The Influence of Liquidity Information on Liquidity Holdings in the Banking System *

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Abstract

I study how liquidity information influences banks' liquidity holdings, using the disclosure of bank liquidity coverage ratio (LCR) mandated for a group of large US banks. While the disclosure rule aims to increase liquidity in the banking system, I find that non-disclosing banks responded by reducing liquid asset holdings due to the impact of liquidity information on banks' strategic interactions in holding liquidity. I use bank network relationships to measure how much a bank learns from the disclosure, and find that banks learning more cut their liquidity significantly more. In the aggregate, the new disclosure rule lowered liquidity in the banking system, concentrated liquidity within a group of large disclosing banks, and ultimately increased systemic risk. My findings highlight the important, and potentially unanticipated, influence of liquidity information on the liquidity and stability of the banking system.

Keywords: Liquidity disclosure regulation, spillover effect, strategic interactions

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1 Introduction

Liquidity holdings among banks are crucial for financial stability. Illiquidity in the banking system amplified the severity of the 2008 financial crisis (Brunnermeier, 2009), while liquidity risk contributed to the crash of bank stock prices during the COVID-19 pandemic (Acharya, Engle, and Steffen, 2021). One important determinant of liquidity holdings is the information about the liquidity in the banking system. This is because liquidity information reveals the risk of bank runs, which in turn influences banks' demand for liquid assets (Diamond and Dybvig, 1983; Diamond and Kashyap, 2016). Moreover, the breadth and intensity of banks' reactions to liquidity information can be significant, given the potential domino effect of illiquidity and bankruptcies following an initial bank run (see survey by Allen and Babus, 2009). Despite the importance of liquidity information, we have limited empirical evidence on the impact of liquidity disclosures on liquidity holdings and financial stability or the role of liquidity disclosure mandates.

To shed some light on these issues, I exploit bank liquidity coverage ratio (LCR) disclosure regulation implemented in the US in 2017. The regulation requires a group of large banks to disclose key liquidity information related to their LCR, which is the ratio of high quality liquid assets to expected short-term net cash outflows. The LCR disclosure rule aims to increase liquidity in the banking system by enhancing market discipline on the few disclosing banks (81 FR 94922). However, the disclosure can actually discourage banks, especially non-disclosing banks, from holding liquidity. This spillover effect results from 1) banks' strategic interactions, in which a bank's liquidity decision depends on peers' liquidity, and 2) the influence of peers' liquidity information on these strategic decisions.

In particular, strategic interactions affect liquidity holdings in the sense that a bank holds more liquidity when its peer banks hold less, as low-liquidity peer banks increase liquidity risk in the market. For example, a run on a bank due to its low liquidity can trigger a market-wide panic that sets off runs on other banks.[1] In such cases, creditors cut short-term

[1]While deposit insurance largely prevents traditional depositor runs, modern banks are subject to runs

funding while borrowers accelerate credit line drawdowns, both of which drain liquidity from the market and increase banks' cash needs.

In the presence of strategic interactions, information about peer actions can influence a firm's behavior in important ways. (e.g., Bloomfield, 2020; Darmouni and Sutherland, 2020; Kim, Verdi, and Yost, 2020). In my setting, knowing less about peers' liquidity makes a bank more uncertain about the level of liquidity risk in the system. The uncertainty leads to a demand for safe, liquid assets, as the uncertainty-averse bank is concerned about being unprepared for a potential liquidity crisis (Caballero and Krishnamurthy, 2008).[2] The LCR disclosures mitigate this uncertainty and reduce the need for precautionary liquidity, because they provide new and useful liquidity information of the peer banks that contribute the most to aggregate liquidity risk. Therefore, the disclosure rule can result in lower liquidity holdings. This effect is formalized in a simple model presented in Appendix A.

The LCR disclosure rule is part of the overall Basel III LCR regulation, which is the first global bank liquidity standard. Beginning on January 1 of 2015, 2016, and 2017, large US banks were required to maintain an LCR of at least 80%, 90%, and 100%, respectively. In addition to this minimum LCR requirement, an LCR disclosure rule was adopted in three stages. In the first stage, starting the second quarter of 2017, the eight US global systemically important banks (G-SIBs) were required to disclose information about their LCR calculations. In the following two stages, more large banks were required to disclose starting the second and fourth quarters of 2018. I focus on the first-stage disclosures for my main analysis, because they were made by the most influential banks. The next two stages are used in additional tests to strengthen the identification.

The LCR disclosure provides important new information about the liquidity of key banks.

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and their contagion effect in the forms of short-term credit withdrawals and credit line drawdowns, which were central issues in the the 2008 financial crisis (Brunnermeier, 2009; Gorton, 2009; Gorton and Metrick, 2012).

[2]While the Federal Reserve often provides emergency liquidity in a crisis, the availability, coverage, or timing of this liquidity aid is not guaranteed and is uncertain ex ante. Therefore, the possibility of receiving emergency liquidity in a crisis does not preclude banks from holding precautionary liquidity and adjusting liquidity holdings based their knowledge about peer banks' liquidity.

Although banks disclose liquid assets in financial reports, the challenge of interpreting this information is "placing it in appropriate context" (Diamond and Kashyap, 2016). That is, we also need to know banks' near-term cash outflows to evaluate how well liquid assets can cover liquidity needs. The LCR disclosure not only reports liquid assets but, more importantly, reveals near-term cash outflows in detail. The latter information on liquidity needs is new to the market, and is difficult to estimate using other bank disclosures.[3]

In studying the impact of liquidity information on liquidity holdings, I focus on the spillover effect of LCR disclosures on non-disclosing banks, which were only affected by the availability of new liquidity information from the disclosures.[4] I first examine whether non-disclosing banks, on average, reduced their liquid asset holdings in response to the disclosure and the resulting reduction in uncertainty about key banks' liquidity holdings. I then use a difference-in-differences design to test whether banks that learned more from the new disclosure cut liquidity more.[5] A non-disclosing bank can learn more from the LCR disclosure if it knew less about disclosing banks, including their liquidity, before the disclosure was made, and it tends to know less if it had less business interactions with these banks. Therefore, I measure how much liquidity information a non-disclosing bank gained from the LCR disclosure, which I term *InfoGain*, based on its position in the bank interaction network, and assign higher *InfoGain* if it is less interconnected with the disclosing banks. I use the frequency of banks co-issuing syndicated loans as a proxy for their interconnectedness. This proxy reflects banks' knowledge about each other, including their liquidity, because syndicate members have the incentive and ability to learn a counterparty's liquidity condition and

[3]For more details, see Section 2.3, where I attempt to estimate key information in an LCR report.

[4]A disclosing bank should also be affected by the new liquidity information from LCR disclosures, but to a lesser extent because its own disclosure was not new to itself. More importantly, a disclosing bank was also affected by the consequences of providing its own liquidity information, such as greater market scrutiny on its liquidity position. Therefore, I exclude disclosing banks from my sample when testing the effect of the availability of liquidity information. That said, I include them when estimating the aggregate effect of the LCR disclosure rule on the liquidity and stability of the banking system.

[5]One might expect these effects for the minimum LCR rule, because knowing that peer banks are increasing liquidity under the minimum LCR rule could discourage banks' liquidity holdings. However, since the effect of minimum LCR rule can be anticipated, non-disclosing banks should have reacted before rule adoption (as I will show later). More importantly, I focus on the LCR disclosure rule because this paper is interested in disclosure regulation.

because banks tend to enter syndicates with banks they know and trust.

Several unique features of my setting help me identify the spillover effect of the mandatory disclosure. First, since the LCR disclosure rule was implemented more than two years after the first minimum LCR requirement, it is unlikely that the rule was a regulatory response to an industry-wide shock (e.g., a liquidity crisis) that also affected non-disclosing banks' liquidity (Ball, 1980). Second, since only a few banks were required to disclose (especially in the first stage), I have a large sample of non-disclosing banks that were not directly affected. I can then identify the disclosure externality by comparing non-disclosing banks that were more treated by the indirect effect and those that were less treated. Constructing the bank network enables me to measure the extent to which a non-disclosing bank was treated. Finally, analyzing the bank network structure helps me validate the measure of treatment intensity and verify that the disclosure matters to all banks in the system.

I find that non-disclosing banks significantly reduced liquid asset holdings after the first-stage LCR disclosure, while disclosing banks increased theirs, but statistically insignificantly. Moreover, the non-disclosing banks that learned more from the new disclosures (i.e., those with higher *InfoGain*) cut their liquid asset holdings significantly more. This spillover effect is economically meaningful: the average non-disclosing bank experienced a 11% decline in liquid asset holdings (or 15% of the standard deviation) after the disclosure. In the aggregate, the negative externality was sizable enough to more than offset the increase in disclosing banks' liquidity: liquid assets held by all banks in the sample fell by $10 billion (0.3%). The disclosure also considerably changed the distribution of liquidity: while disclosing banks increased their liquid assets by 1%, non-disclosing banks decreased theirs by 13%.

It needs to be pointed out that how these changes can affect financial stability is unclear ex ante. If disclosing banks' liquidity matters much more than non-disclosing banks' to liquidity risk, then the shift in liquidity holdings will have little or positive impact on financial stability. The change in financial stability also depends on which banks are holding more or less liquidity and their systemic importance. While evaluating the net effect on financial stability is challenging, I explore it by examining whether the disclosure reduced systemic risk. Using two measures of systemic risk based on stock return correlations and expected capital shortfall in adverse times (Billio, Getmansky, Lo, and Pelizzon, 2012; Acharya, Engle, and Richardson, 2012), I find that the LCR disclosure led to higher systemic risk. Additional analyses suggest that the higher systemic risk was more likely contributed by disclosing banks than non-disclosing banks. This result suggests that non-disclosing banks still kept enough liquidity for their own needs but supplied less liquidity to the interbank market. This change, in turn, made the system riskier because large disclosing banks rely more on interbank borrowings to manage liquidity risk (Bech and Atalay, 2010; Afonso, Kovner, and Schoar, 2013).

I provide additional evidence to mitigate concerns about two key alternative explanations to my main findings. The first concern is that non-disclosing banks may have cut liquidity not because the disclosure reduced uncertainty about disclosing banks' liquidity, but because disclosing banks increased the level of their liquid asset holdings, which reduced aggregate liquidity risk.[6] If this were the case, the shift in liquidity holdings should also happen when disclosing banks were required to maintain a higher minimum LCR. In contrast, I find that non-disclosing banks that learned more from the LCR disclosure did not reduce liquid asset holdings (relative to those that learned less) after the minimum LCR rule adoption dates, but they did reduce liquidity after the LCR regulation was first announced. This suggests that the increase in disclosing banks' liquidity was anticipated when the rule was announced, and that non-disclosing banks reacted before the rule adoption (Roberts, Sarkar, and Shachar, 2019, find similar result).

Another concern is that my results could be driven by omitted variables that are correlated with both the measure of how much banks learned from the disclosure, *InfoGain*, and changes in banks' liquid asset holdings. To mitigate this concern, I extend my analysis to

[6]Both the minimum LCR rule and the disclosure rule could have increased disclosing banks' liquidity. 100% minimum LCR was required only one quarter before the disclosure rule, so its effect could manifest in periods after the disclosure rule adoption. The LCR disclosure rule could also increase disclosing banks' liquidity, if the disclosure enhanced market discipline on liquidity reserving.

the second and third stages of the disclosure rule implementation, using two newly defined *InfoGain*'s that capture information gained from newly compliant disclosing banks in each stage. Consistent with the first-stage results, the second- and third-stage *InfoGain*'s are also negatively correlated with changes in liquid assets holdings. In this case, the omitted variable explanation would require the three *InfoGain*'s be positively correlated with each other, so that the omitted variables can drive them in the same direction (and drive liquidity change in the opposite direction). Inconsistent with this explanation, I find that the three *InfoGain*'s are negatively correlated with each other. In addition, I conduct a series of sensitivity tests, and my results are robust to changes in sample selection criteria, sample period, additional control variables, and alternative measures of *InfoGain*.

Taken together, my findings highlight the important, and potentially unanticipated, spillover effects of disclosing liquidity information: the LCR disclosure rule reduced non-disclosing banks' liquidity and increased systemic risk, undercutting its goal of improving liquidity and stability in the banking system (81 FR 94922).

My paper contributes to three strands of literature. First, it contributes to the literature on bank liquidity and liquidity regulation, an important but understudied topic (Allen and Gale, 2017). Existing research focuses on causes of illiquidity during the crisis period, including strategic cash hoarding (e.g. Acharya, Gromb, and Yorulmazer, 2012; Gale and Yorulmazer, 2013), large liquidity shocks (e.g. Babus, 2016), counterparty risk (e.g. Afonso, Kovner, and Schoar, 2011), and untapped loan commitments (e.g. Cornett, McNutt, Strahan, and Tehranian, 2011; Acharya and Mora, 2015). Only a few studies examine the role of liquidity disclosure (e.g. Kleymenova, 2018) or banks' liquidity holding incentives in normal times (e.g. Acharya, Shin, and Yorulmazer, 2011). Research on the LCR regulation focuses mostly on the liquidity holding rule (e.g. Macchiavelli and Pettit, 2019; Sundaresan and Xiao, 2020). To the best of my knowledge, I am the first to study the LCR disclosure rule.

Second, this paper adds to the literature on the externalities of corporate disclosure and disclosure regulation, which is key to the economic justification for disclosure regulations (e.g., Dye, 1990; Admati and Pfleiderer, 2000) but not well understood (Leuz and Wysocki, 2016; Roychowdhury, Shroff, and Verdi, 2019). Prior research has documented disclosure externalities that affect a wide range of outcomes, including stock performance (e.g., Bushee and Leuz, 2005; Chen, Dou, and Zou, 2020), investment decisions (e.g., Durnev and Mangen, 2009; Badertscher, Shroff, and White, 2013; Beatty, Liao, and Yu, 2013; Shroff, Verdi, and Yu, 2014; Rauter, 2020), cost of capital (e.g., Shroff, Verdi, and Yost, 2017), industry-level resource allocation (e.g., Breuer, 2018), and firm innovation (e.g., Kim and Valentine, 2019; Breuer, Leuz, and Vanhaverbeke, 2020). Adding to this literature, I examine the externality of bank liquidity disclosures. My paper also relates to studies on how strategic interactions and disclosure influence each other (e.g., Bernard, 2016; Darmouni and Sutherland, 2020; Kim, Verdi, and Yost, 2020; Bloomfield, 2020; Noh, 2020; Seo, 2020; Zhang, 2020).

Finally, my paper relates to the literature on the effect of information and networks on financial stability. Prior studies mostly examine how imperfect information and uncertainty in the financial system can lead to contagion (e.g. Allen, Babus, and Carletti, 2012; Caballero and Simsek, 2013), and whether disclosure policies can mitigate this problem (e.g. Alvarez and Barlevy, 2015; Faria-e Castro, Martinez, and Philippon, 2017; Goldstein and Leitner, 2018). These papers focus on uncertainty about counterparty risk, and how disclosures made by all banks can reduce uncertainty and can lead to a trade-off between mitigating adverse selection (Akerlof, 1970) and losing risk-sharing (Hirshleifer, 1971). My paper complements these studies by showing how the disclosures of a few large banks can have network effects on the liquidity of other banks by reducing uncertainty about aggregate liquidity risk. More generally, my paper is relevant to the discussion of the link between transparency and financial stability (Acharya and Ryan, 2016; Goldstein and Sapra, 2014).

The rest of the paper is organized as follows. Section 2 provides background on the LCR disclosure requirement. Section 3 describes the bank network and the related measure. Section 4 describes the empirical design. Section 5 discusses the data and sample. Section 6 reports the results. Section 7 concludes.

2 Background of the LCR disclosure regulation

The liquidity coverage ratio (LCR) is defined as the following ratio:

$$\text{LCR} = \frac{\text{Amount of high quality liquid assets}}{\text{Projected total net cash outflows over a 30-day stress period}} \tag{1}$$

The LCR regulation is the first global liquidity standard, and has the goal of enhancing banks' liquidity risk management. The regulation required minimum LCR levels and later introduced the mandate for the disclosures of LCR information. Appendix B Figure B1 shows the timeline of the US implementation of the LCR regulation.[7]

2.1 Minimum LCR requirement

The Basel III LCR standard was announced by the Basel Committee on Banking Supervision (BCBS) in January 2013. The US version of the LCR requirement (79 FR 61440) was finalized on September 3rd, 2014. Under this rule, large banks are required to maintain a gradually increasing minimum LCR. In particular, depository institution (DI) holding companies[8] with $250 billion or more in total consolidated assets or $10 billion or more in on-balance-sheet foreign exposure and their consolidated DI subsidiaries that have total consolidated assets of $10 billion or more (collectively, "covered banks") are required to maintain an LCR of at least 80%, 90%, 100% beginning on January 1 of 2015, 2016, and 2017, respectively. DI holding companies with $50 billion or more in total consolidated assets that are not covered banks ("modified LCR banks") must maintain a "modified LCR" of at least 90% and 100% by January 1 of 2016 and 2017, respectively. The "modified LCR" is simpler and less stringent.[9]

[7]The LCR regulation is related to the Basel III capital regulation and to the regulatory relief in the banking sector, which are both discussed in Appendix C.

[8]DI holding companies are bank holding companies and savings-and-loan holding companies without significant insurance or commercial operations.

[9]For example, the denominator of "modified LCR" is net cash outflows multiplied by 0.7.

2.2 LCR disclosure requirement

The LCR disclosure requirement (81 FR 94922) was finalized on December 19, 2016, and was enacted shortly after the implementation of the 100% LCR requirement. The disclosure requirement was implemented in three stages. Beginning on April 1, 2017, "covered banks" that have \$700 billion or more in total consolidated assets or \$10 trillion or more in assets under custody (i.e., US G-SIBs) were required to disclose quarterly on their websites both quantitative information about their LCR calculation and a qualitative discussion about the key drivers of LCR. Beginning on April 1, 2018, this disclosure was required for all "covered banks." Finally, beginning on October 1, 2018, "modified LCR banks" had to comply with this disclosure requirement. Eight banks in my sample disclosed in the first stage.[10] Three and nine more disclosed in the next two stages. I focus on first stage disclosures in my main analyses with a sample period ending at the beginning of the second stage (i.e., 2Q2018), because these disclosures were made by the most important banks, which should be the most influential.[11]

The most important part of the LCR disclosure is a standardized table of quantitative LCR components. As an example, I provide the table from JPMorgan's 2017 fourth quarter LCR report in Figure B2, Panel A. The first four rows report the numerator of LCR, i.e., high-quality liquid assets (HQLA), and break it down based on three levels of asset quality. "Average Unweighted Amount" reports the amount of assets that contribute to each level of HQLA. "Average Weighted Amount" reports the amount that is considered HQLA, and is calculated by multiplying the unweighted amount and 1 minus the corresponding regulatory-prescribed haircut rate. A lower haircut rate is applied to assets of higher quality and liquidity. Rows 5 to 28 report the denominator of LCR, and provide disaggregated infor-

[10]The eight disclosing banks are Bank of America, Bank of New York Mellon, Citigroup, Goldman Sachs, JP Morgan, Morgan Stanley, State Street, and Wells Fargo.

