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# Measuring Liquidity Mismatch in the Banking Sector

JENNIE BAI, ARVIND KRISHNAMURTHY, and CHARLES-HENRI WEYMULLER*

**ABSTRACT**

This paper constructs a liquidity mismatch index (LMI) to gauge the mismatch between the market liquidity of assets and the funding liquidity of liabilities, for 2,882 bank holding companies over 2002 to 2014. The aggregate LMI decreases from +\$4 trillion precrisis to −\$6 trillion in 2008. We conduct an LMI stress test revealing the fragility of the banking system in early 2007. Moreover, LMI predicts a bank's stock market crash probability and borrowing decisions from the government during the financial crisis. The LMI is therefore informative about both individual bank liquidity and the liquidity risk of the entire banking system.

LIQUIDITY PLAYS AN ENORMOUS ROLE in financial crises. In the classic model of Diamond and Dybvig (1983), the illiquidity of bank assets coupled with the liquidity promised through bank liabilities leaves banks vulnerable to runs and financial crises. During the 2007 to 2009 financial crisis, the U.S. government provided several trillion dollars of reserves to the financial sector to forestall and ameliorate a liquidity crisis.[1] Regulators have taken steps to improve the liquidity of banks since the financial crisis. For instance, the Basel

*Jennie Bai is with McDonough School of Business at Georgetown University. Arvind Krishnamurthy is with Stanford University Graduate School of Business and NBER. Charles-Henri Weymuller is with French Treasury. We thank Michael Roberts (the Editor), two referees, Viral Acharya, Christa Bouwman, Markus Brunnermeier, Allen Berger, Adam Copeland, Darrell Duffie, Michael Fleming, Itay Goldstein, Gary Gorton, Samuel Hanson, Song Han, Larry Harris, Benjamin Hébert, Yi Li, Angela Maddaloni, Antoine Martin, Stefan Nagel, Mitchell Petersen, Klaus Schaeck, Philipp Schnabl, Mark Seasholes, David Skeie, Philip E. Strahan, and seminar participants at AFA (2016), WFA (2014), EFA (2014), SFS Finance Calvacade (2014), FDIC Annual Conference (2014), BIS Research Network Meeting (2014), European Bank Association's Annual Financial Stability Conference (2014), Mitsui Finance Symposium (2015), the Role of Liquidity in the Financial System Conference (2015), Stanford University, New York University, Copenhagen Business School, Georgetown University, and University of Rhode Island for helpful comments. We also thank participants at the BIS, European Central Bank, International Monetary Fund, the Federal Reserve Board, Federal Reserve Bank of New York, Federal Reserve Bank of Atlanta, Deutsche Bundesbank, Bank of France, Bank of England, and the Department of the Treasury's Office of Financial Research. Jonathan Choi, Jay Im, Jiacui Liu, and Yiming Ma provided excellent research assistance. Arvind Krishnamurthy received a Research Grant from Goldman Sachs Global Markets Institute from 2012 to 2015 to study ECB policy. The authors declare that they have no relevant or material financial interests related to the research in this paper.

[1] Fleming (2012) notes that, across its many liquidity facilities, the Federal Reserve provided over \$1.5 trillion of liquidity support during the crisis. This number is much higher if one includes other forms of government liquidity support. Lending by the Federal Home Loan Bank peaked at \$1

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III committee has implemented minimum liquidity standards for commercial banks, including the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), and the Federal Reserve has incorporated a liquidity stress test (the Comprehensive Liquidity Assessment and Review (CLAR)) as part of its oversight of large banks.

These policy responses have run ahead of research and raise important questions for researchers to answer. First, we lack an agreed-upon framework for examining when government regulation of private liquidity choices is desirable, and what instruments should be used to implement liquidity regulations. A small but growing literature has sought to address these questions (see Holmstrom and Tirole (1998), Caballero and Krishnamurthy (2004), Farhi, Golosov, and Tsyvinski (2009), Perotti and Suarez (2011), Allen (2014), Diamond and Kashyap (2016)). Second, we lack an agreed-upon framework for how to measure the liquidity of financial firms and the financial sector. Beyond simple intuitions for special cases (e.g., long-term loans are illiquid assets, while cash is liquid, and short-term debt liabilities leave a bank prone to liquidity risk, while long-term debt liabilities reduce liquidity risk), we lack a general system for measuring liquidity that can handle a sophisticated financial sector.

As Allen (2014) and Diamond and Kashyap (2016) note, there is a striking contrast between the analysis of capital and liquidity regulations. With capital, there is a consensus on how to measure capital and why it should be regulated, although disagreement persists on the optimal level of capital requirements. With liquidity, there is little consensus beyond the recognition that liquidity is hard to measure.

In this paper, we develop and implement a liquidity measurement system. This paper builds on earlier theoretical work by Brunnermeier, Gorton, and Krishnamurthy (2012) and is also related to Berger and Bouwman's (2009) empirical approach to measuring liquidity. Adopting the terminology in Brunnermeier, Gorton, and Krishnamurthy (2012), the "liquidity mismatch index" (LMI) measures the mismatch between the market liquidity of assets and the funding liquidity of liabilities. The LMI is based on a stress liquidity-withdrawal scenario: all claimants on the firm are assumed to act under the terms of their contract to extract the maximum liquidity possible, and the firm reacts by maximizing the liquidity it can raise from its assets. The net liquidity under this scenario gives the LMI for the firm. Brunnermeier, Gorton, and Krishnamurthy (2012) derive their liquidity metric in settings with a fixed liquidity stress horizon (i.e., overnight). We extend their measure to encompass dynamic settings: the LMI today is the appropriately "discounted" value of the expected LMI tomorrow. The recursive construction captures the liquidity of different maturity liabilities as, for example, a two-day liability today will become a one-day liability tomorrow. Our approach also accounts

trillion in September 2008. The Federal Deposit Insurance Corporation insurance limit increases in the crisis provided further guaranteed support of $336 billion as of March 2009 (He, Khang, and Krishnamurthy (2010)). The U.S. Treasury also offered $431 billion of funding through the Troubled Asset Relief Program (TARP) (see page 3).

for the time-varying state of liquidity conditions, which we achieve by linking the liquidity stress horizon to asset market measures of market and funding liquidity. Existing measures, including Basel's liquidity ratios and the Berger and Bouwman (2009) metric, restrict measurement to a fixed liquidity stress horizon.

A good liquidity measure must be theoretically coherent and shed light on data. The recursive principle and incorporation of market prices favor our construction theoretically. The bulk of this paper shows that the LMI performs well empirically. First, we show that the LMI is useful from a macroprudential perspective. A liquidity metric should capture liquidity imbalances in the financial system, offering an early indicator of financial crises. It should also quantitatively describe the liquidity condition of the financial sector and the amount of liquidity the Fed may be called upon to provide in the event of a financial crisis. The LMI performs well on each of these dimensions. Another important feature of the LMI is that it can be aggregated across banks to measure the liquidity mismatch of a group of banks or of the entire financial sector. Liquidity measures that are based on ratios, such as Basel's LCR, do not possess this aggregation property. The LMI is also well suited to stress test analysis. The market liquidity of assets and funding liquidity of liabilities, which form the LMI, can be described in terms of their exposures to a set of underlying factors. In our implementation, we use repo market haircuts to extract the asset liquidity factor and the spread between the Treasury bill rate and the Overnight Indexed Swap rate (hereafter the OIS-Tbill spread) as the funding liquidity factor. A stress test can be conducted by shocking the haircut factor and the OIS-Tbill spread and then measuring the change in the LMI of a bank or of the financial system. In a one-sigma ($1\sigma$) shock at the beginning of 2007, for example, we show that the aggregate liquidity of the banking sector dips by nearly \$1 trillion below zero, providing an early warning signal of the fragility of the financial sector. In 2007Q2, a $3\sigma$ shock takes the LMI of the banking sector to $-$\$4.71 trillion. Our stress test and its predictions provide an anchor for estimating the Fed's liquidity provision during a systemic/aggregate liquidity crisis and capture the banking sector's liquidity risk.

Our second set of empirical criteria arises from microconsiderations. We argue that a good liquidity measure should capture liquidity risk in the cross section of banks, identifying which banks carry the most liquidity risk. We show that our measure performs well, and better than other measures, in this dimension. We examine the cross section of banks and show that banks with a lower LMI before the crisis have higher crash risk during the peak of the financial crisis. Banks with a lower LMI are also more likely to borrow from Federal Reserve facilities and the Troubled Asset Relief Program (TARP), and they receive larger liquidity injections. The LMI thus helps describe the cross section of liquidity risk in the financial sector. For regulatory purposes, our approach can help identify systemically important institutions on a liquidity dimension.

We compare our liquidity measure to two Basel III metrics: namely, the LCR (BCBS (2013)) and the NSFR (BCBS (2014)). As noted above, the Basel ratios cannot be aggregated to provide the overall view of the banking system to a liquidity stress event. We also compare the power of these measures to explain banking liquidity outcomes during the crisis, including their crash probability and their decision to borrow from the government. The two Basel measures have little predictive power. The LMI therefore performs better along both macro- and microdimensions.

We also compare our measure to that in Berger and Bouwman (2009), which is the first academic paper to measure banking sector liquidity. Our approach differs from Berger and Bouwman (2009) in offering a theoretical grounding to liquidity measurement that is recursive and bases liquidity weights on contract maturity and measures of market liquidity. Empirically, the difference between the LMI and the Berger and Bouwman (2009) measure is driven largely by our incorporation of market liquidity conditions. We show that if we fix the liquidity weights in our computation, then the LMI varies little between normal and crises periods and thus does not accurately represent the liquidity stress of the banking system. With time-varying weights, our preferred liquidity aggregate ("LMI-minus," to be formally defined in Section I.D) decreases from near zero to −\$1 trillion over the period 2007Q1 to 2007Q3, and falls to −\$6 trillion at the peak of the crisis. If we hold the weights constant based on liquidity conditions measured in 2002Q2 (i.e., good conditions), the decline in the LMI over the crisis is about \$50 billion. At a macro level, the incorporation of time-varying weights is thus critical to capture liquidity stress during a financial crisis. We also compare the explanatory power of the Berger and Bouwman (2009) measure to our measure for banks' crash probability and borrowing from the government during the crisis. We find that the Berger and Bouwman (2009) measure does not perform as well as the LMI.

This paper is most directly related to the literature examining firms' liquidity management. Financial firms hold liquidity on their asset side and provide liquidity on their liability side through the issuance of short-term debt. Liquidity management thus amounts to a joint decision over assets and liabilities, and it is most natural to focus on a single measure of bank liquidity that combines both asset liquidity and liability liquidity. In this regard, we build on the work of Berger and Bouwman (2009). Cornett et al. (2011), Hanson et al. (2015), and Krishnamurthy and Vissing-Jorgensen (2015) study banks' asset liquidity choices jointly with their liabilities.[2] In corporate finance research, liquidity is often measured solely from the asset side, abstracting from considerations of liquidity provision on the liability side. Bates, Kahle, and Stulz (2009), for example, examine the rise in cash holdings across the corporate sector, where cash is defined as the sum of cash and marketable securities.[3] On the policy side, central bank studies such as Banerjee (2012) and de Haan and van den

[2] A separate literature examines banks' hoarding of liquidity and its implications for interbank markets. See Heider, Hoerova, and Holhausen (2015), Acharya and Merrouche (2013), and Acharya and Rosa (2015).

[3] Practitioners use a number of metrics to help firms manage liquidity, ranging from the accounting quick ratio to more sophisticated measures.

End (2013) investigate measures of bank liquidity regulation in conjunction with Basel III.

The paper proceeds as follows. Section I. develops a theoretical model for the liquidity mismatch measure and Section II. constructs the empirical measure. Section III. evaluates the LMI along the macrodimension, while Section IV. evaluates the LMI along the microdimension. Section V. concludes and discusses future work.

## I. Liquidity Mismatch Index: Theoretical Framework

We are interested in measuring a bank's liquidity using the bank's balance sheet information. We expand on the approach proposed by Brunnermeier, Gorton, and Krishnamurthy (2012). They define the LMI as the "cash equivalent value" of a firm in a given state assuming that:

(i) Counterparties act most adversely, that is, parties that have contracts with the firm extract as much cash as possible from the firm under the terms of their contracts. The liquidity promised represents the *liability-side liquidity.*
(ii) In an effort to withstand the cash withdrawals, given the assumed stress event, the firm computes how much cash it can raise from asset sales, preexisting contracts such as credit lines, and collateralized loans such as repo backed by assets currently held by the firm. This computation assumes that the firm is unable to raise unsecured debt or equity. The total cash raised represents the *asset-side liquidity.*
(iii) The LMI is the net of these computations, that is, asset-side liquidity minus liability-side liquidity.

To illustrate, consider a hypothetical Diamond-Dybvig bank with \$100 of assets financed by \$90 of overnight wholesale (uninsured) debt and \$10 of equity. Moreover, suppose that the assets can be used as collateral in the repo market at a haircut of 20% to raise \$80 on short notice. Then, in part (i), we have −\$90, as the maximum liquidity that can be extracted by counterparties is repayment on the debts of overnight creditors; in part (ii), we have +\$80, as the firm can raise at most \$80, on short notice; and in part (iii), the LMI is −\$10.

What does the LMI measure? The negative LMI in the example above indicates that a bank-run equilibrium can exist, and in the event of the bank-run equilibrium, the liquidity shortfall—the bank's potential liquidity need from the Fed—is +\$10. More broadly, with more complex contracts than just overnight deposit contracts, (i) and (ii) above together indicate whether a coordinated liquidity withdrawal can trigger firm failure and measure the shortfall in the case of failure.

The LMI is very simple to compute, which is its appeal. But it is based on simplifying assumptions. For example, it may be that the haircut of 20% depends not only on the collateral used, but also on the equity capital of the firm. This may be the case since, in the event of failure, lenders are protected by both the specific collateral in the repo as well as the firm's balance sheet. In practice, repo haircuts appear to be largely a function of collateral rather than bank identity[4] so that the simplification is unlikely to introduce much error into our computation. But it is worth noting that the construction of the LMI measure ignores balance sheet interdependencies.

In the general case, Brunnermeier, Gorton, and Krishnamurthy (2012) propose that the LMI for entity $i$ at time $t$ be computed as the net of the asset and liability liquidities, that is,

$$LMI_t^i = \sum_k \lambda_{t,a_k} a_{t,k}^i + \sum_{k'} \lambda_{t,l_{k'}} l_{t,k'}^i. \tag{1}$$

Assets ($a_{t,k}^i$) and liabilities ($l_{t,k'}^i$) are balance sheet counterparts that vary over time and across asset or liability classes ($k, k'$). The liquidity weights, $\lambda_{t,a_k} > 0$ and $\lambda_{t,l_{k'}} < 0$, are the key items to compute. They come from calculating (i) and (ii) for each asset and liability. For example, an overnight debt liability will have a liability weight of $\lambda_{t,l_{k'}} = -1$ because, under (i), a debtor can refuse to roll over debt, demanding cash repayment. Likewise, cash or an overnight repo held on the asset side will have an asset weight of $\lambda_{t,a_{k'}} = 1$ because the firm can use these assets toward any liquidity shortfall. Brunnermeier, Gorton, and Krishnamurthy (2012) provide several examples of assets and liabilities, explaining why (i) and (ii) should drive the measurement of liquidity.

