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ABSTRACT

This paper implements a liquidity measure, "Liquidity Mismatch Index (LMI)," to gauge the mismatch between the market liquidity of assets and the funding liquidity of liabilities. We construct the LMIs for 2882 bank holding companies during 2002-2014 and investigate the time-series and cross-sectional patterns of banks' liquidity and liquidity risk. Aggregate banking sector liquidity worsens from +$4 trillion before the crisis to -$6 trillion in 2008, and reverses back to the pre-crisis level in 2009. We also show how a macro-prudential liquidity stress test can be conducted with the LMI metric, and that such a stress test could have revealed the fragility of the banking system in early 2007. In the cross section, we find that banks with more ex-ante liquidity mismatch have a higher stock-market crash probability and are more likely to borrow from the government during the financial crisis. Thus the LMI measure is informative regarding both individual bank liquidity risk as well as the liquidity risk of the entire banking system. We compare the LMI measure of liquidity to other measures such as Basel III's liquidity coverage ratio and net stable funding ratio, and show that LMI performs better in many dimensions. The outperformance of LMI partially results from the contract-specific time-varying liquidity sensitivity weights which are driven by market prices.

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1 Introduction

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. In the 2007-2009 financial crisis, the US government provided several trillion dollars of reserves to the financial sector to forestall and ameliorate a liquidity crisis.[1] Recognizing the importance of liquidity, regulators have taken steps to improve the liquidity of banks since the financial crisis. The Basel III committee has implemented minimum liquidity standards for commercial banks, including the liquidity coverage ratio and the net stable funding ratio. In 2012, the Federal Reserve incorporated a liquidity stress test (the Comprehensive Liquidity Assessment and Review) as part of its oversight of the largest banks.

These policy measures have run ahead of research, and raise important questions for researchers to answer. We lack an agreed upon framework for examining when government regulation of private liquidity choices is desirable, and what instruments should be used to best implement liquidity regulations. A small and growing academic 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 (2015)). We also lack an agreed upon framework for how to measure the liquidity of financial firms and the financial sector. Beyond simple intuitions for special cases — 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 measurement system for liquidity that can handle a sophisticated financial sector.

As Allen (2014) and Diamond and Kashyap (2015) note, there is a striking contrast between the analysis of capital and liquidity regulations. With capital, there is consensus on how to measure capital and why it should be regulated, although disagreements persist on the optimal level of requirements. With liquidity, there is little consensus beyond the recognition that liquidity is hard to measure.

This paper develops and implements a liquidity measurement system. It builds on earlier theo-

[1] Fleming (2012) notes that across its many liquidity facilities, the Federal Reserve provided over $1.5 trillion of liquidity support during the crisis. The number is much higher if one includes other forms of government liquidity support. Lending by the Federal Home Loan Bank peaked at $1 trillion in September 2008. The Federal Deposit Insurance Corporation guarantees whereby insurance limits were increased in the crisis provided a further guaranteed support of $336 billion as of March 2009 (He, Khang, and Krishnamurthy (2010)). The US Treasury also offered $431 billion of liquidity support through the Troubled Asset Relief Program (TARP).

retical work by Brunnermeier, Gorton, and Krishnamurthy (2012) and is also related to Berger and Bouwman (2009)'s empirical approach to measuring liquidity. Adopting the terminology in Brunnermeier et al. (2012), the "Liquidity Mismatch Index (LMI)," measures the mismatch between the market liquidity of assets and the funding liquidity of liabilities. LMI is based on a stress liquidity-withdrawal scenario. In short, it measures the liquidity of a firm assuming that all claimants on the institution act under the terms of their contract to extract the maximum liquidity from the firm, and the firm reacts by maximizing the liquidity it can raise from its assets. Brunnermeier et al. (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 handles the measurement of the liquidity of different maturity liabilities, as for example, a two-day liability today will become a one-day liability tomorrow.

In addition to incorporating time (maturity) in the liquidity measure, our approach also accounts for the time-varying state of liquidity conditions. We do so by linking the liquidity stress-horizon underlying the liquidity computation to asset market measures of market and funding liquidity. Other measures, including Basel's liquidity measures and the Berger and Bouwman (2009) measure restrict measurement to a fixed liquidity-stress horizon. On both of these points, coherently incorporating time and states via the market measures of liquidity premia, our approach improves on Berger and Bouwman (2009). As we will show in empirical results, varying the time-horizon contributes significantly to the superior performance of the LMI to other liquidity measures.

What makes a good liquidity measure? The measure must be theoretically founded. The preceding arguments regarding the recursive principle and incorporation of market prices are theoretical arguments in favor of our construction. The bulk of this paper shows that our theoretically founded LMI performs well on empirical dimensions. First, we show that the LMI is useful for macroprudential purposes. 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 a financial crisis. The LMI performs well on these dimensions. An important aspect of the LMI is that it can be aggregated across banks to measure the liquidity mismatch of a group of banks or the entire financial sector. Liquidity measures which are based on ratios, such as Basel's liquidity coverage ratio, do not possess this aggregation property.[2] Second, the LMI is 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 OIS-Treasury Bill spread as the funding liquidity factor. A stress test of a bank or the financial system can be conducted by stressing the haircut and OIS-Treasury Bill factors and measuring the change in the LMI of a bank or the entire financial sector. We stress the market and funding liquidity factor by N-sigma, for $N = 1, 2$, and 3. We show that the aggregate liquidity of the banking sector dips by nearly \$1 trillion below zero in the one-sigma shock at the beginning of 2007, providing an early warning signal of the fragility of the financial sector. In 2007Q2, a 3-sigma event takes the LMI of the banking sector to -\$4.71 trillion. In 2007Q3, a 2-sigma shock takes the LMI to -\$7.95 trillion. These numbers, and our stress test, provide an anchor for estimating how much liquidity the Fed may need to provide to banks in the event of an aggregate liquidity crisis, and measure prospectively the liquidity risk of the banking sector.

Our second set of empirical criteria arise from micro considerations. 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 in this dimension, and better than other measures. We examine the cross section of banks and show that banks with a worse LMI, measured before the crisis, have a higher crash risk during the peak of the financial crisis. Banks with worse LMI also are more likely to borrow from Federal Reserve facilities and the Troubled Asset Relief Program, and they receive larger liquidity injections. The LMI thus helps to describe the cross-section of liquidity risk in the financial sector. For regulatory purposes, the cross-sectional LMI can help identify systemically important institutions, but here using a liquidity metric.

We compare our liquidity measure to the Basel III measures, the liquidity coverage ratio (BCBS (2013)) and the net stable funding ratio (BCBS (2014)). The Basel measures cannot be aggregated to provide an aggregate view of the banking system to a liquidity stress event. We also compare the explanatory power of these measures to explain banking liquidity outcomes in the crisis, including the crash risk probability and borrowing decision from the government. The two Basel measures have little predictive power. Thus, in both micro and macro dimensions the LMI performs better

[2] Though Basel's liquidity coverage ratio does not possess aggregation property, its denominator, total net cash outflow, is in dollar value and hence can be aggregated. However, it adopts a fixed 30-day stress window which can lead to biases, too long in normal times and too short in stressed times. In our approach, the appropriate liquidity-stress horizon is determined by market prices.

than the Basel III liquidity measures.

