As suggested by our hypothesis, higher level of complexity raises monitoring cost and increase a bank's propensity to become more opaque.

To evaluate the linkage between bank complexity and opacity, we regress bank opacity on complexity variables, namely business diversification index (Org), total off-balance sheet items

Table 4.4: Deregulation, bank diversification and business complexity

Panel A: Bank complexity and opacity

	(1)	(2)	(3)
Dependent variable:	$Opac_{ma}$	$Opac_{ma}$	$Opac_{ma}$
Org	3.0979***		
	(2.99)		
OBS		0.4207***	
		(2.82)	
NII			2.2610***
			(3.05)
Control variables	YES	YES	YES
BHC FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	22,590	22,590	22,590
KP F-statistic	63.77	129.7	296.3
Number of Banks	716	716	716

Panel B: Deregulation and bank complexity

	(1)	(2)	(3)
Dependent variable:	Org	OBS	NII
$T^{S20} \cdot Dereg$	0.1397***	0.3438***	0.1164***
	(4.34)	(3.64)	(6.04)
$T^{NS20} \cdot Dereg$	-0.0716***	0.0183	0.0226*
	(-2.70)	(0.41)	(1.85)
Control variables	YES	YES	YES
BHC FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	22,590	22,590	22,590
R-squared	0.3394	0.2758	0.4709
Number of Banks	716	716	716

Notes: Panel A of this table reports . Panel B reports estimates of equation (4.3) using Org (organizational complexity as outlined by Cetorelli and Goldberg (2014)0, OBS (total off-balance sheet items to assets), and NII (non-interest income from trading revenues, commissions and fees to total income) as the outcome variables. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The standard errors are clustered at the bank holding company level and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

to assets (OBS), and non-interest income from trading revenues, commissions and fees to total income (NII). Because our complexity variables are potentially endogenous, we instrument these variables using the number of total employees within a bank holding company ($Employee$). The instrument is plausibly exogenous because number of employees is unrelated to bank opacity. Banking literature suggests that opacity can be driven by factors such as reporting quality, discretionary earnings, and balance sheet composition but not employee size (Bushman and Williams, 2012; Chen et al., 2015; Danisewicz et al., 2021; Jiang et al., 2016). However, more subject-matter experts and analysts increase the bank's capacity to engage more complex business characteristics and banking transactions. Hence, we expect our complexity variables to be positively correlated with the number of employees. Moreover, number of employees is unlikely to endogenously react to bank complexity since hiring usually depends on the company's budget and top-down managerial decision (Ghaly et al., 2020). For example, a reduction in bank complexity does not immediately lead to employee downsizing.

Panel A of Table 4.4 presents these estimates. Diagnostic checks indicate the instrument is relevant: the coefficient estimate is significant at 1% and the Kleibergen-Paap F-statistic exceeds the Stock-Yogo critical value. Across all regressions, we find positive and statistically significant effects of our complexity measures (Org, BAS, and NII) on bank opacity. This evidence confirms the presence of positive linkage between bank opacity and complexity, and is in line with previous work (Klein et al., 2021).

We also examine the effect of the deregulation of bank opacity. So far our findings show the economically sizeable effect of bank deregulation on opacity. If greater opacity was driven by the complexity channel, the deregulation should also have significant effect on bank complexity. We test this by estimating equation (4.3) using our complexity measures as the outcome variables.

Panel B of Table 4.4 reports the results. In column 1, we estimate bank opacity significantly increased business diversification index by 13.97 points within section 20 banks. The deregulation also increased off-balance sheet items and non-interest income by 34.4 and 11.6 percentage points, respectively. Within non-section 20 banks, business diversification declined after the deregulation. The deregulation, however, increased off-balance sheet items and non-interest income within non-section 20 banks even though the magnitude is small and the evidence is statistically weak. The findings from Panels A and B of Table 4.4 are consistent with our complexity channel hypothesis, where the significant increase in bank opacity after the deregulation was primarily driven by more complex bank characteristics.

4.4.4 Bank diversification and return volatility

Now we address the question of why complex banks want to become more opaque. Our hypothesis suggests that diversified banks increase opacity to hide income volatility arising from their complex business activities. To test this, we estimate equation (4.3) using ROA volatility (ROA_σ), income volatility from non-commercial banking activities ($Return_\sigma^{nb}$), and income volatility from commercial banking activities ($Return_\sigma^{bank}$).

Table 4.5 reports the estimates. Column 1 documents the effect of the deregulation on ROA volatility. Following the regulation, ROA volatility increased by 57% (pre-deregulation average=0.186) within section 20 banks, while the effect is statistically insignificant among non-section 20 banks. Next, we examine whether the source of this volatility came from non-commercial banking activities or commercial banking activities. Columns 2 and 3 report the effects of the deregulation on income volatility from non-commercial banking activities and commercial banking activities, respectively. In column 2, income volatility from non-commercial banking activities increased by 190% (pre-deregulation average=0.154) within section 20 banks. Section 20 banks' income volatility from commercial banking activities also increased by 67%

Table 4.5: Bank diversification and return volatility

	(1)	(2)	(3)
Dependent variable:	ROA_σ	$Return_\sigma^{nb}$	$Return_\sigma^{bank}$
$T^{S20} \cdot Dereg$	0.1063***	0.2925*	0.5766**
	(3.32)	(1.88)	(2.05)
$T^{NS20} \cdot Dereg$	0.0003	-0.4521	-0.0714
	(0.01)	(-1.18)	(-0.63)
Control variables	YES	YES	YES
BHC FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	22,590	22,590	22,590
R-squared	0.0963	0.0094	0.0807
Number of Banks	716	716	716

Notes: This table reports estimates of equation (4.3) using ROA_σ (earnings volatility), $Return_\sigma^{bank}$ (income from banking activities), and $Return_\sigma^{nb}$ (income from non-banking activities) as the outcome variables. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The sample is split at the median level of each year's capital ratio. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

(pre-deregulation average=0.863). Meanwhile, we find no significant effects of the deregulation on return volatility within non-section 20 banks.

The key message emanating from these results is that more complex banks have higher return volatility. Since complex banks have greater opacity, this implies that banks use opacity to obscure their risk taking activities arising from more complex business characteristics. Further evaluation shows that more complex business does not only increase income volatility of non-commercial banking division but also their commercial banking division. The creation of universal banks through the enactment of the GLBA strove for the incorporation of non-commercial and commercial banking activities into a single bank holding company. When a bank's investment banking subsidiary is allowed to securitize, it gives the incentives to other commercial bank subsidiaries to lower the standards of borrower screening (Keys et al., 2010; Wang and Xia, 2014). Our evidence suggests that the deregulation did not only increase the volatility of non-commercial bank subsidiaries but also commercial bank subsidiaries.

4.4.5 Bank diversification, opacity and risk

Studies show the presence of linkages between bank capital, opacity and risk appetite (Acosta-Smith et al., 2020; Begley et al., 2017; Landier and Thesmar, 2014). As a validation check, we examine how bank return volatility and bank opacity respond to the deregulation within low capital (high solvency risk) banks. To test this relationship, we create a dummy variable, $Equity^{low}$ that is equal to one if a bank's capital ratio is among the lowest 5^{th} percentile during a particular year and zero otherwise. We interact this dummy with our interaction variables and append equation (4.3) with these triple difference-in-difference variables. Then, we estimate this appended model using ROA volatility and opacity measures as the outcome variables.

Table 4.6: Bank diversification, opacity, and risk taking activity

	(1)	(2)	(3)
Dependent variable:	ROA_σ	$Opac$	$Opac_{ma}$
$T^{S20} \cdot Dereg$	0.0986***	0.3328**	0.3650***
	(3.07)	(2.31)	(2.67)
$T^{NS20} \cdot Dereg$	-0.0038	0.3152**	0.2556*
	(-0.12)	(2.14)	(1.68)
$T^{S20} \cdot Dereg \cdot Equity^{low}$	0.2010**	1.0329***	1.1057***
	(2.29)	(3.00)	(3.86)
$T^{NS20} \cdot Dereg \cdot Equity^{low}$	0.1181	0.2940*	0.3227
	(0.71)	(1.68)	(1.39)
Control variables	YES	YES	YES
BHC FE	YES	YES	YES
Time FE	YES	YES	YES
Observations	22,590	22,590	22,590
R-squared	0.0969	0.0621	0.1148
Number of Banks	716	716	716

Notes: This table reports estimates of extended equation (4.3) using ROA_σ, $Opac$, and $Opac_{ma}$ as the outcome variables. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. $Equity^{low}$ is a dummy variable equal to one if bank b capital ratio is among the lowest 5^{th} percentile during the year and zero otherwise. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The sample is split at the median level of each year's capital ratio. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.6 presents the estimates. Column 1 of Table 4.6 shows the regression result using ROA volatility as the outcome variable. We find that banks with lower capitalization are more likely to take more risk after the deregulation. The effect, however, is only significant within section 20 banks. Columns 2 and 3 report the effect of capital level on bank opacity. The estimates show that banks with lower capital or higher insolvency risk are more opaque. Similarly, the results are only significant within section 20 banks. Overall, this suggests that complex banks with lower capital levels are more likely to take more risk to increase capital levels, while simultaneously increase their opacity to hide their internal instability and avoid adverse selection.

4.5 Robustness checks

We conduct further robustness checks in this section to rule out potential threats to identification and alternative explanations.

4.5.1 Geographic factor, competition, and industry consolidation

The sample period features the staggering process of interstate deregulation, which also induced competition and increased bank opacity (Jiang et al., 2016; Strahan, 2003; Zhang, 2021). To check that our results are not dependent on this factor, we examine the evolution of interstate banking reforms by calculating the number of accessible states for expansion (Goetz et al., 2013; Jiang et al., 2016, 2020).

Specifically, we weigh the number of accessible states for expansion for each BHC b in quarter t with the inverse of their distance from the state, whereas the nearest state receives a weight of one and the farthest state receives a weight of zero. We then compute the natural logarithm of one, plus the number of other distance-weighted accessible states ($Access$).[8] This variable, along with its interactions with our treated groups are added to our baseline equation. Columns 1 and 2 of Table 4.7 show that our results remain consistent after controlling for these additional factors.

Table 4.7: Organizational & geographic diversification, and industry consolidation

	(1)	(2)	(3)	(4)
	Geographic		Consolidation	
Dependent variable:	$Opac$	$Opac_{ma}$	$Opac$	$Opac_{ma}$
$T^{S20} \cdot Dereg$	0.4035**	0.4289**	0.3476**	0.3865***
	(2.36)	(2.55)	(2.38)	(2.75)
$T^{NS20} \cdot Dereg$	0.3399**	0.2796*	0.3360**	0.2759*
	(2.19)	(1.74)	(2.15)	(1.79)
$T^{S20} \cdot Dereg \cdot Access$	0.0942	0.1207		
	(0.10)	(0.12)		
$T^{NS20} \cdot Dereg \cdot Access$	-0.5055	-0.4399		
	(-0.59)	(-0.47)		
$Access$	1.8686	1.4470		
	(1.34)	(1.17)		
$M\&A^{Assets}$			0.3889*	0.2119
			(1.66)	(1.15)
$M\&A^{Count}$			0.0314**	0.0267
			(2.14)	(1.62)
Control variables	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	22,590	22,590	22,590	22,590
R-squared	0.0620	0.1138	0.0621	0.1140
Number of Banks	716	716	716	716

Notes: This table reports estimates of extended equation (4.3) using $Opac$ and $Opac_{ma}$ as the outcome variables. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. $Access$ is the log of number of accessible states; $M\&A^{assets}$ is the M&A target assets to one year lagged bank assets; and $M\&A^{counts}$ is the total three subsequent quarters of number of M&As for each banks in every quarter. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

The 1996 "firewalls" elimination and the enactment of GLBA also coincided with the enactment of the Riegle-Neal Interstate Banking and Branching Efficiency Act (RNA) that was signed in 1994Q3 and became fully effective in 1997Q2. Literature suggests that this reform accelerated the pace of industry consolidation through mergers and acquisitions (McLaughlin, 1995; Strahan, 2003). Even though many states already eliminated many restrictions on interstate bank acquisitions before the enactment of the RNA, we are still concerned about the possibility of this reform affecting the diversified banks (our treated group).

[8] We obtain geographic distance data from Yu (2007) that computes the Eucledian distance (measured in kilometers) between US states.

To ensure that this effect does not drive our inferences, we append equation (4.3) with controls that capture this factor. Following Chernobai et al. (2020), our control variables are the total assets of merger and acquisition (M&A) targets relative to the total assets of the banks in the previous year ($M\&A^{assets}$) and the accumulated number of M&As in the past three years ($M\&A^{counts}$). We attain M&A data from the Federal Reserve Bank of Chicago's M&A database. We then merge the data with FR Y-9C data to compute the total assets of the target companies. In some cases where the target companies are non-bank institutions, we also merge the data with our non-bank assets data from FR Y-9LP. In the process, we drop some outliers and missing values. Columns 3 and 4 of Table 4.7 report the results. Despite these additional controls, the effects of the deregulation on our bank opacity measures remain robust.[9]

4.5.2 Other robustness checks

Literature shows that banks were unlikely to anticipate the deregulation in the late 1990s due to the numerous failed attempts that happened until early 1990s. However, we also conduct a formal anticipation effect test to ensure the exogeneity of our shock. Following Schepens (2016), we amend our baseline model by including interactions between diversified banks with a placebo dummy, $Placebo$, that is equal to 1 for the period between 1992-1995 and zero otherwise. Estimates in columns 1 and 2 of Online Appendix Table C.5 show that the interactions between our treated groups and the placebo dummy are insignificant across all columns, which rules out the possibility of anticipation effects.