We go beyond Brunnermeier, Gorton, and Krishnamurthy (2012) in three ways. First, we propose a set of numerical liquidity weights $\lambda_{t,a_k}$ and $\lambda_{t,l_{k'}}$ for asset and liability categories. Second, we offer a methodology to handle different maturity liabilities that is based on dynamic considerations. Last, we show how to incorporate market levels of liquidity stress (e.g., asset market liquidity premia) into the liquidity measurement.

### *A. Bank Recursion and LMI Derivation for Liabilities*

We first focus on computing the liability-side LMI, $\sum_{k'} \lambda_{t,l_{k'}} l_{t,k'}^i$. It is easier to explain our methodology by moving to a continuous-maturity setting, although we implement the LMI based on a sum of discrete liability classes as in equation (1). We use $T$ to denote the maturity of liability class $k'$. Thus, let $l_{t,T}^i$ be the liability of bank $i$ due at time $T$, where $\{l_{t,T}^i\}$ denotes the stream of maturity-dated liabilities. We are interested in summarizing the stream $\{l_{t,T}^i\}$ by a single number, $LMI(\{l_{t,T}^i\}, t)$.

We derive the value of a bank, where liquidity enters explicitly, to motivate the liquidity measurement. Suppose that, a bank at date $t$ has issued liabilities $\{l_{t,T}^i\}$ and used the proceeds to invest in a long-term illiquid asset. For liquidity measurement, we hold this balance sheet fixed, assuming that the bank does not issue more liabilities at $s > t$ nor make further investments in illiquid

[4] See figure 9 in Krishnamurthy, Nagel, and Orlov (2014).

assets. The illiquid investment "carry trade" can generate profits to the bank. In particular, $\pi_{t,T}$ is the liquidity premium the bank earns by issuing a liability of maturity $T$ and investing in long-term assets. Here, $\pi_{t,T'} > \pi_{t,T}$ for $T' < T$, and $\pi_{t,T} = 0$ for large $T$ (i.e., short-term liabilities earn a liquidity premium). Given this liquidity premium structure, the bank is incentivized to issue short-term debt. The cost of short-term debt is liquidity stress. Suppose that, at time $t$, the bank is in a liquidity stress episode where any liability holders with liabilities coming due refuse to rollover their debts, as in (i). Denote by $V^S(\{l^i_{t,T}\}, t)$ the time-$t$ value of a bank with liability structure $\{l^i_{t,T}\}$ that sees stress event $S$. The bank pays $\theta^i$ per dollar to obtain cash that is due to creditors.[5] We thus have,

$$V^S(\{l^i_{t,T}\}, t) = \overbrace{\left(\int_t^\infty l^i_{t,T}\pi_{t,T}\,dT\right)dt}^{\text{flow of profits}} + \overbrace{\left(-\theta^i l^i_{t,t}\right)dt}^{\text{cost of liquidity}}$$
$$+ \mu_t dt\; V^{NS}\left(\{l^i_{t,T}\}, t+dt\right) + (1-\mu_t dt)V^S\left(\{l^i_{t,T}\}, t+dt\right), \quad (2)$$

where $\mu_t dt$ is the probability that at date $t + dt$ the stress episode ends, and $V^{NS}$ is the value of the bank in the state in which the stress episode ends (we assume for simplicity that the bank does not again transit into a stress state). Note that, in writing this expression, and in all derivations below, we assume for simplicity that the interest rate is effectively zero. We can think about $\theta^i$ as the implicit and explicit cost that a bank pays to the discount window. This interpretation is natural for a bank risk manager. If we take a regulatory perspective, $\theta^i$ can be interpreted as the regulator's cost of having a bank come to the discount window to access liquidity.

To illustrate, again consider the hypothetical Diamond-Dybvig bank. We modify the previous example by assuming that the bank's assets are fully illiquid (that is, the repo haircut is 100%) and that the bank has no equity capital (i.e., is funded only by demandable debt). The bank buys \$100 of illiquid assets at date 0 that pay off at date 2 and earn a return of 10%. The bank finances itself with \$100 of debt that is demandable at date 1 and again at date 2. The interest rate on this debt is zero. The relevant liquidity stress for this bank is the bank-run equilibrium at date 1, in which case the bank obtains \$100 from the discount window at a cost of $\theta^i = 0.2$. The spread that the bank earns on holding illiquid assets financed by short-term demandable debt is $\pi = 10\%$. The value of this asset and liability structure in the stress event is equal to

$$100 \times 0.10 - 0.20 \times 100 = -\$10.$$

[5] Note that $\theta^i$ is defined as a per dollar cost of obtaining cash once and for all, rather than a rate on borrowing cash from, say, the discount window. These two costs can be readily related to each other. Take the case of on overnight liability, $l^i_{t,t}$, that has to be funded at overnight cost $R^i$. If the liquidity stress continues tomorrow, the funding has to be renewed at cost $R^i$. Then, the total expected cost of funding the liability depends on $R^i$ and the expected stress of the episode, which is equal to $\frac{1}{\mu_t}$, that is, $\theta^i = \frac{R^i}{\mu_t}$.

We can think about a bank optimizing assets and liabilities based on the probability of entering a stress episode, with this value the bank's value in the stress episode.

We next define the LMI. Specifically, define

$$V\left(\{l^i_{t,T}\}, t\right) \equiv \Pi\left(\{l^i_{t,T}\}, t\right) + \theta^i LMI\left(\{l^i_{t,T}\}, t\right). \tag{3}$$

The first term on the right-hand side is the value of the profits to the carry trade. The second term is the cost of liquidity, that is, $\theta^i$ times the LMI of the bank. We can write the profit function recursively as

$$\Pi\left(\{l^i_{t,T}\}, t\right) = \left(\int_t^\infty l^i_{t,T}\pi_{t,T}dT\right)dt + \Pi\left(\{l^i_{t+dt,T}\}, t+dt\right).$$

Then, the LMI is the difference between the bank's value and profits, which can be written recursively as

$$LMI\left(\{l^i_{t,T}\}, t\right) = -l^i_{t,t}dt + (1-\mu_t dt)LMI\left(\{l^i_{t+dt,T}\}, t+dt\right). \tag{4}$$

To illustrate, we return to the two-period Diamond–Dybvig bank. We have that $LMI(t=1)$ is $-\$100$ because $l_{t=1,t=1}$ =\$100, and $LMI(t=2)$ =\$0. To understand why recursion matters, consider a three-period version of the Diamond–Dybvig bank. Suppose that bank assets are bought at date 0 but pay off at date 3, rather than date 2. The bank issues \$50 of short-term debt that is demandable at date 1, date 2, and date 3. The bank also issues \$50 of longer term debt that is demandable at date 2 and date 3, but not at date 1. How should we incorporate maturity and time into the LMI? If we roll forward to date 1, the example bank is now a \$50 version of the simple Diamond–Dybvig bank funded solely by \$50 of short-term debt. We now have that $LMI(t=1)$ for this bank is –\$50. At date 0, our recursive construction makes $LMI(t=0)$ the sum of the "discounted value" of $LMI(t=1)$ and the liquidity due at $t=0$ of $-\$50$. The discount rate is the probability that the stress episode has not ended by $t=1$ (i.e., $1-\mu_t dt$). Thus, for the three-period Diamond-Dybvig bank, if the probability that the stress episode ends is 10%, then $LMI(t=0) = -\$50 + 0.90 \times LMI(t=1) = -\$95$. This bank has a less negative LMI (less mismatch) than the two-period bank because it is funded partly with longer term debt.

Equation (4) can be used to derive the liability liquidity weights, $\lambda_{t,l_{k'}}$, as a function of maturity. We look for an LMI function that depends only on the remaining maturity of liabilities, that is, a function such that the liquidity cost measured at time $t$ of a liability maturing at time $T$ is a function only of $T-t$. Consider the function

$$LMI\left(\{l^i_{t,T}\}, t\right) = \int_t^\infty l^i_{t,T}\lambda_{T-t}dT, \tag{5}$$

where $\lambda_{T-t}$ is the liquidity weight at time $t$ for a liability that matures at time $T$. The weight captures the marginal contribution of liability $l^i_T$ to the liquidity pressure on the bank. Substituting the candidate weighting function into recursion equation (4) and solving, we find that

$$\lambda_{T-t} = -e^{-\mu_t(T-t)}. \tag{6}$$

The liquidity weight is an exponential function of $\mu_t$ and the liability's time to maturity $T-t$. A high $\mu_t$ implies a low chance of illiquidity, and hence high liquidity. The liquidity weights that we have constructed embed the expected duration of liquidity needs.

### *B. Measuring $\mu_t$*

A key variable in the construction of the LMI is $\mu_t$, which controls the expected duration of the stress event—the higher the $\mu_t$, the shorter the duration of the stress event. We aim to map $\mu_t$ to an observable asset price. Consider a hypothetical bank that is choosing its liabilities $\{l^i_{t,T}\}$. The bank chooses its liabilities to earn carry-trade profits, $\Pi(\{l^i_{t,T}\})$, but there is a probability $\psi^i$ that the bank will enter a liquidity stress episode and pay cost $\theta^i LMI(\{l^i_{t,T}\}, t)$. The bank solves therefore

$$\max_{\{l^i_{t,T}\}} \Pi\left(\{l^i_{t,T}\}, t\right) + \psi^i\theta^i LMI\left(\{l^i_{t,T}\}, t\right). \tag{7}$$

The first-order condition (FOC) for the bank in choosing $l^i_{t,T}$ is

$$\int_t^T \pi_{s,T}\, ds = \psi^i\theta^i e^{-\mu_t(T-t)}. \tag{8}$$

The bank earns a liquidity premium on issuing liabilities of maturity $T$, but at liquidity cost governed by $e^{-\mu_t(T-t)}$. The FOC indicates a relation between $\mu_t$ and the liquidity premium, which is governed by the market's desire for liquidity.

We measure the liquidity premium using the OIS-Tbill spread. For a liability that has a maturity of one year ($T-t=1$), we rewrite (8),

$$-\mu_t = \ln\left(\frac{1}{\psi^i\theta^i}\int_t^{t+1} \pi_{s,T}\, ds\right). \tag{9}$$

We assume that $\pi_{s,T}$ is an increasing function of the OIS-Tbill spread. In particular, we make the parametric assumption that the right-hand side of (9) is proportional to the log of the OIS-Tbill spread:

$$-\mu_t = \kappa \ln(\text{OIS-Tbill}). \tag{10}$$

Here, $\kappa$ is a free parameter that scales the relation between OIS-Tbill and $\mu_t$. We discuss how $\kappa$ is chosen in the next section.

When investors have a strong desire to own liquid assets, as reflected in a high OIS-Tbill spread, any financial intermediary that can issue a liquid liability can potentially earn profits by issuing such liquid liabilities. However, doing so exposes the intermediary to liquidity risk. The FOC says that the potential profits must balance the potential risks, which means that $\mu_t$, which parameterizes the liquidity cost, must be related to the OIS-Tbill spread. There is clear evidence (see Krishnamurthy and Vissing-Jorgensen (2013) and Nagel (2016)) on the relation between the liquidity premia on bank liabilities and market measures of the liquidity premium. The OIS-Tbill spread is a pure measure of the liquidity premium, as it is not contaminated by a credit risk premium. We therefore use time-series variation in the OIS-Tbill spread to pin down $\mu_t$.

The derivation above is carried out under the assumption that $\mu_t$ varies over time but is a deterministic function of $T$, that is, the "term structure" of $\mu_t$ is driven purely by a single level factor. In our implementation of liquidity weights, we make this assumption and thus use the three-month OIS-Tbill spread to proxy for $\mu_t$. However, $\mu_t$ itself has a term structure that reflects an uneven speed of exit from the liquidity event. This term structure will be reflected in the term structure of the OIS-Tbill spread, so that a more sophisticated implementation of the LMI could include information on OIS-Tbill at different maturities.

### C. LMI Derivation Including Assets

Let us next consider asset-side liquidity, $\sum_k \lambda_{t,a_k} a^i_{t,k}$. In a liquidity stress event, the bank can use its assets to cover liquidity outflows rather than turn to the discount window (or other sources) at the cost $\theta^i$ per unit liquidity. The asset-side LMI measures the benefit from assets in covering the liquidity shortfall. Our formulation follows definition (ii) from the earlier discussion of Brunnermeier, Gorton, and Krishnamurthy (2012).

For each asset, $a_{t,k}$, define its cash-equivalent value as $(1 - m_{t,k})a_{t,k}$. Here, $m_k$ is most naturally interpreted as a haircut on a term repurchase contract, so that $(1 - m_{t,k})a_{t,k}$ is the amount of cash the bank can immediately raise using $a_{t,k}$ as collateral. Then, the total cash available to the bank is

$$w_t = \sum_k (1 - m_{t,k}) a^i_{t,k}. \tag{11}$$

The bank can use these assets to cover the liquidity outflow. Define the LMI including assets as $LMI(\{l^i_{t,T}\}, w_t, t)$, and note that the LMI satisfies the recursion

$$\begin{aligned} LMI(\{l^i_{t,T}\}, w_t, t) = \max_{\Delta_t \geq 0} \big(&-\max(l^i_{t,t} - \Delta_t, 0)dt + (1 - \mu dt) LMI(\{l^i_{t+dt,T}\}, w_t \\ &+ dw_t, t + dt)\big), \end{aligned} \tag{12}$$

where

$$dw_t = -\Delta_t.$$

At every $t$, the bank chooses how much of its cash pool, $\Delta_t$, to use toward covering its liability at date $t$, $l_{t,t}$. Given that there is a chance that the liquidity stress episode will end at $t + dt$, and given that the cost of the liquidity shortfall is linear in the shortfall, it is obvious that the solution calls for $\Delta_t = l_{t,t}$ as long as $w_t > 0$, after which $\Delta_t = 0$. We compute the maximum duration that the bank can cover its outflow, $T^*$, as the solution to

$$w_t = \int_t^{T^*} l^i_{t,T} dT. \tag{13}$$

Thus, after $T^*$, the bank will have run down its cash pool. By using its assets to cover liquidity outflows until date $T^*$, the bank avoids costs of

$$\psi^i \theta^i \int_t^{T^*} l^i_{t,T} \lambda_{T-t} dT,$$

which is therefore also the value to the bank of having assets $w_t$.