We also compare our measure to Berger and Bouwman (2009), which is the first academic paper to recognize the importance of measuring liquidity and propose a liquidity measure. The principal theoretical difference between our approach and Berger and Bouwman (2009) is that we offer a theoretical grounding to liquidity measurement that is recursive and derive liquidity weights as a function of maturity and market measures of the liquidity conditions. Empirically, the difference between the LMI and the Berger and Bouwman (2009) measure is largely driven by our incorporation of market liquidity conditions. In the language of Berger and Bouwman, our liquidity weights are time-varying, while their liquidity weights are constant across normal and crises periods. We show that if we fix the liquidity weights in our computation, then the LMI display little variation 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") goes from near zero to -\$1 trillion from 2007Q1 to 2007Q3, and falls to -\$6 trillion at the depth of the crisis. If we hold the weights constant based on liquidity conditions measured in 2002Q2 (i.e., good conditions), the dip in the LMI in the crisis does not exceed \$50 billion. On the macro dimension the incorporation of time-varying weights is thus critical to capture liquidity stress during a financial crisis. On the micro dimension the time-varying weights is important in identifying the cross-section of banks' liquidity risk and its evolution in normal and stressed times. In testing the predictive power on banks' crash probability as well as borrowing decision from the government, we find that the Berger-Bouwman measure does not perform as well as the LMI.

This paper is most directly related to the literature examining banks' liquidity management. Financial firms hold liquidity on their asset side and provide liquidity via their liabilities, through the issuance of short-term debt. Thus liquidity management amounts to a joint decision over assets and liabilities. Cornett et al. (2011), Hanson et al. (2015), and Krishnamurthy and Vissing-Jorgensen (2015) all study banks' asset liquidity choices jointly with their liabilities.[3] In a world where bank assets and liabilities are jointly determined, it is most natural to focus on a single measure of bank liquidity that combines both asset liquidity and liability liquidity. This is what we do, and in this regard, we follow on the work of Berger and Bouwman (2009). The LMI is a comprehensive measure of bank liquidity as it is constructed from both asset and liability side of the balance sheet, and is

[3] There is also a literature examining 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).

furthermore dependent on market-wide liquidity conditions. In corporate finance research, liquidity is often measured solely from the asset side of the balance sheet, putting aside considerations of liquidity provision on the liability side. See, for example, Bates, Kahle, and Stulz (2009) which examines the reasons for the increase in cash holdings across the corporate sector, where cash is defined as the sum of cash and marketable securities.[4] On the policy side, several central bank studies including Banerjee (2012), de Haan and van den End (2013) investigate measures for bank liquidity regulation in conjunction with Basel III.

The paper proceeds as follows. The next section builds up a theoretical model for the liquidity mismatch measure and Section 3 constructs the empirical measure. Section 4 evaluates the LMI in the macro dimension while Section 5 evaluates the LMI in the micro dimension. Section 6 concludes the paper and discuss future work.

2 Liquidity Mismatch Index: Theoretical Framework

We are interested in measuring a bank's liquidity utilizing the bank's balance sheet information. We expand on the approach proposed by Brunnermeier et al. (2012). They define the Liquidity Mismatch Index (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. This defines the liquidity promised through *liabilities.*

ii the firm computes its best course of action, given the assumed stress event, to raise as much cash against its balance sheet as it can to withstand the cash withdrawals. That is, the firm computes how much cash it can raise from asset sales, pre-existing contracts such as credit lines, and collateralized loans such as repo backed by assets currently held by the firm. The computation assumes that the firm is unable to raise unsecured debt or equity. The total cash raised is the *asset-side liquidity.*

iii the LMI is the net of these computations, the asset-side liquidity minus the liability-side liquidity.

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

To be concrete, 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 the answer to [i] is \$-90, as the maximum liquidity that can be extracted by counterparties is that overnight creditors demand repayment on their debts. The answer to [ii] is \$+80 as the firm can raise at most \$80 on short notice. The LMI is \$-10.

What does the LMI measure? The negative LMI in this case indicates that the bank-run equilibrium can exist, and that in the event of the bank run equilibrium, the liquidity shortfall, which is potentially the bank's liquidity need from the Fed, is \$+10. More broadly, with more complex contracts than just overnight deposit contracts, the answers to [i] and [ii] get at whether a coordinated liquidity withdrawal can trigger firm failure, and measures the shortfall in case of failure.

The LMI construction is very simple, which is its appeal. But it makes simplifying assumptions. For example, it may be that the haircut of 20% depends not just 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[5] so that the simplification is unlikely to introduce too much error into our computation. But, it is worth noting that the LMI construction ignores balance sheet interdependencies.

In the general case, Brunnermeier et al. (2012) propose that the LMI for an entity i at a given time t be computed as the net of the asset and liability liquidity,

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

Assets ($a_{t,k}^i$) and liabilities ($l_{t,k'}^i$) are balance sheet counterparts, varying 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 answering questions [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 rollover 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 towards any liquidity shortfall. Brunnermeier et al. (2012) provide several examples of assets and liabilities,

[5] See Figure 9 in Krishnamurthy, Nagel, and Orlov (2014).

explaining why [i] and [ii] should drive the measurement of liquidity.

We go beyond Brunnermeier et al. (2012) in three ways. First, we propose a set of numerical liquidity weights λ_{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 gauges of liquidity stress (e.g., asset market liquidity premia) into the liquidity measurement.

2.1 Bank recursion and LMI derivation for liabilities

We first focus on computing the liability side LMI, $\sum_{k'} \lambda_{t,l_{k'}} l^i_{t,k'}$. 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 formula (1). We use T to denote the maturity of liability class k'. Thus, let $l^i_{t,T}$ be the liability of the bank i due at time T, where the notation $\{l^i_{t,T}\}$ denotes the stream of maturity-dated liabilities. We are interested in summarizing the stream $\{l^i_{t,T}\}$ as a single number, $LMI(\{l^i_{t,T}\}, t)$.

We derive the value of a bank, where liquidity enters explicitly, in order to motivate the liquidity measurement. Suppose that a bank at date t has issued liabilities $\{l^i_{t,T}\}$, and used the proceeds to invest in a long-term illiquid asset. For the liquidity measurement we hold this balance sheet fixed, assuming the bank does not issue more liabilities at $s > t$ and make further investments in illiquid assets. The illiquid investment "carry trade" can generate profits to the bank. In particular, $\pi_{t,T}$ is a liquidity premium the bank earns by issuing a liability of maturity T and investing in long term assets. Here $\pi_{t,S} > \pi_{t,T}$ for $S < T$, 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 $V^S(\{l^i_{t,T}\}, t)$ as the value to a bank with a liability structure $\{l^i_{t,T}\}$ at time t in the stress event S. The bank pays θ^i per dollar in order to obtain any cash that is due to creditors.[6]

[6] Note that θ^i is defined as a per dollar cost of obtaining cash once and for all, rather than a rate on borrowing cash say from 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, $\theta^i = \frac{R^i}{\mu_t}$.

Then,

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

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

To be concrete, consider again the hypothetical Diamond-Dybvig bank which buys \$100 of illiquid assets at date 0 which pay off at date 2 and earns return of 10%. Suppose that the bank finances itself fully with debt that is demandable at date 1 and then 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 cost of $\theta^i = 0.2$. The spread the bank earns on holding illiquid assets financed by short-term demandable debt is $\pi = 10\%$. The value in the stress event of choosing this asset and liability structure is equal to:

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

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

We next define the LMI. We define:

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

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, i.e., θ^i times the LMI of the bank. We can write the profit function recursively as:

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

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

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

To illustrate, return to the two-period Diamond-Dybvig bank. The $LMI(t=1)$ 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 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. The $LMI(t=1)$ 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 the $LMI(t=0) = -\$50 + 0.90 \times LMI(t=1) = -\$95$. 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 only depends on the remaining maturity of liabilities; that is, a function where the liquidity cost measured at time t of a liability maturing at time T is only a function of $T-t$. Thus consider the function

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

where λ_{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 the 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 the μ_t and the liability's time to maturity $T - t$. A high μ_t implies a low chance of illiquidity, and hence high liquidity. The liquidity weights we have constructed embed the expected duration of liquidity needs.