Our sample period spans between 1988 and 2006. This period corresponds with eight years before the 1996 deregulation and seven years after the enactment of GLBA. In this robustness check, we trim our dataset and only use sample period between 1998 and 2003 (four years after the enactment of GLBA). The objective of this exercise is to reduce the possibility of measuring the impact of other shocks that have an impact on bank opacity measures. We estimate equation (4.3) using a sample ending in 2003. Columns 3 and 4 of Online Appendix Table C.5 report the estimates and shows that our baseline findings endure across all results.

The "dotcom" bubble happened when the Nasdaq Composite stock market index reached it peak in March 2000 and fell by 78% in October 2000, giving up all its gains. To capture this effect, we construct a dummy variable $Dotcom$ that is equal to one between 1999Q1 and 2000Q1 and zero otherwise. We interact this dummy variable with our treated groups. The findings in columns 1 and 2 of Online Appendix Table C.6 show our key findings are invariant to controlling for "dotcom" bubble.

We are aware that our results could be affected by several macro-financial conditions of the time. Our first attempt is to control for macroeconomic environment by appending equation (4.3) with the Gross State Products (GSP) of which the banks are headquartered and the treated

[9] Online Appendix Table C.4 also presents further robustness checks related to industry environment and competition by appending equation (4.3) with bank b's loan share and number of office branches.

groups. Columns 3 and 4 of Online Appendix Table C.6 report the results. Throughout the results, our key findings endure.

4.6 Conclusions

Since the financial crisis, the consequences of opaque diversified financial institutions once again attract the attention of economists and policymakers. Most of post-crisis regulations, such as the enactment of Dodd-Frank Act, are addressed to contain the spillover risks of these institutions into the whole financial system.

We empirically document how the 1996 deregulation affected bank opacity in U.S. banks. We find strong evidence that the deregulation increased the opacity of diversified banks. The effect of the deregulation on bank opacity was more sizeable within section 20 banks. Higher opacity is associated with intensified business complexity and non-traditional financial transactions that increase monitoring costs and reduce transparency. This higher monitoring cost is exploited by banks to shroud their risk taking activities. The linkages between bank opacity, complexity and risk taking are more aggravated among low capital banks. Our findings show that banks with lower capital take more risk to increase their equity ratio and have greater opacity to hide their vulnerabilities from the outsiders.

Our findings provide novel insights into the ongoing debate regarding the consequences of opacity within universal banks with complex and diversified business lines. Bank diversification reached its peak prior to the financial crisis and see a downward trend afterwards (Goldberg and Meehl, 2020). So far, existing literature focuses on documenting the positive correlation between bank risks and opacity (Danisewicz et al., 2018, 2021; Klein et al., 2021). Our empirical findings, however, show how banks use opacity to hide their risk taking activities. Examining the possible policy design that can regulate such optimum level of transparency to avoid excessive risk taking is an interesting avenue for future research.

Chapter 5

Summary

This thesis empirically examine the relationships between financial regulations, bank opacity and risk. Using cutting edge econometric techniques and supported further by a battery of robustness checks, we show how bank opacity can have negatively affect liquidity risk and give banks incentives to hide their risk-taking activities. We also show how regulations can have unintended consequences on bank opacity, which exacerbate rollover risk and increase financial instability.

Our findings complement the existing theoretical work discussing the relationships between bank opacity, financial regulations, and bank risk. Examining the possible policy design that can regulate such optimum level of transparency to minimize bank risk is an interesting avenue for future research.

APPENDIX A

APPENDIX OF CHAPTER 2

A.1 LMI liquidity weights and balance sheet classes

Table A.1: LMI category, component, weight, schedule, and source

Panel A: Asset side				
Category	Asset components ($a^i_{t,k}$)	Asset weights (λ_{t,a_k})	Schedule	Source
Cash	Cash, Fed funds sold, reverse repo	1.00	FR Y-9C HC	1a, 1b, 3a, 3.b
Trading securities	Trading treasury	0.96	FR Y-9C HC-B Col A	1
	Trading agency bonds	0.96	FR Y-9C HC-B Col A	2a, 4a, 4b, 4d
	Trading municipal bonds	0.80	FR Y-9C HC-B Col A	3
	Trading structured products	0.86	FR Y-9C HC-B Col A	4c, 4e, 5a
	Trading corporate bonds	0.81	FR Y-9C HC-B Col A	5b
AFS securities	AFS treasury	0.96	FR Y-9C HC-B Col D	1
	AFS agency bonds	0.96	FR Y-9C HC-B Col D	2, 4a(1)-(2), 4b(1)-(2), 4c(1)(a), 4c(2)(a)
	AFS municipal bonds	0.80	FR Y-9C HC-B Col D	3, 4a(3), 4b(3), 4c(1)(b), 4c(2)(b)
	AFS structured products	0.86	FR Y-9C HC-B Col D	5a, 5b
	AFS corporate bonds	0.81	FR Y-9C HC-B Col D	6
	AFS equity	0.76	FR Y-9C HC-B Col D	7
HTM securities	HTM treasury	0.96	FR Y-9C HC-B Col B	1
	HTM agency bonds	0.96	FR Y-9C HC-B Col B	2, 4a(1)-(2), 4b(1)-(2), 4c(1)(a), 4c(2)(a)
	HTM municipal bond	0.81	FR Y-9C HC-B Col B	3, 4a(3), 4b(3), 4c(1)(b), 4c(2)(b)
	HTM structured products	0.86	FR Y-9C HC-B Col B	5a, 5b
	HTM corporate bonds	0.81	FR Y-9C HC-B Col B	6
Semi-liquid assets	Real estate loans	0.68	FR Y-9C HC-C Col A	1a
	Commercial and industrial loans	0.68	FR Y-9C HC-C Col A	4a, 4b
	Lease financing	0.68	FR Y-9C HC-C Col A	10
	Other loans	0.68	FR Y-9C HC-C Col A	
Fixed assets & intangible assets	Other assets	~0	FR Y-9C HC	6-11
Panel B: Liability side				
Category	Liability components ($l^i_{t,k'}$)	Liability weights ($\lambda_{t,l_{k'}}$)	Schedule	Source
Overnight Debt	Overnight fed fund	1.00	FR Y-9C HC	14a
	Repo	1.00	FR Y-9C HC	14b
Deposits	Domestic and foreign deposits	0.10	FR Y-9C HC	13a, 13b
Trading liabilities	Trading liabilities	0.94	FR Y-9C HC-D	13a
Other borrowed money	Commercial paper	0.91	FR Y-9C HC-M	14a
	Short-term commercial paper	0.31	FR Y-9C HC-M	14b
	Long-term commercial paper	~0	FR Y-9C HC-M	14c
Other liabilities	Subordinated debt	~0	FR Y-9C HC	19a, 19b
	Other liabilities	~0	FR Y-9C HC	20
Equity capital	Equity	~0	FR Y-9C HC	28
Contingent liabilities	Unused commitments	~0	FR Y-9C HC	1a, 1b, 1c, 1e, 3a
	Credit lines	~0	FR Y-9C HC	2, 3, 4
	Securities lent	~0	FR Y-9C HC	6, 8, 9
	Collateral	~0	FR Y-9C HC	11, 14

Note: This table shows the asset (Panel A) and liability (Panel B) side components of the liquidity mismatch index. We follow Bai et al. (2018)'s LMI categorization of the balance sheet items that belong to each category. The weights are the same as those in Bai et al. (2018). Schedule indicates the data source of each item. Bai et al. (2018) point out that deposits can be broken down in several ways, including: insured and uninsured deposits; and domestic and foreign deposits. Owing to data limitations, we cannot observe individual depositor accounts, and we therefore decompose deposits into domestic and foreign deposits with a weighted average maturity of 5.9 years.

A.2 HQLA calculation method

Table A.2: HQLA calculation method

Level	Constraint	LCR haircut	Liquid asset	Schedule	Source
Level 1	≥60% of HQLA	0%	Excess reserves	FFIEC 031/041 RC-A	4
			Treasuries	FR Y-9C HC-B & HC-D	HC-B (Col B 1 + Col D 1) + HC-D Col A 1
			GNMA MBS	FR Y-9C HC-B	Col B 4a(1) + Col D 4a(1)
			Non-GSE agency debt	FR Y-9C HC-B	Col B 2a + Col D 2a
Level 2A	<40% of HQLA	15%	GSE debt	FR Y-9C HC-B & HC-D	HC-B (Col B 2b + Col D 2b) + HC-D Col A 2
			GSE MBS	FR Y-9C FR Y-9C HC-B & HC-D	HC-B (Col B 4a(2),4b(1) + Col D 4a(2), 4b(1)) + HC-D Col A 4d
			GSE CMBS	FR Y-9C FR Y-9C HC-B & HC-D	HC-B (Col B 4c(1)(a),4c(2)(a) + Col D 4c(1)(a), 4c(2)(a)) + HC-D Col A 4d

We follow the method proposed by Ihrig et al. (2019) to calculate total, Level 1, and Level 2A HQLA. Following Ihrig et al. (2019), we do not include Level 2B assets, which comprise corporate debt securities since they account for a negligible portion (<1%) of BHCs' balance sheets and are subject to a 50% hair cut and a constraint of ≤15% of total HQLA.

A.3 Validation checks

Table A.3: Validation checks

Panel A: Baseline results without control variables								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0715***	0.0730***	-0.0014	-0.0251**	0.0437***	-0.0268***	0.0606***	0.0338**
	(5.68)	(4.56)	(-0.13)	(-2.16)	(3.19)	(-6.63)	(3.35)	(2.00)
$T_i^M \cdot$ LCR	0.0605***	0.0396***	0.0209**	-0.0143	0.0371**	-0.0113***	0.0461	0.0347
	(4.67)	(3.46)	(2.08)	(-1.36)	(2.56)	(-3.26)	(1.37)	(1.10)
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,784	2,784	2,784	2,784	2,784	2,784	2,784	2,784
R^2	0.1798	0.1646	0.0519	0.2027	0.0776	0.9109	0.5626	0.7469
Number of BHCs	87	87	87	87	87	87	87	87
Panel B: Propensity score matching results								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0154**	0.0260***	-0.0106	-0.0625***	0.0750***	-0.0322***	0.0592***	0.0270***
	(2.37)	(3.33)	(-1.63)	(-18.41)	(10.10)	(-26.29)	(13.88)	(6.03)
$T_i^M \cdot$ LCR	0.0345***	0.0198*	0.0147	-0.0023	0.0152***	-0.0028*	-0.0025	-0.0053*
	(5.26)	(1.94)	(1.11)	(-0.61)	(2.96)	(-1.95)	(-0.77)	(-1.66)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,356	2,356	2,356	2,356	2,356	2,356	2,356	2,356
R^2	0.3512	0.1133	0.2803	0.2488	0.1086	0.9687	0.7663	0.9041
Number of BHCs	76	76	76	76	76	76	76	76

Notes: This table reports estimates of equation (2.10). Panel A reports estimates of equation (2.10) without control variables to avoid the possibility of bad control bias. Panel B reports estimates of equation (2.10) using a matched sample to ensure the comparability between the control and treatment groups. We match LCR banks with their nearest neighbor with replacement using the Z-score, return-on-assets, capital ratio, loan to assets ratio, and off-balance-sheet commitments to assets ratio as matching variables and a 2.5% caliper. Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4: The LCR Rule and HQLA

	(1)	(2)	(3)	(4)	(5)	(6)
		Net effects			Standard and modified banks	
Dependent variable:	HQR	HQ1	HQ2	HQR	HQ1	HQ2
$T_i \cdot$ LCR	0.0518***	0.0486***	0.0032			
	(5.52)	(4.32)	(0.38)			
$T_i^S \cdot$ LCR				0.0568***	0.0648***	-0.0080
				(4.96)	(4.13)	(-0.74)
$T_i^M \cdot$ LCR				0.0470***	0.0331***	0.0140
				(3.90)	(2.68)	(1.59)
$SIZE_{i,t-1}$	0.0177	0.0028	0.0149	0.0179	0.0033	0.0146
	(1.43)	(0.17)	(1.32)	(1.44)	(0.21)	(1.30)
$ILA_{i,t-1}$	-0.7549**	-0.5269*	-0.2280	-0.7596**	-0.5421*	-0.2175
	(-2.14)	(-1.66)	(-0.78)	(-2.14)	(-1.68)	(-0.74)
$NBL_{i,t-1}$	-0.4333***	-0.1291***	-0.3042***	-0.4333***	-0.1291***	-0.3042***
	(-7.77)	(-2.76)	(-6.72)	(-7.72)	(-2.79)	(-6.78)
$OBS_{i,t-1}$	0.0103	0.0098	0.0005	0.0117	0.0142	-0.0026
	(0.45)	(0.48)	(0.03)	(0.49)	(0.66)	(-0.16)
$DOM_{i,t-1}$	0.0693	0.1281**	-0.0588	0.0642	0.1118**	-0.0475
	(1.44)	(2.25)	(-1.23)	(1.34)	(2.05)	(-0.96)
$CAP_{i,t-1}$	0.0283	-0.1852	0.2135*	0.0216	-0.2069	0.2284*
	(0.25)	(-1.35)	(1.84)	(0.19)	(-1.55)	(1.92)
BHC FE	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4015	0.1934	0.2739	0.4025	0.2064	0.2831
Number of BHCs	87	87	87	87	87	87

Notes: Columns 1-3 report estimates of equation (2.9). Columns 4-6 report estimates of equation (2.10). Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The standard errors are block bootstrapped, drawing 50 samples. In columns 1-3 there are two blocks: LCR and exempt banks. In columns 4-6 there are three blocks: standard LCR, modified LCR and exempt banks. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

A.4 Strategic manipulation of LCR status and size dynamics

A bank's total consolidated assets determine whether it is exempt from or subject to the LCR. In principle, banks could manage their assets to avoid the regulation. Prior research documents such behavior occurs in the European Union where banks attempt to remain below asset thresholds that define regulatory intensity. If certain types of banks systematically move across the LCR size threshold in conjunction with the LCR announcement, a simultaneity problem will exist.