In implementing our LMI measure, we opt to simplify further. Rather than solving the somewhat complicated equation (13) to compute $T^*$ as a function of $w_t$ and then computing $\int_t^{T^*} l^i_{t,T} \lambda_{T-t} dT$, we instead assume that the cost avoided of having cash $w_t$ is simply $\psi^i \theta^i w_t$. This approximation is valid as long as $T^*$ is small, so that $\lambda_{T^*-t}$ is near one, in which case $\int_t^{T^*} l^i_{t,T} \lambda_{T-t} dT \approx \int_t^{T^*} l^i_{t,T} dT = w_t$. For example, in the case in which $T^*$ is one day, the approximation is exact since in effect the cash $w_t$ is being used to offset today's liquidity outflows one-for-one, saving the cost of $\psi^i \theta^i w_t$.

Furthermore, we categorize liabilities into maturity buckets rather than compute a continuous maturity structure since, in practice, we have data only for a coarse categorization of maturity. Putting the above together, the LMI is given as

$$LMI^i_t = \sum_k \lambda_{t,a_k} a^i_{t,k} + \sum_{k'} \lambda_{t,l_{k'}} l^i_{t,k'},$$

where the asset-side weights are

$$\lambda_{t,a_k} = 1 - m_{t,k}, \tag{14}$$

and the liability-side weights are

$$\lambda_{t,l_{k'}} = -e^{-\mu_t T_{k'}}, \tag{15}$$

and where $T_{k'}$ is the remaining maturity of liability $k'$.

To summarize, we expand on Brunnermeier, Gorton, and Krishnamurthy (2012) by considering an explicit dynamic optimization problem for a bank. This problem leads us to an explicit specification of the liquidity weights as a function of a contract's maturity ($T_{k'}$) and the state of the economy. We also show how market prices can measure the state of the economy, and how they enter into the construction of the LMI.

*D. Liquidity Metrics*

The variable $LMI_t^i$ measures bank $i$'s liquidity at time $t$. We also construct a number of other metrics based on the LMI.

We define the liquidity risk of a bank as follows. The vector of haircuts $m_{t,k}$ and the OIS-Tbill spread ($\mu_t$) capture the liquidity state of the economy, that is, market and funding liquidity conditions. We shift the haircuts and the OIS-Tbill spread by one $\sigma$, in a manner, that we explain in Section III.E, and compute

$$Liquidity\ risk_t^i = LMI_t^i - LMI_{t,\ 1\sigma}^i. \tag{16}$$

The liquidity risk of a bank is the exposure of that bank to a $1\sigma$ change in market and funding liquidity conditions.

While the LMI is measured at the bank level, it can be aggregated across the banking sector. We construct two such aggregates. The first, LMI-minus, denoted by $[LMI]^-$ measures the aggregate liquidity vulnerability of the banking system, that is,

$$[LMI]_t^- = \sum_i \min[LMI_t^i, 0]. \tag{17}$$

This measure aggregates liquidity across negative-LMI banks. It tells us what the aggregate liquidity shortfall would be if every bank for which the bank-run equilibrium exists suffers a bank run.

Our second aggregate of interest, aggregate LMI, denoted by $\widetilde{LMI}$, is the simple sum of the liquidity positions of the banking system, that is,

$$\widetilde{LMI}_t = \sum_i LMI_t^i. \tag{18}$$

This measure captures the health of the entire banking system under the assumption that liquidity can flow freely between surplus and deficit banks. In many cases of interest, such as a financial crisis, this assumption is likely violated, in which case LMI-minus is a better measure of the banking system's health.

Finally, as with a single bank, we are also interested in measuring the liquidity risk of the entire banking system. To do so, we compute,

$$[LMI]_{t,\ 1\sigma}^- = \sum_i \min[LMI_{t,\ 1\sigma}^i, 0], \tag{19}$$

which is the LMI-minus in a $1\sigma$ shock. More generally, we compute this measure for any $N\sigma$ event. We will show that these aggregates can inform a liquidity stress test.

## II. Liquidity Mismatch Index: Empirical Design

Following our theoretical model, we collect assets and liabilities for each bank and define their liquidity weights accordingly. The asset-side liquidity weights are driven by haircuts of underlying securities, while the liability-side liquidity weights are determined by liabilities' maturity structure and easiness of rollover ("stickiness"). Both are affected by the expected stress duration, which is pinned down by the market liquidity premium. In this section, we explain in detail how we calculate the LMI.

We construct the LMI for the universe of bank holding companies (BHCs) regulated by the Federal Reserve system. The key source of balance sheet information for BHCs comes from the FRY-9C Consolidated Report of Condition and Income, which is completed on a quarterly basis by each BHC with at least $150 million in total assets before 2006 or $500 million thereafter.[6] Our sample covers the period 2002Q2 to 2014Q3. The data set contains 2,882 BHCs over the sample period,[7] of which 54 are U.S. subsidiaries of foreign banks (e.g., Taunus Corporation, whose parent is Deutsche Bank, and Barclays's U.S. subsidiary). Table I, Panel A, presents summary statistics for these BHCs, including total assets, risk-adjusted assets, Tier 1 leverage ratio and Tier 1 risk-based capital ratio (both ratios are Basel regulatory measures), and return on assets (ROAs). Table I, Panel B, provides a snapshot of the top 50 BHCs, ranked by their total assets as of 2006Q1. The top 50 BHCs together have total assets of $11 trillion, which amounts to 76% of U.S. real GDP in 2006.

Internet Appendix Section I. provides step-by-step instructions regarding how to construct the LMI.[8] Much of its construction is mechanical. Here, we highlight three areas where we have to use our judgment in the implementation.

1. We assign a maturity $T'_k$ to each liability. In some cases, such as overnight debt, the bank's accounting information provides an exact maturity (e.g., $T'_k = 0$ for overnight debt), but in many other cases, the accounting information provides maturity buckets (e.g., maturity$<$1 year, or maturity$>$ 1 year). In these cases, we have to use some judgment in choosing $T'_k$. Table IAII of the Internet Appendix provides the exact mapping we use. The one choice worth pointing out is that we set $T'_k = 10$ years for insured deposits, even though some of these deposits are demandable. We base this choice on the accepted wisdom that insured bank deposits in the United States do not face a run in the event of a liquidity stress episode (see Gatev and Strahan (2006)).

[6] The Y-9C regulatory reports provide data on the financial condition of a BHC, based on U.S. GAAP consolidation rules, as well as the capital position of the consolidated entity. The balance sheet and income data include items similar to those contained in SEC filings, but the regulatory reports also contain a rich set of additional information, including data on regulatory capital and risk-weighted assets, off-balance-sheet exposures, securitization activities, and so on.

[7] Some BHCs' main business is insurance, for example, Metlife. We exclude these insurance-type bank holding companies to facilitate cross-sectional comparisons, given that they have different business models.

[8] The Internet Appendix is available in the online version of the article on the *Journal of Finance* website.

**Table I**

**Summary Statistics on Bank Holding Companies, 2002 to 2014**

Our sample contains 2,882 bank holding companies (BHCs), of which 754 are public BHCs and 758 are U.S.-headquartered public BHCs. Panel A reports the time-series average of the cross-sectional mean and standard deviation for a set of metrics. Panel B provides data from the first quarter of 2006 for a subset of the top 50 BHCs (ranked by total assets).

Panel A: Total

| | Universe ($N = 2{,}882$) | | Public ($N = 754$) | | Public United States ($N = 748$) | | Top 50 United States ($N = 50$) | |
|---|---|---|---|---|---|---|---|---|
| | Mean | *SD* | Mean | *SD* | Mean | *SD* | Mean | *SD* |
| Total assets ($Bil) | 10.13 | 95.67 | 26.42 | 164.17 | 25.17 | 163.47 | 250.12 | 468.31 |
| Risk-adj. assets ($Bil) | 6.54 | 59.40 | 17.77 | 103.25 | 17.08 | 103.45 | 161.88 | 289.70 |
| Tier 1 leverage ratio | 9.45 | 10.33 | 9.48 | 8.68 | 9.51 | 8.74 | 7.66 | 2.68 |
| Tier 1 capital ratio | 13.36 | 15.33 | 12.87 | 9.13 | 12.91 | 9.18 | 10.07 | 3.89 |
| ROA (annualized %) | 1.30 | 4.70 | 1.03 | 5.00 | 1.04 | 5.03 | 1.07 | 3.39 |

Panel B: Top 50 BHCs (rank is based on total asset value as of 2006Q1)

| Rank | Company | Size($Bil) | Risk-adj Asset($Bil) | Tier1 Lev Ratio | Tier1 Cap Ratio | ROA |
|---|---|---|---|---|---|---|
| 1 | CITIGROUP | 1,748.79 | 974.24 | 6.01 | 10.55 | 1.07 |
| 2 | JPMORGAN CHASE & CO | 1,703.68 | 1,033.92 | 6.40 | 9.90 | 2.01 |
| 3 | BANK OF AMER CORP | 1,683.36 | 1,110.79 | 6.58 | 9.71 | 1.14 |
| 4 | WELLS FARGO & CO | 889.35 | 703.69 | 8.07 | 9.41 | 2.74 |
| 5 | WACHOVIA CORP | 540.05 | 406.83 | 6.35 | 7.88 | −0.42 |
| 6 | TAUNUS CORP | 400.18 | 93.93 | −1.34 | −6.36 | 0.04 |
| 7 | HSBC NORTH AMER HOLD | 375.69 | 245.20 | 6.59 | 11.10 | −0.77 |
| 8 | BARCLAYS GROUP US | 344.03 | 53.87 | 0.97 | 8.35 | 0.01 |
| 9 | U S BC | 263.39 | 222.44 | 8.44 | 9.43 | 3.69 |
| 10 | BANK OF NY MELLON CORP | 205.82 | 97.42 | 6.22 | 10.75 | 2.04 |
| 20 | COUNTRYWIDE FC | 125.41 | 84.51 | 7.39 | 11.65 | 4.80 |
| 30 | M&T BK CORP | 64.44 | 56.88 | 8.17 | 8.69 | 2.76 |
| 40 | NEW YORK CMNTY BC | 32.49 | 19.11 | 8.34 | 13.56 | 2.32 |
| 50 | DORAL FNCL CORP | 10.65 | 6.72 | 9.16 | 13.75 | −4.02 |
| Total | | 11,073.21 | 7,096.00 | 7.56 | 10.08 | 1.36 |

2. We choose $\mu_t$ based on the time-series variation in the three-month OIS-Tbill spread. We calibrate the free parameter $\kappa$. In particular, we try different values of $\kappa$ aiming to hit two targets: (1) the aggregate LMI of the banking sector is around −$5 trillion during the financial crisis, roughly matching the amount of liquidity provided by the government,[9] and (2) the informativeness of the LMI for the cross section of bank liquidity risks is maximized.

[9] Direct liquidity support from the Fed, FHLB, FDIC, and U.S. Treasury total about $3.3 trillion (see footnote 1). We target a number somewhat higher than $3.3 trillion, to include an increase in implicit liquidity support via the government's deposit insurance on $6 trillion of bank deposits.

3. We base the asset liquidity weights on repo haircuts, but our repo haircut data are incomplete. To fill in the gaps, we place some structure on the liquidity weights. This approach leaves us with one free parameter, denoted by $\delta$ in the computation that follows. We choose the value of $\delta$ to match the LMI under our structured approach to the computation of the LMI using actual data for the subsample for where the repo data are complete and bilateral repo data are available.

### *A. Asset-Side Liquidity Weight*

The assets of a bank consist of cash, securities, loans and leases, trading assets, and intangible assets. The asset liquidity weight specifies the amount of cash that a bank can raise over a short horizon for a given level of assets. Note that weights vary by asset class and over time. For assets like cash and federal funds, which are ultra-liquid, we set $\lambda_{t,a_k} = 1$. For fixed and intangible assets, which are extremely difficult or time-consuming to convert into liquid funds, we set $\lambda_{t,a_k} = 0$. Below, we present our procedure for calibrating the weights on assets whose liquidity falls between these extremes. Further details are presented in Table IAI of the Internet Appendix.

We base our calibration on repo market haircuts. One minus the haircut in a repo transaction directly measures how much cash a firm can borrow against an asset. Haircuts are observable for most assets and reflect real-time market prices. Haircuts are also known to vary with measures of asset price volatility and tail risk for a given asset class, which are commonly associated with the market liquidity of the asset. Thus, the haircut on a repo is particularly attractive as a single measure of asset-side liquidity weights.

We form a panel of repo haircuts that vary by asset and over time. In an ideal world, the haircut data would reflect real transactions for all banks by collateral class. Such data do not exist. Our most comprehensive data come from both the tri-party market, which covers transactions between the largest banks and money market funds, and the secondary market for syndicated loans. Using these data, which cover all major asset categories, we extract the first principal component, $m_{PC1,t}$, from the panel of haircuts. This principal component captures 60% of the common variation across collateral types (asset classes). We also compute a loading, $\beta_k$, on this principal component for each asset class $k$. We define the asset liquidity weight as

$$\lambda_{t,a_k} = \exp(-(\overline{m}_k + \delta \times \beta_k m_{PC1,t})), \tag{20}$$

where $\overline{m}_k$ is the average haircut for asset $k$ over the sample. The variation in asset liquidity weights comes from $m_{PC1,t}$ over time and $(\overline{m}_k, \beta_k)$ across asset classes. Figure 1 plots the time series of $m_{PC1}$. We discuss the parameter $\delta$ below.

There are three advantages to this structured approach. First, it preserves a liquidity ranking across asset categories, which can otherwise be distorted by noise in the individual haircut series. Second, it can be easily extended to

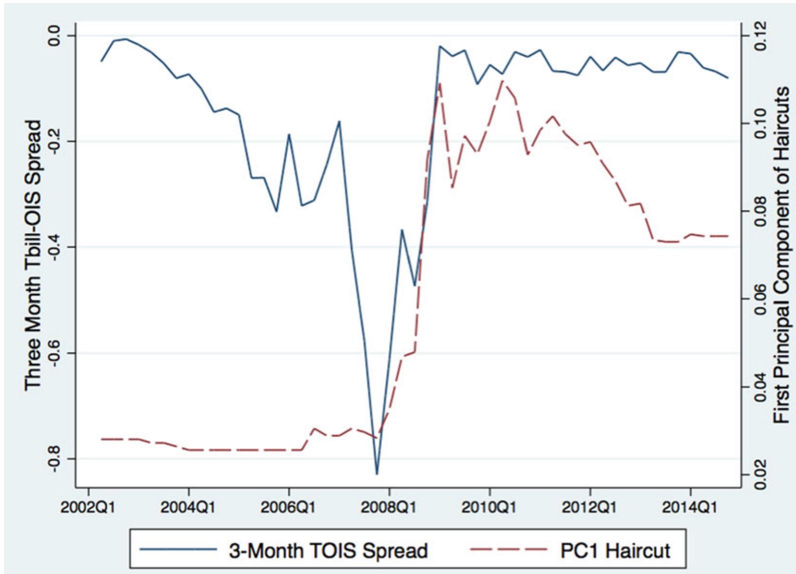


**Figure 1. Market factors for asset and liability liquidity weights.** The funding liquidity factor, the three-month Tbill-OIS (TOIS) spread in percentage, is plotted in solid blue (left axis). The first principal component (PC1) of haircuts across all asset categories, $m_{PC1}$ (measured in decimals), is plotted in dashed red (right axis). (Color figure can be viewed at wileyonlinelibrary.com)

time periods when haircut information is missing or incomplete as if it only requires knowledge about $\beta_k$ and $m_{PC1,t}$. This is an important advantage since most researchers and market participants do not have access to the time series of individual haircut data, and even regulators lack a full panel of historical data on haircuts, and thus to extend the LMI to a longer sample period or to a large set of users requires this simplification. Indeed, under this approach a researcher can model $m_{PC1,t}$ as a function of, say, asset price volatility and extend the measurement to periods with no haircut data. Last, as all haircuts are driven by a single factor, $m_{PC1,t}$, it is straightforward to conduct a liquidity stress test by shocking this factor. It is worth noting that, while we adopt a one-factor structure for simplicity, our approach can be readily extended to account for multiple haircut factors.