[11]There are two other reasons for this focus. First, with more banks disclosing in the second and third stages, there are fewer non-disclosing banks to test spillover effects. Second, the effects of LCR disclosure in the latter two stages can be confounded by other regulatory changes, as discussed in Appendix C.2. Despite this, my robustness tests show that the main results still hold for the second- and third-stage disclosures.

mation about the balances of assets, liabilities, and off-balance sheet items that give rise to cash outflows and inflows over a 30-day stress period ("Average Unweighted Amount"), and the corresponding cash outflows and inflows ("Average Weighted Amount"). The weighted amount is calculated by multiplying the unweighted amount and the corresponding prescribed outflow or inflow rate.[12] Rows 29 to 33 show the final steps in calculating LCR.

2.3 LCR disclosure provides important new liquidity information

LCR disclosure provides important new information about the liquidity of the largest banks. The disclosure reveals both the amount of high quality liquid assets and the expected net cash outflows. While we can get liquid asset position information from banks' financial reports, we are unable to estimate expected net cash outflows using bank disclosures other than the LCR disclosure. The latter part is not only new and the majority of the disclosure (occupying 24 rows in the 33-row LCR table), but also critical in interpreting the liquidity of a bank. Information on the amount of liquid assets alone is hard to interpret without being placed in appropriate context (Diamond and Kashyap, 2016). That is, one needs to use banks' near-term cash outflows as a benchmark to evaluate how well the liquid asset holdings can cover liquidity needs. The new disclosure about expected net cash outflows provides precisely this benchmark, which gives outsiders a better idea about whether the liquid assets held by a bank is sufficient. Besides, this disclosure provides disaggregated information about different sources of cash inflows and outflows, which further helps identifying the exact channels through which liquidity can change.[13]

[12]The outflow rate is higher for outflow sources with lower deposit insurance coverage (e.g., partially insured, third-party placed deposits), less stable counterparties (e.g., wholesale and unaffiliated claim holders), lower quality collateral (e.g., repo secured by non-HQLA assets), and shorter maturities (e.g., a brokered deposit that matures in 30 days). The inflow rate is lower for inflow sources that help a bank maintain business continuity (e.g., retail loans), where collateral is rehypothecated by the bank in another transaction (e.g., reverse repo collateral is pledged in a repo agreement), and where HQLA asset collateral has higher quality and has been counted in HQLA (e.g., reverse repo secured by level 1 liquid assets).

[13]Large banks also assess their liquidity position in stress scenarios in the Dodd-Frank Act Stress Tests (DFAST) since 2013, and they are required to disclose a summary of these results annually. However, while these summaries report the conditions of capital, leverage, revenue, and loan losses under stress scenarios, they do not include any liquidity test result.

To check whether or which parts of the LCR disclosure is new, I estimate the numbers from Panel A of Figure B2 using JPMorgan's financial reports (i.e., the annual report and regulatory filings). The remainder of the panels in Figure B2 report the results, and Section B3 explains the methods. The estimated HQLA is quite close to the reported number, which is expected given similar information on liquid asset holdings from financial statements. However, the cash outflow and inflow numbers are very difficult to estimate. This is primarily due to the lack of disaggregated information about the amount of (off-)balance sheet items that correspond to each source of cash outflow and inflow, or information about the likelihood of cash out(in)flows, such as contractual duration, counterparty type, collateral asset quality, and deposit insurance coverage. For example, calculating operational deposit outflow (row 10 in the LCR table) requires the amount of operational deposit that can be withdrawn over the next 30 days, and a breakdown of this number by whether or not the deposit is insured. None of this information is available in financial reports. I ended up with an estimated LCR of 103%, which is 16% lower than the reported 119%. This is a very inaccurate estimation, considering that the actual LCR of G-SIBs banks in my sample ranges from 108% to 154%.

The LCR disclosure is new also because banks do not have the incentive to voluntarily disclose before the regulation. Disclosing more liquidity information is costly because it can attract closer market scrutiny, which gives banks pressure to hold more liquidity. Holding more liquidity (and forgoing lending opportunities) is costly to these banks, especially when minimum LCR rules have already pushed up their liquidity holdings. Moreover, as I will discuss in more detail in Section 6.3.2, the disclosure can reduce non-disclosing banks' liquidity provision in the interbank market, making the disclosing banks riskier.

In sum, the LCR disclosure, especially the expected net cash outflow part, provides useful and new information about the liquidity conditions of the most important banks. The disclosed information is hard to estimate using other sources of bank disclosures, and banks do not have incentives to voluntarily disclose.

3 Measure of information gained from LCR disclosure

My identification strategy relies in part on the cross-sectional variation in how much information non-disclosing banks gained from the LCR disclosure, which I term *InfoGain*. To measure *InfoGain*, I build a business interaction network based on the frequency of banks co-issuing syndicated loans. *InfoGain* is the inverse of the proportion of syndicated loans that a non-disclosing bank has issued with disclosing banks. In the following subsections, I describe the measure of business linkage with disclosing banks and the calculation of *InfoGain*. I then discuss why this linkage is a proper proxy for existing knowledge about disclosing banks' liquidity.

3.1 Measure of business linkage and *InfoGain*

First, I measure bank i's business linkage with disclosing banks, using the ratio of syndicated loans issued with disclosing banks to the total number of bank i's syndicated loans. Formally,

$$LinkDisc_i = \frac{\sum_j Interactions_{i,j} * Disclose_j}{\sum_j Interactions_{i,j}}, \tag{2}$$

where $Interactions_{i,j}$ is the number of syndicated loans bank i and bank j have issued together during 2010 – 2017.[14] $Disclose_j$ is an indicator variable equal to one if bank j is required to disclose LCR information after the second quarter of 2017 and zero otherwise.

LinkDisc is used as a proxy for a bank's existing knowledge about disclosing banks' liquidity. From an absolute point of view, if a bank interacts more with disclosing banks (a larger numerator of *LinkDisc*), the bank will have more *opportunities* to learn their liquidity. From a relative point of view, if a bank's interactions are more concentrated on those with LCR disclosing banks (i.e., a larger *LinkDisc*), the bank will pay more *attention* to their

[14] I end the period in 2017 to capture banks' interconnectedness with each other before the LCR disclosures started to influence non-disclosing banks' behaviors. The results are robust to having the period end in 2016 or 2018. The beginning of the period (2010) is chosen so that the period is long enough to have sufficient observations to capture general business interconnectedness among banks but not so long as to include early interactions not representative of those in the sample periods of my tests (during 2012-2019).

liquidity. Moreover, banks with more opportunity to learn disclosing banks' liquidity are also more likely to pay attention to it, as suggested by the negative correlation between *InfoGain* and *Interactions* (Table 1, Panel C). Therefore, *LinkDisc* reflects existing knowledge about disclosing banks' liquidity by capturing both the opportunities to learn and the attention paid to disclosing banks' liquidity.

Next, I calculate *InfoGain* using 1 minus *LinkDisc*:

$$InfoGain_i = 1 - LinkDisc_i \tag{3}$$

InfoGain captures the incremental information a bank gains from LCR disclosure on top of what it has already known.[15] Figure 1 illustrates the calculation of *InfoGain* using a hypothetical bank network. The key independent variable in my difference-in-differences tests is $InfoGain_i * Post_t$, where $Post_t$ is an indicator variable equal to one in or after the third quarter of 2017 (when the first LCR disclosure was released) and zero otherwise.

Admittedly, this definition of *InfoGain* does not necessarily capture all the factors that affect a bank's learning. In robustness tests, I use two alternative definitions of *InfoGain*. One captures the influence of bank size on bank interaction, and the other considers the importance of disclosing banks. The main results are robust to using these alternative definitions, as discussed in Section 6.5.

3.2 Co-syndication as a proxy for existing liquidity knowledge

Key to my research design is the measure of existing knowledge about other banks' liquidity before LCR disclosures. I use banks' co-syndication frequency as a proxy for this measure, because syndicate members usually have the incentive and ability to learn each other's liquidity condition and because banks tend to enter syndicates with banks they know and

[15]Note that the absolute value of *InfoGain* is not meaningful on its own, and it is only useful when compared with other banks' *InfoGain*. For example, $InfoGain_i = 0$ does not suggest that bank i learns nothing from the disclosure. However, when compared with $InfoGain_j = 0.5$, $InfoGain_i = 0$ tells us that bank i learns less than bank j.

trust.

A bank is motivated to learn about syndicate members' liquidity conditions, because if a member fails to provide the committed amount of a loan due to liquidity problems, the others in the syndicate will often need to make up the difference.[16] While a bank does not have any legal responsibility to provide extra funding, it is pressured to do so in order to maintain a good reputation and client relationships. Additionally, if a bank choses not to provide extra funding and a deal fails, the bank loses all its earlier investment in that deal. As an extreme example of how a syndicate member's liquidity matters to other members, Ivashina and Scharfstein (2010) show that banks co-syndicating more credit lines with Lehman Brothers experienced greater drawdowns and cut their lending more than did other banks during the 2008 financial crisis. This is because these banks had to meet commitments that Lehman could no longer honor after its liquidity evaporated, and because firms funded by Lehman accelerated drawdowns out of the concern that credit lines would shortly be cut.

A bank is also able to acquire syndicate members' liquidity information. For example, liquidity information of other banks can be collected by a bank's risk management department to evaluate interbank transactions. This information can then be shared with the syndicated loan department. A bank can also ask for liquidity information from syndicate members that it is unfamiliar with.

More generally, banks tend to form syndicates with banks they know and trust. Syndicate members do not explicitly examine each other's liquidity or request private information every time they start a syndicate. Instead, they self-select into groups where the members are familiar with each other. Therefore, banks with closer co-syndication relationships is likely to know more about each other, including each other's liquidity.[17]

If banks know more about syndicate members' liquidity condition, they should know even

[16]In the case of syndicated credit lines, other members will have to (at the least) fund a larger piece when borrowers draw down less than the maximum amount of their credit lines. Other members are also more likely to experience accelerated drawdowns when borrowers are concerned that they may not be able to access their credit lines in the future (Ivashina and Scharfstein, 2010).

[17]I thank two anonymous bankers from Goldman Sachs for providing institutional details related to co-syndication and the liquidity of syndicate members.

more about lead arrangers' because the latter take the most responsibility in a syndicate. Consistent with this idea, in one of the robustness test, I find that replacing the existing liquidity knowledge measure with a measure of co-syndication with lead arrangers results in a stronger effect (Table 11, column (1)).

Of course, co-syndication interaction is not a perfect proxy for information about other banks' liquidity, as counterparty liquidity is not the most important concern in these transactions, although it does matter. A potentially better proxy is bank interactions in federal funds transactions, because of the close connection of these transactions with bank liquidity. Although this data is not publicly available, I compare determinants of the interconnectedness of the federal funds network documented by Afonso, Kovner, and Schoar (2013) with those of my co-syndication network, and I find them very similar (see Section 6.1.1 for more details). This validation test supports my network measure of banks' liquidity knowledge.[18]

4 Empirical design

I exploit several unique features of the LCR disclosure regulation and bank network interconnectedness to analyze the spillover effect of the disclosure rule. In particular, the fact that LCR disclosure was introduced after the minimum LCR rule and is mandated for a group of large banks helps alleviate typical concerns in identifying spillover effects of a disclosure regulation. The network-based measure of incremental liquidity information gained from the LCR disclosure allows me to identify these effects using a difference-in-differences design. I describe my identification strategy and the specifications of my tests below.

[18] Another concern with my measure of liquidity knowledge is a potential survival bias: a bank that is more informed about another bank's bad news will stop interacting with the latter (in the interbank or syndicate markets). If this bias exists, my measure based on bank interactions cannot capture banks' superior information about other banks' weakness. In other words, my measure could be biased in the direction of capturing informed banks with good news. This is an inevitable bias in my measure, and it exist even if I could use interbank transactions as my measure. However, the impact of this bias at the aggregate level is likely to be small. Considering that bad news is usually more transitory than good and that low interaction intensity could captures either 1) uninformed banks or 2) informed banks with bad news, it is reasonable to believe that a low interaction intensity largely captures less informed banks.

4.1 Identification strategy

An ideal experiment to test the spillover effect of LCR disclosures is to randomly provide different levels of liquidity information to otherwise identical non-disclosing banks before the disclosure, and to examine whether those with less existing liquidity knowledge will cut more liquidity after seeing LCR disclosures. Absent this experiment, empirically identifying spillover effects of disclosure is challenging (Leuz and Wysocki, 2016).[19] Unique features of the LCR disclosure setting help alleviate many of the difficulties.

First, regulation is often introduced in response to an industry-wide shock (e.g., a liquidity crisis), which can also drive the observed spillover effects (Ball, 1980). In my setting, the LCR disclosure rule was implemented more than two years after the first LCR rule adoption. Thus, even if the LCR regulation was a response to a certain event, it is unlikely that the effect of the disclosure requirement is confounded by that event. A related concern is that the effect of the disclosure regulation can be confounded by concurrent regulation, in this case, the minimum LCR rules. However, because the LCR disclosure rule was adopted after the last (100%) minimum LCR requirement, I can single out the disclosure effect. My additional analyses also show that the adoption of the minimum LCR rule did not significantly change non-disclosing banks' liquidity.

Second, identifying the externality of a regulation requires comparing firms only indirectly affected and those unaffected, or at least less affected, by both the direct and the indirect effects. It is typically difficult to identify these two groups of firms. This is less of a concern in my setting, because the LCR disclosure requirement only applied to eight banks (out of 174) in the sample period of my main analyses, which allows me to observe a large number of non-disclosing banks that were only indirectly affected. I then exploit variation in the influence of LCR disclosure on different non-disclosing banks to differentiate between those

[19]In particular, in the presence of externalities, the stable unit treatment value assumption (SUTVA) is violated. SUTVA is satisfied if non-disclosing banks are unaffected by the disclosure mandated for disclosing banks. When SUTVA is violated and non-disclosing banks are indirectly affected, identification require an additional control group that is unaffected, or at least less affected, by both the direct and the indirect effects.

that were more and less affected by the indirect effect, which then enables an identification of the disclosure externality using a difference-in-differences design.

Finally, the setting allows me to construct the bank interaction network in order to measure information gained from LCR disclosures, and I can validate this measure by analyzing the determinants of network relationships. Besides, I can use the network to descriptively assess whether a few banks' disclosures are important to the network overall. The disclosure is more likely to be relevant to other banks if all banks are closely connected through business interactions, and it is more likely to be important if the disclosing banks are widely connected in the system. Consistent results from this network analysis can strengthen my confidence that the identified effect comes from a disclosure externality.

In my main analysis, I run a difference-in-differences regression, controlling for bank fixed effects, year-quarter fixed effects, and bank-level determinants of liquidity holdings. This design compares changes in liquidity for banks with more and with less improvement in liquidity knowledge after the disclosure regulation. The fixed effects control for time-invariant bank characteristics and market-wide time trends. The remaining concern is that banks learning more and less from LCR disclosures (i.e., banks with high and low *InfoGain*) could be fundamentally different, which means that omitted variables correlated with *InfoGain* could account for the observed effects. This concern is mitigated by the findings that non-disclosing banks' liquidity correlates negatively with three versions of *InfoGain* over all three stages of LCR disclosure rule implementation, and that the three *InfoGain*'s are negatively correlated. Omitted variables are unlikely to correlate with all the negatively-correlated *InfoGain*'s in the same direction, and thus are unlikely the driver of my findings (see more discussion in Section 6.4).

4.2 Specification

My main analyses adopts a difference-in-differences design to examine the effect of LCR disclosure on non-disclosing banks' liquidity. I estimate the following model on non-disclosing banks:

$$LiquidAssets_{i,t+1} = \alpha_i + \alpha_t + \beta InfoGain_i * Post_t + \gamma X_{i,t} + \epsilon_{i,t} \tag{4}$$

The dependent variable is next quarter's liquid assets scaled by total assets. Liquid assets include cash balances, non-MBS and non-ABS held-to-maturity (HTM) securities, non-MBS and non-ABS available-for-sale(AFS) securities, fed funds sold, and securities purchased under agreements to resell. The key independent variable is $InfoGain_i * Post_t$, where $InfoGain_i$ is bank i's incremental liquidity information gained from the LCR disclosure and $Post_t$ is an indicator variable equal to one after 2Q2017 and zero otherwise. The controls $X_{i,t}$ include the current quarter's $LiquidAssets$ as well as other bank-level drivers of future liquidity holdings, including $CoreDeposit$, $Capital$, $Commitment$, and $Size$, following Cornett, McNutt, Strahan, and Tehranian (2011). $CoreDeposit$ is core deposits (all transactions deposits and other insured deposits) scaled by total assets. Core deposits are a relatively stable source of funding (compared to short-term debt), and are a natural hedge to liquidity risk because deposit insurance attracts deposit inflows in a crisis, when depositors are seeking a safe haven (Gatev, Schuermann, and Strahan, 2009; Gatev and Strahan, 2006). Hence, banks with a higher core deposits ratio have a lower incentive to increase their liquidity. $Capital$ is the ratio of total equity to total assets. On the one hand, a higher capital ratio creates a buffer for depositors, so that banks are less concerned about liquidity risk and are more willing to lend (i.e., reduce liquidity). On the other hand, holding too much equity reduces banks' ability to lend. $Commitment$ is unused loan commitments scaled by the sum of unused commitments and total assets. Commitments increase banks' liquidity risk, especially in downturns, when takedown demand increases. Therefore, banks with a higher level of unused commitments are more likely to increase liquidity in order to reduce this risk. $Size$ is the natural logarithm of total assets. Size affects liquidity holdings, because larger banks are perceived by the market as safer ("too big to fail"), which can reduce banks' incentive to hold liquidity. Finally, I include bank fixed-effects, α_i, and year-quarter fixed effects, α_t, to control for time-invariant bank characteristics and time trends.

5 Data and sample

I collect data on banks' loan co-syndication history from Thomson-Reuters' LPC DealScan. A bank is included in my sample if it is a syndicated loan lender classified as a US bank, thrift/S&L, mortgage bank, or investment bank and if its executive office is in the US. Banks belonging to a common holding company are aggregated to the top bank holding company and treated as a single banking organization. Financial data for bank holding companies are from FR Y-9C reports published on the website of the Federal Reserve Bank of Chicago. Since DealScan and FR Y-9C Reports use different bank identifiers, I manually match banks in the two datasets by name, state, and city. I drop lender banks when the correct match is not obvious. Finally, market data for listed bank holding companies come from the Center for Research in Security Prices (CRSP).