The raw data indicate this issue is not present. Appendix Figure A.1 shows that no banks cross the $50 billion asset threshold that defines whether a bank is exempt from the LCR. Similarly, Appendix Figure A.2 illustrates that no bank's foreign exchange holdings exceed the $10 billion threshold during the sample period.

To more formally investigate whether banks strategically manipulate their asset holdings, we use instrumental variables to generate plausibly exogenous variation in whether a bank is subject to the LCR. We instrument a bank's LCR status (T_i) using its assets in 2005 ($SIZE_i^{2005}$). The instrument is plausibly exogenous because contemporary HQLA, opacity, and funding liquidity risk are unrelated to historic asset values. Moreover, historic assets cannot endogenously react to the LCR as they are pre-determined before either the FRB or the Basel III committee announced the LCR. The instrument is, however, relevant because bank size is correlated through time.

In the first-stage we estimate

$$T_i = \alpha + \varphi SIZE_i^{2005} + v_i, \tag{A.1}$$

where T_i is the dummy variable equal to 1 if BHC i has assets of at least \$50 billion; $SIZE_i^{2005}$ is a dummy variable equal to 1 if BHC i's assets in 2005Q4 were at least \$50 billion, 0 otherwise; v_i is the error term. The second-stage equation is

$$y_{i,t} = \alpha_i + \gamma_t + \theta(\hat{T}_i \times \mathrm{LCR}_t) + X_{i,t-1} + \varepsilon_{i,t}. \tag{A.2}$$

where all variables are defined as in equation (2.9) except $\hat{T}_i$ which is the instrumented treatment identifier from equation (A.1).

Online Appendix Table A.5 presents first- and second-stage results of equations (A.1) and (A.2). The first-stage estimates show the probability that a bank with assets of at least \$50 billion in 2005 is subject to the LCR during the sample period is 90.6%. Diagnostic checks indicate the instrument is relevant: the coefficient estimate is significant at 1% and the Kleibergen-Paap F-statistic exceeds the Stock-Yogo critical value. Columns 2 to 11 of the table report second-stage estimates using the same dependent variables as in Table 2.3. We continue to find the LCR provokes significant increases in banks' liquidity buffers, opacity, and liquidity risk.

Next, we append equation (2.11) with additional interaction variables as controls that capture potential asset manipulation. Specifically we estimate

$$\begin{aligned} y_{i,t} = {} & \alpha_i + \gamma_t + \theta_1(T_i^S \times \mathrm{LCR}_t) + \theta_2(T_i^M \times \mathrm{LCR}_t) + \theta_3(T_i^S \times SIZE_{i,t}) + \theta_4(T_i^M \times SIZE_{i,t}) \\ & + \theta_5(T_i^S \times \mathrm{LCR}_t \times SIZE_{i,t}) + \theta_6(T_i^M \times \mathrm{LCR}_t \times SIZE_{i,t}) + X_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{A.3}$$

where $SIZE_{i,t}$ is the natural logarithm of total assets in bank i during quarter t. All other variables are defined as previously. The size interactions in equation (A.3) remove any confounding size effects from the estimates of θ_1 and θ_2. The estimates in Table A.6 show the findings are robust.

Table A.5: Instrumental variables estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	1st Stage	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	T_i	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
T_i *LCR		0.0527***	0.0532***	-0.0005	-0.0204**	0.0365***	-0.0147***	0.0593***	0.0446**
		(4.59)	(4.05)	(-0.05)	(-2.41)	(2.63)	(-5.83)	(2.86)	(2.20)
$SIZE_{i,t-1}$		0.0124	-0.0015	0.0139	0.0086	-0.0277*	-0.0011	-0.0266***	-0.0277***
		(0.95)	(-0.09)	(1.26)	(1.33)	(-1.65)	(-0.67)	(-2.61)	(-2.64)
$ILA_{i,t-1}$		-0.7107*	-0.4851	-0.2256	-0.1028	0.1484	-0.1544***	0.9681**	0.8137**
		(-1.93)	(-1.52)	(-0.76)	(-0.58)	(0.26)	(-2.96)	(2.48)	(2.06)
$NBL_{i,t-1}$		-0.4489***	-0.1408***	-0.3081***	-0.0071	-0.0305	0.1703***	-0.0062	0.1641***
		(-7.83)	(-2.93)	(-7.03)	(-0.39)	(-0.58)	(25.95)	(-0.12)	(3.21)
$OBS_{i,t-1}$		0.0137	0.0116	0.0020	-0.0255*	0.0428	0.0015	0.0450**	0.0465**
		(0.61)	(0.59)	(0.12)	(-1.75)	(1.38)	(0.40)	(2.16)	(2.45)
$DOM_{i,t-1}$		0.0559	0.1106*	-0.0546	-0.0321	-0.0449	-0.0363***	-0.1979*	-0.2342**
		(1.15)	(1.92)	(-1.13)	(-1.08)	(-0.49)	(-3.64)	(-1.94)	(-2.47)
$CAP_{i,t-1}$		0.0688	-0.1485	0.2174*	0.0328	-0.0298	-0.0062	-0.2826**	-0.2887**
		(0.56)	(-1.01)	(1.89)	(0.38)	(-0.19)	(-0.30)	(-2.46)	(-2.57)
$SIZE_i^{2005}$	0.9055***								
	(13.31)								
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.7796	0.3890	0.1908	0.2733	0.2471	0.1062	0.9624	0.5876	0.7660
Number of BHCs	87	87	87	87	87	87	87	87	87
KP F-statistic	177.13								

Notes: This table reports estimates of equation (A.1) in column 1. Columns 2 to 11 report estimates of equation (A.2). KP F-statistic denotes the Kleibergen-Paap F-statistic. Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The standard errors are block bootstrapped (there are two blocks: LCR and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.6: Size dynamics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0561***	0.0641***	-0.0080	-0.0209*	0.0351**	-0.0182***	0.0643***	0.0460**
	(4.67)	(4.04)	(-0.76)	(-1.91)	(2.28)	(-5.37)	(3.15)	(2.44)
$T_i^M \cdot$ LCR	0.0481***	0.0351***	0.0131	-0.0082	0.0259**	-0.0045**	0.0378	0.0334
	(3.68)	(2.71)	(1.47)	(-1.03)	(2.27)	(-2.32)	(1.17)	(1.08)
$T_i^S \cdot$ LCR $\cdot SIZE_{i,t}$	-0.0933	-0.0996	0.0063	-0.0602	0.1558	-0.0002	0.6972	0.6969
	(-0.83)	(-0.58)	(0.05)	(-0.52)	(0.82)	(-0.01)	(1.24)	(1.28)
$T_i^M \cdot$ LCR $\cdot SIZE_{i,t}$	0.2716*	0.3349**	-0.0633	0.0453	0.0442	-0.0040	-0.1035	-0.1075
	(1.88)	(2.44)	(-1.18)	(0.42)	(0.23)	(-0.09)	(-0.91)	(-0.99)
$T_i^S \cdot SIZE_{i,t}$	-0.0774	-0.0686	-0.0088	0.1059	0.0888	-0.0074	0.0993	0.0919
	(-0.58)	(-0.54)	(-0.15)	(1.25)	(0.69)	(-0.20)	(0.52)	(0.49)
$T_i^M \cdot SIZE_{i,t}$	-0.3478***	-0.3595**	0.0117	0.0245	-0.1100	0.0392	0.2468*	0.2860**
	(-2.81)	(-2.56)	(0.28)	(0.48)	(-1.08)	(1.52)	(1.74)	(2.40)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4071	0.2120	0.2834	0.2407	0.1046	0.9634	0.5932	0.7703
Number of BHCs	87	87	87	87	87	87	87	87

Notes: This table reports estimates of equation (2.10) with additional interactions between the standard and modified LCR bank indicators and *SIZE*. Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

A.5 Macroprudential reforms and stress tests

To ensure the inferences reflect liquidity regulation rather than GSIB capital surcharges and capital regulation, we append equation (2.10) with controls that capture macroprudential reforms. We create the dummy variable $GSIB_i$ that equals 1 if a bank is a global-systemically important bank, 0 otherwise. *Capital Surcharges* is the additional annual percentage capital surcharge for GSIBs announced annually by the Bank for International Settlements since 2012Q2. Depending on how globally systemically important a bank is the surcharge ranges between 1% and 2.5%. The estimates in Panel A of Table A.7 include the interaction between the $GSIB_i$ and *Capital Surcharges* variable. Despite this change, the main findings are robust.

We address the introduction of new capital requirements in Panel B of Table A.7. We generate a dummy variable, *Capital Requirement*, that equals 1 for 2011Q1 onward, 0 otherwise, and interact it with the T_i^S and T_i^M variables. While we find some evidence that capital regulation provokes changes in the outcomes of interest, the baseline results are robust.

Each year the CCAR assesses large BHCs' capital adequacy and includes stress testing mandated by the Dodd-Frank Act. The assessment identifies whether a BHC has adequate capital, a stable capital structure under several stress scenarios, and whether dividends and share repurchases compromise regulatory capital requirements. CCARs rely on qualitative and quantitative data, and a BHC must satisfy both categories to pass the test. To control for this factor, we employ a similar approach to that of Acharya et al. (2018) by including a triple-difference interaction between banks subject to stress testing, banks failing the stress test, and a post-stress test four-quarter dummy. To capture the effect of living wills, we interact T_i^S and T_i^M with *Living Wills*, a dummy variable equal to 1 after the announcement of the living wills requirement in 2011Q4 onward, 0 otherwise. Panel A (B) in Table A.8 shows that stress tests (living wills) do not confound the estimates.

Table A.7: GSIB capital surcharges and capital regulation

Panel A: GSIB capital surcharge								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Variables	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0518***	0.0590***	-0.0072	-0.0200**	0.0273*	-0.0138***	0.0527***	0.0390**
	(4.58)	(3.69)	(-0.70)	(-1.98)	(1.90)	(-4.86)	(2.80)	(2.28)
$T_i^M \cdot$ LCR	0.0474***	0.0335***	0.0139	-0.0092	0.0265**	-0.0050**	0.0374	0.0323
	(3.93)	(2.71)	(1.58)	(-1.09)	(2.07)	(-2.34)	(1.19)	(1.09)
$GSIB_i \cdot$ Capital Surcharges	0.8624*	1.0013*	-0.1389	-0.0780	1.1606	-0.7724***	1.0616	0.2892
	(1.87)	(1.83)	(-0.39)	(-0.09)	(1.13)	(-2.88)	(1.21)	(0.33)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4044	0.2095	0.2832	0.2374	0.1051	0.9654	0.5843	0.7643
Number of BHCs	87	87	87	87	87	87	87	87

Panel B: Capital requirement								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0469***	0.0536***	-0.0067	-0.0208*	0.0245*	-0.0114***	0.0511***	0.0396***
	(3.66)	(3.30)	(-0.75)	(-1.95)	(1.76)	(-4.92)	(3.43)	(2.83)
$T_i^M \cdot$ LCR	0.0427***	0.0300**	0.0128	-0.0100	0.0226*	-0.0034***	0.0338	0.0304
	(3.06)	(1.98)	(1.48)	(-1.30)	(1.84)	(-2.88)	(1.32)	(1.20)
$T_i^S \cdot$ Capital Requirement	0.0185**	0.0208***	-0.0023	0.0007	0.0178	-0.0126***	0.0147**	0.0020
	(2.49)	(3.05)	(-0.46)	(0.07)	(1.52)	(-4.08)	(2.10)	(0.27)
$T_i^M \cdot$ Capital Requirement	0.0086	0.0065	0.0021	0.0016	0.0069	-0.0029	0.0064	0.0035
	(1.38)	(0.89)	(0.39)	(0.33)	(0.72)	(-1.05)	(0.48)	(0.32)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4057	0.2111	0.2833	0.2374	0.1045	0.9652	0.5839	0.7643
Number of BHCs	87	87	87	87	87	87	87	87

Notes: Panel A reports estimates of equation (2.10) that includes an interaction variable between $GSIB_{i,t}$ and the annual BIS additional capital surcharge. Panel B reports estimates of equation (2.10) that includes the interactions between the standard and modified LCR bank indicators and the capital requirement dummy variable. Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

A.6 Spillover effects

We randomly assign exempt banks to a placebo LCR condition to mimic T_i in the main tests, and interact this dummy variable with the LCR dummy variable. If spillovers are absent, the placebo LCR-LCR interaction coefficients should be statistically insignificant. The only cases where this will not be so is if, 1) there are type-1 errors, or 2) if spillover effects are present in which case we will reject the null hypothesis at a higher frequency than with type-1 errors.

Column 1 of Table A.9 shows that for HQLA holdings, the null hypothesis on the placebo LCR interaction is rejected at a frequency consistent with type-1 errors. We find similar results using the deposit market share in column 2 of the table. These pieces of evidence suggest spillovers are not present in the data.