Our haircut data in the tri-party market cover transactions between money market funds and banks/dealers. From 2006Q3 to 2009Q4, we use data collected manually from the financial statements of money market funds. Our approach follows Krishnamurthy, Nagel, and Orlov (2014). For each fund, we parse forms N-Q, N-CSR, and N-CSRS from the SEC's Edgar website. We obtain the following information for each repo loan at its filing date: collateral type, collateral fair value, notional amount, repurchase amount at maturity, borrower identity, and lender identity. Using this information, we compute the haircut from the collateral fair value and the notional amount. Since 2010Q1, we use the tri-party repo data collected by the Federal Reserve Bank of New

**Table II**
## Haircuts by Collateral Type

For asset classes except bank loans, haircuts are collected from the tri-party repo market based on (i) manual collection from the financial statements of money market funds from 2006Q3 to 2009Q4, and (ii) the public release from the Federal Reserve Bank of New York from 2010Q1 to 2014Q3. Before 2006Q3, we use the haircut values as of 2006Q3 given that tri-party haircuts remain stable in normal times and thus can be reasonably extended to the earlier sample period. For bank loans, haircuts are based on the bid price as a percentage of par value in the secondary loan market, using data from 2002Q2 to 2014Q3. PC1 refers to the first principal component of the panel of haircuts.

| Collateral | Mean | *SD* | P5 | P25 | P50 | P75 | P95 |
|---|---|---|---|---|---|---|---|
| Panel A: Tri-Party Repo Market | | | | | | | |
| Treasury bonds | 0.018 | 0.003 | 0.012 | 0.016 | 0.020 | 0.020 | 0.020 |
| Agency bonds | 0.017 | 0.002 | 0.016 | 0.016 | 0.016 | 0.017 | 0.020 |
| Municipal bonds | 0.033 | 0.020 | 0.016 | 0.016 | 0.016 | 0.050 | 0.062 |
| Commercial paper | 0.034 | 0.009 | 0.027 | 0.027 | 0.035 | 0.039 | 0.044 |
| Corporate debt | 0.049 | 0.018 | 0.031 | 0.031 | 0.042 | 0.066 | 0.073 |
| Structured products | 0.059 | 0.013 | 0.039 | 0.045 | 0.068 | 0.068 | 0.068 |
| Equity | 0.073 | 0.023 | 0.052 | 0.052 | 0.066 | 0.090 | 0.114 |
| Panel B: Secondary Loan Market | | | | | | | |
| Bank loans | 0.061 | 0.083 | 0.010 | 0.020 | 0.020 | 0.060 | 0.255 |
| Average | 0.043 | 0.022 | 0.025 | 0.028 | 0.035 | 0.051 | 0.082 |
| PC1 | 0.054 | 0.032 | 0.030 | 0.034 | 0.077 | 0.106 | 0.141 |

York from two custodian banks, namely, Bank of New York Mellon and JP Morgan Chase. The haircut data are released monthly on the website of the Federal Reserve Bank of New York.[10] Before 2006Q3, we use the haircut values as of 2006Q3 given that tri-party haircuts are stable in normal times and thus can be reasonably extended to the earlier sample periods.

Between the extremes of liquid (cash) and illiquid (intangible) assets, there are a number of asset classes. These include Treasury securities, agency securities, municipal securities, commercial paper, corporate debt, structured products, and equity. Table II, Panel A, presents the distribution of tri-party repo haircut rates across the collateral types in our sample. It is clear that Treasury and agency bonds have the lowest haircuts when serving as collateral, with an average rate of slightly less than 2%. Municipal bonds and commercial paper have higher haircuts, with an average rate of 3%. Corporate debt, structured finance products, and equities have much lower collateral quality and hence even higher haircuts, with rates above 5%.

[10] See https://www.newyorkfed.org/banking/tpr_infr_reform_data.html.

Bank loans are the most important asset on a bank's balance sheet.[11] During the financial crisis, the value of bank loans plunged, which had a significant effect on asset-side liquidity. We measure the loan haircuts based on the bid price, as a percentage of par value, in the secondary loan market.[12] Table II, Panel B, reports haircut summary statistics for the secondary loan market. The loan haircut in the secondary market is relatively constant and remains less than 5% in normal times, then increases to as high as 40% during the 2008 to 2009 crisis. The average haircut over our sample is about 6% with a standard deviation of 8.3%.

As noted earlier, the tri-party repo market covers transactions between the largest banks and money market funds. Many financial institutions, including smaller ones, also transact in the bilateral repo market. It is well known that the haircuts in the tri-party market were much more stable than in the bilateral repo market (see Copeland, Martin, and Walker (2014) and Gorton and Metrick (2012)), and hence they may not accurately capture liquidity conditions for all banks, especially during the financial crisis. To address this concern, we introduce the parameter $\delta$ to bridge the gap between bilateral repo haircuts and tri-party repo haircuts (see equation (20)).

We experiment with different values of $\delta$, and settle on $\delta = 5$. For a short period of our sample, which includes the financial crisis, we have both bilateral and tri-party repo data.[13] The difference between bilateral data and tri-party data for selected asset classes is plotted in Figure 2 in Copeland, Martin, and Walker (2014). We regress the time series of bilateral repo haircuts on the tri-party repo haircuts, by asset class. The regression coefficients vary from 3.5 (Treasury bonds) to 7.9 (structured products). These numbers thus provide a lower and upper boundary for $\delta$. Table IAIII in the Internet Appendix recomputes the LMI for $\delta = \{3.5, 5.0, 7.9\}$. We also compute the LMI using the actual bilateral haircut data for the period August 2007 to February 2010 when the data are available. We note that lowering $\delta$ increases the LMI, as expected. Using $\delta = 5.0$ sets the aggregated LMI at the trough of the financial crisis (min LMI) closest to the corresponding value when using the actual bilateral data. We thus settle on $\delta = 5$.

[11] Over our sample, on average bank loans account for slightly more than 50% of total assets. The proportion of other asset classes on bank balance sheets is 16.9% for cash and its equivalents, 1.6% for Treasury securities, 10.2% for agency securities, 1.4% for municipal securities, 2.0% for structured products, 2.8% for corporate debt, 0.4% for equity securities, and the remainder for intangible, fixed, and other assets.

[12] The historical average data are collected from http://www.lsta.org for the secondary loan market.

[13] We thank Adam Copeland for the bilateral data.

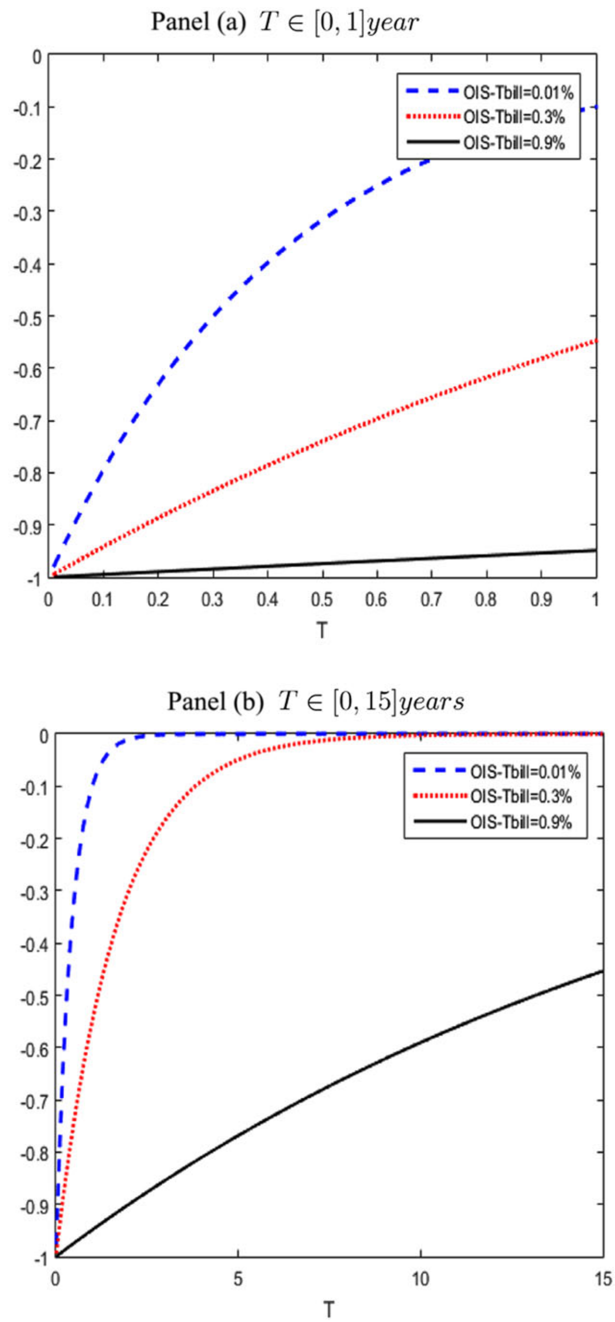


**Figure 2. Liability liquidity weights.** $\lambda_{L_k} = -\exp(\kappa \cdot \ln(OIS - Tbill)T_{k'})$. We set $\kappa = 0.5$ as in our calibration. (Color figure can be viewed at wileyonlinelibrary.com)

### B. Liability-Side Liquidity Weights

According to our model, the liability-side liquidity weights are determined jointly by $\{\mu_t, T_{k'}\}$:

$$\lambda_{t,l_{k'}} = -e^{-\mu_t T_{k'}}. \tag{21}$$

The parameter $\mu_t$ captures the expected stress duration, which is measured as

$$-\mu_t = \kappa \ln(\text{OIS-Tbill}),$$

where OIS-Tbill is the spread between the three-month OIS rate and the Treasury bill at time $t$. We then have,

$$\lambda_{t,l_{k'}} = -e^{\kappa \, ln(\text{OIS-Tbill}) T_{k'}}.$$

The parameter $T_{k'}$ indicates a liability's time-to-maturity. Figure 2 plots the liability-side liquidity weight as a function of the maturity parameter $T_{k'}$, for different values of the market liquidity premium and for $\kappa = 0.5$. The left panel focuses on time-to-maturity of less than one year, $T_{k'} \in [0, 1]$, while the right panel shows a longer maturity spectrum, $T_{k'} \in [0, 15]$ years. In normal times when the OIS-Tbill spread is small (dashed blue line, OIS-Tbill(%) = 0.01), only the very short-term liabilities have high weights (in absolute value, which means higher liquidity pressure). During a liquidity crisis (solid black line, OIS-Tbill(%) = 0.9), many types of liabilities have larger weights except for the very long-duration securities such as equity.

We set overnight financing (federal funds and repo) to have a maturity of zero ($T = 0$) and commercial paper to have a maturity of one month. Debt with a maturity of less than or equal to one year has $T = 1$, debt with a maturity longer than one year has $T = 5$, subordinated debt has $T = 10$, and equity has $T = 30$. For insured deposits, which are free from the risk of a run, we use $T = 10$, while for uninsured deposits, which are more vulnerable to liquidity outflows and hence have a shorter effective maturity, we use $T = 1$. We also examine the liquidity sensitivity of off-balance-sheet securities. We label these off-balance-sheet items as *contingent liabilities*, which include unused commitments, credit lines, securities lent, and derivative contracts. Contingent liabilities have played an increasingly important role in determining a bank's liquidity condition, especially during the 2007 to 2009 financial crisis. Given their relative stickiness to rollover in normal times, we assign a maturity of $T = 5$ or $T = 10$ years depending on the liquidity features of the contingent liability. For more details, see Table IAII of the Internet Appendix. There is some subjectivity in our choices for $T$ in cases in which $T$ is not explicitly specified in the terms of a contract.[14]

The literature considers many proxies for the liquidity premium. Figure 3 plots a number of common spreads, including the Libor-OIS spread, the TED

[14] We have consulted extensively with central bankers and economists at the BIS, ECB, and Federal Reserve Board in making these choices. The choices of $T$ reflect their collective wisdom.

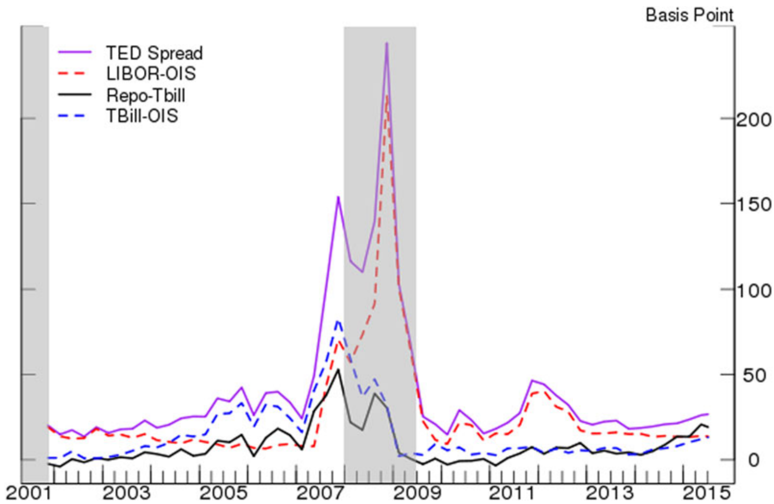


**Figure 3. Proxies for funding liquidity premium.** The TED spread is the spread between three-month euro and Treasury bill rates. LIBOR-OIS is the spread between three-month LIBOR and OIS swap rates. Repo-Tbill is the spread between three-month repo and Treasury bill rates. Tbill-OIS is the spread between three-month OIS and Treasury bill rates. All spreads are measured in basis points. (Color figure can be viewed at wileyonlinelibrary.com)

spread (Libor-Tbill), the Repo-Tbill spread, and the OIS-Tbill spread. We note that the Libor-OIS and the TED spreads both increase in the fall of 2007, and then increase higher in the fall of 2008. In contrast, the Repo-Tbill and the OIS-Tbill spreads reach their highest point in late 2007. One concern with Libor-indexed spreads is that they are contaminated by credit risk (Smith (2012)), which is not directly related to liquidity. For this reason, we use the OIS-Tbill spread as such a spread is likely to be minimally affected by credit risk—since Treasury bills are more liquid than overnight federal funds loans, this measure captures any time variation in the valuation of liquid securities. Nagel (2016) proposes an alternative liquidity premium measure, the Repo-Tbill spread. Figure 3 shows that both the Repo-Tbill spread and the OIS-Tbill spread have similar time-series patterns, both peaking in late 2007. Indeed, the two measures have a correlation coefficient of 0.90. All of our empirical results (magnitude and significance) remain unchanged if we use the Repo-Tbill spread to proxy for the liquidity premium tasks.[15]

The parameter $\kappa$ scales the OIS-Tbill spread in the liability liquidity weights. We choose $\kappa = 0.5$. Table IAIII in the Internet Appendix presents the results for $\kappa = \{0.25, 0.50, 1.50, 2.00\}$. With a larger $\kappa$, the liquidity weight (in absolute value) in liabilities is lower, that is, liabilities generate less liquidity pressure.