2.2 Measuring μ_t

A key variable in the construction of the LMI is μ_t, which controls the expected duration of the stress event — the higher μ_t, the shorter duration of the stress event. We aim to map μ_t into an observable asset price. Consider a hypothetical bank which is making a choice of 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 ψ^i that the bank will enter a liquidity stress episode and pay cost $\theta^i LMI(\{l^i_{t,T}\}, t)$. Thus the bank solves,

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

The first order condition 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 μ_t and the liquidity premium, which is governed by the market's desire for liquidity.

We propose to measure the liquidity premium using the OIS-Tbill spreads. We rewrite (8) for a one year ($T - t = 1$) maturity liability,

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

Further suppose 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, κ is a free parameter which scales the relation between OIS-Tbill and μ_t. We discuss how κ is chosen in the next section.

When investors have a strong desire to own liquid assets, as reflected in a high spread between

OIS and Tbill, any financial intermediary that can issue a liquid liability can earn potentially earn profits on issuing such liquid liabilities. However, doing so exposes the intermediary to liquidity risk. The first order condition says that the potential profits must balance with the potential risks, which then means that μ_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 (2014)), on the relation between the liquidity premia on bank liabilities and market measures of liquidity premium. The OIS-Tbill spread is one pure measure of the liquidity premium, as it is not contaminated by credit risk premium. Thus we use time-series variation in the OIS-Tbill spread to pin down μ_t.

The derivation above is carried out with the assumption that μ_t varies over time, but is a deterministic function of T. That is the "term structure" of μ_t is driven purely by a single level factor. In our implementation of liquidity weights, we make this assumption and thus use the 3-month OIS-Tbill spread to proxy for μ_t. However, μ_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.

2.3 LMI derivation including assets

Let us next consider the 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 turning to the discount window (or other sources) at the cost θ^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 et al. (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

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

where

$$dw_t = -\Delta_t.$$

At every t, the bank chooses how much of its cash pool, Δ_t, to use towards covering 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 will call 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

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

That is, after T^*, the bank will have run down its cash pool. By using the 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 of 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 w_t of cash is simply $\psi^i \theta^i w_t$. This approximation is valid as long as T^* is small, so that λ_{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 where T^* is one day, the approximation is exact since effectively the cash of w_t is being used to offset today's liquidity outflows one-for-one, saving cost of $\psi^i \theta^i w_t$.

Furthermore, we categorize the liabilities into maturity buckets rather than computing a continuous maturity structure since in practice we only have data for a coarse categorization of maturity.

Putting all of these together, the LMI is

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

where the asset-side weights are

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

and the liability-side weights are

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

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

To summarize, we have expanded on Brunnermeier et al. (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 maturity ($T_{k'}$) of a contract and the state of the economy. We have also shown how market prices can measure the state of the economy, and how they enter into the LMI construction.

2.4 Liquidity metrics

The LMI_t^i measures bank-i's liquidity at time t. There are a number of other metrics derived from the LMI which we also construct.

We define the *liquidity risk* of a bank as follows. The vector of haircuts $m_{t,k}$ and the OIS-Tbill spread (μ_t) measures the liquidity state of the economy, i.e., the market and funding liquidity conditions. We shift the haircuts and the OIS-Tbill spread by one-sigma, in a manner we explain in further detail in the next section (see Section 4.5), and compute:

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

The liquidity risk of a bank is the exposure of that bank to a one-sigma change in market and funding liquidity conditions.

The LMI is measured at the bank level, but it will also be interesting to aggregate the LMI across the banking sector. We define two aggregates. $[LMI]^-$ (*LMI-minus*) measures the aggregate liquidity vulnerability of the banking system as,

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

This metric answers the question of, if every bank for which the bank-run equilibrium exists suffers the bank-run, what will be the aggregate liquidity shortfall of these banks.

LMI-minus aggregates liquidity across negative-LMI banks. Another metric that will be of interest is,

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

which is the simple sum of the liquidity positions of the banking system (*aggregate LMI*). This measure is indicative of the entire banking system's health under the assumption that liquidity can flow freely between surplus and deficit banks. In many cases of interest, as in a financial crisis, this assumption is likely violated, so that the LMI-minus is a better measure of the banking system's health.

Finally, as with a single bank, we will be interested in measuring the liquidity risk of the entire banking system. We compute,

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

as the LMI-minus in a one-sigma shock. More generally, we compute this measure for any N-σ event. We will show that these computations can inform a liquidity stress test.

3 Liquidity Mismatch Index: Empirical Design

Following our theoretical model, we collect assets and liabilities for each bank and define their liquidity weights correspondingly. 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 market liquidity premium. In this section we explain in detail how we design and calculate the liquidity mismatch index. In the online appendix A, we provide a step-by-step manual for the calculation of LMI.

We construct the LMI for the universe of bank holding companies (BHC) under regulation of the Federal Reserve system. The key source of balance sheet information of 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 asset before 2006 or \$500 million afterwards.[7] Our sample period covers from 2002Q2 to 2014Q3. The dataset includes 2882 BHCs throughout the sample period.[8] Among them, there are 54 U.S. subsidiaries of foreign banks, such as Taunus Corporation (parent company is Deutsche Bank) and Barclays U.S. subsidiary. Table 1 lists the 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), as well as the return on assets. Panel B provides a snapshot of the top 50 BHCs, ranked by their total asset values as of 2006Q1. The top 50 BHCs together have total assets of \$11 trillion dollars, comprising 76% of U.S. real GDP in 2006.

Appendix A provides detailed steps in constructing the LMI. Much of the construction is mechanical. Here we highlight three areas where we have had 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 accounting information provides an exact maturity (i.e. $T'_k = 0$ for overnight debt). But in many cases, accounting information only provides maturity buckets (i.e., maturity$<$ 1 year, or $>$ 1 year). In these cases, we have to use some judgment in choosing T'_k. Table A.2 of the appendix A 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 US do not run in a liquidity stress episode (see Gatev and Strahan (2006)).

2. We choose μ_t based on the time series variation in the three-month OIS-Tbill spread. We calibrate the free parameter κ. In particular, we try different values of κ aiming to hit two targets: (1) The aggregate LMI of the banking sector to be around -\$5 trillion in the financial crisis, roughly matching the amount of liquidity provided by the government;[9] and (2) maximizing

[7] The Y-9C regulatory reports provide data on the financial condition of a bank holding company, based on the US 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; however, 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.

[8] Some BHCs have the main business in insurance, for example Metlife. We exclude them to make the cross-sectional comparison more consistent, given that they have different business models.

[9] Direct liquidity support from the Fed, the FHLB, FDIC, and the US 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.

the informativeness of the LMI for the cross-section of bank liquidity risks.

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

3.1 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 defines the amount of cash a bank can raise over a short-term horizon for a given asset. 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 $\lambda_{t,a_k} = 0$. We present our procedure below to calibrate the weights on assets whose liquidity falls between these extremes. Further details are presented in Table A.1 of the online appendix A.

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. The haircut is also known to vary with measures of asset price volatility and tail risk for a given asset class, which are commonly associated with market liquidity of the asset. Thus, the haircut is particularly attractive as a single measure of asset-side liquidity weights.

We form a panel of repo haircuts, varying by asset and over time. In an ideal world, this haircut data would reflect real transactions for all banks varying by collateral class. Such data do not exist. Our most comprehensive data is from the tri-party market, covering transactions between the largest banks and Money Market Funds, and from the secondary market of 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 collaterals (asset classes). We also compute a loading, β_k, on this principal component for each asset class k. We define the asset liquidity weight as

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

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 δ below.