Table A.8: Stress test and living wills

Panel A: Stress tests								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0523***	0.0614***	-0.0091	-0.0227**	0.0351**	-0.0170***	0.0527***	0.0357**
	(4.87)	(4.19)	(-0.88)	(-2.43)	(2.41)	(-5.45)	(3.03)	(2.23)
$T_i^M \cdot$ LCR	0.0371***	0.0255**	0.0116	-0.0141	0.0282*	-0.0020	0.0232	0.0213
	(3.99)	(2.24)	(1.31)	(-1.00)	(1.91)	(-0.94)	(1.32)	(1.24)
$ST_i \cdot$ Post ST	0.0181**	0.0139*	0.0043	0.0083	-0.0040	-0.0050***	0.0253	0.0203
	(2.22)	(1.95)	(0.80)	(0.73)	(-0.34)	(-2.64)	(0.91)	(0.74)
$ST_i \cdot$ Post ST $\cdot ST_i^{Failed}$	-0.0130**	-0.0116	-0.0014	0.0167	0.0010	0.0007	-0.0244*	-0.0236
	(-2.10)	(-1.49)	(-0.13)	(0.98)	(0.11)	(0.62)	(-1.71)	(-1.59)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4070	0.2100	0.2835	0.2550	0.1018	0.9637	0.5873	0.7661
Number of BHCs	87	87	87	87	87	87	87	87

Panel B: Living wills								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0507***	0.0577***	-0.0070	-0.0211**	0.0257*	-0.0140***	0.0549***	0.0409***
	(3.92)	(3.43)	(-0.71)	(-2.12)	(1.78)	(-5.14)	(3.40)	(2.74)
$T_i^M \cdot$ LCR	0.0445***	0.0310**	0.0135	-0.0107	0.0250**	-0.0041***	0.0368	0.0327
	(3.11)	(2.00)	(1.51)	(-1.31)	(2.08)	(-2.70)	(1.32)	(1.21)
$T_i^S \cdot$ Living Wills	0.0159**	0.0182***	-0.0023	0.0019	0.0212	-0.0108***	0.0101	-0.0007
	(2.18)	(2.89)	(-0.49)	(0.19)	(1.47)	(-3.82)	(1.58)	(-0.10)
$T_i^M \cdot$ Living Wills	0.0075	0.0065	0.0010	0.0039	0.0041	-0.0022	0.0010	-0.0012
	(0.92)	(0.63)	(0.16)	(0.78)	(0.36)	(-0.98)	(0.08)	(-0.11)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4048	0.2100	0.2832	0.2379	0.1054	0.9647	0.5835	0.7643
Number of BHCs	87	87	87	87	87	87	87	87

Notes: Panel A reports estimates of equation (2.10) that includes interaction terms between a bank subject to a stress test (ST_i), a bank failing a stress test (ST_i^{Failed}), and post-stress test four-quarter dummies (Post-ST). Panel B reports estimates of equation (2.10) that includes interactions between the standard and modified LCR bank indicators and the living wills dummy variable. Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.9: Monte Carlo spillover tests

	(1)	(2)
Variable	HQR	DOM
Number of Simulations	1,000	1,000
Rejection rate at 10% (2-tailed test)	9.5%	10.6%
Rejection rate at 5% (2-tailed test)	4.2%	5.0%
Rejection rate at 1% (2-tailed test)	0.9%	1.0%

Notes: This table reports the rejection rate of the null hypothesis at the 10%, 5% and 1% levels in Monte Carlo simulation tests. The sample includes only exempt banks. We randomly assign exempt banks to a placebo treatment status, $PLACEBO_{i,t}$, that equals 1 for the period 2013Q4 to 2017Q4 for placebo treatment banks, and 0 otherwise. We then estimate the equation $y_{i,t} = \alpha_i + \gamma_t + \theta \text{PLACEBO}_{i,t} + X_{i,t-1} + \varepsilon_{i,t}$, where all variables are defined as in equation (2.9) except $y_{i,t}$ is either HQR (column 1) or deposit market share, DOM (column 2). We save the p-value of θ. We repeat the process 1,000 times and compute the rejection rate that $\theta = 0$ at the 10%. 5%, and 1% levels. Variable definitions are provided in Table 2.1.

A.7 Robustness to Quantitative Easing

Table A.10: Additional Quantitative Easing controls

Panel A: Dummy variable approach								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0573***	0.0651***	-0.0078	-0.0188*	0.0301**	-0.0167***	0.0541***	0.0374**
	(4.69)	(3.79)	(-0.73)	(-1.90)	(2.06)	(-5.40)	(3.27)	(2.47)
$T_i^M \cdot$ LCR	0.0455***	0.0321**	0.0135	-0.0092	0.0253**	-0.0046**	0.0341	0.0295
	(3.45)	(2.37)	(1.62)	(-1.19)	(2.07)	(-2.18)	(1.17)	(1.07)
$T_i^S \cdot$ QE1	0.1499	0.1032	0.0467	0.0213	0.2486	-0.1634***	0.1080	-0.0553
	(0.99)	(0.56)	(0.29)	(0.21)	(1.10)	(-2.69)	(1.09)	(-0.57)
$T_i^M \cdot$ QE1	0.3249	0.2438	0.0811	0.1270**	0.0450	-0.0296	-0.1062	-0.1357
	(1.02)	(0.86)	(0.69)	(2.09)	(0.35)	(-0.55)	(-0.55)	(-0.76)
$T_i^S \cdot$ QE2	-0.0416	-0.0614	0.0197	0.0418	-0.2280*	0.1180***	-0.0696*	0.0484
	(-0.46)	(-0.76)	(0.56)	(0.52)	(-1.67)	(3.43)	(-1.66)	(0.85)
$T_i^M \cdot$ QE2	-0.0600	-0.0336	-0.0265	-0.0229	-0.0452	0.0141	-0.0041	0.0100
	(-0.46)	(-0.21)	(-0.49)	(-0.53)	(-0.69)	(0.85)	(-0.06)	(0.16)
$T_i^S \cdot$ QE3	0.1376**	0.1525	-0.0148	0.1279	-0.0842	-0.0249	-0.5197***	-0.5447***
	(1.97)	(1.54)	(-0.27)	(1.27)	(-1.11)	(-1.60)	(-3.64)	(-3.67)
$T_i^M \cdot$ QE3	-0.0679	-0.0563	-0.0116	0.0497	-0.0264	0.0000	-0.3596*	-0.3596*
	(-1.22)	(-0.86)	(-0.21)	(0.97)	(-0.22)	(0.00)	(-1.82)	(-1.73)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4044	0.2091	0.2832	0.2424	0.1035	0.9641	0.5922	0.7702
Number of BHCs	87	87	87	87	87	87	87	87
Panel B: Size of the Federal Reserve's balance sheet								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0591***	0.0672***	-0.0081	-0.0182*	0.0313**	-0.0179***	0.0508***	0.0329**
	(4.90)	(3.85)	(-0.74)	(-1.84)	(2.11)	(-5.20)	(3.23)	(2.30)
$T_i^M \cdot$ LCR	0.0457***	0.0321**	0.0136*	-0.0086	0.0253**	-0.0046**	0.0316	0.0270
	(3.65)	(2.56)	(1.65)	(-1.10)	(2.12)	(-1.98)	(1.12)	(1.02)
$T_i^S \cdot CBA_t$	0.0910	0.0964	-0.0055	0.0956	-0.1179**	0.0143**	-0.3490***	-0.3347***
	(1.27)	(1.06)	(-0.15)	(1.49)	(-2.55)	(2.34)	(-3.56)	(-3.41)
$T_i^M \cdot CBA_t$	-0.0498	-0.0339	-0.0159	0.0289	-0.0357	0.0037	-0.2300*	-0.2263
	(-1.36)	(-0.72)	(-0.50)	(0.80)	(-0.55)	(0.41)	(-1.68)	(-1.59)
CBA_t	0.2801	0.3088	-0.0277	0.2329**	0.0419	-0.3681***	-0.5715***	-0.9410***
	(1.43)	(1.62)	(-0.17)	(2.47)	(0.21)	(-11.63)	(-3.47)	(-5.71)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
R^2	0.4035	0.2076	0.2832	0.2410	0.1029	0.9633	0.5887	0.7673
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4054	0.1964	0.2742	0.2447	0.1080	0.9607	0.6181	0.7838
Number of BHCs	87	87	87	87	87	87	87	87

Notes: This table reports estimates of equation (2.10). Panel A includes interactions between the standard and modified LCR bank indicators and the three quantitative easing episodes dummy variables $QE1$, $QE2$, and $QE3$. Panel B includes interactions between the standard and modified LCR bank indicators and central bank assets (CBA). Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.11: Robustness to Quantitative Easing using Oster (2019) Coefficient Stability

Panel A: No controls to all controls								
	QE controls		All controls		R^2_{max}		Bounding values	
Specification	$\dot{\beta}$	$\dot{R}^2$	$\tilde{\beta}$	$\tilde{R}^2$	″ = 1.3	″ = 1.5	$\beta^*_{″=1.3}$	$\beta^*_{″=1.5}$
HQR	0.0490	0.102	0.0518	0.402	0.523	0.603	0.0530	0.0537
DQ	-0.0214	0.087	-0.0147	0.231	0.300	0.347	-0.0114	-0.0093
AOP	0.0322	0.046	0.0300	0.101	0.131	0.152	0.0287	0.0279
LRISK	0.1168	0.135	0.0363	0.764	0.993	1.000	0.0070	0.0061
Panel B: The Fed's assets controls to all controls								
	QE controls		All controls		R^2_{max}		Bounding values	
Specification	$\dot{\beta}$	$\dot{R}^2$	$\tilde{\beta}$	$\tilde{R}^2$	″ = 1.3	″ = 1.5	$\beta^*_{″=1.3}$	$\beta^*_{″=1.5}$
HQR	0.0558	0.115	0.0561	0.405	0.527	0.608	0.0562	0.0563
DQ	-0.0241	0.132	-0.0184	0.245	0.319	0.368	-0.0147	-0.0122
AOP	0.0387	0.060	0.0356	0.108	0.140	0.162	0.0335	0.0322
LRISK	0.1247	0.265	0.0562	0.784	1.000	1.000	0.0277	0.0277

Notes: This table estimates bounding values for the baseline estimates following the procedure outlined by Oster (2019). The procedure assumes that selection on unobservables is proportional to selection on observables. The bounding value β^* is estimated as $\beta^* = \tilde{\beta} - \frac{(\dot{\beta}-\tilde{\beta})(R^2_{max}-\tilde{R}^2)}{\tilde{R}^2-\dot{R}^2}$, where $\dot{\beta}$ and $\dot{R}^2$ are the point estimate and R^2 for the regression without controls and $\tilde{\beta}$ and $\tilde{R}^2$ are the respective values from the regression with controls. The calculations assume that the degree of proportionality between selection on unobservables and selection on observables is one ($\triangle = 1$). Since the procedure requires making an assumption about the maximum possible R^2, we follow Oster (2019) by using $R^2 = \min(1, ″ \cdot \tilde{R}^2)$ with ″ = 1.3 as our benchmark and our more conservative value of ″ = 1.5. Panel A reports the bounding value when moving from equation (2.9) without controls to the specification with all controls (i.e. $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$). Panel B presents the bounding values when moving from equation (2.10) to equation (2.10) with additional interactions between the standard and modified LCR indicators and central bank assets (CBA).

A.8 Further robustness checks

Table A.12: Bank-level and macroeconomic risks

Panel A: Credit risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0566***	0.0644***	-0.0078	-0.0207*	0.0334**	-0.0179***	0.0578***	0.0399**
	(4.73)	(4.01)	(-0.74)	(-1.91)	(2.20)	(-5.15)	(3.32)	(2.51)
$T_i^M \cdot$ LCR	0.0477***	0.0338***	0.0140*	-0.0094	0.0225*	-0.0053**	0.0439	0.0387
	(3.72)	(2.64)	(1.65)	(-1.05)	(1.76)	(-2.37)	(1.28)	(1.18)
$T_i^S \cdot \triangle NPL$	0.4171	0.5764	-0.1593	0.3937	0.9097*	-0.5114***	1.2050	0.6936
	(0.46)	(0.70)	(-0.33)	(0.79)	(1.75)	(-2.65)	(0.82)	(0.49)
$T_i^M \cdot \triangle NPL$	-0.2832	-0.3778	0.0946	0.1633	1.8482	0.3190*	-4.1008	-3.7818
	(-0.35)	(-0.45)	(0.12)	(0.17)	(0.94)	(1.94)	(-1.20)	(-1.12)
$\triangle NPL$	-0.1907	-0.0329	-0.1578	-0.0149	0.4438**	-0.0058	-0.0594	-0.0652
	(-0.81)	(-0.16)	(-1.21)	(-0.23)	(2.49)	(-0.16)	(-0.69)	(-0.62)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4030	0.2067	0.2837	0.2378	0.1066	0.9636	0.5856	0.7654
Number of BHCs	87	87	87	87	87	87	87	87

Panel B: Solvency risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0517***	0.0604***	-0.0087	-0.0212*	0.0402**	-0.0187***	0.0701***	0.0514***
	(5.10)	(4.15)	(-0.80)	(-1.77)	(2.47)	(-5.08)	(3.50)	(2.80)
$T_i^M \cdot$ LCR	0.0470***	0.0320**	0.0150*	-0.0076	0.0187**	-0.0046**	0.0464	0.0418
	(3.79)	(2.50)	(1.69)	(-1.05)	(2.02)	(-2.41)	(1.31)	(1.23)
$T_i^S \cdot ZSC_{i,t}$	0.0003**	0.0002*	0.0000	0.0000	-0.0004***	0.0000	-0.0005***	-0.0005***
	(2.31)	(1.89)	(0.56)	(0.61)	(-3.18)	(0.04)	(-3.51)	(-3.58)
$T_i^M \cdot ZSC_{i,t}$	0.0000	0.0001	-0.0001	-0.0001	0.0004	-0.0000	-0.0006*	-0.0006*
	(0.45)	(1.06)	(-0.60)	(-0.89)	(1.31)	(-0.57)	(-1.89)	(-1.81)
$ZSC_{i,t}$	-0.0001	-0.0001	-0.0000	-0.0000	0.0003*	0.0000*	0.0000	0.0000
	(-1.00)	(-0.89)	(-0.23)	(-0.40)	(1.96)	(1.86)	(0.08)	(0.44)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4051	0.2086	0.2835	0.2387	0.1142	0.9634	0.5883	0.7672
Number of BHCs	87	87	87	87	87	87	87	87