[15] Furthermore, as opposed to other measures of the liquidity premium, say microstructure measures drawn from stocks or bonds, the OIS-Tbill spread is more closely aligned with the funding conditions of financial intermediaries. Indeed, this spread has been volatile and strikingly large since the subprime crisis of 2007, suggesting a deterioration in funding liquidity.

We note that $\kappa = 0.5$ sets the minimum value of the aggregated LMI to be around $-\$6$ trillion (the range is from roughly $-\$10$ trillion to $+\$1$ trillion). We are aiming for a target of $-\$5$ trillion, which is roughly the magnitude of government support to the banking system during the crisis and thus is a guide as to the liquidity shortfall of the banking system. The table also reports the performance of the LMI in describing the cross section of bank liquidity risks. We discuss these results more fully in the section below. For now, we note that setting $\kappa = 0.5$ maximizes the informativeness of the LMI in the cross section.

With the detailed balance sheet information, haircut data, and liquidity premium proxy, one can construct the LMI for any institution in the banking system using the steps outlined in Internet Appendix Section I. We next examine the macro- and microperformance of the LMI in the following two sections.

## III. LMI as a Macroprudential Barometer

An LMI aggregate is a useful macroprudential barometer of systemic risk, which is a principal advantage of our method in measuring liquidity. When the aggregate is low, the banking sector is more susceptible to a liquidity stress (i.e., bank runs). In this section, we first document the time-series variation in LMI aggregates. We then provide evidence on the factors that drive the time-series variation. Finally, we conduct a stress test using the aggregate LMI and show that such a stress test could have signaled the fragility of the banking system in early 2007.

### *A. Time-Series Variation in the Aggregated LMI*

We present two LMI aggregates, LMI-minus ($= \sum_i \min(LMI^i, 0)$) and aggregate LMI ($= \sum_i LMI^i$). Summed across all BHCs, aggregate LMI equals the overall liquidity mismatch in the banking system. LMI-minus, which is our preferred measure, is the sum across only those banks with a negative LMI and thus measures the liquidity shortfall in the event that every bank that is susceptible to a run suffers that run. Note that an important advantage of the LMI metric is that it can be aggregated across firms and sectors. In contrast, Basel's liquidity measures, which are ratios, cannot be meaningfully aggregated.

Figure 4 plots these liquidity aggregates for the universe of BHCs over the 2002Q2 to 2014Q3 sample period. In normal times, LMI-minus is near zero, meaning that the banking sector is healthy and faces little risk of a run. Beginning in early 2007, when the banking sector started to face stress LMI-minus turns significantly negative. Recall that a lower LMI at the firm level indicates a balance sheet that is more vulnerable to liquidity stress. At its trough, LMI-minus is $-6.6$ trillion, which is of similar magnitude as the Fed and other government liquidity provision actions. Note that we have calibrated the parameter $\kappa$ to match this magnitude. Turning to aggregate LMI ($\widetilde{LMI}$), this measure is significantly positive before and after the crisis, indicating that,

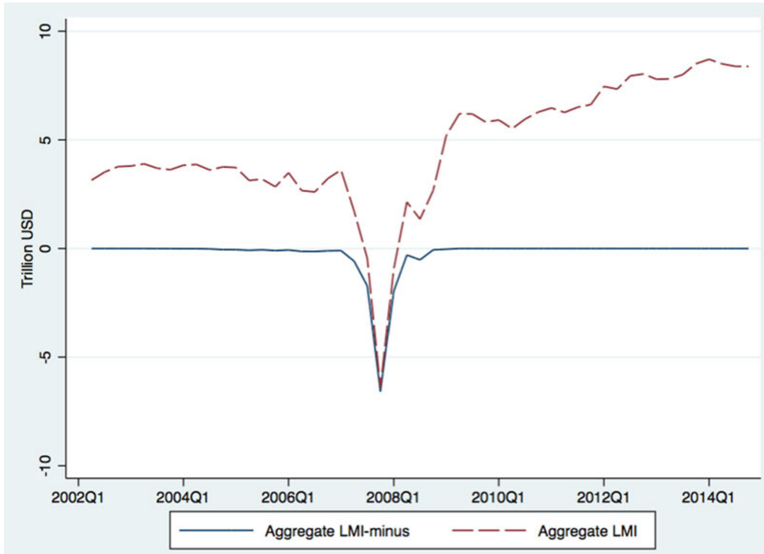


**Figure 4. Aggregate liquidity mismatch for all BHCs ($trillion).** We present time-series plots of the two LMI aggregates, $\widetilde{LMI}_t = \sum_i LMI_t^i$ and $[LMI]_t^- = \sum_i \min(LMI_t^i, 0)$. (Color figure can be viewed at wileyonlinelibrary.com)

typically, the average bank is sufficiently liquid to service its liabilities. During the financial crisis, however, aggregate LMI turns negative, approaching the value of LMI-minus. The trough of the liquidity mismatch occurs three quarters before Lehman Brothers' bankruptcy and six quarters before the low of the stock market.

To shed further light on the composition of aggregate LMI, in Figure 5, we present the liquidity mismatch for on- and off-balance-sheet items. Off-balance-sheet liquidity pressure is minimal in normal times, but increases rapidly to −$5.0 trillion during the crisis period. Such evidence suggests that off-balance-sheet contingent liquidity plays an important role particularly during periods of market stress. Panel A plots the values of aggregated LMI, while Panel B zooms in on the crisis period, plotting LMI-minus.

### *B. Federal Reserve Liquidity Injection and the Increase in the LMI in 2008*

We next discuss the impact of the government's liquidity injection on the LMI and show that the increase in the LMI in 2008 is driven, in part, by these injections. The Fed launched a range of new programs for the banking sector to support overall market liquidity (see the survey paper of Fleming (2012)). This liquidity support began in 2007Q4 with the Term Auction Facility and continued with other programs (see Table IAIV of the Internet Appendix). It is apparent from Figure 4 that the improvement in the aggregate liquidity position of the banking sector coincides with the Fed's liquidity injection. While

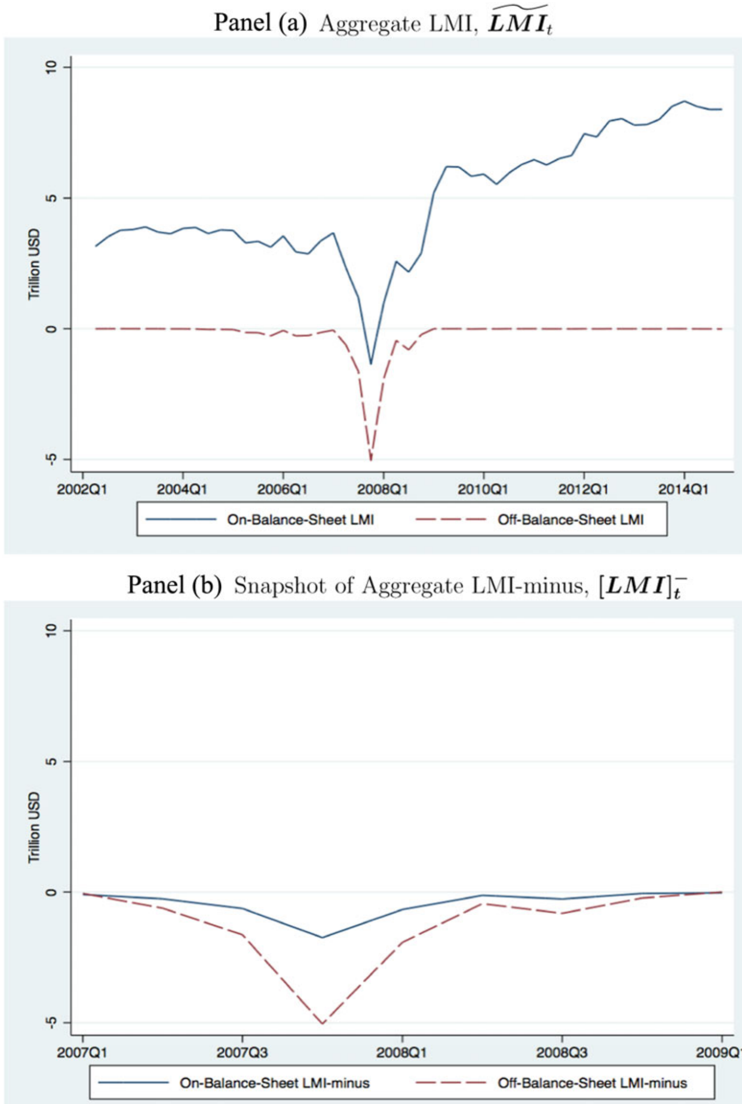


**Figure 5. Liquidity mismatch on and off balance sheet.** (Color figure can be viewed at wileyonlinelibrary.com)

we cannot demonstrate causality, it is likely that the liquidity injection played a role in the increase in aggregate LMI in 2008.

We study the effect of the Fed injections on the cross section of the LMI. A total of 559 financial institutions received liquidity from the Fed,[16] of which

[16] One parent institution may have different subsidiaries receiving the liquidity injection. For example, AllianceBearnStein is an investment asset management company. Under this company,

87 are BHCs. These BHCs borrowed on average \$95.8 billion, with a median value of \$0.7 billion. The bank-level borrowing amount ranges from \$5 million to \$2 trillion. The 10 BHCs that received the most liquidity are Citigroup, Morgan Stanley, Bear Sterns, Bank of America, Goldman Sachs, Barclays's U.S. subsidiary, JP Morgan Chase, Wells Fargo, Wachovia, and Deutsche Bank's U.S. subsidiary, Taunus.

Figure 6 plots the relation between the Fed liquidity injection and the change in LMI, cross sectionally. The liquidity injection is captured by the log of the dollar amount of loans received by a given BHC, and the change in LMI is captured by the log of the difference in the LMI between the postcrisis (2009Q3 to 2012Q1) and the precrisis (2006Q1 to 2007Q2) periods (Panel A) and between the postcrisis (2009Q3 to 2012Q1) and the crisis (2007Q3 to 2009Q2) periods (Panel B). Both panels document a strong positive correlation between the change in LMI and the level of the Fed liquidity injection. This evidence confirms that the Fed's liquidity facilities increased banking sector liquidity.

### C. LMI Decomposition: Asset versus Liability

The calculation of the LMI depends on assets, liabilities, and liquidity weights. Panel A of Figure 7 shows the dollar amount of asset-side and liability-side liquidity (in absolute values) for the universe of BHCs. Two patterns stand out. First, movements in both asset-side and liability-side liquidity contribute to the movement in the LMI, but movements in the liability side play a larger role during times of stress. During stress periods, the rollover problem of short-term debt and calls from contingent liabilities create the biggest liquidity problems. The off-balance-sheet contingent liability contributes almost half of the increase in the liability-side LMI. This is consistent with the observations that shadow banking played a crucial role in reducing liquidity during the crisis. Second, although changes in asset-side liquidity seem relatively small compared to changes in liability-side liquidity, the absolute decrease in asset liquidity is by no means small. Around the Lehman event, asset liquidity drops by around \$1.2 trillion, mostly due to the reduction in secondary market prices of relatively low-quality assets such as loans (the haircut of loans fell on average to 40% after the Lehman event).

Panel B of Figure 7 plots the effective liquidity weights of assets and liabilities. The effective liquidity weights are defined as liquidity-weighted assets (or liabilities) divided by total assets (liabilities) used in the bank-level LMI calculation. The weights are average effective weights across banks. The figure provides a sense of the extent to which the variation in haircuts, as captured by $m_{PC1}$, and funding liquidity condition, as captured by the OIS-Tbill spread, drives the LMI.

seven borrowers are listed in the Fed data, such as AllianceBearnStein Global Bond Fund, Inc., AllianceBearnStein High Income Fund, Inc., AllianceBearnStein TALF Opportunities Fund, etc.

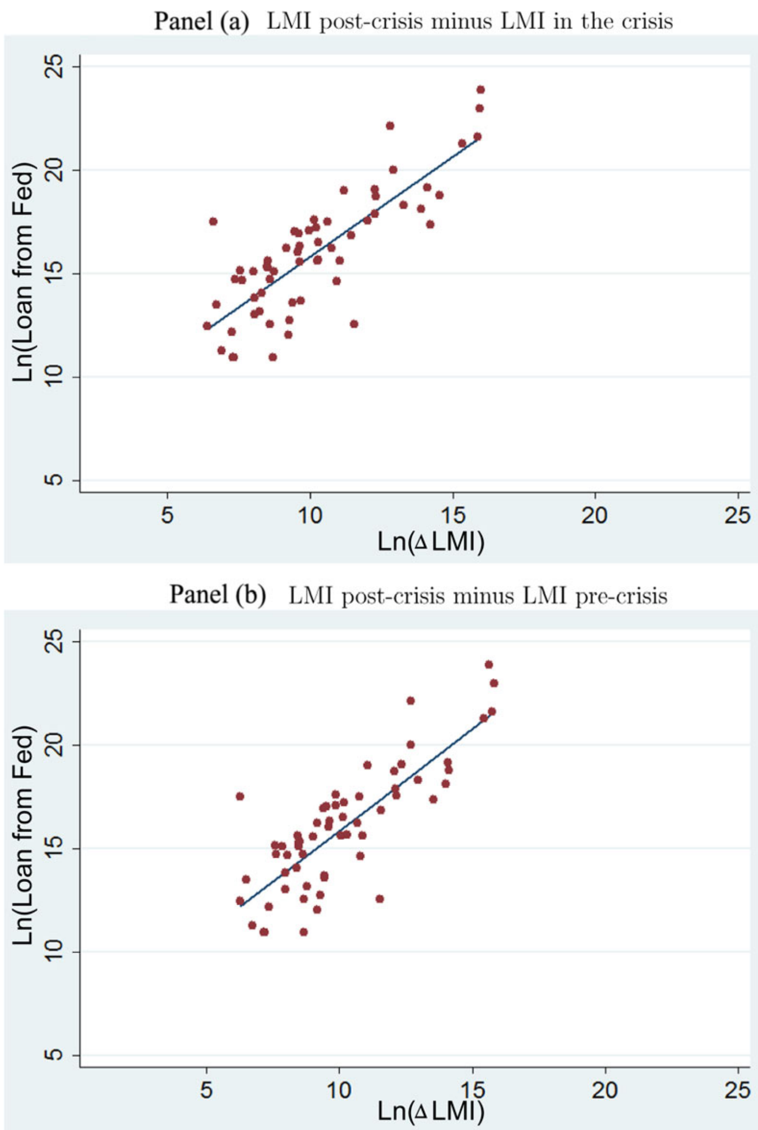


**Figure 6. Correlation between Federal Reserve injections (ln(*loan*)) and the change in LMI (ln(Δ*LMI*).** The precrisis sample period is from 2006Q1 to 2007Q2, the crisis period is from 2007Q3 to 2009Q2, and the postcrisis period is from 2009Q3 to 2012Q1. (Color figure can be viewed at wileyonlinelibrary.com)