There are three advantages of this structured approach. First, the structure preserves a liquidity ranking across asset categories, which can otherwise be distorted by noise in the individual haircut series. Second, the approach can easily be extended to time periods when haircut information is missing or incomplete, requiring only knowledge of β_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. In order to expand the LMI to a longer sample period or to a large set of users, the simplification is necessary. Indeed, under this approach a researcher can model $m_{PC1,t}$, say as a function of asset price volatility, and extend the measurement to periods with no haircut data. Last, as all haircuts are driven by a single factor, it is straightforward to conduct a liquidity stress test by shocking the factor, $m_{PC1,t}$. It is worth noting that while we adopt a one-factor structure for simplicity, our approach can be readily expanded to account for multiple haircut factors.

Our haircut data in the tri-party market covers transactions between Money Market Funds and banks/dealers. From 2006:Q3 to 2009:Q4, we use data manually collected from 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 Edgar website. We obtain the following details for each repo loan at the date of filing: collateral type, collateral fair value, notional amount, repurchase amount at maturity, and the identities of borrower and lender. Using this information, we compute the haircut from the collateral fair value and the notional amount. Since 2010:Q1, we use the tri-party repo data collected by the Federal Reserve Bank of New York from two custodian banks, Bank of New York Mellon and JP Morgan Chase. The haircut data is released monthly at the website of the Federal Reserve Bank of New York.[10] Before 2006:Q3, we use the haircut values as of 2006:Q3 given that tri-party haircuts remain stable in normal times thus can be reasonably extended to the earlier sample periods.

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

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 2 shows 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 papers have higher haircuts with an average of 3%. Corporate debt, structured finance products and equities have much lower collateral quality, hence even higher haircuts, above 5%.

Bank loans are the most important asset in a bank's balance sheet.[11] In the financial crisis, the value of bank loans plunged, which had a significant influence 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] and report haircut summary statistics in Table 2. The loan haircut in the secondary market is relatively constant and remains smaller than 5% in normal times, while it falls to as low as 40% during the 2008-2009 crisis. The average haircut through 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)), hence they may not accurately capture liquidity conditions for all banks, especially during the financial crisis. To accommodate this concern, we introduce the parameter, δ, to bridge the gap between bilateral repo haircuts and tri-party repo haircuts (see equation (20)).

We experiment with different values of δ, 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 δ. Table A.3 in the online

[11] Over our sample, bank loans on average account for slightly more than 50% of total assets. The proportion of other asset classes in bank balance sheets is 16.9% for cash and its equivalent, 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 remaining for intangible, fixed, and other assets.

[12] The historical average data is collected from www.lsta.org for secondary loan market.

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

appendix recomputes the LMI for different values of $\delta = \{3.5, 5.0, 7.9\}$. We also compute the LMI using the actual bilateral haircut data for the period of August 2007 to February 2010 when the data is available. We note that lowering δ increases the LMI, as would be 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 $\delta = 5$.

3.2 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 μ_t captures the expected stress duration which is measured as,

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

where OIS-Tbill is the spread of three-month OIS rate and Treasury bill at time t. Then,

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

The parameter $T_{k'}$ indicates the time-to-maturity of a liability. 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 setting $\kappa = 1$. The left panel focuses on time-to-maturity less than one year, $T_{k'} \in [0, 1]$, and the right panel illustrates a longer maturity spectrum, $T_{k'} \in [0, 15]$ years. In normal times when the OIS-Tbill spread is small (dash blue line, OIS-Tbill(%)=0.01), only the very short-term liabilities have high weights (in absolute value, which means higher liquidity pressure). In 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 ($T = 0$), commercial paper has a maturity of one month, debt with maturity less than or equal to one year has $T = 1$, debt with maturity longer than one year has $T = 5$, subordinated debt has $T = 10$, and equity has a maturity of 30 years. For insured deposits which are free of run risk, we use $T = 10$, while uninsured deposits, which are more vulnerable to liquidity outflows and hence have a shorter effective maturity, for which we use $T = 1$. We also examine the liquidity sensitivity of off-balance-sheet securities. We label these off-balance-sheet data 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 financial crisis of 2007 - 2009. 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, refer to Table A.2 of the online appendix A. There is some subjectivity in our choices for T in the cases where T is not explicitly specified in the terms of a contract.[14]

The literature has considered many proxies to measure the liquidity premium. Figure 3 plots a number of common spreads, including the Libor-OIS spread, the TED spread (Libor-Tbill), the Repo-Tbill spread and the OIS-Tbill spread. We note that the Libor-OIS and the TED spread both rise in the fall of 2007, and then rise higher in the fall of 2008. On the other hand, the Repo-Tbill and the OIS-Tbill spread reach their highest point in late 2007. One concern with the Libor indexed spreads is that they are contaminated by credit risk (Smith, 2012), which is not directly related to liquidity. For this reason, we choose to 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 will capture any time variation in the valuation of liquid securities. Nagel (2014) proposes an alternative liquidity premium measure, the Repo-Tbill spread. Figure 3 shows that both the Repo-Tbill spread and OIS-Tbill spread have similar time-series patterns, both peaking in the late 2007. Indeed, these two measures have a correlation coefficient of 0.90. All of our empirical results (magnitude and significance) remain unchanged if using the Repo-Tbill spread as the proxy for liquidity premium.[15]

The parameter κ scales the OIS-Tbill spread in the liability liquidity weights. We choose $\kappa = 0.5$. Table A.3 presents the results for different choices of $\kappa = \{0.25, 0.50, 1.50, 2.00\}$. The larger the κ value is, the less liquidity weight (in absolute value) in liabilities. That is, liabilities generate less liquidity pressure. We note that setting $\kappa = 0.5$ sets the minimum value of the aggregated LMI to be around [negative] \$6 trillion (the range is from roughly -\$10 trillion to +\$1 trillion). We are aiming for a target of [negative] \$5 trillion, which is on the order of magnitude of government support to

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

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

the banking system in the crisis and is thus a guide 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 next sections. 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, the haircut data, and the liquidity premium proxy, one can construct the LMI for any institution in the banking system through the guidance in the online appendix A. We proceed to examine the macro- and micro-performance of the LMI in the next two sections.

4 LMI as a macroprudential barometer

An LMI aggregate is a useful barometer for a macroprudential assessment 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 ("runs"). This section first documents the time-series variation in LMI aggregates. We then explain what drives the time-series variation. Finally, we conduct a stress test using the aggregate LMI and show that such a stress test offers an indicator of the fragility of the banking system in early 2007.

4.1 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, the aggregate LMI equals the overall liquidity mismatch in the banking system. The 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 systemic event that every bank that is susceptible to a run, suffers that run. Note that an important advantage of the LMI is that it can be aggregated across firms and sectors. Basel's liquidity measures, which are ratios, cannot be meaningfully aggregated.

Figure 4 plots these liquidity aggregates for the universe of bank holding companies over the sample period of 2002Q2 to 2014Q3. In normal times, LMI-minus is near zero, meaning that the banking sector is healthy and faces little run risk. In stressed times, beginning in early 2007, the LMI-minus turns significantly negative. Recall that a lower value of LMI at the firm level indicates a balance sheet that is more vulnerable to liquidity stress. At its trough, LMI-minus is about [negative] 6.6 trillion, which is of a similar magnitude as the Fed and other government liquidity provision actions. Note that we have calibrated the parameter κ in order to match this magnitude. The figure also presents the aggregate LMI ($\widetilde{LMI}$). This number is significantly positive before and after the crisis, indicating that typically the average bank is sufficiently liquid to service its liabilities. During the financial crisis, the aggregate LMI also turns negative approaching that of LMI-minus. The trough of the liquidity mismatch occurs three quarters before the Lehman Brothers' bankruptcy and six quarters before the low of the stock market.