Panel C: Macroeconomic risk

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0495***	0.0563***	-0.0068	-0.0201**	0.0153	-0.0132***	0.0508***	0.0375***
	(3.87)	(3.17)	(-0.73)	(-2.02)	(0.96)	(-4.76)	(3.27)	(2.65)
$T_i^M \cdot$ LCR	0.0442***	0.0305*	0.0136	-0.0107	0.0159	-0.0036***	0.0336	0.0300
	(2.98)	(1.88)	(1.55)	(-1.26)	(1.32)	(-2.59)	(1.29)	(1.19)
$T_i^S \cdot UNEMP_t$	-0.2348***	-0.2682***	0.0334	0.0769	-0.0468	0.0658***	-0.0701	-0.0044
	(-3.13)	(-2.98)	(0.78)	(1.50)	(-0.72)	(2.91)	(-1.10)	(-0.06)
$T_i^M \cdot UNEMP_t$	-0.3442**	-0.2942**	-0.0500	0.0873	-0.0515	0.0541*	-0.0298	0.0243
	(-2.47)	(-2.52)	(-0.90)	(1.30)	(-0.61)	(1.74)	(-0.47)	(0.48)
$T_i^S \cdot GSP_t$	-0.0217	-0.0106	-0.0110	0.0091	-0.0449	0.0396***	0.1379***	0.1775***
	(-0.33)	(-0.16)	(-0.98)	(0.68)	(-1.28)	(2.92)	(3.04)	(3.78)
$T_i^M \cdot GSP_t$	0.0005	0.0128	-0.0123	0.0286	-0.0001	0.0039	0.0967**	0.1006**
	(0.01)	(0.23)	(-0.54)	(1.35)	(-0.00)	(0.24)	(2.43)	(2.02)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,088	2,088	2,088	2,088	2,088	2,088	2,088	2,088
R^2	0.3991	0.1888	0.2410	0.2494	0.1325	0.9314	0.5735	0.6922
Number of BHCs	87	87	87	87	87	87	87	87

Notes: This table reports estimates of equation (2.10). Panel A includes the interactions between the standard and modified LCR bank indicators and $\triangle NPL$. Panel B includes the interactions between the standard and modified LCR bank indicators and the *Z-Score*. Panel C includes the interactions between the standard and modified LCR bank indicators and macroeconomic variables (GSP and $UNEMP$). Variable definitions are provided in Table 2.1. Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

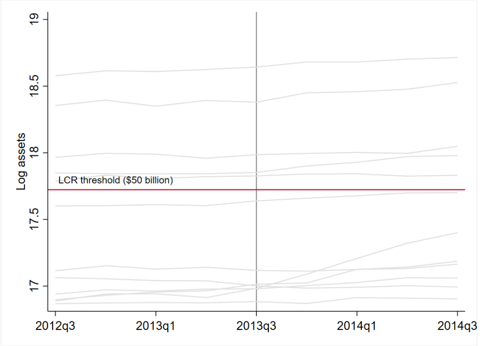
Table A.13: Disclosure rule and Basel III capital regulation

Panel A: Disclosure Rule (Pre-2017 Results)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0576***	0.0659***	-0.0083	-0.0160*	0.0329**	-0.0174***	0.0436***	0.0261**
	(5.21)	(3.88)	(-0.75)	(-1.87)	(2.26)	(-5.17)	(3.35)	(2.20)
$T_i^M \cdot$ LCR	0.0448***	0.0324***	0.0124	-0.0073	0.0225**	-0.0043**	0.0273	0.0230
	(3.49)	(2.72)	(1.58)	(-1.15)	(2.55)	(-1.97)	(1.08)	(0.98)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,349	2,349	2,349	2,349	2,349	2,349	2,349	2,349
R^2	0.3756	0.1962	0.2691	0.2275	0.0865	0.9604	0.5601	0.7624
Number of BHCs	87	87	87	87	87	87	87	87
Panel B: Effects of Basel III Capital Regulation on Opacity								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Liquidity buffers			Bank opacity		Liquidity risk		
Dependent variable:	HQR	HQ1	HQ2	DQ	AOP	LRISKA	LRISKL	LRISK
$T_i^S \cdot$ LCR	0.0586***	0.0494***	0.0463***	-0.0217*	0.0350**	-0.0200***	0.0553***	0.0353**
	(5.57)	(3.18)	(3.28)	(-1.93)	(2.25)	(-5.02)	(3.11)	(2.22)
$T_i^M \cdot$ LCR	0.0501***	0.0220**	0.0246**	-0.0063	0.0193*	-0.0048**	0.0435	0.0387
	(3.52)	(2.19)	(2.40)	(-0.98)	(1.88)	(-2.15)	(1.25)	(1.17)
$T_i^S \cdot CDIFF_{i,t-1}$	0.1138	0.0042	0.0955	-0.0492	0.0082	-0.0937***	-0.1568	-0.2505***
	(0.85)	(0.03)	(0.54)	(-0.59)	(0.05)	(-3.07)	(-1.54)	(-3.07)
$T_i^M \cdot CDIFF_{i,t-1}$	-0.1510	0.3963***	0.4088***	-0.1503	0.3462**	-0.0022	-0.3412	-0.3434
	(-0.59)	(2.98)	(3.06)	(-1.16)	(2.47)	(-0.11)	(-0.61)	(-0.61)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES	YES	YES	YES	YES
Quarter-Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2,697	2,697	2,697	2,697	2,697	2,697	2,697	2,697
R^2	0.4045	0.2317	0.2008	0.2420	0.1067	0.9642	0.5856	0.7663
Number of BHCs	87	87	87	87	87	87	87	87

Notes: This table reports estimates of equation (2.9). Panel A shows results from a sample that excludes observations from 2017Q1 onward. Variable definitions are provided in Table 2.1. Panel B appends (2.9) with $CDIFF_{i,t-1}$, which is the difference between a bank's capital adequacy ratio during quarter t and the minimum Basel III capital adequacy ratio (10.5%). Quarter-year FE denotes quarter × year fixed effects. The unreported control variables are $SIZE_{i,t-1}$, $ILA_{i,t-1}$, $NBL_{i,t-1}$, $OBS_{i,t-1}$, $DOM_{i,t-1}$, and $CAP_{i,t-1}$. The standard errors are block bootstrapped (there are three blocks: standard LCR, modified LCR, and exempt banks) drawing 50 samples. The corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

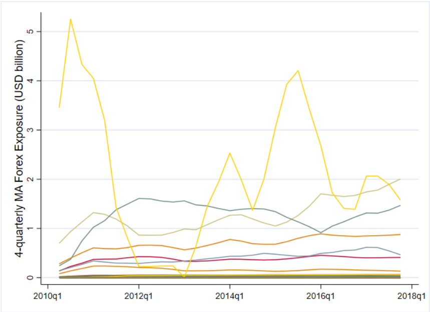
A.9 Supplementary figures

Figure A.1: BHC's total assets at the $50 billion threshold

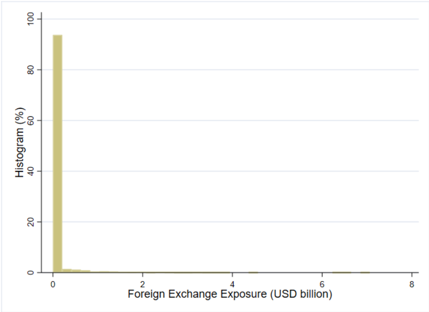


Notes: This figure shows the evolution of total assets of our sample BHCs. No BHCs cross the LCR asset threshold of $50 billion during the sample period.

Figure A.2: BHC's foreign exchange exposures



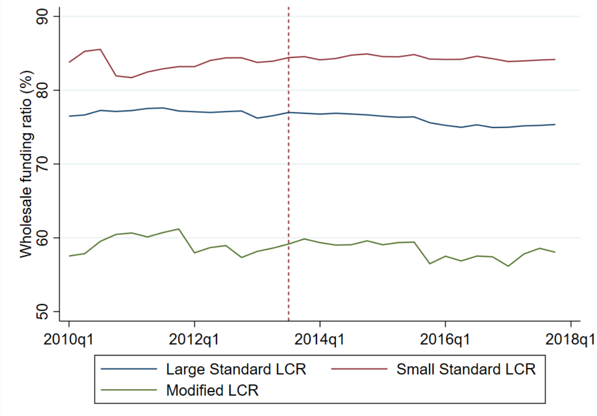
(a) Trends



(b) Histogram

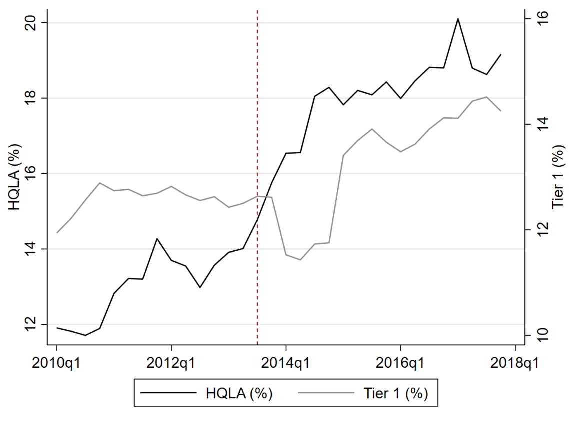
Notes: Panel A illustrates the foreign exchange exposures of banks during the sample period. No bank has foreign exposure of $10 billion or more during the sample window. Panel B depicts the density of foreign exchange exposure across the banks in our sample. The overwhelming majority of banks have zero or close to zero foreign exchange exposures. Source: FR Y-9C Schedule HI Memo.

Figure A.3: Wholesale funding contribution



Notes: The figure illustrates the evolution of the ratio of wholesale funding to total funding within standard and modified LCR banks. Wholesale funding includes overnight federal funds purchased, foreign deposits, uninsured deposits, trading liabilities and other liabilities. We separate standard LCR banks into 'large' and 'small' standard LCR banks. 'Small' standard LCR banks are those with log assets (in thousands) between 19.34 (the standard LCR threshold of $250 billion) and, 20.44 (the midpoint between the standard LCR threshold and the maximum value). 'Large' standard LCR banks are those with log assets (in thousands) greater than 20.44. The figure shows that smaller standard LCR banks rely most heavily on wholesale funding which exposes them more to potentially larger funding withdrawal. Source: FR Y-9C Schedule HC.

Figure A.4: The evolution of HQLA and regulatory tier 1 ratios



Notes: The figure illustrates the evolution of HQLA (left axis) and regulatory tier 1 ratios (right axis) of LCR banks. The figure shows that the tier 1 capital ratio fell shortly after the announcement of the LCR. This drop may be attributed to banks increasing their holding of complex assets such as C&I loans and heterogenous loans that have higher asset risk weights. Higher capital levels prior to the LCR announcement may give banks some headroom to meet the LCR requirement by sacrificing capital for liquidity. This illustration is consistent with our analysis in section 2.4.5 which shows LCR banks' increasing balance sheet complexity after implementation of the LCR.

APPENDIX

B

APPENDIX OF CHAPTER 3

B.1 Liquidity risk measure

Our liquidity risk measure follows closely the methodology outlined by Bai et al. (2018). The Online Appendix Table B.1 depicts the details of each asset and liability component used to compute the index. The first and second columns of the table show the balance sheet categories and classes, respectively. The third column show the weights of the balance sheet classes, and the last column depicts the call report (FFIEC 031/041) source form of the balance sheet classes.

A major difference between our method and that of Bai et al. (2018) is the data source. Bai et al. (2018) collect Bank Holding Companies (BHCs) data mainly from the FR Y-9C and we collect bank subsidiaries data from the call report (FFIEC 031/041). As shown by Table B.1, while most of the variables from these data sources are comparable, we make small adjustments due to data unavailability, particularly with regard to the calculation of "Other borrowed money". Specifically, our liquidity mismatch index aggregates all "other borrowed money" components, while Bai's et al. (2018) version breaks it into total commercial paper, short-term commercial paper ($T_{k'} \leq 1$), and long-term commercial paper ($T_{k'} > 1$).

Despite this slight deviation, since the weighted values of these classes are relatively small, we believe this deviation does not alter the liquidity risk measure significantly since the average weighted shares of these balance sheet classes are negligible.

Table B.1: LMI category, item, weight, and schedule

Panel A: Asset-side

Category	$a_{i,t,k}$	λ_{t,a_k}	FFIEC Schedule
Cash	Cash, Fed Funds sold, reverse repo	1.00	RC
Trading securities	Trading treasury	0.96	RC-B
	Trading agency bond	0.96	RC-B
	Trading municipal bond	0.80	RC-B
	Trading structured products	0.86	RC-B
	Trading corporate bond	0.81	RC-B
AFS securities	AFS treasury	0.96	RC-B
	AFS agency bond	0.96	RC-B
	AFS municipal bond	0.80	RC-B
	AFS structured products	0.86	RC-B
	AFS corporate bond	0.81	RC-B
	AFS equity	0.76	RC-B
HTM securities	HTM treasury	0.96	RC-B
	HTM agency bond	0.96	RC-B
	HTM municipal bond	0.81	RC-B
	HTM structured products	0.86	RC-B
	HTM corporate bond	0.81	RC-B
Semi-liquid assets	Real estate loans	0.68	RC-C
	Commercial & industrial loans	0.68	RC-C
	Lease financing	0.68	RC-C
	Other loans	0.68	RC-C
Fixed and intangible assets	Other assets	~ 0	RC

Panel B: Liability-side

Category	$l_{i,t,k'}$	$\lambda_{t,l_{k'}}$	FFIEC Schedule
Overnight debt	Overnight Fed Funds	1.00	RC
	Repo	1.00	RC
Deposits	Insured deposits	~ 0	RC-E
	Non-insured deposits	0.31	RC-E
Trading liabilities	Trading liabilities	0.91	RC-D
Other borrowed money*	Other borrowed money	0.91	RC
Other liabilities	Subordinated debt	~ 0	RC
	Other liabilities	~ 0	RC
Equity capital	Equity	~ 0	RC
Contingen liabilities	Unused commitments	~ 0	RC
	Credit lines	~ 0	RC
	Securities lent	~ 0	RC
	Collateral	~ 0	RC

Note: The original method based on Bai et al. (2018), other borrowed money comprises of commercial paper, commercial paper with maturity ≤ 1 year and commercial paper with matruity > 1 year. Due to data limitation, we only include total commercial paper with $T_{k'} = 1/12$ as outlined in Bai et al. (2018).