### *D. The Importance of Time-Varying Liquidity Weights*

Changes in liquidity weights play an important role in the movements of the LMI. Figure 8 plots aggregate LMI, $\widetilde{LMI}$, in Panel A and LMI-minus, $[LMI]^{-}$,

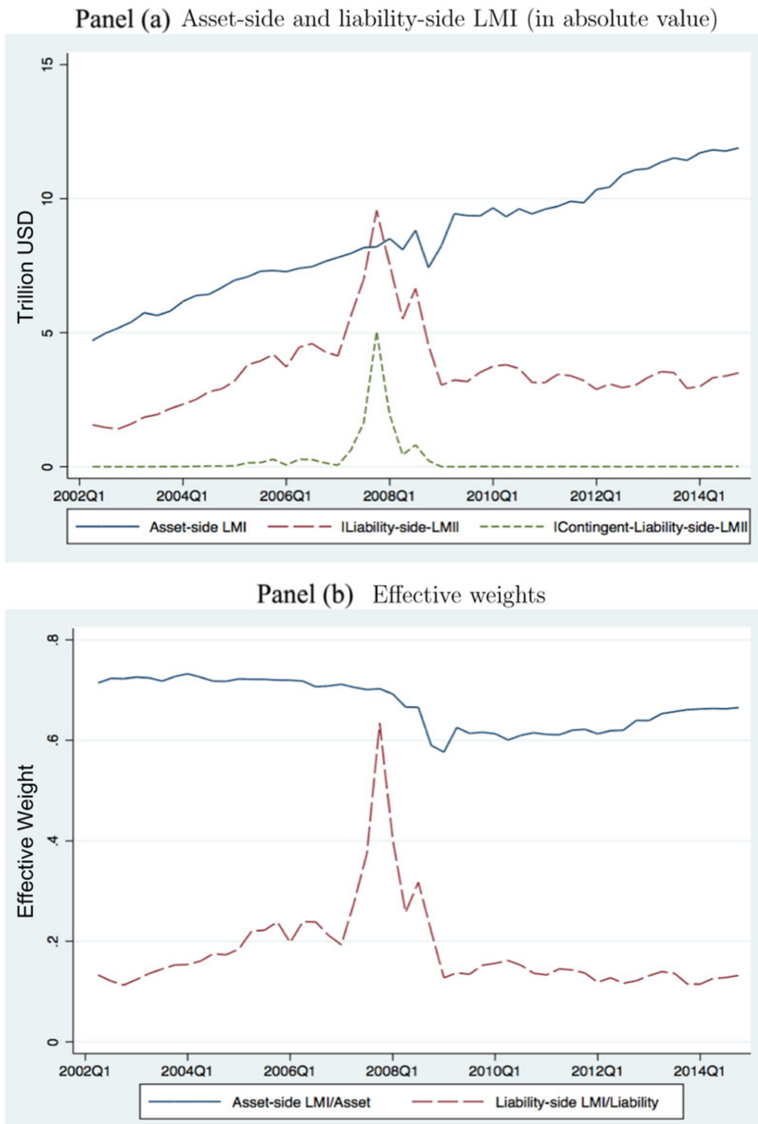


**Figure 7. Decomposition of LMI by assets and liabilities.** To facilitate comparison, we use the absolute value of liability-side and contingent-liability-side LMI in Panel A. Panel B depicts the average effective weights across banks, defined as the liquidity-weighted assets (liabilities) divided by the total assets (liabilities) used in the bank-level LMI calculation. (Color figure can be viewed at wileyonlinelibrary.com)

in Panel B, under three weighting schemes: the blue line is our baseline case with time-varying weights as shown in Figure 4; the red dashed line uses a fixed set of weights as of 2002Q2 (beginning of the sample), which represents normal liquidity conditions; and the green dashed line uses weights as of 2007Q4,

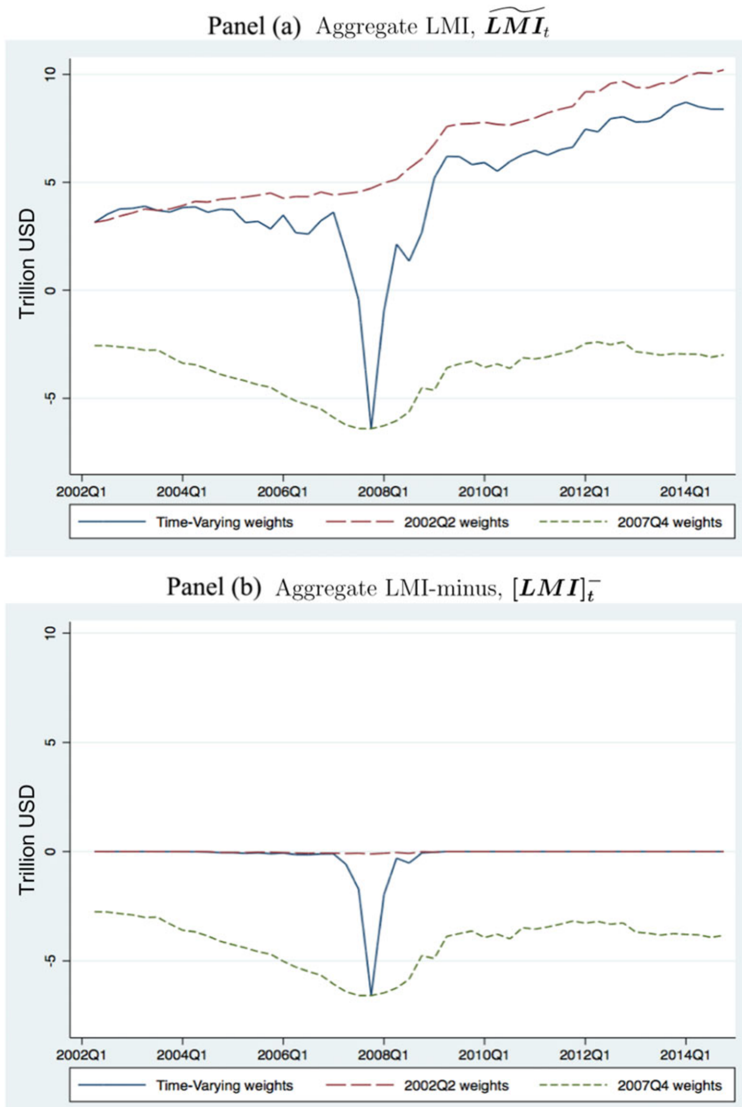


**Figure 8. LMI under various liquidity weights.** The blue solid line is our baseline case with time-varying weights; the red dashed line uses a fixed set of weights as of 2002Q2 (beginning of sample), which captures normal liquidity conditions; and the green dashed line uses weights as of 2007Q4, which captures stressed liquidity conditions. All three lines use the same contemporaneous balance sheet information. (Color figure can be viewed at wileyonlinelibrary.com)

which captures stressed liquidity conditions. All three lines use actual balance sheet information for each quarter. The figure therefore highlights the role of changing liquidity weights in driving changes in the LMI. The three variations show that the time-varying weights contribute to a difference in liquidity of approximately \$12 trillion in the trough of 2007Q4 compared with using the weight as of 2002Q2.

The figure also highlights the importance of adopting a time-varying weight that is linked to market conditions to accurately measure banking sector liquidity. If we were to use the constant weights calibrated to normal times, we would severely underestimate liquidity conditions during times of market stress. For example, Panel B indicates that, under the weighting scheme of 2002Q2, $[LMI]^{-} \approx 0$ during the financial crisis, which would suggest that there was no liquidity problem in the banking sector. This is clearly absurd. In this fixed-weight case, aggregate banking liquidity remains good because it is driven primarily by the growing assets of the banking sector. At the other extreme, if we were to use the constant weights calibrated to time of market stress, we would overestimate the liquidity stress in normal periods and underestimate the transition to a crisis. For example, LMI-minus in normal times under the severely stressed weights is around −\$3 trillion and falls to only −\$6 trillion during the crisis.

### *E. Fragility Measures: Liquidity Stress Test and Liquidity Risk*

Since 2012 the Federal Reserve has engaged in liquidity stress tests under its CLAR. The liquidity stress test is an addition to the Supervisory Capital Assessment Program (SCAP), which has become a standard process to test whether a bank has sufficient capital to cover a given stress event. The decomposition in Figure 8 illustrates a simple methodology for running along a liquidity stress test within our measurement framework. The only difference across the three lines in the figure pertains to the liquidity weights, which are determined by the time-varying repo haircuts and the funding liquidity factor. We argue that a liquidity stress test can be implemented as a set of realizations of repo haircuts and the funding liquidity factor, with these realizations traced through the liquidity weights to compute stress effects on the liquidity of a given bank.

We run a liquidity stress test at three points in time: 2007Q2, which is two quarters before the liquidity trough; 2007Q3, which is one quarter before the liquidity trough; and 2012Q4, which is the first time the Federal Reserve ran its liquidity stress test. Table III reports the results. Consider the first set of columns, which correspond to 2007Q2. The first row in the benchmark, denoted by "T," corresponds to the value as of 2007Q2. The next line, denoted by "[0,T]," reports the historical average value up to this point. We then compute LMI-minus, $[LMI]^{-}$, and aggregate LMI, $\widetilde{LMI}$, under three stress scenarios: both cross-collateral haircuts ($m_{PC1,t}$) and the funding liquidity factor (OIS-Tbill) worsen $1\sigma$, $2\sigma$, and $3\sigma$ from their time-$T$ values. Here, $\sigma$ is calculated as the historical standard deviation between 2002Q2 and time $T$.

Recall that the aggregate liquidity shortfall, $[LMI]^{-}$, was −\$6.6 trillion in the liquidity trough of 2007Q4. Given the stress test table, this severe liquidity

**Table III**

## Liquidity Stress Test

The table reports LMI-minus, $[LMI]^-$, and aggregate LMI, $\widetilde{LMI}$, under stress scenarios when both the funding liquidity factor (OIS-Tbill) and the haircut factor deviate $1\sigma$, $2\sigma$, and $3\sigma$ from their values at time $T$, for $T = $ 2007Q2, 2007Q3, 2012Q4. Here, $\sigma$ is calculated based on data from 2002Q2 to time $T$. We present two benchmarks. Benchmark $T$ refers to the aggregate estimated at time $T$; benchmark $[0, T]$ refers to the historical average value of the aggregate from 2002Q2 to time $T$. All entries in the table are in trillions of dollars. The three dates $T$ correspond to: 2007Q2, which is two quarters ahead of the liquidity crunch (the trough of aggregate liquidity occurs in 2007Q4); 2007Q3, which is one quarter ahead of the liquidity crunch; and 2012Q4, which is the first system-wide stress test of bank liquidity by the Federal Reserve.

| $T = $ 2007Q2 | | | $T = $ 2007Q3 | | | $T = $ 2012Q4 | | |
|---|---|---|---|---|---|---|---|---|
| | $[LMI]^-$ | $\widetilde{LMI}$ | | $[LMI]^-$ | $\widetilde{LMI}$ | | $[LMI]^-$ | $\widetilde{LMI}$ |
| Benchmark | | | Benchmark | | | Benchmark | | |
| $T$ | −0.59 | 1.72 | $T$ | −1.72 | −0.45 | $T$ | −0.00 | 8.03 |
| $[0, T]$ | −0.07 | 3.37 | $[0, T]$ | −0.15 | 3.19 | $[0, T]$ | −0.30 | 4.02 |
| Stress Scenario | | | Stress Scenario | | | Stress Scenario | | |
| $1\sigma$ | −1.26 | 0.29 | $1\sigma$ | −3.80 | −3.37 | $1\sigma$ | −0.00 | 5.95 |
| $2\sigma$ | −2.45 | −1.68 | $2\sigma$ | −7.95 | −7.80 | $2\sigma$ | −0.01 | 3.56 |
| $3\sigma$ | −4.71 | −4.44 | $3\sigma$ | −14.55 | −14.45 | $3\sigma$ | −0.88 | 0.16 |

dryup approximates a $2\sigma$ event in 2007Q3 (one quarter head) and a more than $3\sigma$ event in 2007Q2 (two quarters ahead).

The stress test provides a measure of liquidity risk, that is, the fragility of the banking system to market or funding liquidity shocks. Such a measure can be an early warning indicator of a crisis. In 2007Q2, LMI-minus under a $1\sigma$ shock is $-\$1.26$ trillion. Figure 9, Panel B, plots LMI-minus, along with LMI-minus in the $1\sigma$ and $2\sigma$ cases over the period 2004Q4 to 2011Q4. We see that the stress test indicates fragility in early 2007 when LMI-minus starts to dip significantly below zero. The liquidity shortage for the entire U.S. banking sector starts to explode in 2007Q2. To make the figure visually readable, we truncate the $y$-axis at $-\$8$ trillion. Dashed lines under stress scenarios 1 and 2 are thus not visible during the most extreme period.

## IV. LMI and the Cross Section of Banks

In the previous section, we present one set of criteria for evaluating the LMI, namely, its utility from a macroprudential viewpoint. We now consider another set of criteria for evaluating the LMI. If the LMI contains information regarding the liquidity of a given bank, then changes in market and funding liquidity conditions will affect banks' performance differently depending on their LMIs, that is, as liquidity conditions deteriorate, a bank with a lower LMI should experience worse performance. Moreover, during the financial crisis, banks with a lower ex-ante LMI should depend more on liquidity support from the government.

We begin this section descriptively. We first examine which bank characteristics correlate with their LMIs. We then examine the informativeness of the LMI in predicting a bank's borrowing decision and a bank's stock market crash risk during the financial crisis.