To understand further the composition of aggregate LMI, we present in Figure 5 the liquidity mismatch for on- and off-balance sheet items. Off-balance-sheet liquidity pressure is minimal in normal times, but increases rapidly to [negative] $ 5.0 trillion in the crisis period. Such evidence suggests that off-balance-sheet contingent liquidity plays an important role particularly during stressed marking conditions. Panel A shows the values of the aggregated LMI and Panel B zooms in on the crisis period, plotting the aggregate LMI-minus.

4.2 Federal Reserve liquidity injection and the increase in 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 to the banking sector in order to support overall market liquidity. The online appendix C provides the background on these programs. The liquidity support began in 2007:Q4 with the Term Auction Facility and continued with other programs (see Table A.4). 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 we cannot demonstrate causality, it is likely that the liquidity injection played a role in the increase of the aggregate LMI in 2008.

We study the effect of the Fed injections on the cross-section of LMI. There are 559 financial institutions receiving liquidity from the Fed,[16] among them there are 87 bank holding companies. These BHCs on average borrowed 95.8 billion dollars, with a median value of 0.7 billion dollars. The bank-level borrowing amount ranges from $5 million to $2 trillion. The ten bank holding companies which have received the most liquidity are Citigroup, Morgan Stanley, Bear Sterns, Bank of America, Goldman Sachs, Barclays U.S. subsidiary, JP Morgan Chase, Wells Fargo, Wachovia and Deutsche

[16] One parent institution may have different subsidiaries receiving the liquidity injection. For example, AllianceBearnStein is an investment asset management company. Under this company, there are seven borrowers listed in the Fed data such as AllianceBearnStein Global Bond Fund, Inc, AllianceBearnStein High Income Fund, Inc, AllianceBearnStein TALF Opportunities Fund, etc.

Bank's US subsidiary, Taunus.

Figure 6 plots the relation between the Fed liquidity injection and the change in LMI, cross-sectionally. The liquidity injection is measured by the log of the dollar amount of loans received by a given BHC, and the change in LMI is measured by the log of the difference in LMI between the post-crisis (2009Q3-2012Q1) and the pre-crisis (2006Q1-2007Q2) period (panel A) and between the post-crisis (2009Q3-2012Q1) and the crisis (2007Q3-2009Q2) period (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 the effect of the Fed's liquidity facilities in increasing banking sector liquidity.

4.3 LMI decomposition: asset vs liability

The calculation of LMI depends on assets, liabilities, and liquidity weights. Panel A in Figure 7 shows the dollar amount of asset-side and liability-side (in absolute values) for the universe of BHCs. There are two patterns to note. First, movements in both asset-side and liability-side liquidity contribute to the movement in the LMI, but movements in the liability side plays a larger role in stressed times. During stress periods it is the rollover problem of short-term debt and the calls from contingent liabilities that create the biggest liquidity problems. The off-balance-sheet contingent liability contributes to almost one-half of the increase in the liability-side LMI. This is consistent with the observed facts during the crisis that shadow banking played a crucial role in reducing liquidity. Second, although the changes in asset-side liquidity seems 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 on average fell 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 the liquidity-weighted asset (or liability) divided by the total amount of asset (liability) used in the bank-level LMI calculation. Panel B plots the average effective weights across banks. The figure provides a sense of how much the variation in haircuts, as captured by m_{PC1}, and funding liquidity condition, as captured by the OIS-Tbill spread, drives the LMI.

4.4 The importance of time-varying liquidity weights

Changes in liquidity weights play an important role in the movements of the LMI. Figure 8 plots the aggregate LMI, $\widetilde{LMI}$, in Panel A and the aggregate LMI-minus, $[LMI]^{-}$, 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 good liquidity conditions; and the green dashed line uses weights as of 2007Q4, which captures stressed liquidity conditions. All three lines use the actual balance sheet information for each quarter. Thus the figure 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 linked to market conditions in order to accurately measure banking sector liquidity. If we were to use the constant weights calibrated to good times, we would severely underestimate liquidity conditions in bad times. For example, Panel B indicates that under the weighting scheme of 2002Q2, $[LMI]^{-} \approx 0$ during the financial crisis, suggesting no liquidity problem in the banking sector. This is clearly absurd. In this fixed-weight case, the aggregate banking liquidity remains good because it is driven primarily by the growing assets of the banking sector. At the other extreme, if we use the constant weights calibrated to stressed times, we would overestimate the liquidity stress in normal periods and underestimate the transition to a crisis. For example, LMI-minus during good times under the severely stressed weights is around -\$3 trillion and only falls to -\$6 trillion in the crisis.

4.5 Fragility measures: liquidity stress test and liquidity risk

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

We run a liquidity stress test at three time points: A. 2007Q2 which is two quarters before the liquidity trough; B. 2007Q3 which is one quarter before the liquidity trough; and C. 2012Q4 which is the first time the Federal Reserve ran its liquidity stress test. Table 3 reports the results. Consider the first set of columns corresponding to 2007Q2. The first row in the benchmark, denoted as "T", corresponds to the value as of 2007Q2. The next line, denoted as "[0,T]", reports the historical average value up to this time point. We then compute the aggregate LMI-minus, $[LMI]^-$, and the aggregated LMI, $\widetilde{LMI}$, under three stress scenarios: both cross-collateral haircuts ($m_{PC1,t}$) and funding liquidity factor (OIS-Tbill) worsen 1σ, 2σ, 3σ from their time-T values. Here sigma is calculated as the historical standard deviation from 2002Q2 to 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 dryup is about a 2σ event in 2007Q3, one quarter in advance, and a more than 3σ event in 2007Q2, two quarters ahead. Standing at 2007Q3, the liquidity shortage under 2σ scenario will be the difference between the aggregate LMI value under 2σ and the value under contemporaneous market value, that is 7.35 trillion dollars $(= -0.45 - (-7.80))$.

The stress test provides a measure of liquidity risk, i.e. 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, the LMI-minus under a one-sigma shock is -\$1.26 trillion suggesting an increased fragility of the banking system. Figure 9, Panel B, plots LMI-minus, along with the LMI-minus in the one and two-sigma cases over the period from 2004Q4 to 2011Q4. We see that the stress test indicates fragility in early 2007 when the LMI-minus starts to dip significantly below zero. The liquidity shortage for the entire U.S. banking sector explodes starting in 2007Q2. To make the figure visually readable, we truncate the y-axis at negative eight trillion level. Dashed lines under stress scenarios 1 and 2 thus are not visible during the most extreme period.

5 LMI and the Cross-Section of Banks

The previous section presented 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 bank performance differentially depending on their LMIs. That is, as liquidity conditions deteriorate, a firm with a lower LMI should experience worse performance. Moreover, in the financial crisis, we would expect that firms with a worse ex-ante LMI would depend more on liquidity support from the government.

We begin this section descriptively. We first examine what characteristics of banks 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.

5.1 Bank characteristics and liquidity

We investigate the relationship between the LMI and bank characteristics for the universe of BHCs. Table 4 shows the results of regressing LMI (Panel A) and the LMI risk exposure (Panel B) metric, both scaled by total assets, on a set of bank characteristics including risk-adjusted assets, Tier 1 capital ratio, Tier 1 leverage ratio, and the return on assets (ROA). Columns (1) - (5) in Panel A present regressions where we pool all of the data together, and columns (6) - (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 change from pre-crisis, crisis, to post-crisis. The common finding from the top panel is that a higher risk-adjusted assets is correlated with a lower level of liquidity. That is, larger banks skate closer to the edge when it comes to liquidity. The effect is more pronounced pre-crisis, 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 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 correlated with higher liquidity, and higher leverage correlated with lower liquidity.