The dataset consists of the bank-quarter level observations of bank characteristics and loan co-syndication interactions. The full sample period covers the first quarter of 2011 through the fourth quarter of 2019, which ends before the COVID-19 crisis and dates back far enough to give me enough data to conduct my tests. Banks in the sample must have participated at least one syndicated loan from 2010 to 2017, during which I construct the measure of the co-syndication network (see Section 3.1). Since my main analyses compare outcomes in the pre-period of 1Q2016-2Q2017 and the post-period of 3Q2017-2Q2018, banks in the sample must have observations in both subperiods. To mitigate the effect of large mergers and acquisitions, I drop banks that participated in an M&A and that experienced over 20% in asset growth during any of the quarters from 3Q2017-2Q2018.[20]

Table 1 reports descriptive statistics for key bank characteristics and bank interaction network variables. Panel A reports bank characteristic variables. Banks in the sample have a mean (median) liquid-assets-to-total-assets ratio of 15% (12%). Based on both mean and

[20]The main concern here is that a bank can experience large changes in its liquidity and network linkages in the post-period because of an M&A transaction, confounding the effects of the disclosure. Dropping all M&A banks, however, will considerably reduce the number of observations, as small M&A happens quite frequently. Therefore, I keep banks that did not increase their assets more than 20% after an M&A. The main results are robust to dropping or to keeping all the M&A banks.

median measures, core deposits are around 60% of total assets, capital ratio is around 11%, and unused commitments are around 14% of the sum of unused commitments and total assets. These statistics resemble those reported in the literature (e.g. Cornett, McNutt, Strahan, and Tehranian, 2011; Acharya and Mora, 2015), and are slightly closer to the statistics of large banks reported by Cornett, McNutt, Strahan, and Tehranian (2011). This is expected, as my sample selection process tends to keep larger banks.

Panel B reports descriptive statistics of bank interaction network variables. There are 174 banks in my sample. The mean (median) number of *Connections* (i.e., banks with co-syndication histories) is 25 (15), and the mean (median) number of *Interactions* (i.e., co-syndicated loans) is 1,906 (29). The distributions of the two variables are significantly right skewed, indicating that a few banks participated in many more syndications. The key independent variable, *InfoGain*, which by design ranges from 0 to 1, has a mean of 0.72 and a median of 0.73. The fact that this ratio is closer to 1 than to 0 suggests that an average bank interacts more with non-disclosing banks, despite the fact that the disclosing banks are major players in bank interactions. Figure 4 plots the histogram of the three variables.

Note that *InfoGain* is noisier when *Interactions* is smaller, as a few missing observations or random co-syndications with disclosing banks can considerably change *InfoGain*.[21] Thus, to improve the accuracy of the measure, it is useful to only keep banks above a certain *Interactions* threshold. However, since many banks in my sample have small *Interactions* (lower than seven in the first quartile, as shown in Panel B), I will lose too many observations if the threshold is too high. Therefore, I drop banks with *Interactions* smaller than seven in regressions with *InfoGain*. I also exclude banks with *Interactions* greater than 10,000 in these regressions, as banks with large number of co-syndications can be fundamentally very different from other banks. My main results are robust to keeping as many as all banks with

[21]For example, a bank with $Interactions = 5$ where two of the interactions are with disclosing banks would have $InfoGain = 0.6$. However, if there were three additional interactions with non-disclosing banks that the database failed to capture, then the actual *InfoGain* should be 0.75. Including the three missing observations moves *InfoGain* from the first quartile to over the median (Table 1, Panel B). The influence of missing observations will be smaller for banks with larger *Interactions*.

$Interactions \geq 4$ and as few as only those with $Interactions \in [10, 100]$, as discussed in Section 6.5.

Panel C reports the correlation matrix of network variables. *InfoGain* is negatively correlated with *Interactions*. This suggests that banks that have more interactions with all other banks (i.e., higher *Interactions*) are more likely to interact with LCR disclosing banks (i.e., to have a lower *InfoGain*). In other words, it is less likely to see a bank with frequent interactions with other banks but few interactions with the LCR disclosing banks. This feature, along with the feature of *LinkDisc* discussed in Section 3.1, supports *InfoGain* as a proxy for liquidity information gained from LCR disclosures.

6 Results

6.1 Network analysis

As a first step, I analyze the bank business network based on co-syndications to evaluate my underlying assumption that the interconnectedness of the network captures banks' knowledge of each other's liquidity, and that the network structure makes it possible that the LCR disclosure affects all banks in the system.

6.1.1 Determinants of the co-syndication network vs. the federal funds network

I validate my proxy for existing knowledge of other banks' liquidity by comparing key determinants of co-syndication linkages with those of the federal funds transaction linkages documented in the literature. Federal funds are one of the main sources of banks' liquidity. They are the interbank borrowings of reserve balances from the Federal Reserve banks used to maintain reserve requirements and to clear financial transactions. Most borrowings are overnight, uncollateralized, and booked without a contract, so that they rely heavily on relationships and trust. Because federal funds transactions are closely related to bank liquidity and depends on relationships, banks more interconnected in these transactions are more likely to have private information about each other's liquidity. Therefore, if co-syndication and federal funds interconnectedness have similar determinants, the former is more likely to capture banks' knowledge about each other's liquidity.

Although federal funds transaction data is not publicly available, key determinants of the network's interconnectedness are documented by Afonso, Kovner, and Schoar (2013).[22] Their paper finds that banks are more likely to have a federal funds relationship if they are geographically close to each other, have a greater difference in asset size, and have negative correlations in their liquidity needs and in their nonperforming loans. I conduct a similar test for banks' co-syndication relationship in Table 1, Panel D. The determinants of a co-syndication relationship resemble those of federal funds: banks are are more likely to co-syndicate if they are located in the same area, differ in asset size, and have negatively correlated liquidity needs (although the coefficient of the correlation in nonperforming loans is insignificant).[23]

6.1.2 Structure of the co-syndication network

To evaluate whether the way banks are interconnected in the business network contributes to the relevance and importance of LCR disclosures, I analyze the structure of the network. The disclosure is more impactful if banks are more closely connected and if disclosing banks contribute more to business interactions.

First, I plot the network of bank co-syndication in Figure 2. Each node represents a bank, and an edge connects nodes that have co-syndicated at least once. The size of each node increases with the number of co-syndicated banks. Nodes are partitioned and color coded based on their modularity class (i.e., nodes in the same module are more likely to

[22] Afonso, Kovner, and Schoar (2013) note that the interbank transaction data used in their paper may include transactions that are not federal funds trades and may discard transactions that are federal funds trades. While the data has been used as federal funds data in prior studies (e.g., Afonso, Kovner, and Schoar, 2011), it is more accurate to refer these transactions as interbank loans.

[23] Afonso, Kovner, and Schoar (2013) use the correlation coefficient between two banks' net customer transfers over Fedwire as a proxy for the correlation of their liquidity needs. Absent this data, my proxy is the correlation coefficient between two banks' ratios of liquid assets to total assets.

connect with each other than with nodes in other modules). The node layout is conducted by the "ForceAtlas2" algorithm, which groups (separates) nodes that are more (less) likely to be interconnected. While the plotting algorithm tries to push away (cluster) nodes that are less (more) connected, all banks are closely interconnected in a single network: there is not a group of nodes located apart from other nodes, and nodes with different colors are mixed together. Because of this close business connection, the LCR disclosure is relevant to all banks.

Second, I verify that the eight disclosing banks are major players in the business interaction network, which means that their LCR disclosures are important to all banks in the banking system. Figure 3 plots the top 30 banks in terms of the number of issued syndicated loan, *Interactions*, where the black bars represent the disclosing banks. The eight disclosing banks in my main analysis are major players in the network, as they contribute 55% of the total *Interactions* from all 174 banks in the sample.

6.2 Effect of the LCR disclosure rule on liquidity holdings

My main analysis examines the effect of the LCR disclosure regulation on non-disclosing banks' liquidity holdings. I begin by examining changes in liquidity holdings after the first-stage LCR disclosure rule implementation for disclosing and non-disclosing banks. I then conduct a difference-in-differences regression to compare the liquidity change of non-disclosing banks that learned more and less from the disclosure.

6.2.1 Spillover effect on non-disclosing banks' liquidity

I report liquidity changes after the LCR disclosure rule in Table 2. Column 1 suggests that the liquid asset holdings of disclosing banks insignificantly increased after the disclosure requirement. On the contrary, column 2 suggests that non-disclosing banks significantly reduced their liquidity. Column 3 indicates that non-disclosing banks' liquidity holdings changed significantly more negatively than disclosing banks'.

Table 3 reports the results of my main specification, described in Equation 4. In column 1, I regress non-disclosing banks' liquid assets scaled by total assets on the incremental liquidity information gained from the LCR disclosure, and I include bank-level controls and bank and quarter fixed effects. The regression coefficient of *InfoGain*Post* is -0.0236 and statistically significant at the 1% level. This effect is also economically significant: an average bank had a 0.72 *InfoGain* after the LCR disclosure (Table 1 Panel B), which translates into a 1.7 percentage point decrease in the ratio of liquid assets to total assets (i.e., 0.72×-0.0236). This is approximately 11% of the average and 15% of the standard deviation of the ratio (Table 1 Panel A).

If this result is due to better information about liquidity risk in the market as I predicted, then non-disclosing banks that are more concerned about liquidity risk should react more to the disclosure. In column 2, I find that non-disclosing banks with less core deposits (i.e., those with less stable funding and thus are more concerned about liquidity risk) react more strongly to the disclosure. This result supports my underlying assumption that LCR disclosures contain important information about liquidity risk, and that non-disclosing banks care about liquidity risk when making liquidity decisions.

To alleviate the concern that my main result in column 1 is driven by a general trend of lowering liquidity for banks with high *InfoGain* during the sample period (which would violate the parallel-trends assumption), I map out the LCR disclosure treatment effect over time in Figure 5. In support of the parallel-trends assumption, non-disclosing banks had similar liquidity levels until the introduction of the LCR disclosure rule in 2Q2017.

6.2.2 Aggregate effect on liquidity in the banking system

Based on the treatment effects estimated above, I calculate the aggregate effect of the LCR disclosure on the liquidity holdings of all banks after the disclosures were released. To calculate the total increase in disclosing banks' liquid assets, I multiply the coefficient of

Post in column 1 of Table 2 (0.0038) and the lagged total assets of these banks:

$$\Delta LiqAsset(Disclosing)_t = \sum_{i \in Disclosing\ banks} 0.0038 * TotalAssets_{i,t-1} \tag{5}$$

I then calculate the sum of liquidity cuts for all non-disclosing banks in my sample, where each bank's liquidity cut is the multiple of the coefficient of *InfoGain*Post* in column 1 of Table 3 (-0.0236), the bank's *InfoGain* value, and its lagged assets:

$$\Delta LiqAsset(NonDisclosing)_t = \sum_{i \in NonDisclosing\ banks} -0.0236 * InfoGain_i * TotalAssets_{i,t-1} \tag{6}$$

Table 4 reports the results. While disclosing banks' liquid assets increased (insignificantly) by $42 billion, disclosing banks' declined by $53 billion. Net net, total liquid assets fell by $10 billion, or by 0.3%, for all banks in my sample. Moreover, liquidity distribution in the banking system changed significantly: while disclosing banks increased total liquid assets by 1%, non-disclosing banks' liquidity holdings dropped by 13%.

6.3 Effect of the LCR disclosure rule on systemic risk

Although the LCR disclosure led to lower and more concentrated liquidity in the banking system, whether these changes undermined or improved financial stability is unclear ex ante. If non-disclosing banks previously had held excess liquidity that was not useful for themselves or for disclosing banks (via interbank borrowing), then LCR disclosures could enhance financial stability by improving disclosing banks' liquidity and by reducing non-disclosing banks' unnecessary stockpiles. On the other band, if the previous liquidity holdings of non-disclosing banks were necessary for those banks or if these holdings were an important source of interbank borrowing for disclosing banks, LCR disclosure could increase systemic risk by making non-disclosing banks, disclosing banks, or both riskier. To assess whether LCR disclosure achieved its ultimate goal of enhancing financial stability (81 FR 94922), I examine the impact of the disclosure rule on systemic risk.

6.3.1 Measure of systemic risk

I measure systemic risk using two methods that focus on different aspects of the nature of systemic risk. The first one, a Granger-causality measure (Billio, Getmansky, Lo, and Pelizzon, 2012), is based on banks' stock return correlations, and the second one, SRISK (Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2017), is based on the expected capital shortfall of banks in adverse times. Higher stock return correlations and greater expected capital shortfall means that distress can spread faster in the banking system and that the losses from distress are greater, both indicating higher systemic risk.

I calculate the Granger-causality measure following Billio, Getmansky, Lo, and Pelizzon (2012). In quarter t, bank i is defined to be "Granger caused" by j, i.e., $(i \leftarrow j)_t = 1$, if i's return today correlates with j's return yesterday, and $(i \leftarrow j)_t = 0$ otherwise. Specifically, I first scale bank i's daily return with the standard error estimated with a GARCH(1,1) model using its daily returns in quarter t to control for heteroskedasticity. Then, using the filtered returns, I identify bank i as "Granger caused" by bank j in quarter t if, for daily returns in quarter t, j's return today significantly predicts i's return for the next day after controlling for i's return today. Then, systemic risk is the number of linkages through which a bank is Granger caused by another bank:[24] $GC_{i,t} = \sum_{j \neq i} (i \leftarrow j)_t$

Following Acharya, Engle, and Richardson (2012), SRISK of bank i in quarter t is calculated using the formula: $SRISK_{i,t} = k \times Debt_{i,t} - (1-k)(1 - LRMES_{i,t}) \times Equity_{i,t}$, where $Debt$ is the book value of debt at the end of quarter t; $Equity$ is the average equity value in quarter t; k is the prudential capital ratio, which is set to 8 percent; $LRMES$ is Long Run Marginal Expected Shortfall, which is approximated as $1 - exp(-18 \times MES)$, where MES is the one day loss expected if market returns are less than -2 percent.[25]

[24] In Billio, Getmansky, Lo, and Pelizzon (2012), the systemic risk measure, Degree of Granger Causality, is the number of linkages scaled by the total number of bank-pairs. I do not scale by this constant to make the regression coefficient easier to read.

[25] SRISK is scaled by total assets following Roberts, Sarkar, and Shachar (2019) to facilitate cross-bank

6.3.2 Effect of the LCR disclosure on systemic risk

Table 5 reports the changes in the two systemic risk measures after the adoption of LCR disclosure rule and minimum LCR rule. As indicated by Columns 1 and 3, both measures of systemic risk decreased after the minimum LCR rule adoption, but increased after the LCR disclosure became available. Next, I examine whether the overall increase in systemic risk after LCR rule adoption was due to riskier non-disclosing banks. In Columns 2 and 4, I find that non-disclosing banks more affected by the LCR disclosure (and thus cut liquidity more) were not more likely to contribute to systemic risk. This indicates that cutting liquidity did not weaken non-disclosing banks, which suggests that the increased systemic risk is likely due to systemically riskier disclosing banks. These results are consistent with the conjecture that, although the liquidity of non-disclosing banks was excessive for themselves before LCR disclosure, it was an important source of interbank borrowing for disclosing banks. As a result, less liquidity held by non-disclosing banks reduces liquidity supply to the interbank market, increasing the liquidity risk of disclosing banks and weakening the stability of the financial system (Bech and Atalay, 2010; Afonso, Kovner, and Schoar, 2013).

6.4 Mechanism of the disclosure externality

While the disclosure externality identified in Section 6.2 is consistent with LCR disclosures dampening liquidity holding incentives by reducing uncertainty about aggregate liquidity risk, the externality could come from other channels. To pin down the channel, I provide additional evidence to rule out several alternative explanations.

First, non-disclosing banks may have cut liquidity not because the disclosure reduced uncertainty about disclosing banks' liquidity, but because disclosing banks increased the level of liquidity holdings. To examine this possibility, I compare the liquidity holdings of non-disclosing banks with higher and with lower *InfoGain* around the time when the

comparisons. If a quarter does not have a day when market return is below -2 percent, I calculate the one day expected loss on the day with the lowest market return in that quarter.

minimum LCR requirement increased from 80% to 100% (from 1Q2015 to 1Q2017) and when the Basel III LCR regulation was announced (in 1Q2013). The results are reported in Table 6. *Post_n* is an indicator variable equal to one in and after quarter n and zero otherwise, where $n = 1Q13$, $1Q15$, $1Q16$, or $1Q17$. In columns 2 to 4, the coefficients of *InfoGain*Post_n*, where n is $1Q15$, $1Q16$, or $1Q17$, are insignificant, which suggest that non-disclosing banks did not shift liquidity holdings after the implementation of minimum LCR requirements. In column 5, the coefficient of *InfoGain*Post_1Q13* is significantly negative, which suggests that non-disclosing banks reacted to the anticipated increases in disclosing banks' liquidity shortly after the announcement of the LCR rule. When controlling for all *InfoGain*Post_n*'s in the main regression in column 6, only the coefficients of *InfoGain*Post* and *InfoGain*Post_1Q13* are significant. Figure 5, Panel B visualizes the same results. These findings indicate that the increase in disclosing banks' liquidity from LCR rules was anticipated and thus the rule adoption had little impact on non-disclosure banks' liquidity.

Second, the reduction of non-disclosing banks' liquidity could be driven by omitted variables that correlate with *InfoGain* and bank liquidity change. To alleviate this concern, I extend the main analysis to the second and third stages of the LCR disclosure. In Table 7, I define *InfoGain_2Q18* and *InfoGain_4Q18* using non-disclosing banks' co-syndication with banks that are newly compliant with the disclosure rule in the second (three banks, beginning in 2Q18) and third stages (nine banks, beginning in 4Q18). The main result holds in both stages, as coefficients of *InfoGain_2Q18*Post_2Q18* and *InfoGain_4Q18*Post_4Q18* in Panel A are significantly negative. In this case, the omitted variable explanation would require the three *InfoGain*'s be positively correlated with each other, so that the omitted variables can drive them in the same direction. However, I predict and find in Panel B that if a bank has low *InfoGain* in the first stage due to close connections with first-stage disclosing banks, it mechanically connects less with newly compliant disclosing banks and has higher *InfoGain* during the following two stages (i.e., *InfoGain*'s are negatively correlated with each other). Panel C further shows that the three *InfoGain*'s correlate with bank characteristics in very different directions. These findings alleviate the omitted variable concern.