### *A. Bank Characteristics and Liquidity*

We investigate the relationship between the LMI and bank characteristics for the universe of BHCs. Table IV presents the results from regressing the LMI (Panel A) and the LMI risk exposure metric (Panel B), both scaled by total assets, on a set of bank characteristics including risk-adjusted assets, the Tier 1 capital ratio, the Tier 1 leverage ratio, and ROAs. In Panel A, columns (1) to (5) present regressions where we pool all of the data together, and columns (6) to (9) report regressions based on the data at a single point in time. The latter columns better characterize the data because the strength of the relation between the different variables changes between precrisis, crisis, and postcrisis periods. The common finding from this panel is that a higher quantity of risk-adjusted assets is associated with a lower level of liquidity. That is, larger banks skate closer to the edge when it comes to liquidity. This effect is more pronounced precrisis, and falls over time, perhaps because of increased prudence by large banks and their regulators. We also see that a higher ROA is associated with a lower level of liquidity. Plausibly, holding less liquidity is

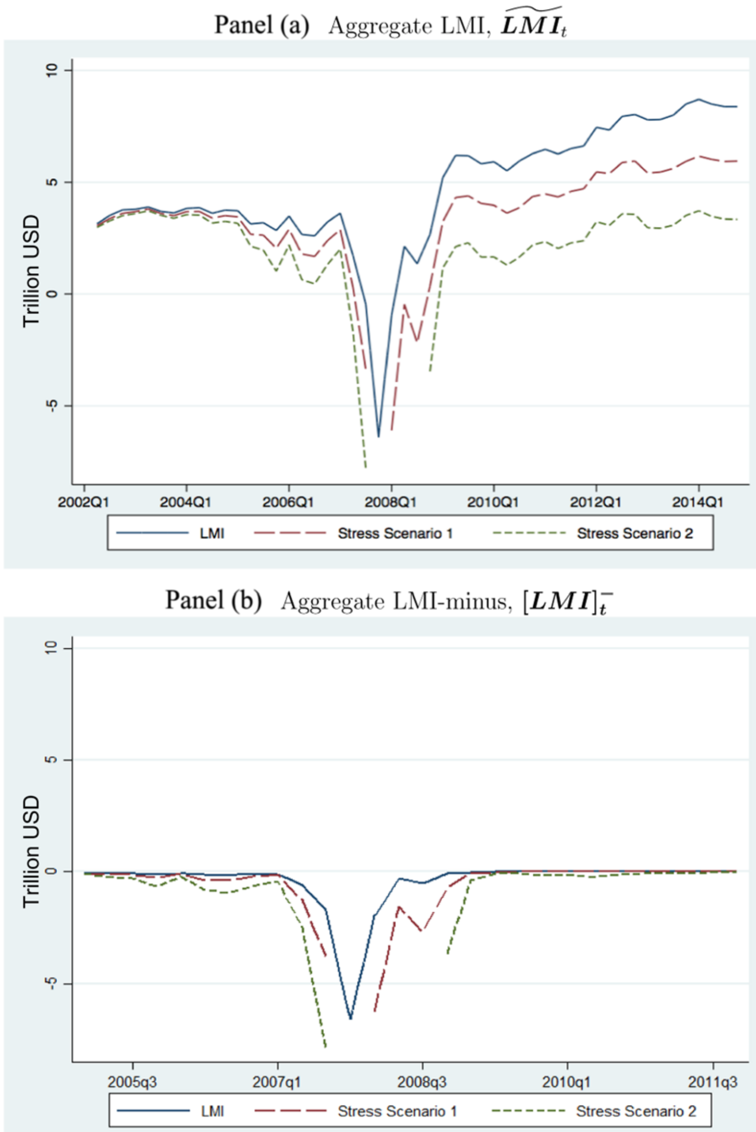


**Figure 9. LMI under $1\sigma$ and $2\sigma$ stress scenarios.** In stress scenario 1, both the haircut factor ($m_{PC1}$) and the funding liquidity factor (OIS-Tbill spread) are shocked $1\sigma$ from their time $-t$ values, where $\sigma$ is calculated as the historical standard deviation using data up to time $t$. Stress scenario 2 refers to a $2\sigma$ situation. To make the figure readable, we truncate the $y$-axis at $-\$8$ trillion level. Dashed lines under stress scenarios 1 and 2 are therefore not visible during the most extreme period. (Color figure can be viewed at wileyonlinelibrary.com)

**Table IV**

**The Relationship between LMI and Bank Characteristics**

This table relates the bank-level LMI to bank characteristics for the universe of public BHCs from 2002Q2 to 2014Q3. Panel A uses LMI scaled by total assets as the dependent variable. Panel B evaluates liquidity risk and uses the scaled LMI–$\text{LMI}_{1\sigma}$ as the dependent variable, where $\text{LMI}_{1\sigma}$ refers to the LMI under a $1\sigma$ stress scenario when both the haircut factor and the OIS-Tbill factor are shocked by $1\sigma$. Bank characteristics include risk-adjusted assets, the Tier 1 capital ratio, the Tier 1 leverage ratio, and return on assets (ROA). Columns (1) to (5) report pooled regressions using the full sample, and columns (6) to (9) report cross-sectional regressions for selected quarters: 2002Q2 (beginning of sample), 2007Q4 (trough of funding liquidity), 2008Q3 (Lehman event quarter), and 2014Q3 (end of sample). In the pooled regressions, the standard errors are robust and clustered by bank. We report $p$-value for the estimation in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Panel A: Dependent Variable = Scaled LMI

| | Full Sample | | | | | 2002Q2 | 2007Q4 | 2008Q3 | 2014Q3 |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Risk-adj assets | −0.35*** | | | | −0.34*** | −0.91*** | −0.67*** | −0.33*** | −0.14*** |
| | (0.00) | | | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Tier 1 capital ratio | | 0.16 | | | 0.65*** | −0.02 | 2.01* | 0.35 | 0.54*** |
| | | (0.19) | | | (0.00) | (0.96) | (0.06) | (0.55) | (0.00) |
| Tier 1 leverage ratio | | | 0.17 | | −0.57** | −0.03 | −0.25 | 0.07 | −0.29 |
| | | | (0.23) | | (0.04) | (0.96) | (0.92) | (0.95) | (0.23) |
| ROA | | | | −0.50*** | −0.63*** | −1.06*** | −1.56*** | −0.35*** | −0.50*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) |
| Intercept | 0.56*** | 0.53*** | 0.54*** | 0.56*** | 0.53*** | 0.70*** | −0.17* | 0.32*** | 0.53*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.09) | (0.00) | (0.00) |
| $N$ | 21,277 | 21,277 | 21,278 | 22,033 | 21,271 | 510 | 400 | 388 | 332 |
| Adj $R^2$ | 0.05 | 0.01 | 0.00 | 0.01 | 0.09 | 0.23 | 0.17 | 0.18 | 0.30 |

(*Continued*)

**Table IV**—*Continued*

| Panel B: Dependent Variable = Scaled (LMI – $LMI_{1\sigma}$) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Full Sample | | | | | 2002Q2 | 2007Q4 | 2008Q3 | 2014Q3 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Risk-adj assets | 0.06*** | | | | 0.06*** | 0.01*** | 0.44*** | 0.07*** | –0.00 |
| | (0.00) | | | | (0.00) | (0.00) | (0.00) | (0.00) | (0.88) |
| Tier 1 capital ratio | | 0.03 | | | –0.35*** | –0.04*** | –1.02 | –0.70* | –0.16 |
| | | (0.81) | | | (0.00) | (0.00) | (0.12) | (0.08) | (0.10) |
| Tier 1 leverage ratio | | | 0.04 | | 0.36*** | 0.05*** | 0.23 | 0.72 | –0.17 |
| | | | (0.82) | | (0.00) | (0.00) | (0.87) | (0.32) | (0.29) |
| ROA | | | | 0.21*** | 0.30*** | 0.26*** | 0.75*** | 0.15*** | 0.39*** |
| | | | | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Intercept | 0.09*** | 0.09*** | 0.09*** | 0.09*** | 0.10*** | 0.01*** | 0.45*** | 0.23*** | 0.17*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $N$ | 21,277 | 21,277 | 21,278 | 22,033 | 21,271 | 510 | 400 | 388 | 332 |
| Adj $R^2$ | 0.01 | 0.00 | 0.00 | 0.01 | 0.04 | 0.09 | 0.15 | 0.13 | 0.15 |

**Table V**

**The Relationship between Asset Liquidity and Liability Liquidity**

This table relates asset-side liquidity and liability-side liquidity in the cross section of banks. Columns (1) and (2) report pooled regressions using the full sample from 2002Q2 to 2014Q3, and columns (3) to (6) report cross-sectional regressions for selected quarters: 2002Q2 (beginning of sample), 2007Q4 (trough of funding liquidity), 2008Q3 (Lehman event quarter), and 2014Q3 (end of sample). In the pooled regression, the standard errors are robust and clustered by bank. We report $p$-value for the estimation in parentheses. $^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

| Dependent Variable = Asset_LMI/Total Assets | | | | | | |
|---|---|---|---|---|---|---|
| | Full Sample | | 2002Q2 | 2007Q4 | 2008Q3 | 2014Q3 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| \|Liab_LMI\|/Total assets | 0.10*** | 0.09*** | −0.33** | 0.01 | 0.12** | 0.16** |
| | (0.00) | (0.00) | (0.02) | (0.75) | (0.04) | (0.05) |
| Tier 1 capital ratio | | 0.00*** | 0.01 | −0.01 | 0.00 | 0.01*** |
| | | (0.00) | (0.12) | (0.37) | (0.43) | (0.00) |
| Tier 1 leverage ratio | | −0.00*** | −0.01 | 0.02** | 0.01 | −0.02*** |
| | | (0.00) | (0.35) | (0.03) | (0.38) | (0.00) |
| ROA | | 0.00 | 0.00 | −0.00 | 0.00 | −0.00 |
| | | (0.13) | (0.14) | (0.79) | (0.95) | (0.94) |
| Intercept | 0.61*** | 0.61*** | 0.71*** | 0.58*** | 0.52*** | 0.62*** |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| $N$ | 2,500 | 2,500 | 50 | 50 | 50 | 50 |
| Adj $R^2$ | 0.06 | 0.07 | 0.13 | 0.06 | 0.10 | 0.59 |

less of a drag on profits, or is correlated with bank characteristics that involve more risk-taking. Although the results are weaker, we see that higher levels of capital are associated with higher liquidity, while higher leverage is associated with lower liquidity.

Panel B reports results for the LMI risk exposure metric. The results are broadly similar to those in Panel A, albeit weaker. In particular, larger and more profitable banks have more liquidity risk, while banks with higher capital and lower leverage have less liquidity risk.

### *B. Asset and Liability Liquidity*

We next decompose asset liquidity and liability liquidity, and investigate their cross-sectional relationship. Banks that face more liability-side liquidity pressure (e.g., are funded by more short-term debt) are likely, for liquidity management reasons, to hold more liquid assets and thus carry higher asset-side liquidity. Hanson et al. (2015) present a model in which commercial banks that are assumed to have more stable funding thus own more illiquid assets, whereas shadow banks that are assumed to have more runnable funding and thus more liability liquidity pressure hold more liquid assets.

Table V presents regressions in which the dependent variable is the asset-side LMI, scaled by total assets, and the independent variables are liability-side LMI, scaled by total assets, and other important bank characteristics. The first two columns report regressions where we pool all of the data together, and columns (3) to (6) report regressions based on the data at a single point in time. The main pattern that emerges from the table is that banks with more funding pressure hold more liquid assets. However, the coefficients in these regressions are generally much closer to zero than to one. That is, one benchmark for this relation is that banks hedge their funding liquidity pressure by owning liquid assets to fully offset the pressure. Under this benchmark, the coefficient on these regressions would be one. As the coefficients in the regression are substantially less than one, we see that running a liquidity mismatch is a business strategy for a bank. Together with our previous results showing that the liquidity mismatch is higher for larger banks, the picture that emerges from the data is one of banks earning profits by running a liquidity mismatch, with larger banks willing to tolerate a higher liquidity mismatch.

### *C. The Informativeness of LMI for Bank Borrowing Decisions*

In Table VI, we examine whether banks with a worse liquidity condition rely more on the Federal Reserve and TARP for funds during the crisis, that is, we examine whether the LMI is informative about a bank's liquidity stress and hence a useful indicator of the bank's reliance on government funding. To do so, we estimate

$$\Pr[Y = 1_{\text{borrow},t} | LIQ_{i,s}] = \alpha + \beta LIQ_{i,s} + Controls_{i,s} + \varepsilon_{i,t}, \tag{22}$$

where $Y$ is a future borrowing indicator that takes the value of one if, during the financial crisis (time $t$), a bank ever borrowed from Federal Reserve facilities in Panel A or from TARP in Panel B. In both panels, the independent variable in the first three columns is the LMI scaled by total assets, which is calculated as of $s = \{2006Q1, 2007Q1, 2008Q1\}$. We also include controls for the standard bank characteristics examined in Table IV, including capital and leverage, which may separately indicate a need to borrow from the government. Bayazitova and Shivdasani (2012) show that strong banks opted out of receiving TARP money, and that funds were provided to banks that had high systemic risk and faced high financial distress costs but that had strong asset quality. We provide additional evidence by linking a bank's borrowing decision to its liquidity condition.

The results indicate that the LMI is indeed informative about a bank's decision to obtain funds from the government, above and beyond standard measures. The Probit model specification indicates that a one-standard-deviation increase in the precrisis scaled LMI is associated with a subsequent decrease in the probability of a bank's decision to borrow from the government of between 1.98% and 4.59% for the Fed loans. For TARP, this range is from 1.18% to 1.87%. We also investigate a specification in which the dependent variable is

**Table VI**

## The Relationship between Bank Ex-Ante Liquidity (Risk) and Bank Borrowing Decisions

This table tests whether a BHC's decision to obtain funds from the government during the crisis is related to ex-ante liquidity and liquidity risk measures:

$$\Pr[Y = 1_{\text{borrow},t} | LIQ_{i,s}] = \alpha + \beta LIQ_{i,s} + Controls_{i,s} + \varepsilon_{i,t},$$

where $Y$ is an indicator that takes the value of one if a bank borrows from the Fed (Panel A) or TARP (Panel B) during the financial crisis. Fed Loans refer to a series of liquidity injections by the Federal Reserve system between December 2007 and November 2008. TARP, the Troubled Asset Relief Program, enabled the U.S. Treasury to inject funds into financial institutions between October 2008 and June 2009. Proxies for bank liquidity include LMI scaled by total assets, scaled LMI–$\text{LMI}_{1\sigma}$ (here, $\text{LMI}_{1\sigma}$ refers to the LMI under a $1\sigma$ stress scenario), the liquidity creation measure of Berger and Bouwman (2009), and Basel III's two measures, the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The five liquidity measures are calculated as of 2006Q1, 2007Q1, and 2008Q1. We report $p$-values in parentheses. $^{*}p< 0.10$, $^{**}p<0.05$, $^{***}p<0.01$.