Panel B reports results for the LMI risk exposure metric. The results are broadly similar, albeit weaker. Larger and more profitable banks banks have more liquidity risk. Banks with higher capital and lower leverage have less liquidity risk.

5.2 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 more short-term debt funded) are likely, for liquidity management reasons, to hold more liquid assets and thus carry a higher asset-side liquidity. Hanson, Shleifer, Stein, and Vishny (2015) present a model in which commercial banks who are assumed to have more stable funding thus own more illiquid assets, whereas shadow banks which are assumed to have more runnable funding and thus more liability liquidity pressure, hold more liquid assets.

Table 5 presents regressions where 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) - (6) report regressions based on the data for a single point in time. The main pattern that emerges from the table is that banks with more funding pressure also hold more liquid assets. However, note that 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 model for a bank. In conjunction with our previous results showing that liquidity mismatch is higher for larger banks, the picture that emerges from the data is of banks earning profits by running a liquidity mismatch, with larger banks willing to tolerate a higher liquidity mismatch.

5.3 The informativeness of LMI for bank borrowing decisions

We ask whether banks with a worse liquidity condition rely more on the Federal Reserve and TARP funding during the crisis. That is, is the LMI informative for a bank's liquidity stress, and hence a useful indicator for banks reliance on government liquidity backstop? Table 6 presents the results. We estimate,

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

where Y is a future borrowing indicator which takes on a value of 1 if a bank has ever borrowed during the financial crisis (time t) from Federal Reserve facilities (for details, see Section 4.2 and Appendix C) in Panel A, or a bank has ever borrowed from TARP in Panel B. In both panels, the independent variables in the first three columns are the scaled LMI (scaling is by total assets), calculated as of $s = \{2006Q1, 2007Q1, 2008Q1\}$. We also include controls for standard bank characteristics examined in Table 4, including capital and leverage which may separately indicate a need to borrow from the government. Bayazitova and Shivdasani (2012) shows that strong banks opted out of receiving TARP money, and liquidity infusions were provided to banks that had high systemic risk, faced high financial distress costs, but had strong asset quality. We provide additional evidence by linking bank's borrowing decision to their liquidity condition.

The results indicate that the LMI is indeed informative of 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 rise in the pre-crisis 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, the magnitude ranges from 1.18% to 1.87%. We have also investigated a specification where the dependent variable is the log of the dollar borrowing amount from Fed loans or from TARP. The results in Table A.6 of the online appendix are broadly in line with those presented in Table 6. In sum, banks with lower ex-ante LMI (more liquidity mismatch) have higher probability to borrow from government in the crisis and they also tend to borrow more.

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

The last columns, (7) – (15), report results using other liquidity measures that have been proposed by regulators and academics. In particular, we include Basel III's two measures, the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR), as well as the Berger-Bouwman (BB) measure. Appendix D provides the details of how we replicate the three liquidity measures using our sample of the universe of BHCs. Among 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 in concept 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 Berger-Bouwman measure has little explanatory power in either borrowing decisions. As 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.

5.4 The informativeness of LMI for bank crash risk

We next ask whether bank illiquidity can predict banks' stock market crash risk during the 2008 crisis period, when market and funding liquidity conditions deteriorated dramatically. We estimate the following probit model, which correlates equity crashes during the financial crisis using bank ex-ante liquidity conditions, controlling for standard bank characteristics:

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

Here "Crash" is an indicator of whether there is an equity crash during the peak of financial crisis, 2008Q3 to 2009Q2, and 0 otherwise. The crash indicator takes on the value of 1 if the total return on a bank's stock is less than -25 percent in one quarter or less than -35 percent in two quarters, and 0 otherwise. As with section 5.3, we use the bank liquidity measure are three ex-ante time points: $s = \{2006Q1, 2007Q1, 2008Q1\}$.

Table 7 reports the marginal effects estimated from the probit model. Columns (1) – (3) shows the result using the scaled LMI. The LMI measure again performs well. A one standard deviation increase in the pre-crisis scaled LMI is associated with a subsequent decrease of between 3.11% and 5.33% in the bank's crash probability during the crisis. Other measures, including the two Basel III measures, as well as the Berger-Bouwman measure have insignificant predictive power.

Together, these two sections show that our implementation of the LMI meaningfully measures bank-level liquidity. The Basel III measures and the Berger-Bouwman measure, which were not developed with these considerations in mind, perform poorly in this regard.

6 Conclusion

This paper implements the liquidity measure, LMI, which evaluates the liquidity of a given bank based on bank balance sheet information as well as market measures of market and funding liquidity. We have shown that the LMI improves on its closest precedent, the Berger-Bouwman measure, and has advantages over Basell III's two liquidity measures, the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR). Relative to Berger-Bowman, we offer theory and methodology to incorporate market liquidity conditions in 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 and a stress testing framework. We have shown that the LMI stress test can offer an early warning of banking sector fragility, picking up increased fragility in early 2007. We have also shown that the LMI contains important information regarding the liquidity risks in the cross-section of banks and identifies these risks better than the Berger-Bouwman measure. The LMI has three principal advantages over the Basell III measures. First, the LMI, unlike the LCR and the NSFR which are ratios, can be aggregated across banks and thereby provide a macroprudential liquidity parameter. Second, the LCR uses an arbitrary liquidity horizon of 30 days. Our implementation of the LMI links the liquidity horizon to market-based measures of the liquidity premium. Thus our measurement 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 micro benchmarks. It will be interesting to bring in further data to better pin down liquidity weights. Such data may be more detailed measures of market or funding liquidity drawn from financial market measures. Alternatively, such data may be balance sheet information from more banks, such as European banks, which will 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.

References

Acharya, Viral, and Ouarda Merrouche, 2013, Precautionary hoarding of liquidity and inter-bank markets: Evidence from the sub-prime crisis, *Review of Finance* 17(1), 107–160.

Acharya, Viral, and Nada Rosa, 2015, A crisis of banks as liquidity providers, *Journal of Finance* 70(1), 1–73.

Allen, Franklin, 2014, How should bank liquidity be regulated? working paper.

Armantier, Olivier, Eric Ghysels, Asani Sarkar, and Jeffrey Shrader, 2011, Stigma in financial markets: Evidence from liquidity auctions and discount window borrowing during the crisis, *Federal Reserve Bank of New York Staff Reports* no. 483.

Banerjee, Ryan N., 2012, Banking sector liquidity mismatch and the financial crisis, *Bank of England working* paper.

Bates, Thomas W., Kathleen M. Kahle, and Rene M. Stulz, 2009, Why do u.s. firms hold so much more cash than they used to?, *Journal of Finance* 64(5), 1985–2021.

Bayazitova, Dinara, and Anil Shivdasani, 2012, Assessing tarp, *Review of Financial Studies* 25(2), 377–407.

BCBS, 2013, Basel III: The liquidity coverage ratio and liquidity risk monitoring tools, *Basel Committee on Banking Supervision* policy paper.

BCBS, 2014, Basel III: The net stable funding ratio, *Basel Committee on Banking Supervision* policy paper.

Berger, Allen, and Christa Bouwman, 2009, Bank liquidity creation, *Review of Financial Studies* 22, 3779–3837.

Brunnermeier, Markus K., Gary Gorton, and Arvind Krishnamurthy, 2012, Risk topography, *NBER Macroeconomics Annual* 26, 149–176.

Caballero, Richard, and Arvind Krishnamurthy, 2004, Smoothing sudden stops, *Journal of Economic Theory* 104–127.