My findings could also stem from the disclosure revealing a higher-than-expected level of disclosing banks' liquidity (i.e., a good news) rather than reducing the uncertainty about disclosing banks' liquidity. This is generally consistent with the mechanism I predict, although it emphasizes the disclosure's impact on the expected level, instead of the uncertainty, of disclosing banks' liquidity. That said, since all three stages of LCR disclosures had the same effect, this explanation would require that all three stages brought better-than-expected news, which is unlikely in the rather uneventful sample period. I also examine stock returns of disclosing banks around the days of the first LCR disclosure. Since only Goldman Sachs (GS) and State Street (STT) disclose the filing dates for their LCR reports, I checked their stock returns around their first LCR report filing dates. GS/STT released their first LCR reports on August 28/29, 2017, which were more than a month after their 2Q2017 earnings announcements (on July 18/26, 2017). The stock returns of GS/STT in the three-day window around the first LCR report filing dates were -1.1%/-0.9%, which were not higher than the corresponding returns of the banking sector, BKX (-1.3%/-0.4%), or the S&P 500 (0.1%/0.5%). This result weakens the interpretation that the LCR disclosure brought significant good news.

6.5 Robustness tests

In this section, I conduct a series of robustness tests to further sharpen the identification of my main analysis in Section 6.2. One concern is that banks in my sample vary considerably in their *Interactions*, total number of syndicated loans issued (Table 1 Panel B). A small *Interactions* introduces noise to *InfoGain*, while banks with large *Interactions* can differ fundamentally from other banks (see the discussion in Section 5). Therefore, my results could include too much noise when measuring *InfoGain* or could be skewed by banks with large *Interactions*. While I impose restrictions on the range of *Interactions* in my main analyses, it could still need further tightening. On the other side, however, restricting the range of *Interactions* limits the generalizability of the results. To mitigate these concerns, I test the robustness of my main results to the range of banks' *Interactions*. Table 8 reports that the main result is robust to including as many as all banks with $Interactions \geq 4$ or as few as only those with $Interactions \in [10, 100]$.

Another concern is that the sample period in my main tests could be too short, so that the observed treatment effects could be merely a mean-reversion and become insignificant over a longer sample period. To mitigate this concern, I extend the sample period in Table 9. The main results hold whether I extend the pre-period by as many as five years or extend the post-period by another year. Note that the effect becomes less significant when I extend the post-period and eventually becomes insignificant if the post-period is extended to 4Q2019 (untabulated), potentially because of stage 2 and 3 LCR disclosures.[26]

Next, in Table 10, I investigate whether the variation of my key independent variable *InfoGain* is determined by bank characteristics that also drive bank liquidity. In Panel A, I regress *InfoGain* on a set of bank-level variables that capture several major aspects of a bank's performance, such as business growth, risk-taking, asset quality, and profitability. Column 1 includes only the independent and dependent variables used in the main regression, and Column 2 includes more variables. Among variables not included in the main regression, non-performing loans, interest income, and earnings before provision are significantly correlated with *InfoGain*. I add these three variables as controls in the main regression. Interactions of all control variables and *Post* are also included to allow bank characteristics to have different effects on liquidity before and after the disclosure rule adoption. The additional controls do not meaningfully affect the result as reported in Panel B.

Finally, I examine whether my main results are robust to alternative definitions of *InfoGain*. I use a simple definition (Equation 3) to capture the key concept in a way that is easy to interpret. A simple measure can, however, miss factors that affect a bank's learning

[26]I find that *InfoGain_2Q18* and *InfoGain_4Q18* negatively affect non-disclosing banks' liquidity, and are negatively correlated with *InfoGain* (Table 7, Panels A and B). Thus, the second and third stages of LCR disclosure negatively affect the liquidity of banks with low *InfoGain*, offsetting the effect of the first-stage LCR disclosure.

from the LCR disclosure. For example, a bank probably cares more about a bank in its co-syndication interactions (and knows more about its liquidity) if the latter serves as a lead arranger or is larger. I create two alternative measures of *InfoGain* to reflect these two factors and examine the robustness of the main analysis.

In particular, I define:

$$InfoGain\_LA_i = 1 - \frac{\sum_j Interactions\_LA_{i,j} * Disclosure_j}{\sum_j Interactions_{i,j}}, \tag{7}$$

where $Interactions\_LA_{i,j}$ is the number of syndicated loans bank i has issued with bank j when bank j was the lead arranger. And:

$$InfoGain\_Size_i = 1 - \frac{\sum_j Interactions_{i,j} * Size_j * Disclosure_j}{\sum_j Interactions_{i,j} * Size_j} \tag{8}$$

In Table 11, I replace *InfoGain* with the two alternative measures, and the main results hold. In column 1, the coefficient of *InfoGain_LA*Post* is about 33% more negative than that of *InfoGain*Post* in column 1 of Table 3, with similar statistical significance. This suggests a non-disclosing bank knows more about disclosing banks' liquidity condition when the latter serve as lead arrangers in a syndicate, which makes the non-disclosing bank learn less from the LCR disclosure. In column 2, the coefficient of *InfoGain_Size*Post* is similar to that in my main findings in terms of economic and statistical significance, which suggests that counterparty size is not a key determinant of a bank's existing knowledge about co-syndication counterparty' liquidity.

7 Conclusion

Information about the liquidity condition in the banking system is crucial to banks' liquidity holding decisions. In this paper, I empirically examine the role of liquidity information on bank liquidity using the disclosure of the bank liquidity coverage ratio (LCR) mandated for a group of large US banks. While this regulation aims to increase liquidity in the banking system, I find that LCR disclosures reduced non-disclosing banks' holdings of liquid assets. This spillover effect results from the impact of liquidity information on banks' strategic interactions in holding liquidity. Using bank network relationships to measure how much a bank learns from the disclosure, I find that banks learning more from the disclosure cut their liquidity significantly more. The spillover effect was sizable enough to lower the aggregate liquidity in the system, concentrate liquidity within a group of disclosing banks, and increase systemic risk.

My paper contributes to the literatures in a number of ways. First, my paper adds to the literature on bank liquidity regulation by providing new evidence on the influence of mandatory disclosures of liquidity information. I find that the LCR disclosure's spillover effect undercuts the regulation's goal of improving the liquidity and stability of the banking system. These findings should be of interest to regulators. Second, this paper expands our understanding of the externality of disclosure regulations. I provide evidence that disclosures of bank liquidity information generate externalities that have considerable impact on bank liquidity and financial stability. Finally, my paper adds to the literature on the effect of transparency and networks on financial stability.

My findings should be interpreted with the following caveats in mind. As discussed in more detail in the paper, my key measure of liquidity information gained from LCR disclosures contains noise, non-disclosing banks could be influenced by the increases in disclosing banks' liquidity holdings, and correlated omitted variables could also contribute to my results. Although I provide evidence that these caveats are unlikely to threaten the identification of the spillover effects, they can nevertheless bias the magnitude I estimate upward or downward.

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Appendix A. Model to generate the empirical prediction

I use a simple model to illustrate the dampened liquidity holding incentives of banks when better information reduces their uncertainty about the liquidity risk in the market.

I model an economy of identical banks that make asset allocation choices between illiquid ("loans" for simplicity) and liquid assets ("cash" for simplicity). Banks anticipate a potential negative liquidity shock (i.e., an unexpected large-scale cash outflow). When the liquidity shock is realized, banks with liquidity shortages can either prematurely liquidate their loans for a low fixed price or sell loans in the interbank market to other banks. Selling loans is a simplification of multiple approaches banks can take to raise cash in practice.[27] Banks face a trade-off between holding more cash or more loans. Holding cash comes with an opportunity cost because cash does not generate interest income, but it does reduce the risk of premature loan liquidation, and can be used to purchase loans at a discount when other banks sell their loans. Furthermore, banks face a funding cost that increases with the total cash outflow due to the liquidity shock and decreases with total cash holdings in the system.

Banks are Knightian uncertain (Knight, 1921) about the likelihood of the liquidity shock, in the sense that they don't have a prior about the distribution of the probability of a liquidity shock, and so they consider a range of liquidity shock probabilities as possible.[28] Banks are uncertainty averse, and they use the worst case scenario, i.e., the highest liquidity shock probability in the possible range, to make liquidity decisions. This "maxmin" modeling choice draws from bank liquidity decision models in Caballero and Krishnamurthy (2008)

[27]For example, banks can also borrow cash using illiquid assets as collateral instead of selling them to raise liquidity. The required collateral and interest rate for borrowing cash both increase when aggregate liquidity is low. In this case, the cost of borrowing cash is modeled as the cost of selling illiquid assets. Additionally, while I use "loans" to represent illiquid assets that are sold to raise cash, banks typically start by selling or pledging more liquid assets, such as mortgage-backed securities, in a crisis. These assets become illiquid in a crises, and thus are treated as illiquid assets and are called "loans" for simplicity in my model.

[28]Knightian uncertainty differs from risk in that the former arises when the probability distribution of an event is unknown due to the lack of information about the distribution (e.g., the chance of a terrorist attack), while the latter has a known/measurable probability distribution which can be estimated with confidence from relative frequencies, event histories, or accepted theory (e.g., gambling on tossing a fair coin). Economic agents make decisions by considering a set of possible probability models when facing Knightian uncertainty (Gilboa and Schmeidler, 1989), while they maximize the expected utility with respect to a common prior when facing risks (Savage, 1954).

and Caballero and Simsek (2013) to reflect banks' self-protective reaction to uncertainty.[29] It is also consistent with the practice and regulatory requirement of conducting "stress tests" to evaluate the adequacy of liquidity holdings. In equilibrium, banks' liquidity holdings increase with the upper bound of the possible range of liquidity shock probabilities. LCR disclosure improves the information quality about the aggregate liquidity risk, which reduces banks' uncertainty about the liquidity shock probability. Therefore, the upper and lower bounds of the range move closer to the actual probability after the disclosure, and the lowered upper bound leads to a reduced equilibrium liquidity holding level. In sum, the model predicts a negative effect of liquidity disclosure on banks' liquidity holdings.[30]

Whether the liquidity reduction is socially optimal or not is unclear ex ante. An individual bank does not consider the benefits of holding liquidity in terms of reducing funding cost, because funding cost decreases with aggregate liquidity holdings, not the bank's own holding.[31] Therefore, banks hold less than the socially optimal amount if there were no uncertainty about liquidity shock probability. The existence of such uncertainty increases banks' liquidity holdings, so that the equilibrium liquidity before the disclosure can be either less than, equal to, or greater than the optimal level. Because of this, liquidity reduction after the disclosure can shift liquidity holdings either closer to or further away from the optimal level.

[29] Uncertainty aversion has been widely recognized in decision theory and neural science as a key driver of the choices of individuals (e.g., Ellsberg, 1961; Hsu, Bhatt, Adolphs, Tranel, and Camerer, 2005; Bossaerts, Ghirardato, Guarnaschelli, and Zame, 2010) and institutions (e.g., Dow and da Costa Werlang, 1992; Epstein and Schneider, 2008), particularly in regards to asset holding choices. The maxmin representation is often used to model uncertainty averse choices when economic agents do not have a prior about the probability distribution of an unusual and unpredictable event, such as a negative liquidity shock (Caballero and Simsek, 2013). Alternatively, if assuming that economic agents have a prior about the probability distribution of an event, one can model uncertainty aversion in the spirit of Leland (1968) by making certain assumptions about the third derivative of the utility function with respect to liquidity holdings. I choose the maxmin representation because it better captures the nature of liquidity risk and is more tractable.

[30] This specific disclosure effect impacts both disclosing and non-disclosing banks in the same way, so I do not differentiate between the two in this model. In the empirical part of this paper, I focus on non-disclosing banks for better identification, because disclosing banks were also affected by the direct disciplinary effect of the disclosure.

[31] Modeling funding cost helps capture the general idea that banks tend to hold less than the socially optimal level of liquidity because they bear all the costs of holding liquidity but share the benefits with other financial institutions (e.g., reduced systemic risk and funding costs) (Perotti et al., 2011; Stein, 2013).

A.1 The basic economy

In the economy, there is a continuum of identical banks of measure one and three dates: Days 0, 1, and 2. On day 0, each bank i has one unit of asset, and it chooses to allocate a proportion of it, α_i, in cash, and the rest, $(1 - \alpha_i)$, in loans. $\alpha_i \in [0, 1]$. The aggregate liquidity holdings in the banking system is $\alpha = \int_0^1 \alpha(x)dx$. For each unit of loan holding on Day 0, there will be a certain payoff $(1 + r)$ on Day 2, and not beforehand. r is constant and is greater than 0. Cash holding does not generate income, and can be withdrawn at par value on either Day 1 or Day 2. A liquidity shock happens on Day 1, and loans are paid off on Day 2. Each bank is funded by issuing one unit of deposit, and the funding cost decreases (increases) with the aggregate cash surplus (shortage) in the banking system on Day 1.

On Day 1, each bank will experience either t amount of cash outflow with probability p or no cash outflow with probability $1 - p$. $t \in (0, 1)$ is a constant known to everyone on Day 0, and a bank can always put enough cash aside on Day 0 to meet all possible liquidity needs (i.e., t) on its own. On Day 0, bank managers are Knightian uncertain about the probability of liquidity shock, p, and they consider a range of probabilities as possible. On Day 1, p and α are known to all.

If the liquidity needs are satisfied, a bank's extra cash on Day 1 generates no profit or cost. If a bank' liquidity needs are not satisfied by its own holdings, the bank can raise liquidity by either selling loans to other banks at η dollars per unit of loan, or by prematurely liquidating loans at θ dollars per unit of loan. θ is a constant and $\theta \in (0, 1)$. This ensures that liquidating a loan is worse than not investing in the loan in the first place. η is determined on the interbank market, as discussed below. While an individual bank's liquidity does not affect its funding cost, an aggregate cash surplus (shortage) on Day 1 reduces (increases) funding costs for all banks. This modeling captures the positive externalities of liquidity holdings to the banking system (e.g., enhancing the liquidity of collateral in repo agreement reduces repo rates and haircuts).

A.2 Market clearing model

On Day 1, loans and cash are traded in the interbank market. Clearing the market requires both a price function for the loan and rationing for the traded cash or loans, whichever is under-supplied. Pricing is not enough because all banks are identical, and if the overall liquidity supply is smaller (greater) than the demand, the cash (loans) available for trade needs to be evenly allocated across all banks in need of cash (loans), i.e., through rationing.

Because the price of the loan depends on the liquidity of market participants, I model the functional form of η using a modified version of "cash-in-the-market pricing" (e.g. Allen and Gale, 2005; Acharya and Yorulmazer, 2007). Specifically, η is determined by the interbank market on Day 1 in the following way. First, η increases with the overall liquidity surplus in the market, $(1-p)\alpha$, and decreases with the overall liquidity demand, $p(t-\alpha)$. Thus, η increases with $\lambda \equiv \frac{(1-p)\alpha}{p(t-\alpha)}$. Second, η is greater than or equal to θ, the price of premature liquidation. Otherwise, banks would simply liquidate their loans instead of selling them in the interbank market. Third, η is less than or equal to $1+r$, the payoff of the loan on Day 2. This ensures a nonnegative time value of holding loans from Day 1 to Day 2. Finally, η equals 1, i.e., the loans are traded at par value on Day 1, when $\lambda = 1$. This ensures that banks would be indifferent between holding cash or loans on Day 0 if they knew that the actual liquidity supply, and demand would be the same on Day 1. Combining all these features, I write the price function for the loan on Day 1 as:

$$\begin{aligned} \eta &= \min\{(1-\theta)\lambda + \theta, 1+r\} \\ &= \min\{(1-\theta)\frac{(1-p)\alpha}{p(t-\alpha)} + \theta, 1+r\} \end{aligned} \tag{A.2.1}$$

All the four features described above are met: η increases with λ, is bounded between θ and $1+r$, and equals 1 when $\lambda = 1$. This price function is similar to the "cash-in-the-market pricing" functional form of $\min\{\frac{(1-p)\alpha}{p(t-\alpha)}, 1+r\}$ (e.g. Allen and Gale, 2005; Acharya and Yorulmazer, 2007). The modification allows loans to be liquidated outside the interbank market and creates a lower bound, θ, on η.

Since all banks are identical, the under-supplied assets (either cash or loans) are allocated through rationing on Day 1. That is, a needy bank can raise $\beta = \min\{\lambda, 1\}$ portion of its total liquidity shortage by selling loans (and raise the rest $1-\beta$ by premature liquidation), while a surplus bank can use $\gamma = \min\{\frac{1}{\lambda}, 1\}$ portion of its liquidity surplus to purchase loans (and leave the remaining $1-\gamma$ unused).

A.3 First best liquidity holdings

Society's aggregate liquidity surplus is: $(1-p)\alpha - p(t-\alpha) = \alpha - pt$. When $\alpha - pt < 0$, society's overall liquidity holdings are insufficient to cover its liquidity needs on Day 1, and there will be at least one bank that needs to prematurely liquidate loans. Liquidating loans generates a net cost to society. When $\alpha - pt = 0$, all banks that have liquidity shortages can raise enough liquidity through selling loans to those with extra cash on Day 1, and there will be no extra cash in the economy after these transactions. When $\alpha - pt > 0$, there will be some extra cash left in the economy after all needy banks raise sufficient liquidity through interbank transactions. Holding extra cash reduces interest income, but it also lowers funding cost. Formally, the utility of society is:

$$\pi_{social} = \begin{cases} (1-\alpha)r - \dfrac{1+r-\theta}{\theta}(pt-\alpha) - c(1+pt-\alpha)^2, & \text{if } \alpha \leq pt \\ (1-\alpha)r - c(1+pt-\alpha)^2, & \text{if } \alpha > pt \end{cases} \tag{A.3.1}$$

The right-hand side of the above equation can be interpreted in the following way: when $\alpha \leq pt$, society's overall profit is the interest income that could be earned from loans held on Day 0, $(1-\alpha)r$, minus the loss from prematurely liquidating loans on Day 1, $\frac{1-\theta+r}{\theta}(pt-\alpha)$. The loss has two parts: 1) loss of principal, $\frac{1-\theta}{\theta}(pt-\alpha)$, which is the cost of $\frac{1}{\theta}(pt-\alpha)$ units of loans on Day 0 minus the $(pt-\alpha)$ cash received from liquidating these loans; 2) loss of interest income, $\frac{r}{\theta}(pt-\alpha)$, as $\frac{pt-\alpha}{\theta}$ units of originally held loans cannot to be held to Day 2. The funding cost is $c(1+pt-\alpha)^2$. It equals c if there is no liquidity shock (i.e., $p=0$), and if banks only hold cash (i.e., $\alpha = 1$). The funding cost increases quadratically with the probability of liquidity shock, p, and decreases with cash banks hold, α. When $\alpha > pt$, the overall profit is net interest income minus funding cost.