B.2 Further results tables

Table B.2: Additional robustness checks

Panel A: Without controls

	Tax Increase		Tax Cut	
	(1)	(2)	(3)	(4)
Dependent variable:	*Opacity*	*LR*	*Opacity*	*LR*
$\triangle Tax_t$	0.3178*	0.0895***	0.0079	0.0143
	(2.50)	(6.70)	(0.18)	(1.02)
Control Variables	NO	NO	NO	NO
State FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	3,559	3,559	5,727	5,727
R^2	0.0209	0.9562	0.0242	0.9234

Panel B: Post-crisis sample

	Tax Increase		Tax Cut	
	(1)	(2)	(3)	(4)
Dependent variable:	*Opacity*	*LR*	*Opacity*	*LR*
$\triangle Tax_t$	0.2552*	0.0544**	-0.0307	-0.0030
	(2.45)	(3.42)	(-0.63)	(-0.43)
Control Variables	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	1,650	1,650	4,597	4,597
R^2	0.0077	0.1393	0.0064	0.2079

Notes: This table reports estimates of equation (3.4) without control variables. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.3: Tax effects using matching sample

Panel A: Matching sample comparison

Variable		Mean	Wilcoxon	t-test
		Statistical tests		
Tax increase				
Size	Control	11.691	1.47	1.36
	Treated	11.599		
Loans	Control	0.6606	1.09	0.15
	Treated	0.6590		
LDR	Control	0.7918	0.36	0.33
	Treated	0.7872		
NIM	Control	0.0338	1.38	1.08
	Treated	0.0343		
C&I	Control	0.0172	1.16	0.08
	Treated	0.0169		
CAP	Control	0.1093	1.56	0.52
	Treated	0.1080		
Tax cut				
Size	Control	11.770	1.39	0.01
	Treated	11.770		
Loans	Control	0.6283	0.09	0.18
	Treated	0.6268		
LDR	Control	0.7550	0.23	0.27
	Treated	0.7522		
NIM	Control	0.0326	0.61	0.63
	Treated	0.0329		
C&I	Control	0.0179	0.43	0.44
	Treated	0.0191		
CAP	Control	0.1092	1.00	0.06
	Treated	0.1091		

Panel B: Baseline regressions using matching sample

	Tax Increase		Tax Cut	
	(1)	(2)	(3)	(4)
Dependent variable:	*Opacity*	*LR*	*Opacity*	*LR*
$\triangle Tax_t$	0.2681*	0.0818***	0.0249	0.0096
	(2.64)	(8.71)	(0.57)	(0.79)
Control Variables	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	1,042	1,042	3,334	3,334
R^2	0.0414	0.9391	0.0210	0.9447

Notes: Panel A of this table reports the descriptive statistics of the treated and control groups as well as the Wilcoxon-test and the Kolmogorov-Smirnov test for tax change sample matching. Columns 3 and 4 depict their respective z-score and t-value. We match banks that experience a tax change two years after the matching with their 5 nearest neighbors (banks that do not experience a tax change) using log assets ($Size$), loans to assets ratio ($LOANS$), loan to deposit ratio (LDR), net interest margin (NIM), commercial % industrial loans to total loans ($C\&I$), and capital to assets ratio (CAP) as matching variables. Panel B reports estimates of equation (3.4) using matching sample. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.4: Different nexus threhsolds

	Single-state				85% nexus threshold			
	Tax increase		Tax cut		Tax increase		Tax cut	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	$Opacity$	LR	$Opacity$	LR	$Opacity$	LR	$Opacity$	LR
$\triangle Tax_t$	0.2759*	0.0885***	0.0320	0.0122	0.2746*	0.0886***	0.0232	0.0149
	(2.72)	(8.45)	(0.81)	(0.86)	(2.84)	(8.83)	(0.60)	(1.00)
Control Variables	YES	YES	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,045	3,045	5,270	5,270	3,107	3,107	5,403	5,403
R^2	0.0318	0.9637	0.0350	0.9262	0.0320	0.9636	0.0346	0.9293

Notes: This table reports estimates of equation (3.4). Columns 1-4 use single-state banks as the sample, while columns 5-8 use bank with operational branches concentration of more than 85% in a single state. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

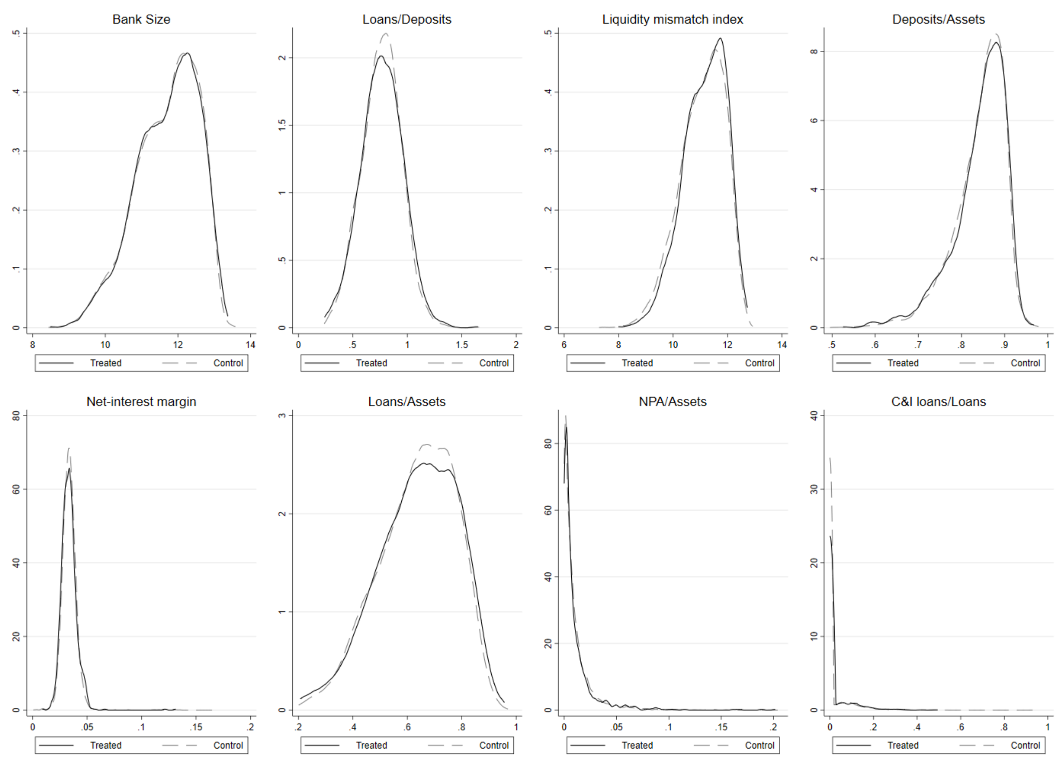
Table B.5: Potential mechanism: Discipline over risk-taking

	Tax increase	Tax cut
	(1)	(2)
Dependent variable:	LLP	LLP
$\triangle Tax_t$	0.0024*	-0.0003
	(3.01)	(-0.87)
$\triangle Tax_t \cdot NPA^{hi}_{t+1}$	0.0002	0.0003
	(0.29)	(0.80)
Control Variables	YES	YES
State FE	YES	YES
Time FE	YES	YES
Observations	3,115	5,435
R^2	0.1505	0.1328

Notes: This table reports estimates of augmented equation (3.4) using loan loss provisions as the outcome variable. $\triangle Tax$ is a dummy variable that is equal to one in the year of a tax change. This main explanatory variable depicts the bank's reaction occurring in the year of the tax change. NPA^{hi}_{t+1} is a dummy variable if the bank's change in non-performing assets from t to $t+1$ is above the median of the year as outlined by Andries et al. (2017). The unreported control variables are asset growth, liquidity mismatch, return to assets, loans ratio, non-performing assets ratio, and net interest margin. Variable definitions are provided in Table 3.1. All regressions include year and regional fixed effects. The standard errors are robust to heteroscedasticity and clustered at the state level. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

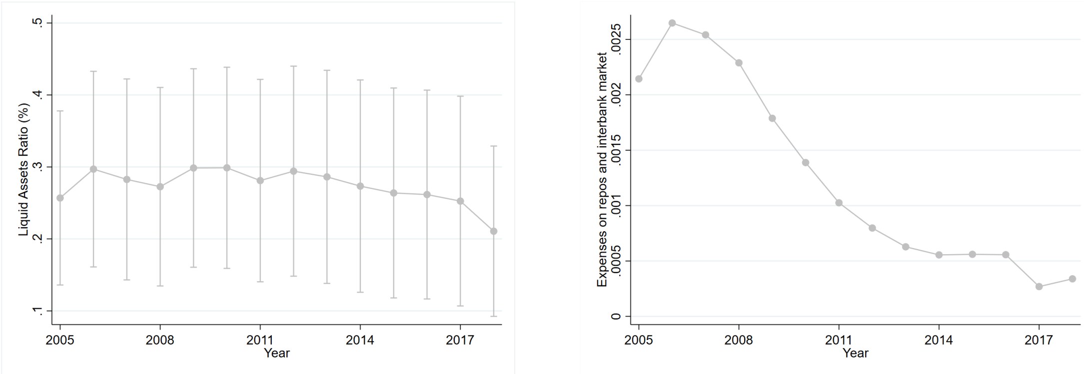
B.3 Supplementary figures

Figure B.1: Kernel density estimates



Notes: The s illustrate the kernel density estimates for the various bank characteristics for the treated and control groups. The treated group refers to banks which experience a tax change (either a tax increase or tax cut) two years later, and the control group depicts the matched banks whose tax rate does not change.

Figure B.2: Proxies for liquidity buffer costs



(a) Liquid assets ratio (b) Expenses on repos and interbank market

Notes: The graphs illustrate the evolution of liquid assets ratio and expenses on repos and interbank market. Liquid assets ratio is computed as cash, excess reserves, cash equivalents, repos, securities to total assets. Expenses on repos and interbank market ratio is computed as expenses of federal funds purchased, repos, trading liabilities and other borrowed money to total assets.

APPENDIX C

APPENDIX OF CHAPTER 4

C.1 Variable descriptions

Table C.1: Variable descriptions

Variables	Definition
Categorical variables	
T	A dummy variable equal to 1 if the bank already has diversified subsidiaries before 1996.
T^{S20}	A dummy variable equal to 1 if a bank owned a section 20 subsidiary before the repeal of the Glass-Steagall Act.
T^{NS20}	A dummy variable equal to 1 if a bank did not own a section 20 subsidiary before the repeal of the Glass-Steagall Act but already has diversified subsidiaries before 1996.
$Dereg$	A dummy variable equal to 1 after the 1996 deregulation.
$Firewall$	A dummy variable equal to 1 between the 1996 deregulation and the enactment of GLBA.
$GLBA$	A dummy variable equal to 1 after the enactment of GLBA.
Bank opacity variables	
$Opac$	Log earnings opacity.
$Opac_{ma}$	4-quarter moving average of log earnings opacity.
BAS	Bid-ask spread as a percent of midpoint.
STD	Annualized standard deviation of stock returns.
Other variables	
$Size$	Natural logarithm of assets.
$Cash$	Cash and cash equivalents to assets.
$Loans$	Loans to assets.
$Deposits$	Domestic deposits to assets.
$Equity$	Capital to assets.
$Allowances$	Loan loss allowances to assets.
NIM	Net interest margin.
ROE	Return-on-equity, estimated as net income divided by total equity.
Org	Inverted Business Diversification Index as defined by Cetorelli and Goldberg (2014).
OBS	Total off-balance sheet items to assets.
NII	Non-interest income from trading revenues, commissions and fees to total income.
ROA_{σ}	4-quarter rolling standard deviation of return-on-assets.
$Return_{\sigma}^{nb}$	4-quarter rolling standard deviation of income from non-commercial banking activities.
$Return_{\sigma}^{bank}$	4-quarter rolling standard deviation of income from commercial banking activities.
$Access$	Natural logarithm of accessible states.
$M\&A^{assets}$	M&A target assets to one year lagged bank assets.
$M\&A^{count}$	Accumulated three subsequent quarters of M&A actions.
$Loans^{\%}$	Share of a bank's outstanding loans to industry outstanding loans at time t.
$Branch^{\%}$	Share of a bank's branches to total branches at time t.
GSP	State gross domestic product.

The table describes the main dependent and control variables we use in the paper.