Panel A: $Y = 1$ If Borrowing from Fed Loans

| | Scaled LMI | | | Scaled LMI – $\text{LMI}_{1\sigma}$ | | | Scaled BB | | | LCR | | | NSFR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| In 2006Q1 | −4.59*** | | | 14.19*** | | | −1.37 | | | −0.00 | | | 0.59** | | |
| | (0.00) | | | (0.00) | | | (0.20) | | | (0.82) | | | (0.05) | | |
| In 2007Q1 | | −4.41*** | | | 11.07*** | | | −0.71 | | | −0.00 | | | −0.00 | |
| | | (0.00) | | | (0.01) | | | (0.50) | | | (0.70) | | | (0.98) | |
| In 2008Q1 | | | −1.98*** | | | 2.94*** | | | −1.72 | | | 0.00 | | | 0.38 |
| | | | (0.00) | | | (0.00) | | | (0.10) | | | (0.75) | | | (0.17) |
| Tier 1 capital ratio | −0.02 | −0.04 | 0.01 | 0.02 | 0.01 | −0.01 | −0.07 | −0.05 | −0.11 | −0.07 | −0.08 | −0.08 | −0.13 | −0.08 | −0.11 |
| | (0.73) | (0.58) | (0.89) | (0.73) | (0.91) | (0.88) | (0.37) | (0.54) | (0.22) | (0.32) | (0.29) | (0.33) | (0.11) | (0.28) | (0.20) |
| Tier 1 leverage ratio | −0.21** | −0.20** | −0.25** | −0.34*** | −0.31*** | −0.21** | −0.18 | −0.23* | −0.06 | −0.24** | −0.22* | −0.20* | −0.16 | −0.22* | −0.16 |
| | (0.02) | (0.04) | (0.02) | (0.00) | (0.00) | (0.05) | (0.17) | (0.08) | (0.67) | (0.03) | (0.06) | (0.09) | (0.17) | (0.06) | (0.20) |
| ROA | 0.00 | 0.34** | −0.03 | 0.00 | 0.38*** | −0.01 | 0.00 | 0.41*** | 0.02 | 0.00 | 0.44*** | 0.06 | 0.00 | 0.44*** | 0.06 |
| | (0.00) | (0.02) | (0.68) | (0.00) | (0.01) | (0.93) | (0.00) | (0.00) | (0.80) | (0.00) | (0.00) | (0.51) | (0.00) | (0.00) | (0.52) |
| Intercept | 2.09*** | 1.73** | −0.15 | −0.67 | −0.99* | −1.55*** | 0.46 | −0.09 | −0.08 | 0.29 | −0.18 | −0.02 | −0.23 | −0.18 | −0.37 |
| | (0.00) | (0.01) | (0.75) | (0.23) | (0.06) | (0.00) | (0.51) | (0.90) | (0.91) | (0.63) | (0.74) | (0.97) | (0.73) | (0.73) | (0.54) |
| $N$ | 1,003 | 985 | 975 | 1,003 | 985 | 975 | 1,002 | 984 | 975 | 897 | 882 | 875 | 897 | 882 | 875 |
| Adj $R^2$ | 0.10 | 0.09 | 0.07 | 0.06 | 0.05 | 0.05 | 0.05 | 0.04 | 0.03 | 0.05 | 0.04 | 0.05 | 0.06 | 0.04 | 0.05 |

*(Continued)*

**Table VI**—*Continued*

| Panel B: $Y = 1$ If Borrowing from TARP | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Scaled LMI | | | Scaled LMI – $LMI_{1\sigma}$ | | | Scaled BB | | | LCR | | | NSFR | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| In 2006Q1 | −1.76*** | | | 6.89** | | | 0.47 | | | −0.04 | | | −1.76*** | | |
| | (0.01) | | | (0.03) | | | (0.50) | | | (0.18) | | | (0.00) | | |
| In 2007Q1 | | −1.87*** | | | 6.17** | | | 1.25* | | | 0.01 | | | 0.00 | |
| | | (0.00) | | | (0.03) | | | (0.06) | | | (0.32) | | | (0.95) | |
| In 2008Q1 | | | −1.18*** | | | 1.76*** | | | 0.87 | | | 0.01 | | | −2.83*** |
| | | | (0.00) | | | (0.01) | | | (0.21) | | | (0.52) | | | (0.00) |
| Tier 1 capital ratio | −0.02 | −0.04 | 0.01 | 0.02 | 0.01 | −0.01 | −0.07 | −0.05 | −0.11 | −0.07 | −0.08 | −0.08 | −0.13 | −0.08 | −0.11 |
| | (0.73) | (0.58) | (0.89) | (0.73) | (0.91) | (0.88) | (0.37) | (0.54) | (0.22) | (0.32) | (0.29) | (0.33) | (0.11) | (0.28) | (0.20) |
| Tier 1 leverage ratio | −0.21** | −0.20** | −0.25** | −0.34*** | −0.31*** | −0.21** | −0.18 | −0.23* | −0.06 | −0.24** | −0.22* | −0.20* | −0.16 | −0.22* | −0.16 |
| | (0.02) | (0.04) | (0.02) | (0.00) | (0.00) | (0.05) | (0.17) | (0.08) | (0.67) | (0.03) | (0.06) | (0.09) | (0.17) | (0.06) | (0.20) |
| ROA | 0.00 | 0.34** | −0.03 | 0.00 | 0.38*** | −0.01 | 0.00 | 0.41*** | 0.02 | 0.00 | 0.44*** | 0.06 | 0.00 | 0.44*** | 0.06 |
| | (.) | (0.02) | (0.68) | (.) | (0.01) | (0.93) | (.) | (0.00) | (0.80) | (.) | (0.00) | (0.51) | (.) | (0.00) | (0.52) |
| Intercept | 2.09*** | 1.73** | −0.15 | −0.67 | −0.99* | −1.55*** | 0.46 | −0.09 | −0.08 | 0.29 | −0.18 | −0.02 | −0.23 | −0.18 | −0.37 |
| | (0.00) | (0.01) | (0.75) | (0.23) | (0.06) | (0.00) | (0.51) | (0.90) | (0.91) | (0.63) | (0.74) | (0.97) | (0.73) | (0.73) | (0.54) |
| $N$ | 1,003 | 985 | 975 | 1,003 | 985 | 975 | 1,002 | 984 | 975 | 897 | 882 | 875 | 897 | 882 | 875 |
| Adj $R^2$ | 0.10 | 0.09 | 0.07 | 0.06 | 0.05 | 0.05 | 0.05 | 0.04 | 0.03 | 0.05 | 0.04 | 0.05 | 0.06 | 0.04 | 0.05 |

the log of the dollar amount borrowed from Fed loans or TARP. The results, represented in Table IAVI of the Internet Appendix, are broadly in line with those presented in Table VI. In sum, banks with a lower ex-ante LMI (greater liquidity mismatch) have a higher probability of borrowing from the government during the crisis.

Columns (4) to (6) report results using the liquidity risk measure. This measure is also highly informative about bank borrowing decisions, although no more informative than the LMI-level measure.

The remaining columns, (7) to (15), report results using other liquidity measures that have been proposed by regulators and academics. In particular, we include Basel III's LCR and NSFR (see Table IAV of the Internet Appendix for the details on the computation of the NSFR ratio), as well as the Berger-Bouwman (BB) measure. Internet Appendix Section III provides details on how we replicate the three liquidity measures using the universe of BHCs. Turning first to the Basel III measures, the LCR addresses liquidity risk by increasing bank holdings of high-quality liquid assets, whereas the NSFR is designed to reduce funding risk arising from the mismatch between assets and liabilities, which is conceptually closer to our LMI. The NSFR does have explanatory power in predicting banks' decision to borrow from TARP using the measure as of 2006Q1 and 2008Q1, but has little power in predicting banks' decision to borrow from the Fed loans. The BB measure has little explanatory power in predicting either borrowing decision. Since the most significant conceptual difference between the LMI and these other measures is our use of time-varying liquidity weights, we conclude that incorporating time-varying weights significantly improves a liquidity measure.

### *D. The Informativeness of LMI for Bank Crash Risk*

We next examine whether bank illiquidity can predict banks' stock market crash risk during the 2008Q3 to 2009Q2 crisis period, when market and funding liquidity conditions deteriorate dramatically. To do so, we estimate the following Probit model, which correlates equity crashes during the financial crisis with bank ex-ante liquidity conditions, controlling for standard bank characteristics:

$$\Pr[Crash = 1|LIQ_{i,s}] = \alpha + \beta LIQ_{i,s} + Controls_{i,s} + \varepsilon_{i,t}. \quad (23)$$

The crash indicator takes the value of one if the total return on a bank's stock is less than $-25\%$ in one quarter or less than $-35\%$ in two quarters, and zero otherwise. As in Section IV.C, we use the bank liquidity measure at three ex-ante points in time: $s = \{2006Q1, 2007Q1, 2008Q1\}$.

Table VII reports the marginal effects estimated from the Probit model. Columns (1) to (3) represent results using the scaled LMI. The LMI measure again performs well. A one-standard-deviation increase in the precrisis scaled LMI is associated with a subsequent decrease of between

## Table VII

## The Relationship between Bank Liquidity and Crash Probability

This table tests whether a BHC's ex-ante liquidity relates to stock price crashes during the financial crisis:

$$\Pr(Crash = 1|LIQ_{i,s}) = \alpha + \beta\ LIQ_{i,s} + Controls_{i,s} + \varepsilon_{i,t}.$$

*Crash* is a dummy that takes the value one if a bank's stock falls more than 25% in one quarter or 35% in two quarters ($t$ and $t-1$) over the period from 2008Q3 to 2009Q2. Proxies for bank liquidity include LMI scaled by total assets, scaled LMI–LMI$_1\sigma$ (here LMI$_1\sigma$ refers to the LMI under a 1$\sigma$ stress scenario), the liquidity creation measure of Berger and Bouwman (2009), and Basel III's two measures, the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). The five liquidity measures are calculated as of 2006Q1, 2007Q1, and 2008Q1. We report $p$-values in parentheses *$p$<0.10, **$p$<0.05, ***$p$<0.01

| | Scaled LMI | | | Scaled (LMI – LMI$_1\sigma$) | | | Scaled BB | | | LCR | | | NSFR | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
| In 2006Q1 | −5.28*** | | | 3.39 | | | 0.43 | | | 0.10 | | | 0.16 | | |
| | (0.00) | | | (0.62) | | | (0.67) | | | (0.15) | | | (0.54) | | |
| In 2007Q1 | | −4.95*** | | | −1.91 | | | −1.07 | | | 0.07 | | | 1.01 | |
| | | (0.00) | | | (0.75) | | | (0.40) | | | (0.57) | | | (0.19) | |
| In 2008Q1 | | | −2.42** | | | 0.26 | | | 0.06 | | | −0.02 | | | 1.17 |
| | | | (0.02) | | | (0.83) | | | (0.96) | | | (0.82) | | | (0.15) |
| Tier1 cap ratio | −0.12*** | −0.22*** | −0.18*** | −0.10** | −0.22*** | −0.23*** | −0.09 | −0.27*** | −0.23** | – −0.17*** | −0.33*** | −0.25*** | −0.18*** | −0.41*** | −0.34*** |
| | (0.01) | (0.00) | (0.01) | (0.02) | (0.00) | (0.00) | (0.13) | (0.00) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| Tier1 lev ratio | 0.22** | 0.31*** | 0.27** | 0.18** | 0.23** | 0.26** | 0.16 | 0.31** | 0.26* | 0.28*** | 0.35*** | 0.33*** | 0.28*** | 0.41*** | 0.41*** |
| | (0.01) | (0.00) | (0.02) | (0.05) | (0.02) | (0.01) | (0.14) | (0.03) | (0.06) | (0.01) | (0.00) | (0.01) | (0.01) | (0.00) | (0.00) |
| ROA | 0.00 | 0.26 | −0.16 | 0.00 | 0.44** | −0.11 | 0.00 | 0.45*** | −0.10 | 0.00 | 0.72*** | −0.08 | 0.00 | 0.57** | −0.10 |
| | (0.00) | (0.15) | (0.26) | (0.00) | (0.01) | (0.41) | (0.00) | (0.01) | (0.42) | (0.00) | (0.00) | (0.58) | (0.00) | (0.02) | (0.53) |
| Intercept | 3.37*** | 3.34*** | 1.27** | 0.28 | 0.98* | 1.06 | 0.28 | 1.36* | 1.13 | 0.27 | 0.80 | 0.76 | 0.26 | 0.53 | 0.10 |
| | (0.00) | (0.00) | (0.03) | (0.61) | (0.10) | (0.14) | (0.64) | (0.07) | (0.16) | (0.64) | (0.12) | (0.26) | (0.62) | (0.33) | (0.86) |
| $N$ | 339 | 345 | 349 | 339 | 345 | 349 | 339 | 345 | 349 | 311 | 319 | 325 | 311 | 319 | 325 |
| Adj $R^2$ | 0.05 | 0.07 | 0.06 | 0.02 | 0.05 | 0.05 | 0.02 | 0.05 | 0.05 | 0.03 | 0.06 | 0.04 | 0.03 | 0.07 | 0.05 |

3.11% and 5.33% in the bank's crash probability during the crisis. The two Basel III measures and the BB measure have insignificant predictive power.

Taken together, the results in this section and the previous section show that our implementation of the LMI meaningfully captures bank-level liquidity. In contrast, the Basel III measures and the BB measure, which were not developed with these considerations in mind, perform poorly in this regard.

## V. Conclusion

This paper implements the liquidity measure LMI, which evaluates the liquidity of a bank based on bank balance sheet information as well as market measures of market and funding liquidity. We show that the LMI improves on its closest precedent, the BB measure, and has advantages over Basel III's two liquidity measures, the LCR and the NSFR. Relative to BB, we offer theory and methodology to incorporate market liquidity conditions into the construction of the liquidity weights. This is an important modification because it naturally links bank liquidity positions to market liquidity conditions, and thus is better suited to serving as a macroprudential barometer. We also show that the LMI stress test can offer an early warning of banking sector fragility, picking up increased fragility in early 2007. We further show that the LMI contains important information regarding liquidity risks in the cross section of banks and identifies these risks better than the BB measure. The LMI has three principal advantages over the Basel III measures. First, unlike the LCR and the NSFR that are ratios, the LMI can be aggregated across banks and thereby provide a macroprudential liquidity parameter. Second, the LCR uses an arbitrary liquidity horizon of 30 days, whereas our implementation of the LMI links the liquidity horizon to market-based measures of the liquidity premium. Thus, our measure has the desirable feature that, during a financial crisis when the liquidity premium is high, the LMI is computed under a longer lasting illiquidity scenario. Third, the LMI framework provides a natural methodology to implement liquidity stress tests.

We do not view the LMI measure in this paper as a finished product. We have made choices in calibrating liquidity weights in computing the LMI. These weights play a central role in the performance of the LMI against our macro- and microbenchmarks. It would be interesting to bring in additional data to better pin down the liquidity weights. Such data may be more detailed measures of market or funding liquidity that are drawn from financial market measures. Alternatively, such data may be balance sheet information from more banks, such as European banks, which would offer further data on which to calibrate the LMI. In either case, the approach of this paper can serve as a template for improving the measurement of bank liquidity.

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## Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

**Appendix S1**: Internet Appendix.