Taking the first derivative of π_{social} with regard to α, we have:

$$\frac{\partial \pi_{social}}{\partial \alpha} = \begin{cases} \dfrac{(1+r)(1-\theta)}{\theta} + 2c > 0, & \text{if } \alpha \leq pt \\ -r + 2c(1 + pt - \alpha), & \text{if } \alpha > pt \end{cases} \tag{A.3.2}$$

It is easy to see that the socially optimal level of α depends on the value of c. I consider the more interesting case where holding some extra liquidity beyond pt (but not holding 100% assets in cash) generates positive externalities by reducing funding cost in the banking system. That is, I assume $c \in (\frac{r}{2}, \frac{r}{2pt})$. Under this assumption, the first best is:

$$\alpha^* = pt + 1 - \frac{r}{2c}, \tag{A.3.3}$$

where $1 - \frac{r}{2c} \in (0, 1 - pt)$. Thus, the optimal level of liquidity holdings for the banking system is $1 - \frac{r}{2c}$ more than the liquidity outflow on Day 1, i.e., pt. The saved funding cost due to the $1 - \frac{r}{2c}$ additional liquidity more than offsets the forgone interest income.

A.4 The individual bank's problem

Next, I study the liquidity holding decisions of an individual bank, Bank A, given the aggregate liquidity holdings α. Bank A chooses its liquidity holdings, α_A, on Day 0. To focus on the more interesting case, I assume $\alpha_A \leq t$. Bank A's utility is:

$$\begin{aligned} \pi_A(\alpha_A) = {} & (1 - \alpha_A)r - p(t - \alpha_A)\beta \frac{1 + r - \eta}{\eta} \\ & - p(t - \alpha_A)(1 - \beta)\frac{1 + r - \theta}{\theta} + (1 - p)\alpha_A \gamma \frac{1 + r - \eta}{\eta} \\ & - c(1 + pt - \alpha)^2 \end{aligned} \tag{A.4.1}$$

The first four terms in the right-hand side of the equation represent four components of Bank A's profit, and the last term represents its funding cost. The first term is the interest income the bank gains if all its loans are held to Day 2. The second term is the expected loss from selling $(t-\alpha_A)\beta$ unit of loans to other banks. In particular, p is the probability of Bank A having t liquidity needs on Day 1. $(t-\alpha_A)\beta$ is the liquidity shortage that can be raised by selling loans to other banks. $\frac{1+r-\eta}{\eta}$ is the loss from raising 1 unit of cash in this way. The third term is the expected loss from prematurely liquidating $(t-\alpha_A)(1-\beta)$ unit of loans. The fourth term is the expected gain from purchasing loans using extra cash. The last term is funding costs, which depend on the aggregate liquidity level, α, instead of on Bank A's own liquidity choice, α_A.

On Day 0, Bank A is uncertain about the probability of liquidity shock, p, and it considers a range of possible probabilities p_A in set P, with support $[\underline{p}, \overline{p}]$, where $\underline{p} \leq p \leq \overline{p}$. Following Gilboa and Schmeidler (1989)'s Maxmin Expected Utility representation of Knightian uncertainty aversion, I write Bank A's optimization problem as:

$$\begin{aligned} &\max_{\alpha_A} \min_{p_A \in P} E[\pi_A(\alpha_A)|p_A] \\ s.t.\ &\alpha_A \in [0,1] \\ &\frac{t-\alpha_A}{\eta}\beta + \frac{t-\alpha_A}{\theta}(1-\beta) \leq 1-\alpha_A \end{aligned} \tag{A.4.2}$$

The second condition above requires that loans exchanged for cash should not be larger than the total loan holding.

Bank A makes decisions based on the "worst-case" probability, i.e., $p_A = \overline{p}$. That is, Bank A maximizes $E[\pi_A(\alpha_A)|p_A = \overline{p}]$. Taking the first derivative of $E[\pi_A(\alpha_A)|p_A = \overline{p}]$ with respect to α_A, we have:

$$\frac{\partial E[\pi_A(\alpha_A)|p_A = \overline{p}]}{\partial \alpha_A} = -r + \overline{p}[\beta\frac{1+r-\eta}{\eta} + (1-\beta)\frac{1+r-\theta}{\theta}] + (1-\overline{p})\gamma\frac{1+r-\eta}{\eta} \tag{A.4.3}$$

With that, we can get the (corner) solution for Bank A's optimization problem[32]:

$$\alpha_A \begin{cases} = 0, & \text{if } \overline{p} < \dfrac{\alpha}{t} \\ \in [0,1], & \text{if } \overline{p} = \dfrac{\alpha}{t} \\ = 1, & \text{if } \overline{p} > \dfrac{\alpha}{t} \end{cases} \tag{A.4.8}$$

It is easy to show that the above solution meets the two conditions in Bank A's problem A.4.2. First, note that the first condition is apparently met. Next, I investigate the second condition:

When $\overline{p} < \frac{\alpha}{t}$ and $\alpha_A = 0$, the second condition simplifies to: $\frac{t}{\eta} \leq 1$. Since $\eta > 1$ in this

[32]Given α, the sign of the partial derivative in Equation A.4.3 depends on $\overline{p}$:
When $\overline{p} < \frac{\alpha}{t}$, we have $\eta > 1$, $\beta = 1$, and $\gamma = \frac{1}{\lambda} < 1$. Therefore:

$$\begin{aligned} \frac{\partial E[\pi_A(\alpha_A)|p_A = \overline{p}]}{\partial \alpha_A} &= -r + \overline{p}\frac{1+r-\eta}{\eta} + (1-\overline{p})\gamma\frac{1+r-\eta}{\eta} \\ &< -r + \overline{p}\frac{1+r-1}{1} + (1-\overline{p})1\frac{1+r-1}{1} \\ &= 0 \end{aligned} \tag{A.4.4}$$

When $\overline{p} = \frac{\alpha}{2t}$, we have $\eta = 1$, $\beta = 1$, and $\gamma = 1$. Therefore:

$$\begin{aligned} \frac{\partial E[\pi_A(\alpha_A)|p_A = \overline{p}]}{\partial \alpha_A} &= -r + \overline{p}\frac{1+r-1}{1} + (1-\overline{p})1\frac{1+r-1}{1} \\ &= 0 \end{aligned} \tag{A.4.5}$$

When $\overline{p} > \frac{\alpha}{2t}$, we have $\eta < 1$, $\beta = \lambda < 1$, and $\gamma = 1$. Therefore:

$$\begin{aligned} \frac{\partial E[\pi_A(\alpha_A)|p_A = \overline{p}]}{\partial \alpha_A} &= -r + \overline{p}[\lambda\frac{1+r-\eta}{\eta} + (1-\lambda)\frac{1+r-\theta}{\theta}] + (1-\overline{p})\frac{1+r-\eta}{\eta} \\ &> -r + \overline{p}[\lambda\frac{1+r-\eta}{\eta} + (1-\lambda)\frac{1+r-\eta}{\eta}] + (1-\overline{p})\frac{1+r-\eta}{\eta} \\ &= -r + \overline{p}\frac{1+r-\eta}{\eta} + (1-\overline{p})\frac{1+r-\eta}{\eta} \\ &= -(1+r) + \frac{1+r}{\eta} \\ &> 0 \end{aligned} \tag{A.4.6}$$

In sum, Equation A.4.3 can be written in the following form:

$$\frac{\partial E[\pi_A(\alpha_A)|p_A = \overline{p}]}{\partial \alpha_A} \begin{cases} < 0, & \text{if } \overline{p} < \dfrac{\alpha}{t} \\ = 0, & \text{if } \overline{p} = \dfrac{\alpha}{t} \\ > 0, & \text{if } \overline{p} > \dfrac{\alpha}{t} \end{cases} \tag{A.4.7}$$

case, the inequality holds.

When $\overline{p} = \frac{\alpha}{t}$ and $\alpha_A \in [0, 1]$, the second condition simplifies to $t - \alpha_A \leq 1 - \alpha_A$, which apparently holds.

When $\overline{p} > \frac{\alpha}{t}$ and $\alpha_A = 1$, the second condition simplifies to $\frac{t-1}{\eta}\lambda + \frac{t-1}{\theta}(1-\lambda) \leq 1-1 = 0$. Since $t < 1$ and $\lambda < 1$, the inequality again holds.

The result in A.4.8 suggests that, given the aggregate liquidity holdings, α, a bank is more likely to increase its own liquidity holdings, α_A, when $\overline{p}$ is larger. When $\overline{p} < \frac{\alpha}{t}$ ($\overline{p} > \frac{\alpha}{t}$), an individual bank is incentivized to under(over)-reserve liquidity, deviating from aggregate liquidity holdings level α. Only when $\overline{p} = \frac{\alpha}{t}$ could an equilibrium of $\alpha_A = \alpha = \overline{p}t$ exist. Therefore, the liquidity holdings decision of all banks will reach a unique equilibrium:

$$\alpha_A^{**} = \alpha^{**} = \overline{p}t \tag{A.4.10}$$

Compared with the first best liquidity holdings, $\alpha^* = pt + 1 - \frac{r}{2c}$, the equilibrium holding, α^{**}, can be either too high or too low, depending on the values of $\overline{p}$ and $1 - \frac{r}{2c}$. Banks are more likely to under-reserve liquidity if the estimated upper bound of the liquidity shock is low (i.e., $\overline{p}$ is low) and/or if the funding cost is more sensitive to changes in aggregate liquidity (i.e., c is high).

A.5 The role of liquidity disclosure

Banks' disclosure of their liquidity condition provides relevant information for all banks about the probability of a future liquidity shortage, p. Such disclosure makes bank managers at least weakly more certain about the value of p. The increased certainty translates into a weakly reduced (increased) upper (lower) bound of p. Formally, the disclosure shrinks the distribution of p to $[p_L, p_H]$, where $\{p\} \subseteq [p_L, p_H] \subseteq [\underline{p}, \overline{p}]$.

Since disclosure weakly reduces $\overline{p}$ to p_H, banks' updated liquidity holdings after liquidity disclosure will be:

$$\alpha^{***} = p_H t \leq \overline{p}t = \alpha^{**} \tag{A.5.1}$$

Note that my model cannot evaluate whether the reduction in liquidity holdings is good or bad at the social level. The reduced liquidity holdings ($\alpha^{***} = p_H t$) could be either closer or further away from the socially optimal level ($\alpha^{*} = pt + 1 - \frac{r}{2c}$) than was the previous holding level ($\alpha^{***} = \overline{p}t$), depending on the values of p, p_H, $\overline{p}$, and c.

A.6 Empirical prediction

To tie the analyses above to my empirical setting, I define how much a bank learned about aggregate liqudity risk from the LCR disclosure:

$$InfoGain \equiv \overline{p} - p_H \tag{A.6.1}$$

In practice, $\overline{p}$ should vary across banks, as some banks were more informed about p (and have lower $\overline{p}$) before the LCR disclosure. The disclosure levels the playing field in the sense that p_H is more homogeneous across banks. Naturally, this results in heterogeneous *InfoGain* across banks. Combining Equations A.5.1 and A.6.1, the relationship between how much a bank learned from the disclosure, *InfoGain*, and change in its liquidity holdings, $\Delta\alpha$, is:

$$\Delta\alpha = \alpha^{***} - \alpha^{**} = -t * InfoGain \tag{A.6.2}$$

Thus, is my empirical prediction is that banks that learn more about aggregate liquidity risk from the the LCR disclosure are more likely to reduce liquidity holdings.

Appendix B. Details of LCR disclosure regulation

Figure B1. Timeline of LCR regulation implementation

This graph shows the timeline of the US implementation of the LCR regulation. Information in the graph comes from Federal Register documents 79 FR 61440 and 81 FR 94922.

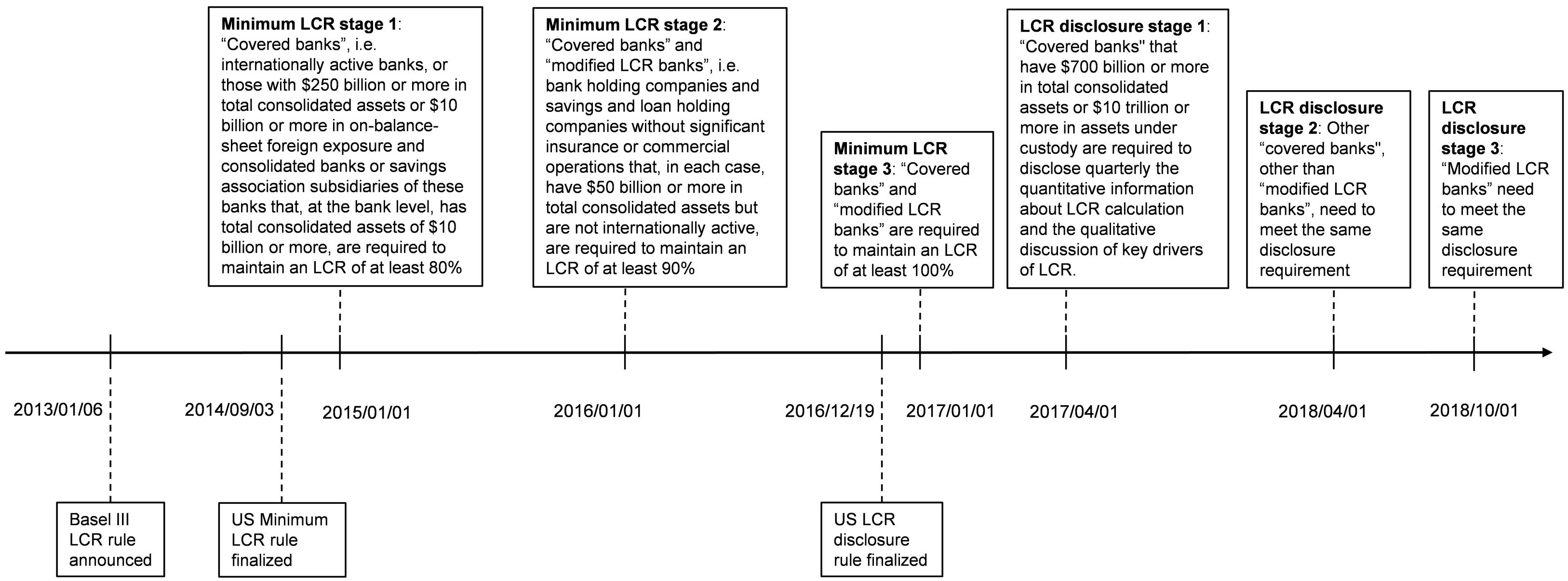


Figure B2. Details of the LCR disclosure

These figures provide an example of the detailed information contained in the disclosures of J.P. Morgan's 4Q2017 LCR report, and an exercise for estimating this information using the related financial reports and regulatory documents.

Panel A: Standardized table of LCR calculation from J.P. Morgan's 4Q2017 LCR report.

	Three months ended December 31, 2017 (in millions)	Average Unweighted Amount[a]	Average Weighted Amount[b]
	HIGH-QUALITY LIQUID ASSETS		
1	**Total eligible high-quality liquid assets (HQLA), of which:**[c]	**$ 568,014**	**$ 560,081**
2	Eligible level 1 liquid assets	515,472	515,472
3	Eligible level 2A liquid assets	52,392	44,534
4	Eligible level 2B liquid assets	150	75
	CASH OUTFLOW AMOUNTS		
5	**Deposit outflow from retail customers and counterparties, of which:**	**$ 704,413**	**$ 43,227**
6	Stable retail deposit outflow	430,531	12,916
7	Other retail funding outflow	249,628	26,224
8	Brokered deposit outflow	24,254	4,087
9	**Unsecured wholesale funding outflow, of which:**	**702,495**	**261,508**
10	Operational deposit outflow	480,652	119,893
11	Non-operational funding outflow	213,074	132,846
12	Unsecured debt outflow	8,769	8,769
13	**Secured wholesale funding and asset exchange outflow**[d]	**601,963**	**163,017**
14	**Additional outflow requirements, of which:**	**531,792**	**126,687**
15	Outflow related to derivative exposures and other collateral requirements	135,580	31,019
16	Outflow related to credit and liquidity facilities including unconsolidated structured transactions and mortgage commitments	396,212	95,668
17	**Other contractual funding obligation outflow**	**6,346**	**6,346**
18	**Other contingent funding obligations outflow**[e]	**281,300**	**9,956**
19	**TOTAL CASH OUTFLOW**	**$ 2,828,309**	**$ 610,741**
	CASH INFLOW AMOUNTS		
20	**Secured lending and asset exchange cash inflow**[d]	**$ 594,830**	**$ 147,975**
21	**Retail cash inflow**	**21,011**	**10,506**
22	**Unsecured wholesale cash inflow**[f]	**16,539**	**12,213**
23	**Other cash inflows, of which:**	**12,322**	**12,322**
24	Net derivative cash inflow	4,359	4,359
25	Securities cash inflow	4,321	4,321
26	Broker-dealer segregated account inflow	3,642	3,642
27	Other cash inflow	–	–
28	**TOTAL CASH INFLOW**	**$ 644,702**	**$ 183,016**
			Average Weighted Amount[b]
29	**HQLA AMOUNT**[c]		**$ 560,081**
30	**TOTAL NET CASH OUTFLOW AMOUNT EXCLUDING THE MATURITY MISMATCH ADD-ON**		**$ 427,725**
31	**MATURITY MISMATCH ADD-ON**		**44,353**
32	**TOTAL NET CASH OUTFLOW AMOUNT**		**$ 472,078**
33	**LIQUIDITY COVERAGE RATIO (%)**		**119%**

Panel B: Estimating the high-quality liquid assets in J.P. Morgan's 4Q2017 LCR report.

This figure reports the results of estimating the high-quality liquid assets in J.P. Morgan's 4Q2017 LCR report. All numbers in the last two columns are estimated based on J.P. Morgan's 2017 financial reports (including annual reports and regulatory filings), as well as LCR regulatory documents 79 FR 61440 and 81 FR 94922.

HIGH-QUALITY LIQUID ASSETS ($ mn)		**Contributing assets**	**Haircut**	**Related items in financial reports**	**JPMorgan Reported Average Unweighted Amount**	**JPMorgan Reported Average Weighted Amount**	**Author Estimated Average Unweighted Amount**	**Author Estimated Average Weighted Amount**
1	**Total eligible high-quality liquid assets (HQLA), of which:**				**568,014**	**560,080**	**570,256**	**555,256**
2	Eligible level 1 liquid assets	Federal Reserve bank balances	0%	Cash and due from banks, deposits with banks	370,126	370,126	430,121	430,121
		Treasury securities, government-guranteed agency securities, sovereign bonds		Treasury securities, government agency securities/MBS, Non-U.S. government debt securities	145,346	145,346	126,353	126,353
3	Eligible level 2A liquid assets	Securities issued or guaranteed by a U.S. government-sponsored enterprise (GSE)	15%	MBS guaranteed or issued by GSE	52,392	44,533	100,000	85,000
4	Eligible level 2B liquid assets	Investment grade corporate debt securities, Russell 1000 Index equity securities	50%	NA	150	75	-	-
				Less: Pledged securities			-86,218	-86,218
Difference between the estimated and the reported total numbers							*0.4%*	*-0.9%*

Additional requirements to qualify as eligible HQLA

- Bank has the operational capability to monetize the HQLA.
- HQLA is unencumbered, i.e. 1) available to raise liquidity without legal, regulatory, contractual, or other restrictions; 2) not pledged to secure or to provide credit enhancement to any transaction.