C.2 Further results tables

Table C.2: Baseline results: Average effects on opacity

	(1)	(2)	(3)	(4)
	Net effects		Section 20 & non-section 20	
Dependent variable:	BAS	STD	BAS	STD
$T \cdot Dereg$	0.8069***	0.0063***		
	(5.92)	(6.47)		
$T^{S20} \cdot Dereg$			0.8707***	0.0069***
			(5.74)	(7.53)
$T^{NS20} \cdot Dereg$			0.6079*	0.0045
			(1.89)	(1.55)
Control variables	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	15,145	15,145	15,145	15,145
R-squared	0.1731	0.1559	0.1734	0.1561
Number of Banks	601	601	601	601

Notes: This table reports estimates of equations (4.2) and (4.3). Outcome variables are bid-ask spread (BAS) and stock volatility (STD). T is equal to one if the bank is a diversified bank and zero otherwise. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. Control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. Data availability constraints prevent complete observation of BAS and STD for 115 BHCs. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.3: Validation checks using matching sample

Panel A: Mean comparison of the treated and control groups

	(1)	(2)	(3)	(4)
	Mean		t-test	
Variable:	Treated	Control	t-value	p-value
$Size$	14.796	14.925	-0.31	0.759
$Cash$	0.092	0.095	-0.17	0.866
$Loans$	0.659	0.628	1.24	0.218
$Deposits$	0.758	0.743	0.55	0.581
$Equity$	0.082	0.081	0.15	0.882
$Allowances$	0.145	0.015	-0.44	0.662
NIM	0.039	0.037	1.04	0.300
ROE	0.126	0.113	0.78	0.436

Panel B: Baseline results using sample matching

	(1)	(2)	(3)	(4)
	Net effects		Section 20 & non-section 20	
Dependent variable:	$Opac$	$Opac_{ma}$	$Opac$	$Opac_{ma}$
$T \cdot Dereg$	0.3759***	0.3635***		
	(3.68)	(3.55)		
$T^{S20} \cdot Dereg$			0.3390**	0.3555**
			(2.03)	(2.25)
$T^{NS20} \cdot Dereg$			0.4375***	0.3768***
			(3.59)	(2.90)
Control variables	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	14,717	14,717	14,717	14,717
R-squared	0.0946	0.1563	0.0946	0.1563
Number of Banks	295	295	295	295

Notes: This table provides validation checks of our main findings using matching sample. We match diversified banks to their nearest neighbor based on the size, cash equivalents, loans, domestic deposits, equity, and return on equity using a 2.5% caliper without replacement. This results in a sample of 295 banks. Panel A highlights the mean comparison between the treated and control groups using matching sample. Panel B reports estimates of equations (4.2) and (4.3) using matching sample. Outcome variables are $Opac$ and $Opac_{ma}$. T is equal to one if the bank is a diversified bank and zero otherwise. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.4: The effects of industry competition

	(1)	(2)	(3)	(4)
	Loan share		Office branches	
Dependent variable:	$Opac$	$Opac_{ma}$	$Opac$	$Opac_{ma}$
$T^{S20} \cdot Dereg$	0.6786**	0.7107**	0.6685***	0.7085***
	(2.32)	(2.33)	(2.77)	(2.80)
$T^{NS20} \cdot Dereg$	0.0605	-0.0068	0.0341	-0.0121
	(0.31)	(-0.04)	(0.17)	(-0.06)
$T^{S20} \cdot Dereg \cdot Loans^{\%}$	-0.7394	-0.7307		
	(-1.54)	(-1.46)		
$T^{NS20} \cdot Dereg \cdot Loans^{\%}$	0.9489	0.9990***		
	(1.64)	(2.81)		
$Loans^{\%}$	0.1944	0.1294		
	(1.53)	(1.03)		
$T^{S20} \cdot Dereg \cdot Branch^{\%}$			-0.7798	-0.7887
			(-1.52)	(-1.52)
$T^{NS20} \cdot Dereg \cdot Branch^{\%}$			1.2552**	1.1943**
			(2.38)	(2.50)
$Branch^{\%}$			0.1306	0.1284
			(0.87)	(0.92)
Control variables	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	22,590	22,590	22,324	22,324
R-squared	0.0626	0.1155	0.0629	0.1164
Number of Banks	716	716	714	714

Notes: Notes: This table reports estimates of extended equation (4.3) using $Opac$ and $Opac_{ma}$ as the outcome variables. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. $Loans^{\%}$ is the share of bank b's outstanding loans at time t and $Branch^{\%}$ is the share of bank b's total office branches at time t. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.5: Anticipation test and pre-2004 sample

	(1)	(2)	(3)	(4)
	Placebo		Pre-2004	
Dependent variable:	$Opac$	$Opac_{ma}$	$Opac$	$Opac_{ma}$
$T^{S20} \cdot Placebo$	-0.0082	-0.0701		
	(-0.05)	(-0.49)		
$T^{NS20} \cdot Placebo$	-0.0872	-0.0359		
	(-0.49)	(-0.20)		
$T^{S20} \cdot Dereg$	0.3686***	0.3798***	0.3139***	0.3697***
	(2.93)	(3.05)	(3.16)	(3.88)
$T^{NS20} \cdot Dereg$	0.2877**	0.2521**	0.3523**	0.2787*
	(2.22)	(2.07)	(2.13)	(1.81)
Control variables	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	22,590	22,590	18,951	18,951
R-squared	0.0614	0.1131	0.0712	0.1306
Number of Banks	716	716	677	677

Notes: This table reports estimates of equation (4.3) using $Opac$ and $Opac_{ma}$ as the outcome variables. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Placebo$ is equal to 1 for the period between 3Q1992-2Q1995 and zero otherwise. $Dereg$ is equal to one after 1996Q3 and zero otherwise. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The sample is split at the median level of each year's capital ratio. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table C.6: Other economic factors

	(1)	(2)	(3)	(4)
	Dotcom		Macroeconomy	
Dependent variable:	$Opac$	$Opac_{ma}$	$Opac$	$Opac_{ma}$
$T^{S20} \cdot Dereg$	0.3424**	0.4010***	0.3751**	0.4084***
	(2.27)	(2.73)	(2.54)	(2.94)
$T^{NS20} \cdot Dereg$	0.3312**	0.2776*	0.3146**	0.2629*
	(2.24)	(1.90)	(2.01)	(1.71)
$T^{S20} \cdot Dotcom$	0.1120	0.0231		
	(0.85)	(0.17)		
$T^{NS20} \cdot Dotcom$	-0.1394	-0.1879		
	(-1.02)	(-1.36)		
$T^{S20} \cdot GSP$			1.1601	0.5628
			(0.78)	(0.59)
$T^{NS20} \cdot GSP$			-7.6055**	-3.2048
			(-2.29)	(-1.07)
Control variables	YES	YES	YES	YES
BHC FE	YES	YES	YES	YES
Time FE	YES	YES	YES	YES
Observations	22,590	22,590	22,590	22,590
R-squared	0.0616	0.1136	0.0620	0.1133
Number of Banks	716	716	716	716

Notes: This table reports estimates of equation (4.3) using $Opac$ and $Opac_{ma}$ as the outcome variables. T^{S20} (T^{NS20}) is equal to one if the diversified bank is a section 20 (non-section 20) bank. $Dereg$ is equal to one after 1996Q3 and zero otherwise. $Dotcom$ is equal to 1 for the period between 1999Q1-2000Q1 and zero otherwise; GSP is state gross domestic product. The unreported control variables are log assets ($Size$), cash equivalents to assets ($Cash$), loans to assets ($Loans$), deposits to assets ($Deposits$), equity to assets ($Equity$), loan loss allowances ($Allowances$), net interest margn (NIM) and return-on-equity (ROE). All variables are defined in Table C.1 of Online Appendix. The sample is split at the median level of each year's capital ratio. The standard errors are block bootstrapped drawing 50 samples and the corresponding t-statistics are shown in parentheses. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Bibliography

Abadie, A., Diamond, A., and Hainmueller, J. (2010).
Synthetic control methods for comparative case studies: Estimating the effect of california's tobacco control program.
Journal of the American Statistical Association, 105(490):493–505.

Abadie, A. and Gardeazabal, J. (2003).
The economic costs of conflict: A case study of the basque country.
American Economic Review, 93(1):113–132.

Acharya, V., Berger, A., and Roman, R. (2018).
Lending implications of u.s. bank stress tests: Costs or benefits?
Journal of Financial Intermediation, 34:58–90.

Acharya, V., Pedersen, L., Philippon, T., and Richardson, M. (2017).
Measuring systemic risk.
Review of Financial Studies, 30(1):2–47.

Acosta-Smith, J., Grill, M., and Lang, J. (2020).
The leverage ratio, risk-taking and bank stability.
Journal of Financial Stability, page 100833.

Adrian, T. and Boyarchenko, N. (2018).
Liquidity policies and systemic risk.
Journal of Financial Intermediation, 35:45–60.

Aebi, V., Sabato, G., and Schmid, M. (2012).
Risk management, corporate governance, and bank performance in the financial crisis.
Journal of Banking & Finance, 36(12):3213–3226.

Agarwal, S., Chang, Y., and Yavas, A. (2012).
Adverse selection in mortgage securitization.
Journal of Financial Economics, 105(3):640–660.

Ahmed, A., McAnally, M., Rasmussen, S., and Weaver, C. (2010).
How costly is the sarbanes oxley act? evidence on the effects of the act on corporate profitability.

Journal of Corporate Finance, 16(3):352–369.

Anderson, R., Duru, A., and Webb, D. (2009).
Founders, heirs, and corporate opacity in the united states.
Journal of Financial Economics, 69(2):205–222.

Andries, K., Gallemore, J., and Jacob, M. (2017).
The effect of corporate taxation on bank transparency: Evidence from loan loss provisions.
Journal of Accounting and Economics, 63(2):307–328.

Bai, J., Krishnamurthy, A., and Weymuller, C.-H. (2018).
Measuring liquidity mismatch in the banking sector.
The Journal of Finance, 73(1):51–93.

Baker, A., Larcker, D., and Wang, C. (2022).
How much should we trust staggered difference-in-differences estimates?
Journal of Financial Economics, 144(2):370–395.

Barth, J., Brumbaugh, D., and Wilcox, J. (2000).
Policy watch: The repeal of glass-steagall and the advent of broad banking.
Journal of Economic Perspectives, 14(2):191–204.

BCBS (2010).
Basel iii: International framework for liquidity risk measurement, stanards and monitoring.
Bank for International Settlements.

BCBS (2011).
Global systemically important banks: Assessment methodology and the additional loss absorbency requirement.
Bank for International Settlements.

BCBS (2013).
Basel iii: The liquidity coverage ratio and liquidity risk monitoring tools.
Bank for International Settlements.

Beatty, A. and Liao, S. (2014).
Financial accounting in the banking industry: A review of the empirical literature.
Journal of Accounting and Economics, 58(2-3):339–383.

Begley, T., Purnanandam, A., and Zheng, K. (2017).
The strategic underreporting of bank risk.
The Review of Financial Studies, 30(10):3376–3415.

Beltratti, A. and Stulz, R. (2012).
The credit crisis around the globe: Why did some banks perform better?
Journal of Financial Economics, 105(1):1–17.

Ben-David, I., Cerulli, G., Fiordelisi, F., and Marques-Ibanez, D. (2020).
The burden of bank supervision.
mimeo.

Berger, A., Bonime, S., Covitz, D., and Hancock, D. (2000).
Why are bank profits so persistent? the roles of product market competition, informational opacity, and regional/macroeconomic shocks.
Journal of Banking and Finance, 24(7):1203–1235.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004).
How much should we trust differences-in-differences estimates?
The Quarterly Journal of Economics, 119(1):249–275.

Bhargava, R. and Fraser, D. (1998).
On the wealth and risk effects of commercial bank expansion into securities underwriting: An analysis of section 20 subsidiaries.
Journal of Banking & Finance, 22(4):447–465.

Boissay, F. and Collard, F. (2016).
Macroeconomics of bank capital and liquidity regulations.
BIS Working Paper No 596.

Bonfim, D. and Felix, S. (2020).
Banks' complexity and risk: agency problems and diversification benefits.
mimeo.

Bouvard, M., Chaigneau, P., and De Motta, A. (2015).
Transparency in the financial system: rollover risk and crises.
Journal of Finance, 70(4):1805–1837.

Bratten, B., Causholli, M., and Omer, T. (2019).
Audit firm tenure, bank complexity, and financial reporting quality.
Contemporary Accounting Research, 36(1):295–325.

Bruno, B., Onali, E., and Schaeck, K. (2018).
Market reaction to bank liquidity regulation.
Journal of Financial and Quantitative Analysis, 53(2):899–935.

Bushman, R., Chen, Q., Engel, E., and Smith, A. (2004).

Financial accounting information, organizational complexity and corporate governance systems.
Journal of Accounting and Economics, 37(2):167–201.

Bushman, R. and Williams, C. (2012).
Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking.
Journal of Accounting and Economics, 54(1):1–18.

Callaway, B. and Sant'Anna, P. (2021).
Difference-in-differences with multiple time periods.
Journal of Econometrics, 225(2):200–230.

Calomiris, C. (2000).
Universal banking, "American style", page 334–349.
Cambridge University Press.

Calomiris, C., Heider, F., and Hoerova, M. (2015).
A theory of bank liquidity requirements.
SSRN Electronic Journal.

Carletti, E., Goldstein, I., and Leonello, A. (2020).
The interdependence of bank capital and liquidity.
BAFFI CAREFIN Centre Research Paper.

Cavallo, E., Galiani, S., Noy, I., and Pantano, J. (2013).
Catastrophic natural disasters and economic growth.
Review of Economics and Statistics, 95(5):1549–1561.

Cecchetti, S. and Kashyap, A. (2018).
What Binds? Interactions between Bank Capital and Liquidity Regulations.
Cambridge University Press.

Cetorelli, N. and Goldberg, L. (2014).
Measures of global bank complexity.
Federal Reserve Bank of New York Economic Policy Review, 20(2):107–126.

Cetorelli, N. and Goldberg, L. (2016).
Organizational complexity and balance sheet management in global banks.
NBER Working Paper No. w22169.

Chen, S., Miao, B., and Shevlin, T. (2015).
A new measure of disclosure quality: The level of disaggregation of accounting data in annual reports.
Journal of Accounting Research, 53(5):1017–1054.