Copeland, Adam, Antoine Martin, and Michael Walker, 2014, Repo runs: evidence from the tri-party repo market, *Journal of Finance* 69(6), 2343–2380.

Cornett, Marcia Millon, Jamie McNutt, Philip Strahan, and Hassan Tehranian, 2011, Liquidity risk management and credit supply in the financial crisis, *Journal of Financial Economics* 101(2), 297–312.

de Haan, Leo, and Jan Willem van den End, 2013, Bank liquidity, the maturity ladder, and regulation, *Journal of Banking and Finance* 37(10), 3930–3950.

Diamond, Douglas, and Phillip Dybvig, 1983, Bank runs, deposit insurance, and liquidity, *Journal of Political Economy* 91, 401–419.

Diamond, Douglas W., and Anil K. Kashyap, 2015, Liquidity requirements, liquidity choice and financial stability, *University of Chicago and National Bureau of Economic Research working* paper.

Dietricha, Andreas, Kurt Hessb, and Gabrielle Wanzenrieda, 2014, The good and bad news about the new liquidity rules of Basel III in Western European countries, *Journal of Banking and Finance* 13–25.

Farhi, Emmanuel, Mikhail Golosov, and Aleh Tsyvinski, 2009, A theory of liquidity and regulation of financial intermediation, *Review of Economic Studies* 76, 973–992.

Fleming, Michael, 2012, Federal reserve liquidity provision during the financial crisis of 2007-2009, *Annual Review of Financial Economics* 4, 161–177.

Furfine, C. H., 2003, Standing facilities and interbank borrowing: Evidence from the federal reserve's new discount window, *International Finance* 6, 329–347.

Gatev, Evan, and Philip Strahan, 2006, Banks advantage in supplying liquidity: theory and evidence from the commercial paper market, *Journal of Finance* 61(2), 867–892.

Gorton, Gary, and Andrew Metrick, 2012, Securitized banking and the run on repo, *Journal of Financial Economics* 104(3), 425–451.

Hanson, Samuel G., Andrei Shleifer, Jeremy C. Stein, and Robert W. Vishny, 2015, Banks as patient fixed income investors, *Journal of Financial Economics* 117(3), 449469.

He, Zhiguo, In Gu Khang, and Arvind Krishnamurthy, 2010, Balance sheet adjustment in the 2008 crisis, *IMF Economic Review* 1, 118–156.

Heider, Florian, Marie Hoerova, and Cornelia Holhausen, 2015, Liquidity hoarding and interbank market spreads: The role of counterparty risk, *Journal of Financial Economics* 118, 336–354.

Holmstrom, Bengt, and Jean Tirole, 1998, Private and public supply of liquidity, *Journal of Political Economy* 106, 1–40.

Hong, Han, Jiang-zhi Huang, and Deming Wu, 2014, The information content of Basel III liquidity risk measures, *Journal of Financial Stability* 91–111.

Krishnamurthy, Arvind, Stefan Nagel, and Dmitry Orlov, 2014, Sizing up repo, *Journal of Finance* 69(6), 2381–2417.

Krishnamurthy, Arvind, and Annette Vissing-Jorgensen, 2013, The ins and outs of large scale asset purchases, *Kansas City Federal Reserve Symposium on Global Dimensions of Unconventional Monetary* Policy.

Krishnamurthy, Arvind, and Annette Vissing-Jorgensen, 2015, The impact of treasury supply on financial sector lending and stability, *Journal of Financial Economics* forthcoming.

Nagel, Stephan, 2014, The liquidity premium of near-money assets, *University of Michigan* working paper.

Peristiani, Stavros, 1998, The growing reluctance to borrow at the discount window: An empirical investigation, *Review of Economics and Statistics* 80, 611 – 620.

Perotti, Enrico, and Javier Suarez, 2011, A pigovian approach to liquidity regulation, *International Journal of Central Banking* 3–41.

Smith, Josephine, 2012, The term structure of money market spreads during the financial crisis, *working* paper.

Table 1: **Summary Statistics of Bank Holding Companies during 2002-2014**

The universe of bank holding companies is 2882 in our sample. Among them, there are 754 public BHCs including 6 foreign companies and 748 BHCs headquartered in the United States. Panel A reports the time-series average of the cross-sectional mean and standard deviation values. Panel B provides a snapshot of the Top 50 BHCs based on the ranking total assets in the first quarter of 2006.

Panel A

	Universe (N=2882)		Public (N=754)		Public US (N=748)		TOP 50 US (N=50)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Total asset ($Bil)	10.13	95.67	26.42	164.17	25.17	163.47	250.12	468.31
Risk-adj. asset ($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 2006:Q1)

Rank	Company	Size($Bil)	Risk-adj Asset($Bil)	Tier1 Lev Ratio	Tier1 Cap Ratio	ROA
1	CITIGROUP	1748.79	974.24	6.01	10.55	1.07
2	JPMORGAN CHASE & CO	1703.68	1033.92	6.40	9.90	2.01
3	BANK OF AMER CORP	1683.36	1110.79	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		11073.21	7096.00	7.56	10.08	1.36

Table 2: **Haircuts by Collateral Type**

For asset classes except bank loans, haircuts are collected from the tri-party repo market. For bank loans, haircuts are based on the bid price as a percentage of par in the secondary loan market. PC1 refers to the first principal component of cross-collateral haircuts, calculated using the panel of individual haircut series for each asset class.

Collateral	Mean	SD	P5	P25	P50	P75	P95
A: Triparty 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 product	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
B: Secondary loan market							
Bank loan	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

Table 3: **Liquidity Stress Test**

The table reports the aggregates LMI and the aggregate LMI-minus, $[LMI]^-$, over all BHCs under stress scenarios when both funding liquidity factor (OIS-TBill) and the cross-collateral haircut deviate 1-, 2-, 3-σ away from T values. Here σ is calculated based on historical standard error from 2002Q2 to time T. We use two benchmarks for comparison. Benchmark T refers to the estimated aggregate level at time T; benchmark $[0, T]$ refers to the historical average value from 2002Q2 to time T, for LMI and $[LMI]^-$ respectively. All entries are in the unit of trillion dollars. We choose three time points for the stress test: A. 2007Q2 which is two quarters ahead of liquidity crunch (the trough of aggregate liquidity happens in 2007Q4, since then the Federal Reserve system starts unconventional monetary policies via a series of liquidity and credit facilities.); B. 2007Q3 which is one quarter ahead of liquidity crunch; and C. 2012Q4 which is the first system-wide stress test of bank liquidity by the Federal Reserve.

A. T=2007Q2			B. T=2007Q3			C. T=2012Q4		
	$[LMI]^-$	LMI		$[LMI]^-$	LMI		$[LMI]^-$	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 Scenarios			Stress Scenarios			Stress Scenarios		
1-σ	-1.26	0.29	1-σ	-3.80	-3.37	1-σ	-0.00	5.95
2-σ	-2.45	-1.68	2-σ	-7.95	-7.80	2-σ	-0.01	3.56
3-σ	-4.71	-4.44	3-σ	-14.55	-14.45	3-σ	-0.88	0.16

Table 4: **The Relationship of LMI with Bank Characteristics**

This table relates the LMI and bank characteristics for the universe of public bank holding companies during 2002Q2 to 2014Q3. The dependent variable in Panel A is liquidity, the scaled LMI, and in panel B is liquidity risk, the scaled (LMI–$\text{LMI}_{1\sigma}$) where $\text{LMI}_{1\sigma}$ refers to LMI under 1-σ stress scenario when both cross-collateral haircut and OIS-Tbill spread are shocked by 1-σ. Bank characteristics include risk-adjusted asset, Tier 1 capital ratio, Tier 1 leverage ratio, and return on asset. Columns (1)-(5) report a pooled regression using the full sample, and columns (6)-(9) report cross-sectional regressions for selected quarters: 2002Q2 (beginning of the sample), 2007Q4 (trough of funding liquidity), 2008Q3 (Lehman event quarter), and 2014Q3 (end of the sample). In the pooled regression, the standard errors are robust and clustered by bank. We report in parentheses the p-value for the estimation.