Key unavailable HQLA information in the the financial report

- No information about the amount of these assets that meet "Additional requirements to qualify as eligible HQLA". FR Y-9C reports the amount of pledged securities ($86,218 mn for JPM in 2017), but the number is not broken down to more detailed categories.

Panel C: Estimating the cash outflow in J.P. Morgan's 4Q2017 LCR report.

This figure reports the results of estimating the cash outflow in J.P. Morgan's 4Q2017 LCR report. All numbers in the second-to-last column are estimated based on J.P. Morgan's 2017 financial reports (including annual reports and regulatory filings), as well as LCR regulatory documents 79 FR 61440 and 81 FR 94922. The number in row 19 of the last column is estimated assuming that the actual total cash outflow ratio (i.e., 610,741/2,828,309) was known.

	CASH OUTFLOW AMOUNTS ($ mn)	**Contributing liabilities and off-balance sheet items**	**Outflow rate**	**Related items in financial reports**	**JPMorgan Reported Average Unweighted Amount**	**JPMorgan Reported Average Weighted Amount**	**Author Estimated Average Unweighted Amount**	**Author Estimated Average Weighted Amount**
5	**Deposit outflow from retail customers and counterparties, of which:**				**704,413**	**43,227**		
6	Stable retail deposit outflow	Stable retail deposits	3%	Deposits, brokered deposits	430,531	12,916	1,443,982	Unable to estimate.
7	Other retail funding outflow	Other retail deposits, deposits placed by a third party that are not brokered deposits.	10-40%		249,628	26,224		
8	Brokered deposit outflow	Brokered deposits	10-100%		24,254	4,087		
9	**Unsecured wholesale funding outflow, of which:**				**702,495**	**261,508**		
10	Operational deposit outflow	Operational deposits	5-25%		480,652	119,893		
11	Non-operational funding outflow	Commercial paper, federal funds purchased, other borrowed funds, brokerage payables	20-100%	Short-term borrowings, federal funds purchased, brokerage payables	213,074	132,846	156,521	
12	Unsecured debt outflow	Long term debt	100%	long-term debt matures within 1 year	8,769	8,769	43,174	
13	**Secured wholesale funding and asset exchange outflow**	Securities loaned or sold under repurchase agreements	0-100%	Securities sold or loaned under repurchase agreements	**601,963**	**163,017**	**425,446**	
14	**Additional outflow requirements, of which:**				**531,792**	**126,687**		
15	Outflow related to derivative exposures and other collateral requirements	Net derivatives payables, collateral	0-100%	Total derivative payables, pledged securities	135,580	31,019	123,995	
16	Outflow related to credit and liquidity facilities including unconsolidated structured transactions and mortgage commitments	Unused commitments	0-100%	Unused commitments	396,212	95,668	461,698	
17	**Other contractual funding obligation outflow**	Other contractual funding obligations	100%	Commitments that expire within 1 year less unused commitments	**6,346**	**6,346**	531,694	
18	**Other contingent funding obligations outflow**	Debt securities issued by the bank	3-5%		**281,300**	**9,956**		
19	**TOTAL CASH OUTFLOW**				**2,828,309**	**610,741**	**3,186,510**	**688,090**
	Difference between the estimated and the reported total numbers						*12.7%*	*12.7%*

Key unavailable LCR cash outflow information in the the financial report

- Breakdowns of the related items in financial report based on LCR classification (e.g., deposits only broken down by domestic or foreign and by interest bearing or not).
- Information about the proportion of related items with contractual maturity within 30 days, which is a key inclusion requirement to calculate Average Unweighted Amount.
- Distributions of the related items across deposit insurance coverage, counterparty type or collateral asset quality, which determine the outflow rates used to calculate Average Weighted Amount.

Panel D: Estimating the cash inflow in J.P. Morgan's 4Q2017 LCR report.

This figure reports the results of estimating the cash inflow in J.P. Morgan's 4Q2017 LCR report. All numbers in the second-to-last column are estimated based on J.P. Morgan's 2017 financial reports (including annual reports and regulatory filings), as well as LCR regulatory documents 79 FR 61440 and 81 FR 94922. The number in row 28 of the last column is estimated assuming that the actual total cash inflow ratio (i.e., 183,016/644,702) was known.

	CASH INFLOW AMOUNTS ($ mn)	Contributing assets and off-balance sheet items	Inflow rate	Related items in financial reports	JPMorgan Reported Average Unweighted Amount	JPMorgan Reported Average Weighted Amount	Author Estimated Average Unweighted Amount	Author Estimated Average Weighted Amount
20	**Secured lending and asset exchange cash inflow**	Securities borrowed or purchased under resale agreements	0-100%	Securities purchased or borrowed under resale agreements (gross).	**594,830**	**147,975**	**562,534**	Unable to estimate.
21	**Retail cash inflow**	Retail loans	50%	Total consumer loans (multipled by % of earning assets mature within 1 year and then divided by 12)	**21,011**	**10,506**	**15,519**	
22	**Unsecured wholesale cash inflow**	Wholesale loans	50-100%	Total wholesale loans (multipled by % of earning assets mature within 1 year and then divided by 12)	**16,539**	**12,213**	**17,011**	
23	**Other cash inflows, of which:**				**12,322**	**12,322**	**80,128**	
24	Net derivative cash inflow	Net derivatives receivables	100%	Total derivative receivables	4,359	4,359	56,523	
25	Securities cash inflow	Securities that are not eligible HQLA	100%	Securities (minus those counted as HQLA)	4,321	4,321	23,605	
26	Broker-dealer segregated account inflow	Required balance of the customer reserve account	100%	NA	3,642	3,642	-	
27	Other cash inflow	NA		NA	-	-	-	
28	**TOTAL CASH INFLOW**				**644,702**	**183,016**	**675,192**	**191,671**
Difference between the estimated and the reported total numbers							*4.7%*	*4.7%*

Key unavailable LCR cash inflow information in the the financial report

- Information about the proportion of related items with contractual maturity within 30 days, which is a key inclusion requirement to calculate Average Unweighted Amount.
- Distributions of the related items across deposit insurance coverage, counterparty type or collateral asset quality, which determine the inflow rates used to calculate Average Weighted Amount.

Panel E: Estimating the final calculation of LCR in J.P. Morgan's 4Q2017 LCR report.

This figure reports the results of estimating the final steps in calculating LCR in J.P. Morgan's 4Q2017 LCR report. With the exception of row 31, all numbers in the last column are calculated based on Panels B, C, and D. The number in row 31 of the last column is estimated assuming that the actual "maturity mismatch add-on" was known.

Final LCR calculation ($ mn)	**JPMorgan Reported**	**Author Estimated**
29 HQLA AMOUNT	**560,080**	**555,256**
30 TOTAL NET CASH OUTFLOW AMOUNT EXCLUDING THE MATURITY MISMATCH ADD-ON	**427,725**	**496,419**
31 MATURITY MISMATCH ADD-ON	**44,353**	**44,353**
32 TOTAL NET CASH OUTFLOW AMOUNT	**472,078**	**540,772**
33 LIQUIDITY COVERAGE RATIO (%)	**119%**	**103%**
Difference between the estimated and the reported LCR		*-16%*

Key unavailable final LCR calculation information in the the financial report

- Information about "maturity mismatch add-on"

B.3 Replication of the LCR calculation

I estimate numbers from the table in J.P. Morgan's 4Q2017 LCR report using its financial reports (i.e., annual reports and regulatory filings). Panel B summarizes my estimated HQLA components. Because the financial reports provide disaggregated items corresponding to each HQLA level and because there is only one haircut ratio for each level, the total estimated HQLA is only about 1% smaller than the reported number. The estimates for individual HQLA levels, however, are off by a greater extent, mainly due to insufficient information about the proportion of assets that meet the requirements of eligible HQLA.

Panels C and D report my estimates of the expected cash outflow and inflow components. They are much harder to estimate, because financial reports provide far less granular information needed to estimate these numbers. First, there is not enough disaggregation of (off-)balance sheet items by categories contributing to cash outflows and inflows,which impedes estimation of the "Average Unweighted Amount." Second, for many cash outflow and inflow categories, the outflow and inflow rates vary depending on detailed and unavailable information about the characteristics of cash flow sources. For example, calculating operational deposit outflow (row 10 in the LCR table) requires knowing the amount of operational deposit that can be withdrawn over the next 30 days, and a breakdown of this number by whether or not the deposit is covered by deposit insurance, none of which is available in financial reports. Therefore, it is virtually impossible to estimate the "Average Weighted Amount." To continue the replication, I estimate the total "Average Weighted Amount" by simply multiplying the estimated "Average Unweighted Amount" by the ratio of reported "Average Weighted Amount" to the reported "Average Unweighted Amount." Using this method, the estimated total outflow/inflow is about 13%/5% higher than the actual numbers.

Panel E shows the final steps in calculating LCR, which requires the estimated numbers in Panels B to D and an estimation of the "maturity mismatch add-on," which adjusts the net cash outflow for the potential of late cash inflows and early outflows during the 30-day stress period.[33] There is no related information from the financial reports for estimating this number, so I use the actual number to finish the replication. I end up with an estimated LCR of 103%, which is 16% lower than the reported 119%. This is a very inaccurate estimation, considering that the actual LCR of G-SIBs banks in my sample ranges from 108% to 154% and that I used key information from the actual LCR report.

[33]The maturity mismatch add-on is calculated by subtracting the difference between daily cumulative outflows and inflows on day 30 from the largest difference of daily cumulative outflows and inflows in the 30-day stress period.

Appendix C. Other related regulations

C.1 Basel III Capital Regulation

In addition to the liquidity regulations, the capital regulation is also an important part of the Basel III Accord. While the Basel III capital requirements have shaped the banking system in profound ways, it is unlikely that these rules have meaningfully contributed to the externalities of LCR disclosures I document.

The Basel III capital regulation increased the minimum requirements for the risk-based capital held by banks. The rule requires a minimum ratio of common equity tier 1 capital to risk-weighted assets of 4.5%, and a common equity tier 1 capital conservation buffer of 2.5% of risk-weighted assets. It also raised the minimum ratio of tier 1 capital to risk-weighted assets from 4% to 6%. Additionally, "advanced approaches" banks (>250 billion in assets or >10 billion in foreign exposure) are also required to hold a common equity tier 1 capital counter-cyclical buffer of 0-2.5% of risk-weighted assets, and the required ratio increases with systemic risk (as determined by bank supervisors). The capital rule was implemented on January 1$^{\text{rd}}$, 2014, and the new requirements were gradually added to the old requirements during a transition period from 2014 to 2019.

The capital regulation also introduced risk-insensitive leverage capital requirements. These include a minimum leverage ratio requirement (tier 1 capital to average total consolidated assets) of 4%, from January 1$^{\text{rd}}$, 2014 for advanced approaches banks, and from January 1$^{\text{rd}}$, 2015 for other banks. These requirements also add a supplementary leverage rule (SLR) for advanced approaches banks, which requires a minimum ratio of tier 1 capital per total leverage exposure (including off-balance sheet assets) of 3%. Global systemically important banks (G-SIBs) need to hold an "enhanced" SLR (eSLR) of 5%. Covered banks were required to disclose their SLR ratios beginning January 2015, and the SLR took effect in January 2018.

These rule changes are unlikely to meaningfully contribute to the LCR disclosure externalities I document. First, these rules have little direct effect on non-disclosing banks in my setting. Non-disclosing banks are generally smaller ones that are less affected by these capital regulations. In fact, according to data from March 2013 (before the capital rule adoption), nine out of ten financial institutions with less than $10 billion in assets would meet the common equity tier 1 minimum plus buffer of 7 percent in the final rule.[34]

Second, while the capital rule could potentially indirectly affect non-disclosing banks through its impact on disclosing banks, its contribution to the LCR disclosure externality is likely to be small. Risk-insensitive leverage capital requirements (such as the SLR) incentivize banks to increase risky illiquid asset holdings because these assets have the same weight as safe assets in the denominator of the required ratios (Choi, Holcomb, Morgan, et al., 2018), a fact that works against the documented effect of LCR. While risk-based capital requirements discourage illiquid asset holdings, they were primarily implemented in 2014-2015 (followed by phase-in periods until 2018 or 2019). Therefore, the change in capital requirements around the LCR disclosure adoption in 2017 was smooth and anticipated, so banks were unlikely to respond sharply at that time.

C.2 EGRRCPA and the Final Tailoring Rules

In response to the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) enacted on May 24, 2018, the Federal Reserve raised the minimum asset threshold for the modified LCR rule from $50 billion to $100 billion.[35] Because of this change, "modified LCR banks" with $50 to $100 billion assets stopped complying with minimum LCR requirements in 2Q2018 (these banks were not required to disclose LCR either before or after 2Q2018).

The Final Tailoring Rules that changed applicability thresholds for liquidity requirements (84 FR 59230) was implemented on December 31, 2019. Under the tailoring rules, most

[34]See Federal Reserve press release https://www.federalreserve.gov/newsevents/pressreleases/bcreg20130702a.htm.

[35]See "Statement regarding the impact of the Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA)" issued by the Federal Reserve on July 6, 2018.

"modified LCR banks" were exempt from all LCR requirements, while a few "modified LCR banks" and a few non-G-SIB "covered banks" were subject to reduced minimum LCR requirements (LCR disclosure still required).[36] Because of this change, beginning in 4Q2019, most "modified LCR banks" no longer comply with any LCR rules and a few larger banks now have less stringent LCR requirements.

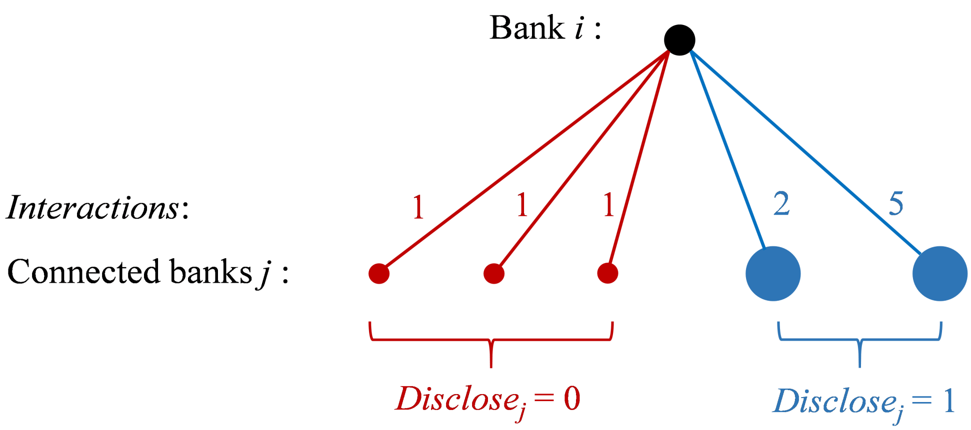
These reduced LCR requirements cause affected banks to lower their liquidity holdings, confounding the potential effects of LCR disclosures in the second and third stages. For example, "modified LCR banks" with $50 to $100 billion assets stopped complying with the minimum LCR rule beginning in 2Q2018, when the second stage LCR disclosure began. Therefore, it is hard to tell whether the change in banks' liquidity after 2Q2018 was due to changes in the minimum LCR rule or the newly available LCR disclosures. This is another reason I focus on the first stage for my main analyses, as discussed in Section 2.2.

[36]Under the Final Tailoring Rules, banks with assets between $100 billion and $250 billion and with less (more) than $50 billion in weighted short-term wholesale funding are exempted from the LCR requirement (subject to reduced monthly LCR requirements with a 70% outflow adjustment percentage). Banks with assets between $250 and $700 billion and with less than $75 billion in weighted short-term wholesale funding are subject to reduced daily LCR requirements with an 85% outflow adjustment percentage. The LCR disclosure is required for these banks unless they are exempted from the LCR requirement. Under the daily (monthly) LCR rule, the LCR is calculated and reported to the federal supervisor on a daily (monthly) basis. A 70% (85%) outflow adjustment percentage means that the unadjusted denominator (i.e., net cash outflows) of LCR is multiplied by 0.7 (0.85).

Figures

Figure 1: Demonstration of *InfoGain* calculation.

This figure demonstrates the calculation of $InfoGain_i$, which is the incremental liquidity information that bank i learned from the LCR disclosure. $InfoGain_i$ equals 1 minus the $Interactions_{i,j}$ weighted average of $Disclose_j$, where $Interactions_{i,j}$ is the number of syndicated loans that banks i and j have issued together during 2010-2017, and where $Disclose_j$ is an indicator variable equal to one if bank j is required to disclose LCR information after 2Q2017 and zero otherwise.



$$InfoGain_i = 1 - \frac{\sum_j Interactions_{i,j} * Disclose_j}{\sum_j Interaction_{i,j}}$$

$$= 1 - \frac{1*0+1*0+1*0+2*1+5*1}{1+1+1+2+5}$$

$$= 0.3$$

Figure 2: Network of bank interactions.

This figure plots the network of co-syndication interactions for banks in the sample. Each node represents a bank, and a line connects nodes that have issued at least one syndicated loan during 2010–2017. The size of each node increases with the number of other banks the bank has co-syndicated with during 2010–2017. Nodes are partitioned and color coded based on their modularity class (i.e., nodes in the same class, or module, have more connections than with nodes in other modules). The node layout is conducted by the ForceAtlas2 algorithm, which clusters nodes with more connections and separates nodes with fewer connections.