Chen, T. and Lin, C. (2017).
Does information asymmetry affect corporate tax aggressiveness?
Journal of Financial and Quantitative Analysis, 52(5):2053–2081.

Chen, Y. and Hasan, I. (2006).
The transparency of the banking system and the efficiency of information-based bank runs.
Journal of Financial Intermediation, 15(3):307–331.

Chernobai, A., Ozdagli, A., and Wang, J. (2020).
Business complexity and risk management: Evidence from operational risk events in u.s. bank holding companies.
Journal of Monetary Economics, 117:418–440.

Cornett, M., Mcnutt, J., Strahan, P., and Tehranian, H. (2011).
Liquidity risk management and credit supply in the financial crisis.
Journal of Financial Economics, 101(2):297–312.

Cornett, M., McNutt, J., and Tehranian, H. (2009).
Corporate governance and earnings management at large U.S. bank holding companies.
Journal of Corporate Finance, 15(4):412–430.

Cornett, M., Ors, E., and Tehranian, H. (2002).
Bank performance around the introduction of a section 20 subsidiary.
Journal of Finance, 57(1):501–521.

Correa, R. and Goldberg, L. (2020).
Bank Complexity, Governance, and Risk.
International finance discussion papers number 1287, Board of Governors of the Federal Reserve System.

Dam, L. and Koetter, M. (2012).
Bank bailouts and moral hazard: evidence from germany.
Review of Financial Studies, 25(8):2343–2380.

Dang, T., Gorton, G., Holmstrom, B., and Ordonez, G. (2017).
Banks as secret keepers.
American Economic Review, 107(4):1005–1029.

Danisewicz, P., McGowan, D., Onali, E., and Schaeck, K. (2018).
Debt priority structure, market discipline and bank conduct.
Review of Financial Studies, 31(11):4493–4555.

Danisewicz, P., McGowan, D., Onali, E., and Schaeck, K. (2021).

Debtholder monitoring incentives and bank earnings opacity.
Journal of Financial and Quantitative Analysis, 56(4):1408–1445.

De Jonghe, O. (2010).
Back to the basics in banking? a micro-analysis of banking system stability.
Journal of Financial Intermediation, 19(3):387–417.

Diamond, D. and Dybvig, P. (1983).
Bank runs, deposit insurance, and liquidity.
Journal of Political Economy, 91(3):401–419.

Diamond, D. W. and Rajan, R. G. (2001).
Liquidity risk, liquidity creation, and financial fragility: A theory of banking.
Journal of Political Economy, 109(2):287–327.

Doidge, C., Karolyi, A., Lins, K., Miller, D., and Stulz, R. (2009).
Private benefits of control, ownership, and the cross-listing decision.
The Journal of Finance, 64(1):425–466.

Duchin, R. and Sosyura, D. (2014).
Safer ratios, riskier portfolios: banks' response to government aid.
Journal of Finance, 113(1):1–28.

Ellul, A., Jappelli, T., Pagano, M., and Panunzi, F. (2015).
Transparency, tax pressure, and access to finance.
Review of Finance, 20(1):37–76.

Fama, E. and Jensen, M. (1983).
Separation of ownership and control.
The Journal of Law & Economics, 26(2):301–325.

Flannery, M. (1996).
Financial crises, payment system problems, and discount window lending.
Journal of Money, Credit and Banking, 28(4):804–824.

Flannery, M., Kwan, S., and Nimalendran, M. (2004).
Market evidence on the opaqueness of banking firms' assets.
Journal of Financial Economics, 71(3):419–460.

Flannery, M., Kwan, S., and Nimalendran, M. (2013).
The 2007–2009 financial crisis and bank opaqueness.
Journal of Financial Intermediation, 22(1):55–84.

Ghaly, M., Dang, V., and Stathopoulos, K. (2020).
Institutional investors' horizons and corporate employment decisions.
Journal of Corporate Finance, 64:101634.

Gilson, S., Healy, P., Noe, C., and Palepu, K. (2001).
Analyst specialization and conglomerate stock breakups.
Journal of Accounting Research, 39(3):565–582.

Goetz, M. R., Laeven, L., and Levine, R. (2013).
Identifying the valuation effects and agency costs of corporate diversification: Evidence from the geographic diversification of u.s. banks.
The Review of Financial Studies, 26(7):1787–1823.

Goldberg, L. and Meehl, A. (2020).
Complexity in large u.s. banks.
Reserve Bank of New York Economic Policy Review, 26(2):1–28.

Goodman-Bacon, A. (2021).
Difference-in-differences with variation in treatment timing.
Journal of Econometrics, 225(2):254–277.

Greenspan, A. (1988).
An overview of financial restructuring.
In proceedings of the 24th annual conference on bank structure and competition, Federal Reserve Bank of Chicago.

Greenspan, A. (1990).
Subsidies and powers in commercial banking.
In proceedings of the 26th annual conference on bank structure and competition, Federal Reserve Bank of Chicago.

Hartlage, A. (2012).
The basel iii liquidity coverage ratio and financial stability.
Michigan Law Review, 111(3):453–483.

Heider, F. and Ljungqvist, A. (2015).
As certain as debt and taxes: Estimating the tax sensitivity of leverage from state tax changes.
Journal of Financial Economics, 118(3):684–712.

Hong, H., Huang, J.-Z., and Wu, D. (2014).
The information content of basel iii liquidity risk measures.
Journal of Financial Stability, 15:91–111.

Huang, R. and Ratnovski, L. (2011).
The dark side of bank wholesale funding.
Journal of Financial Intermediation, 20(2):248–263.

Huizinga, H. and Laeven, L. (2012).
Bank valuation and accounting discretion during a financial crisis.
Journal of Financial Economics, 106(3):614–634.

Huseynov, F. and Klamm, B. (2012).
Tax avoidance, tax management and corporate social responsibility.
Journal of Corporate Finance, 18(4):804–827.

Hutton, A., Marcus, A., and Tehranian, H. (2009).
Opaque financial reports, r^2, and crash risk.
Journal of Financial Economics, 94(1):67–86.

Hwang, H. (2021).
Organizational structure, voluntary disclosure, and investment efficiency.
Available at SSRN: https://ssrn.com/abstract=3411144.

Ihrig, J., Kim, E., Vojtech, C., and Weinbach, G. (2019).
How have banks been managing the composition of high-quality liquid assets?
Federal Reserve Bank of St. Louis Review, 101(3):177–201.

Ivashina, V. and Scharfstein, D. (2010).
Bank lending during the financial crisis of 2008.
Journal of Financial Economics, 97(3):319–338.

Iyer, R. and Peydró, J.-L. (2011).
Interbank Contagion at Work: Evidence from a Natural Experiment.
The Review of Financial Studies, 24(4):1337–1377.

Iyer, R. and Puri, M. (2012).
Understanding bank runs: The importance of depositor-bank relationships and networks.
American Economic Review, 102(4):1414–45.

Jiang, L., Levine, R., and Lin, C. (2016).
Competition and bank opacity.
Review of Financial Studies, 29(7):1911–1942.

Jiang, T., Levine, R., Lin, C., and Wei, L. (2020).
Bank deregulation and corporate risk.
Journal of Corporate Finance, 60:101520.

Jones, J., Lee, W., and Yeager, T. (2012).
Opaque banks, price discovery, and financial instability.
Journal of Financial Economics, 21(3):383–408.

Kahn, C. and Wagner, W. (2021).
Sources of liquidity and liquidity shortages.
Journal of Financial Intermediation, 46:100869.

Kelly, M. and O Grada, C. (2000).
Market contagion: Evidence from the panics of 1854 and 1857.
American Economic Review, 90(5):1110–1124.

Keys, B., Mukherjee, T., Seru, A., and Vig, V. (2010).
Did securitization lead to lax screening? evidence from subprime loans.
The Quarterly Journal of Economics, 125(1):307–362.

Klapper, L. and Love, I. (2004).
Corporate governance, investor protection, and performance in emerging markets.
Journal of Corporate Finance, 10(5):703–728.

Klein, P., Mössinger, C., and Pfingsten, A. (2021).
Transparency as a remedy for agency problems in securitization? the case of ecb's loan-level reporting initiative.
Journal of Financial Intermediation, 46:100853.

Kroszner, R. and Rajan, R. (1997).
Organization structure and credibility: Evidence from commercial bank securities activities before the glass-steagall act.
Journal of Monetary Economics, 39(3):475–516.

Kwan, S. (1998).
Risk and return of banks' section 20 securities affiliates.
Federal Reserve Bank of San Francisco Economic Letter, 1998-32.

Kyle, A. S. (1985).
Continuous auctions and insider trading.
Econometrica, 53(6):1315.

Landier, A. and Thesmar, D. (2014).
2. Regulating Systemic Risk through Transparency: Trade-Offs in Making Data Public, pages 31–44.
University of Chicago Press.

Leuz, C., Nanda, D., and Wysocki, P. (2003).
Earnings management and investor protection: an international comparison.
Journal of Financial Economics, 69(3):505–527.

Liu, C. and Ryan, S. (2006).
Income smoothing over the business cycle: Changes in banks coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom.
The Accounting Review, 81(2):421–441.

Lown, C., Osler, C., Strahan, P., and Sufi, A. (2000).
The changing landscape of the financial services: What lies ahead?
Federal Reserve Bank of New York Economic Policy Review, 6(4):39–55.

Lu, Y. (2021).
The influence of liquidity information on liquidity holdings in the banking system.
mimeo.

Martynova, N. and Vogel, U. (2022).
Banks' complexity risk-nexus and the role of regulation.
Journal of Banking and Finance, 134.

McLaughlin, S. (1995).
The impact of interstate banking and branching reform: Evidence from the states.
Federal Reserve Bank of New York Current Issues in Economics and Finance, 1(2).

Moreno, D. and Takalo, T. (2016).
Optimal bank transparency.
Journal of Money, Credit and Banking, 48(1):203–231.

Morgan, D. (2002).
Rating banks: risk and uncertainty in an opaque industry.
American Economic Review, 92(4):874–888.

Neuhann, D. and Saidi, F. (2016).
Bank deregulation and the rise of institutional lending.
Working paper, Stockhlom School of Economics.

Neuhann, D. and Saidi, F. (2018).
Do universal banks finance riskier but more productive firms?
Journal of Financial Economics, 128(1):66–85.

Oster, E. (2019).
Unobservable selection and coefficient stability: Theory and evidence.
Journal of Business & Economic Statistics, 37(2):187–204.

Pagano, M. and Volpin, P. (2012).
Securitization, transparency, and liquidity.
Review of Financial Studies, 25(8):2417–2453.

Paravisini, D. (2008).
Local bank financial constraints and firm access to external finance.
The Journal of Finance, 63(5):2161–2193.

Pierret, D. (2015).
Systemic risk and the solvency-liquidity nexus of banks.
International Journal of Central Banking, 11:193–227.

Puri, M. (1999).
Commercial banks in investment banking conflict of interest or certification role?
Journal of Financial Economics, 40(3):373–401.

Ratnovski, L. (2013).
Liquidity and transparency in bank risk management.
Journal of Financial Intermediation, 22(3):422–439.

Raz, A., McGowan, D., and Zhao, T. (2022).
The dark side of liquidity regulation: Bank opacity and funding liquidity risk.
Journal of Financial Intermediation, forthcoming.

Roberts, D., Sarkar, A., and Shachar, O. (2018).
The Costs and Benefits of Liquidity Regulations.
FRB of New York Staff Report No. 852.

Roberts, M. and Whited, T. (2013).
Chapter 7 - endogeneity in empirical corporate finance.
Handbook of the Economics of Finance, 2(Part A):493–572.

Rodriguez-Perez, G. and van Hemmen, S. (2010).
Debt, diversification and earnings management.
Journal of Accounting and Public Policy, 29(2):138–159.

Schandlbauer, A. (2017).
How do financial institutions react to a tax increase?
Journal of Financial Intermediation, 30:86–106.

Schepens, G. (2016).
Taxes and bank capital structure.
Journal of Financial Economics, 120(3):585–600.

Serether, J., Eberle, M., and Colavito Jr., M. (2011).
Can you take this to the bank? state taxation of financial institutions.
Tax Analyst, 1:717–724.

Strahan, P. (2003).
The real effects of u.s. banking deregulation.
Federal Reserve Bank of St. Louis Review, 85:111–128.

Sun, L. and Abraham, S. (2021).
Estimating dynamic treatment effects in event studies with heterogeneous treatment effects.
Journal of Econometrics, 225(2):175–199.

Thomas, S. (2002).
Firm diversification and asymmetric information: Evidence from analysts' forecasts and earnings announcements.
Journal of Financial Economics, 64(3):373–396.

Verrecchia, R. (1983).
Discretionary disclosure.
Journal of Accounting and Economics, 5:179–194.

Wahlen, J. (1994).
The nature of information in commercial bank loan loss disclosures.
The Accounting Review, 69(3):455–478.

Wang, Y. and Xia, H. (2014).
Do lenders still monitor when they can securitize loans?
The Review of Financial Studies, 27(8):2354–2391.

Wilmart, A. E. (2017).
The road to repeal of the glass-steagall act.
Research paper no. 2017-61, GWU Law School Public Law.

Yu, F. (2008).
Analyst coverage and earnings management.
Journal of Financial Economics, 88(2):245–271.

Yu, Y. (2007).
SPATDWM: Stata modules for US State and County spatial distance matrices.
Statistical Software Components, Boston College Department of Economics.

Yue, H., Zhang, L., and Zhong, Q. (2022).
The politics of bank opacity.
Journal of Accounting and Economics, 73(2):101452.

Zhang, G. (2021).
Competition and opacity in the financial system.
Mangement Science, 67(3).