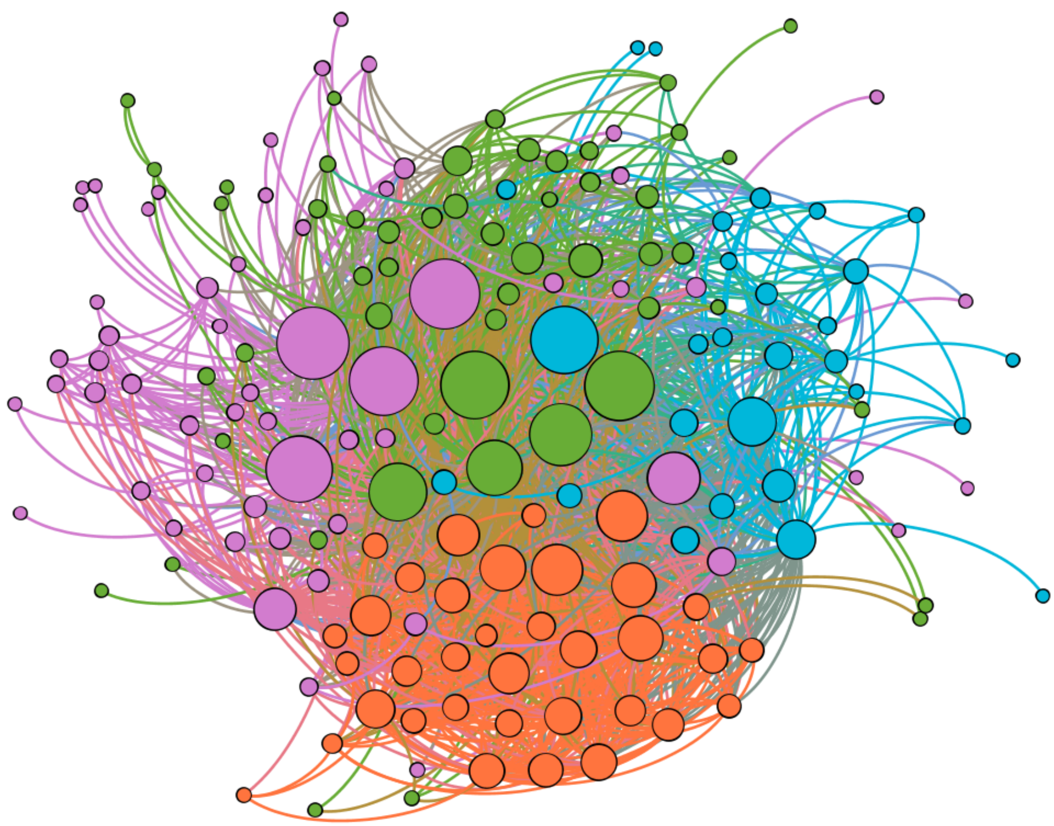


Figure 3: Banks with top 30 *Interactions*.

This figure plots banks with top 30 *Interactions*. *Interactions* is the total number of syndicated loans issued with other banks during 2010–2017.

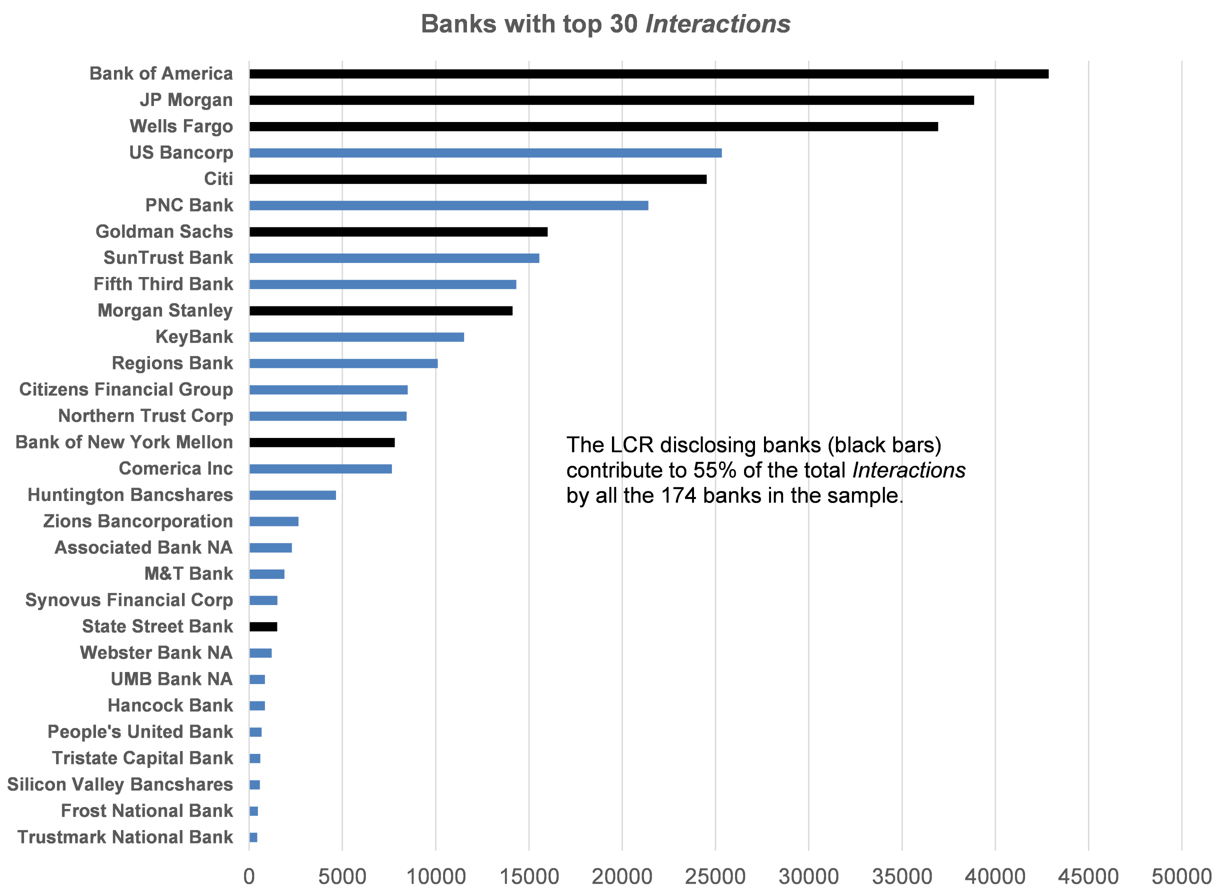
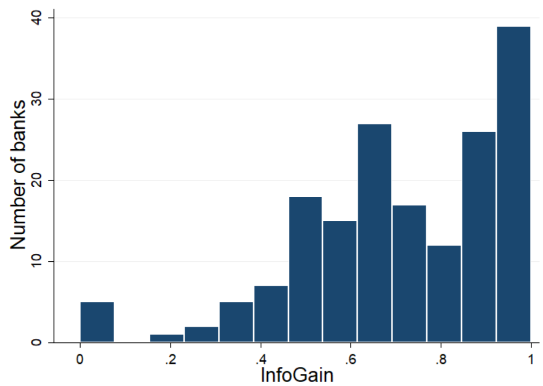
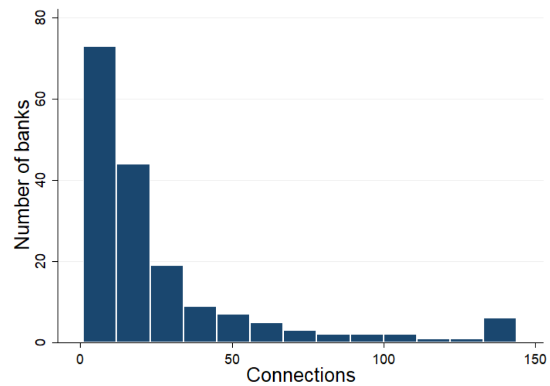


Figure 4: Distributions of bank interaction network variables.

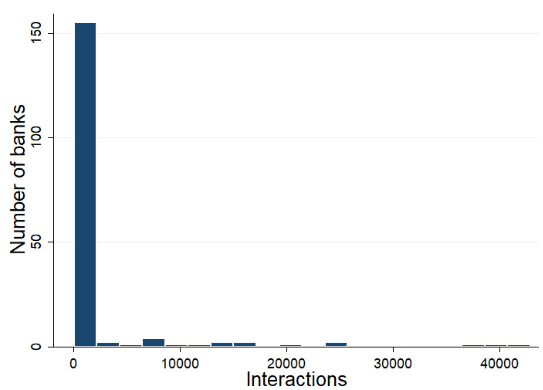
This figure plots the histograms of key network variables. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. *Connections* is the total number of other banks a bank has co-syndicated with during 2010–2017. *Interactions* is the total number of syndicated loans issued with other banks during 2010–2017.



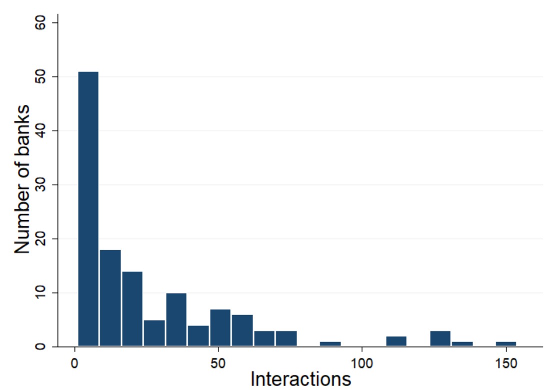
Panel A. *InfoGain*



Panel B. *Connections*



Panel C. *Interactions*: Full sample



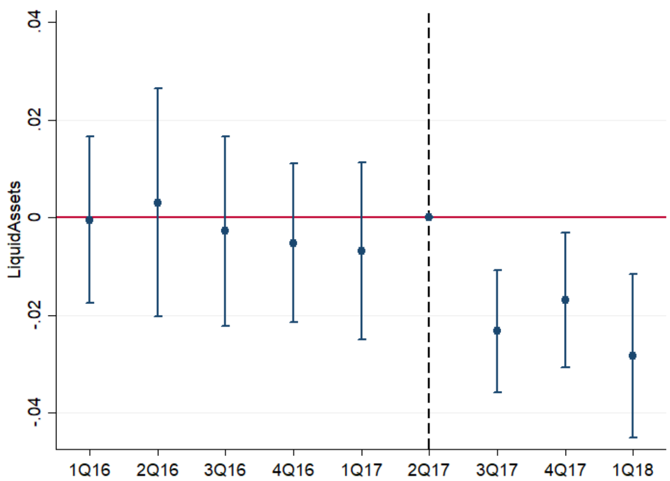
Panel D. *Interactions*: 1-160

Figure 5: Mapping out the LCR disclosure treatment effect over time.

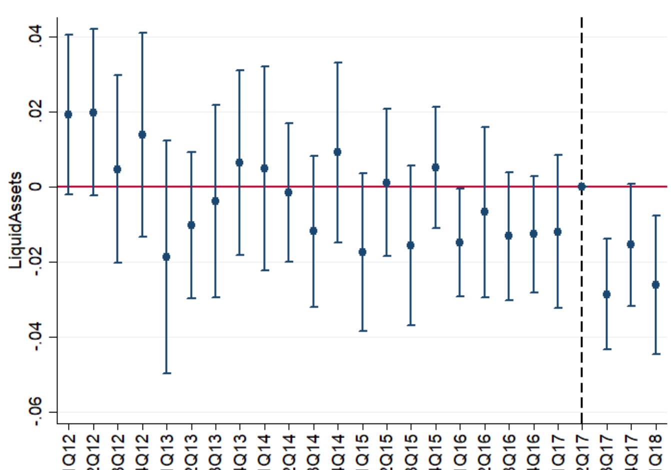
This figure displays OLS regression coefficients and two-tailed 90% confidence intervals (based on standard errors clustered at the bank level) for $InfoGain_i * Quarter_t$'s in the following regression:

$$LiquidAssets_{i,t+1} = \alpha_i + \alpha_t + \sum_{t=t_0(\neq 2Q17)}^{1Q18} \beta_t InfoGain_i * Quarter_t + \gamma X_{i,t} + \epsilon_{i,t}$$

$Quarter$ is an indicator variable equal to one in one of all the quarters from t_0 to 1Q2018 except 2Q2017 (when LCR disclosures were first made; it serves as the benchmark period) and zero otherwise. t_0 is 1Q16 and 1Q12 for Panels A and B, respectively. The full set of control variables with fixed effects from Equation 4 are included. See Table 1 for other variable definitions.



Panel A. 1Q2016 to 1Q2018



Panel B. 1Q2012 to 1Q2018

Tables

Table 1: Descriptive statistics.

Panel A: Bank characteristics

This table reports descriptive statistics for bank characteristics in the sample. *LiquidAssets* is the ratio of liquid assets to total assets. Liquid assets include cash balances, non-MBS and non-ABS held-to-maturity (HTM) securities, non-MBS and non-ABS available-for-sale(AFS) securities, fed funds sold, and securities purchased under agreements to resell. *CoreDeposit* is the ratio of core deposits (all transactions deposits and other insured deposits) to total assets. *Capital* is the ratio of total equity to total assets. *Commitment* is the ratio of unused commitments to the sum of unused commitments and total assets. *Size* is the natural logarithm of total assets (in the 1000s). $\Delta Loan$ is the percentage change in total loans outstanding. NPL is non-performing loans scaled by lagged total loans. *Interest* is total interest income scaled by lagged total loans. EBP is earnings before provisions (net income plus loan loss provision), scaled by lagged total assets. The sample covers quarterly US bank holding companies for the sample period of 1Q2011-4Q2019. To be included, banks must have issued at least one syndicated loan with other banks during 2010–2017 and have relevant data for my main analysis in Equation 4.

	N	Mean	SD	Min	P25	P50	P75	Max
LiquidAssets	5639	0.153	0.116	0.010	0.070	0.118	0.199	0.583
CoreDeposit	5639	0.580	0.153	0.000	0.506	0.605	0.682	0.896
Capital	5639	0.112	0.048	0.019	0.090	0.106	0.124	0.762
Commitment	5639	0.147	0.057	0.000	0.108	0.144	0.184	0.384
Size	5639	15.797	1.806	13.352	14.379	15.376	16.573	21.740
ΔLoan	5639	0.016	0.045	-0.339	0.001	0.009	0.020	1.078
NPL	5639	0.017	0.025	0.000	0.005	0.009	0.018	0.343
Interest	5639	0.015	0.009	-0.140	0.012	0.014	0.016	0.186
EBP	5639	0.003	0.003	-0.035	0.002	0.003	0.004	0.059

Panel B: Bank interaction network

This table reports descriptive statistics for the bank interaction network variables. *Connections* is the total number of other banks a bank has co-syndicated with during 2010–2017. *Interactions* is the total number of syndicated loans issued with other banks during 2010–2017. *InfoGain* is the incremental liquidity information learned from the LCR disclosure.

	N	Mean	SD	Min	P10	P25	P50	P75	P90	Max
Connections	174	25	32	1	2	5	15	29	63	144
Interactions	174	1906	6464	1	2	7	29	162	2644	42864
InfoGain	174	0.72	0.24	0.00	0.43	0.57	0.73	0.91	1.00	1.00

Panel C: Correlation of bank interaction network variables

This table reports the correlation matrix for bank interaction network variables. See Panel B for variable definitions. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

	Connections	Interactions	InfoGain
Connections	1		
Interactions	0.808***	1	
InfoGain	-0.407***	-0.336***	1

Panel D: Determinants of co-syndication relationships

This table reports estimates from the Probit regression of the co-syndication relationships of bank pairs on the characteristics of bank pairs. Each bank is paired once with every other bank in the sample. *Relation* is an indicator variable equal to one if the pair has issued at least one syndicated loan during 2010-2017 and zero otherwise. *SameDistrict* is an indicator variable equal to one if the pair is located in the same Federal Reserve district and zero otherwise. *SameState* is an indicator variable equal to one if the pair is located in the same state and zero otherwise. $DiffAssets$ is the absolute difference between the two banks' assets, scaled by $TotalAssets$ (i.e. the sum of the two banks' assets), where the assets of the banks are in logarithmic form. $CorrLiquidAssets$ is the correlation coefficient between the two banks' $LiquidAssets$. $MeanLiquidAssets$ is the mean of the two banks' $LiquidAssets$. $CorrNPL$ is the correlation coefficient between the two banks' NPL. $MeanNPL$ is the mean of the two banks' NPL. The two correlation variables are calculated using quarterly data from 2014-2017, and other independent variables are calculated using 4Q2017 data. See Panel A for other variable definitions. z-statistics are in parentheses. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) Relation
SameDistrict	0.3571***
	(6.59)
SameState	0.6246***
	(8.38)
DiffAssets	0.5673***
	(3.50)
TotalAssets	0.3553***
	(48.03)
CorrLiquidAssets	-0.0881***
	(-2.67)
MeanLiquidAssets	-1.8093***
	(-9.05)
CorrNPL	0.0281
	(1.00)
MeanNPL	-2.0404
	(-1.32)
Observations	17,205
Pseudo R2	0.320

Table 2: Changes in liquidity holdings after the LCR disclosure regulation.

This table reports estimates from the OLS regression of banks' liquid assets on $Post$ or on $NonDisclosing * Post$:

$$LiquidAssets_{i,t+1} = \alpha_i + \beta Post_t + \gamma X_{i,t} + \epsilon_{i,t}$$

$$LiquidAssets_{i,t+1} = \alpha_i + \alpha_t + \beta NonDisclosing * Post_t + \gamma X_{i,t} + \epsilon_{i,t}$$

$LiquidAssets$ is the ratio of liquid assets to total assets. $Post$ is an indicator variable equal to one after 2Q2017 and zero otherwise. $NonDisclosing$ is an indicator variable equal to one if a bank is a non-disclosing bank and zero otherwise. Columns 1, 2, and 3 report results on LCR disclosing banks, non-disclosing banks, and all banks. See Table 1 for other variable definitions. The sample in this test covers quarterly US bank holding companies from 1Q2016–2Q2018. t-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\text{LiquidAssets}_{t+1}$ (Disclosing)	(2) $\text{LiquidAssets}_{t+1}$ (Non-disclosing)	(3) $\text{LiquidAssets}_{t+1}$ (All)
Post_t	0.0038	-0.0037***	
	(1.09)	(-3.12)	
$\text{NonDisclosing*Post}_t$			-0.0066**
			(-2.05)
LiquidAssets_t	0.4809***	0.4845***	0.4907***
	(5.67)	(8.14)	(8.47)
CoreDeposit_t	0.0116	-0.0644	-0.0458
	(0.14)	(-1.60)	(-1.13)
Capital_t	-0.4244	0.0770	0.0912
	(-0.91)	(0.69)	(0.83)
Commitment_t	-0.1004	0.0436	0.0443
	(-0.48)	(0.82)	(0.86)
Size_t	-0.1306**	-0.0222**	-0.0183*
	(-2.60)	(-2.43)	(-1.92)
Observations	72	1,478	1,550
Adjusted R-squared	0.986	0.975	0.981
Bank Fixed Effects	Yes	Yes	Yes
Year-quarter Fixed Effects	No	No	Yes

Table 3: Effect of the LCR disclosure regulation on liquidity holdings.

This table reports estimates from the OLS regression of non-disclosing banks' liquid assets on *InfoGain*Post* or on *InfoGain*Post*CoreDecile*:

$$LiquidAssets_{i,t+1} = \alpha_i + \alpha_t + \beta InfoGain_i * Post_t + \gamma X_{i,t} + \epsilon_{i,t}$$

$$LiquidAssets_{i,t+1} = \alpha_i + \alpha_t + \beta InfoGain_i * Post_t * CoreDecile_i + \gamma X_{i,t} + \epsilon_{i,t}$$

LiquidAssets is the ratio of liquid assets to total assets. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. *Post* is an indicator variable equal to one after 2Q2017 and zero otherwise. *CoreDecile* is the decile of pre-period (1Q16–2Q17) average of *CoreDeposit*. Banks with *CoreDecile* = 1 (*CoreDecile* = 10) have the lowest (highest) pre-period average of *CoreDeposit* among banks in the regression. *CoreDeposit* is the ratio of core deposits to total assets. See Table 1 for other variable definitions. The sample in this test covers quarterly US bank holding companies from 1Q2016–2Q2018. *t*-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\mathrm{LiquidAssets_{t+1}}$	(2) $\mathrm{LiquidAssets_{t+1}}$
$\mathrm{InfoGain} * \mathrm{Post_t}$	-0.0236***	-0.0679***
	(-2.64)	(-3.28)
$\mathrm{InfoGain} * \mathrm{Post_t} * \mathrm{CoreDecile}$		0.0078**
		(2.52)
$\mathrm{Post_t} * \mathrm{CoreDecile}$		-0.0063***
		(-2.92)
$\mathrm{LiquidAssets_t}$	0.5008***	0.4791***
	(6.48)	(6.25)
$\mathrm{CoreDeposit_t}$	-0.0059	-0.0080
	(-0.11)	(-0.16)
$\mathrm{Commitment_t}$	0.0688	0.0700
	(1.08)	(1.11)
$\mathrm{Size_t}$	-0.0113	-0.0115
	(-1.06)	(-1.01)
$\mathrm{Capital_t}$	0.1754	0.1759
	(1.17)	(1.18)
Observations	1,047	1,047
Adjusted R-squared	0.976	0.976
Bank Fixed Effects	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes

Table 4: Aggregate effect of the LCR disclosure regulation on liquidity holdings.

This table reports the aggregate effect of LCR disclosure regulation on the liquidity level of disclosing banks, non-disclosing banks, and all banks in the sample from 4Q2017–2Q2018. $\Delta LiqAsset$ in column 1 is calculated by multiplying the *Post* coefficient in column 1 of Table 2 and the lagged total assets of LCR disclosing banks in the sample. $\Delta LiqAsset$ in column 2 is calculated by adding the multiples of the *InfoGain*Post* coefficient in column 1 of Table 3, the value of *InfoGain*, and the lagged assets of each bank.

$$\Delta LiqAsset(Disclosing)_t = \sum_{i \in Disclosing\ banks} 0.0038 * TotalAssets_{i,t-1}$$

$$\Delta LiqAsset(NonDisclosing)_t = \sum_{i \in NonDisclosing\ banks} -0.0236 * InfoGain_i * TotalAssets_{i,t-1}$$

LiqAsset in columns 5, 6, and 7 are the total liquid assets of all banks, disclosing banks, and non-disclosing banks, respectively. See Table 1 for other variable definitions.

Year-quarter	(1) ΔLiqAsset, bn$ (Disclosing)	(2) ΔLiqAsset, bn$ (Non-disclosing)	(3) (1)+(2), bn$	(4) |(2)/(1)|	(5) (3)/LiqAsset	(6) (1)/LiqAsset (Disclosing)	(7) (2)/LiqAsset (Non-disclosing)
2017Q4	41.75	-52.36	-10.60	125%	-0.27%	1.21%	-12.42%
2018Q1	42.68	-52.52	-9.84	123%	-0.24%	1.18%	-13.00%
2018Q2	42.26	-52.94	-10.69	125%	-0.27%	1.21%	-13.15%
Average	42.23	-52.61	-10.38	125%	-0.26%	1.20%	-12.86%

Table 5: Effect of the LCR disclosure regulation on systemic risk.

This table reports estimates from the OLS regression of systemic risk measures on *Post*, *Post_1Q15*, *Post_1Q16*, *Post_1Q17* or on *InfoGain*Post*:

$$SysRisk_{i,t+1} = \alpha_i + \beta_1 Post_t + \beta_2 Post\_1Q17_t + \beta_3 Post\_1Q16_t + \beta_4 Post\_1Q15_t + \epsilon_{i,t}$$

$$SysRisk_{i,t+1} = \alpha_i + \alpha_t + \beta InfoGain_i * Post_t + \epsilon_{i,t}$$

SysRisk is one of the two measures of systemic risk, *GC* and *SRISK*, which are defined in Section 6.3.1. *Post* is an indicator variable equal to one after 2Q2017 and zero otherwise. *Post_1Q15*, *Post_1Q16*, and *Post_1Q17* are indicator variables equal to one from 1Q2015, 1Q2016, and 1Q2017, respectively and zero otherwise. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. The sample in this test covers quarterly US bank holding companies from 1Q2014–2Q2018. *t*-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) GC_{t+1} (All)	(2) GC_{t+1} (Non-disclosing)	(3) $SRISK_{t+1}$ (All)	(4) $SRISK_{t+1}$ (Non-disclosing)
$Post_t$	1.0649*		0.0195***	
	(1.81)		(5.27)	
$Post\_1Q17_t$	-0.8937		-0.0482***	
	(-1.37)		(-12.72)	
$Post\_1Q16_t$	-1.8045***		-0.0285***	
	(-3.28)		(-8.06)	
$Post\_1Q15_t$	-1.6768**		-0.0058*	
	(-2.39)		(-1.78)	
$InfoGain * Post_t$		0.4077		-0.0455
		(0.12)		(-1.54)
Observations	1,850	1,274	1,934	1,346
Adjusted R-squared	0.025	0.041	0.617	0.754
Bank Fixed Effects	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	No	Yes	No	Yes

Table 6: Effect of the LCR disclosure regulation vs. the minimum LCR regulation.

This table reports estimates from the OLS regression of non-disclosing banks' liquid assets on *InfoGain*Post_n*:

$$LiquidAssets_{i,t+1} = \alpha_i + \alpha_t + \beta InfoGain_i * Post\_n_t + \gamma X_{i,t} + \epsilon_{i,t}$$

LiquidAssets is the ratio of liquid assets to total assets. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. *Post_n* is an indicator variable equal to one from quarter n (n = 1Q13, 1Q15, 1Q16, or 1Q17) and zero otherwise. *Post* is an indicator variable equal to one after 2Q2017 and zero otherwise. See Table 1 for the definitions of other variables. The sample in this test covers quarterly US bank holding companies from 1Q2014–2Q2018. t-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) Liquid Assets_{t+1}	(2) Liquid Assets_{t+1}	(3) Liquid Assets_{t+1}	(4) Liquid Assets_{t+1}	(5) Liquid Assets_{t+1}	(6) Liquid Assets_{t+1}
$\text{InfoGain} * \text{Post}_t$	-0.0236***					-0.0174***
	(-2.64)					(-2.62)
$\text{InfoGain} * \text{Post\_1Q17}_t$		-0.0122				0.0054
		(-1.36)				(0.77)
$\text{InfoGain} * \text{Post\_1Q16}_t$			-0.0107			-0.0055
			(-1.52)			(-1.10)
$\text{InfoGain} * \text{Post\_1Q15}_t$				-0.0123		-0.0038
				(-1.52)		(-0.74)
$\text{InfoGain} * \text{Post\_1Q13}_t$					-0.0213**	-0.0182***
					(-2.25)	(-2.76)
LiquidAssets_t	0.5008***	0.4255***	0.4974***	0.4068***	0.4906***	0.7993***
	(6.48)	(5.32)	(6.26)	(9.43)	(10.77)	(28.96)
CoreDeposit_t	-0.0059	-0.0077	-0.0051	-0.0153	-0.0278	-0.0103
	(-0.11)	(-0.14)	(-0.13)	(-0.42)	(-0.38)	(-0.57)
Commitment_t	0.0688	0.0408	0.0222	-0.1181	0.0642	-0.0020
	(1.08)	(0.55)	(0.33)	(-1.43)	(0.70)	(-0.06)
Size_t	-0.0113	-0.0154	-0.0076	-0.0063	-0.0083	-0.0035
	(-1.06)	(-1.38)	(-0.74)	(-0.51)	(-0.49)	(-1.10)
Capital_t	0.1754	0.2081	0.2672**	-0.1095	-0.0858	-0.0076
	(1.17)	(1.28)	(2.35)	(-1.33)	(-0.58)	(-0.22)
Observations	1,047	929	913	945	976	2,959
Adjusted R-squared	0.976	0.977	0.976	0.971	0.963	0.966
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Sample Period	1Q16-2Q18	1Q16-1Q18	1Q15-1Q17	1Q14-1Q16	2Q12-2Q14	1Q12-2Q18

Table 7: Effect of the second- and third-stage LCR disclosure requirements.

Panel A: Effect of the second- and third-stage LCR disclosure on liquidity holdings.

This table reports estimates from the OLS regression of non-disclosing banks' liquid assets on the incremental liquidity information learned from the second and third stages of the LCR disclosures, required in 2Q2018 and 4Q2018 respectively:

$$LiquidAssets_{i,t+1} = \alpha_i + \alpha_t + \beta_1 InfoGain\_2Q18_i * Post\_2Q18_t \\ + \beta_2 InfoGain\_4Q18_i * Post\_4Q18_t + \gamma X_{i,t} + \epsilon_{i,t}$$

LiquidAssets is the ratio of liquid assets to total assets. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. *InfoGain_2Q18* and *InfoGain_4Q18* are defined in the same way as *InfoGain*, except that the former two are based on non-disclosing banks' linkages with banks starting LCR disclosures in 2Q2018 (second stage) and 4Q2018 (third stage), respectively. $Post\_2Q18$ and $Post\_4Q18$ are indicator variables equal to one after 2Q2018 and 4Q2018, respectively and zero otherwise. See Table 1 for other variable definitions. The sample in this test covers quarterly US bank holding companies from 3Q2017–4Q2019. *t*-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $LiquidAssets_{t+1}$
$InfoGain\_2Q18 * Post\_2Q18_t$	-0.0225*
	(-1.87)
$InfoGain\_4Q18 * Post\_4Q18_t$	-0.0255*
	(-1.89)
$LiquidAssets_t$	0.4933***
	(8.91)
$CoreDeposit_t$	-0.1035***
	(-3.25)
$Capital_t$	-0.0296
	(-0.32)
$Commitment_t$	0.0010
	(0.02)
$Size_t$	-0.0257*
	(-1.68)
Observations	791
Adjusted R-squared	0.971
Bank Fixed Effects	Yes
Year-quarter Fixed Effects	Yes

Panel B: Correlations among the three versions of *InfoGain*.

This table reports the correlation matrix for the three versions of *InfoGain*. See Panel A in this table and Table 1 for variable definitions. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

	InfoGain	InfoGain_2Q18	InfoGain_4Q18
InfoGain	1		
InfoGain_2Q18	-0.103***	1	
InfoGain_4Q18	-0.347***	-0.315***	1

Panel C: Relationship of the three versions of *InfoGain* with bank characteristics.

This table reports estimates from the OLS regression of the three versions of *InfoGain* on a series of bank characteristics for banks that were not required to make LCR disclosure in any of the three stages. See Panel A of this table and Table 1 for variable definitions. The sample in this test covers quarterly US bank holding companies from 1Q2016–2Q2017. *t*-statistics are in parentheses. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) InfoGain	(2) InfoGain_2Q18	(3) InfoGain_4Q18
LiquidAssets	-0.2003***	-0.0020	0.3020***
	(-3.08)	(-0.04)	(4.48)
CoreDeposit	-0.0495	-0.0902**	0.2018***
	(-0.86)	(-2.07)	(3.37)
Capital	0.0299	-0.2702***	0.4481***
	(0.23)	(-2.82)	(3.40)
Commitment	-0.0438	-0.2146**	0.0678
	(-0.34)	(-2.18)	(0.50)
Size	-0.0630***	-0.0016	0.0039
	(-10.08)	(-0.33)	(0.60)
ΔLoan	0.0313	-0.2274**	-0.1767
	(0.23)	(-2.23)	(-1.26)
NPL	-0.9481**	-0.2199	0.9625**
	(-2.22)	(-0.68)	(2.18)
Interest	5.3033***	0.9557	-1.0790
	(5.19)	(1.24)	(-1.02)
EBP	-20.9073***	-2.3364	3.9522
	(-5.38)	(-0.80)	(0.98)
Observations	629	629	629
Adjusted R-squared	0.211	0.035	0.069

Table 8: Robustness to changing the range of total interactions required for sample banks.

This table reports estimates from the OLS regression of non-disclosing banks' liquid assets on the incremental liquidity information learned from the LCR disclosure. Columns 1 and 2 include banks with $Interactions \geq 4$ and $Interactions \in [10, 100]$, respectively. *Interactions* is the total number of syndicated loans issued with other banks during 2010–2017. *LiquidAssets* is the ratio of liquid assets to total assets. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. *Post* is an indicator variable equal to one after 2Q2017 and zero otherwise. See Table 1 for other variable definitions. The sample in this test covers quarterly US bank holding companies from 1Q2016–2Q2018. *t*-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\text{LiquidAssets}_{t+1}$	(2) $\text{LiquidAssets}_{t+1}$
$\text{InfoGain} * \text{Post}_t$	-0.0164**	-0.0352***
	(-2.16)	(-3.04)
LiquidAssets_t	0.4932***	0.4099***
	(6.95)	(4.28)
CoreDeposit_t	-0.0261	0.0050
	(-0.51)	(0.07)
Commitment_t	0.0462	0.0555
	(0.77)	(0.69)
Size_t	-0.0126	-0.0103
	(-1.20)	(-0.78)
Capital_t	0.1318	0.2984
	(0.91)	(1.59)
Observations	1,209	605
Adjusted R-squared	0.977	0.967
Bank Fixed Effects	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes
Interactions Range	≥ 4	10-100

Table 9: Robustness to changing sample period.

This table reports estimates from the OLS regression of non-disclosing banks' liquid assets on the incremental liquidity information learned from the LCR disclosure. The sample periods of columns 1 and 2 are 1Q2011–2Q2018 and 1Q2016–2Q2019, respectively. *LiquidAssets* is the ratio of liquid assets to total assets. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. *Post* is an indicator variable equal to one after 2Q2017 and zero otherwise. See Table 1 for other variable definitions. *t*-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\text{LiquidAssets}_{t+1}$	(2) $\text{LiquidAssets}_{t+1}$
$\text{InfoGain} * \text{Post}_t$	-0.0212***	-0.0147*
	(-3.00)	(-1.85)
LiquidAssets_t	0.8086***	0.6198***
	(27.95)	(10.75)
CoreDeposit_t	-0.0195	-0.0160
	(-1.03)	(-0.47)
Commitment_t	-0.0195	0.0379
	(-0.59)	(0.63)
Size_t	-0.0034	-0.0094
	(-0.98)	(-0.69)
Capital_t	-0.0135	0.0940
	(-0.39)	(0.94)
Observations	3,293	1,399
Adjusted R-squared	0.963	0.976
Bank Fixed Effects	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes
Sample Period	1Q11-2Q18	1Q16-2Q19

Table 10: Robustness to additional control variables.

Panel A: Potential bank characteristics that drive *InfoGain*

This table reports estimates from the OLS regression of *InfoGain* on a series of bank characteristics for non-disclosing banks. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. See Table 1 for other variable definitions. The sample in this test covers quarterly US bank holding companies from 1Q2016–2Q2017. *t*-statistics are in parentheses. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

	(1)	(2)
VARIABLES	InfoGain	InfoGain
LiquidAssets	-0.2225***	-0.2495***
	(-4.16)	(-4.72)
CoreDeposit	0.0137	-0.0587
	(0.29)	(-1.24)
Capital	-0.3641***	-0.0214
	(-3.75)	(-0.18)
Commitment	-0.1450	-0.0853
	(-1.25)	(-0.73)
Size	-0.0678***	-0.0653***
	(-14.96)	(-14.58)
ΔLoan		0.0451
		(0.36)
NPL		-1.1856***
		(-3.07)
Interest		5.1167***
		(5.27)
EBP		-19.9625***
		(-5.42)
Observations	693	689
Adjusted R-squared	0.280	0.318

Panel B: Main test with additional control variables

This table reports estimates from the OLS regression of non-disclosing banks' liquid assets on the incremental liquidity information learned from the LCR disclosure, with additional control variables and the interactions of all controls and *Post*. *LiquidAssets* is the ratio of liquid assets to total assets. *InfoGain* is the incremental liquidity information learned from the LCR disclosure. *Post* is an indicator variable equal to one after 2Q2017 and zero otherwise. See Table 1 for other variable definitions. The sample in this test covers quarterly US bank holding companies from 1Q2016–2Q2018. *t*-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\mathrm{LiquidAssets}_{t+1}$
$\mathrm{InfoGain} * \mathrm{Post}_t$	-0.0211**
	(-2.24)
$\mathrm{LiquidAssets}_t$	0.4583***
	(6.38)
$\mathrm{CoreDeposit}_t$	-0.0032
	(-0.07)
$\mathrm{Capital}_t$	0.1903
	(1.31)
$\mathrm{Commitment}_t$	0.0271
	(0.41)
Size_t	-0.0158
	(-1.42)
NPL_t	0.4065*
	(1.82)
$\mathrm{Interest}_t$	-0.1726
	(-1.16)
EBP_t	0.6821
	(1.06)
Observations	1,043
Adjusted R-squared	0.977
Controls*Post	Yes
Bank Fixed Effects	Yes
Year-quarter Fixed Effects	Yes

Table 11: Robustness to alternative definitions of *InfoGain*.

This table reports estimates from the OLS regression of non-disclosing banks' liquid assets on two alternative measures of incremental liquidity information learned from the LCR disclosure. *InfoGain_LA* (defined in Equation 7) is the incremental liquidity information learned from lead arrangers' LCR disclosure. *InfoGain_Size* (defined in Equation 8) is the size-weighted measure of *InfoGain*. See Table 1 for definitions of other variables. The sample in this test covers quarterly US bank holding companies from 1Q2016–2Q2018. t-statistics (in parentheses) are based on standard errors clustered at the bank level. ***, **, and * indicate statistical significance at less than 1, 5, and 10%, respectively.

VARIABLES	(1) $\text{LiquidAssets}_{t+1}$	(2) $\text{LiquidAssets}_{t+1}$
$\text{InfoGain\_LA} * \text{Post}_t$	-0.0326***	
	(-2.64)	
$\text{InfoGain\_Size} * \text{Post}_t$		-0.0220***
		(-2.67)
LiquidAssets_t	0.5006***	0.5000***
	(6.39)	(6.44)
CoreDeposit_t	-0.0096	-0.0078
	(-0.19)	(-0.15)
Capital_t	0.1777	0.1755
	(1.16)	(1.16)
Commitment_t	0.0685	0.0689
	(1.09)	(1.07)
Size_t	-0.0119	-0.0114
	(-1.11)	(-1.06)
Observations	1,047	1,047
Adjusted R-squared	0.976	0.976
Bank Fixed Effects	Yes	Yes
Year-quarter Fixed Effects	Yes	Yes