Panel A: Dependent variable = scaled LMI

	Full Sample					2002Q2	2007Q4	2008Q3	2014Q3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk-adj Asset	-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 Cap 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 Lev 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)
Return on Asset				-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	21277	21277	21278	22033	21271	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

Panel B: Dependent variable = scaled (LMI – $\text{LMI}_{1\sigma}$)

	Full Sample					2002Q2	2007Q4	2008Q3	2014Q3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Risk-adj Asset	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 Cap 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 Lev 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)
Return on Asset				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	21277	21277	21278	22033	21271	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

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: **The Relationship of Asset Liquidity and Liability Liquidity**

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

Dependant variable = Asset_LMI / Total Asset

	Full Sample		2002Q2	2007Q4	2008Q3	2014Q3
	(1)	(2)	(3)	(4)	(5)	(6)
$\lvert Liab\_LMI \rvert$ / Total Asset	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 Cap Ratio		0.00***	0.01	-0.01	0.00	0.01***
		(0.00)	(0.12)	(0.37)	(0.43)	(0.00)
Tier 1 Lev Ratio		-0.00***	-0.01	0.02**	0.01	-0.02***
		(0.00)	(0.35)	(0.03)	(0.38)	(0.00)
Return on Asset		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	2500	2500	50	50	50	50
Adj R^2	0.06	0.07	0.13	0.06	0.10	0.59

* p<0.10, ** p<0.05, *** p<0.01

Table 6: **The Relationship of Bank ex ante Liquidity (Risk) and Bank's Borrowing Decision**

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

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

where Y is a future borrowing indicator which takes on a value of 1 if a bank has ever borrowed from Fed loans (panel A) or from TARP (panel B) during the financial crisis. Fed Loans refer to a series of liquidity injections by the Federal reserve system during December 2007 - 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 scaled LMI (scaling by total asset), scaled (LMI–LMI$_{1\sigma}$) (here LMI$_{1\sigma}$ refers to LMI under 1-σ stress scenario when both cross-collateral haircut and OIS-Tbill spread deviated 1-σ away), the liquidity creation measure by Berger and Bouwman (2009) , Basel III's two measures: liquidity coverage ratio (LCR) and net stable funding ratio (NSFR). The five liquidity (risk) measures are calculated as of 2006Q1, 2007Q1, and 2008Q1. In parentheses, we report the p-value for the estimation of regression coefficients.

Panel A: $Y = 1$ if borrowing from Fed loans

	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	-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 Cap 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 Lev 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)
Return on Asset	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	1003	985	975	1003	985	975	1002	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

* p<0.10, ** p<0.05, *** p<0.01

Table 6 (Cont'd) The Relationship of Bank ex ante Liquidity (Risk) and Bank's Borrowing Decision

Panel B: $Y = 1$ if borrowing from TARP

	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	-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 Cap 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 Lev 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)
Return on Asset	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	1003	985	975	1003	985	975	1002	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

* p<0.10, ** p<0.05, *** p<0.01

Table 7: **Bank Liquidity (Risk) and Crash Probability**

This table tests how a bank's *ex ante* liquidity (risk) to crash outcomes during the crisis, when market and funding liquidity conditions deteriorate.

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

where crash is identified if a bank's stock return suffers a 25% loss in one quarter or 35% loss in two quarters (t and $t-1$) during the peak of the financial crisis, from 2008Q3 to 2009Q2. Proxies for liquidity risk include scaled LMI (scaling by total asset), scaled (LMI–$\text{LMI}_{1\sigma}$) (here $\text{LMI}_{1\sigma}$ refers to LMI under 1-σ stress scenario when both cross-collateral haircut and Tbill-OIS spread are shocked by 1-σ), the liquidity creation measure by Berger and Bouwman (2009), Basel III's two measures: liquidity coverage ratio (LCR) and net stable funding ratio (NSFR). All liquidity (risk) measures are calculated as of 2006Q1, 2007Q1, and 2008Q1. In parentheses, we report the p-value for the estimation of regression coefficients. The sample is only for public U.S. BHCs with valid stock returns in CRSP. **N** refers to the total number of qualified BHCs.

	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	-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)
Return on Asse	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

* p<0.10, ** p<0.05, *** p<0.01

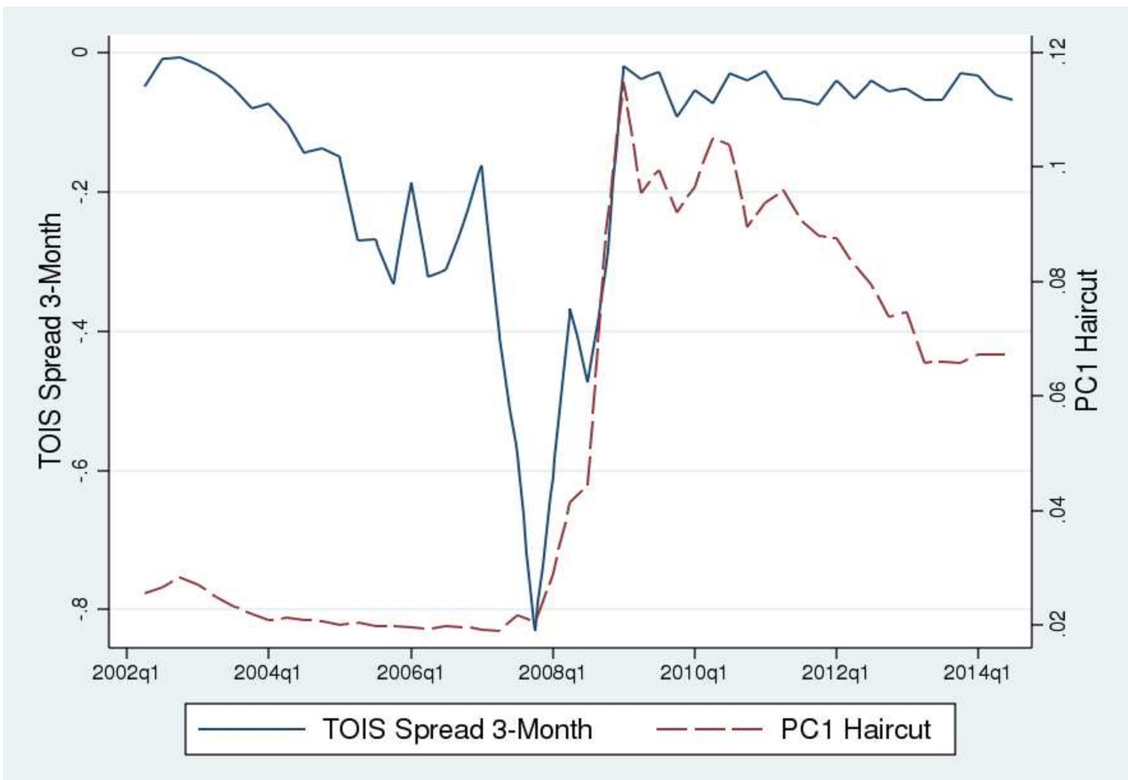


Figure 1: **Market Factors for Asset and Liability Liquidity Weights** The left axis is the funding liquidity factor, the three-month Tbill-OIS spread in percentage, and the right axis is the first principal component of haircuts across all asset categories, m_{PC1} (measured in decimals).

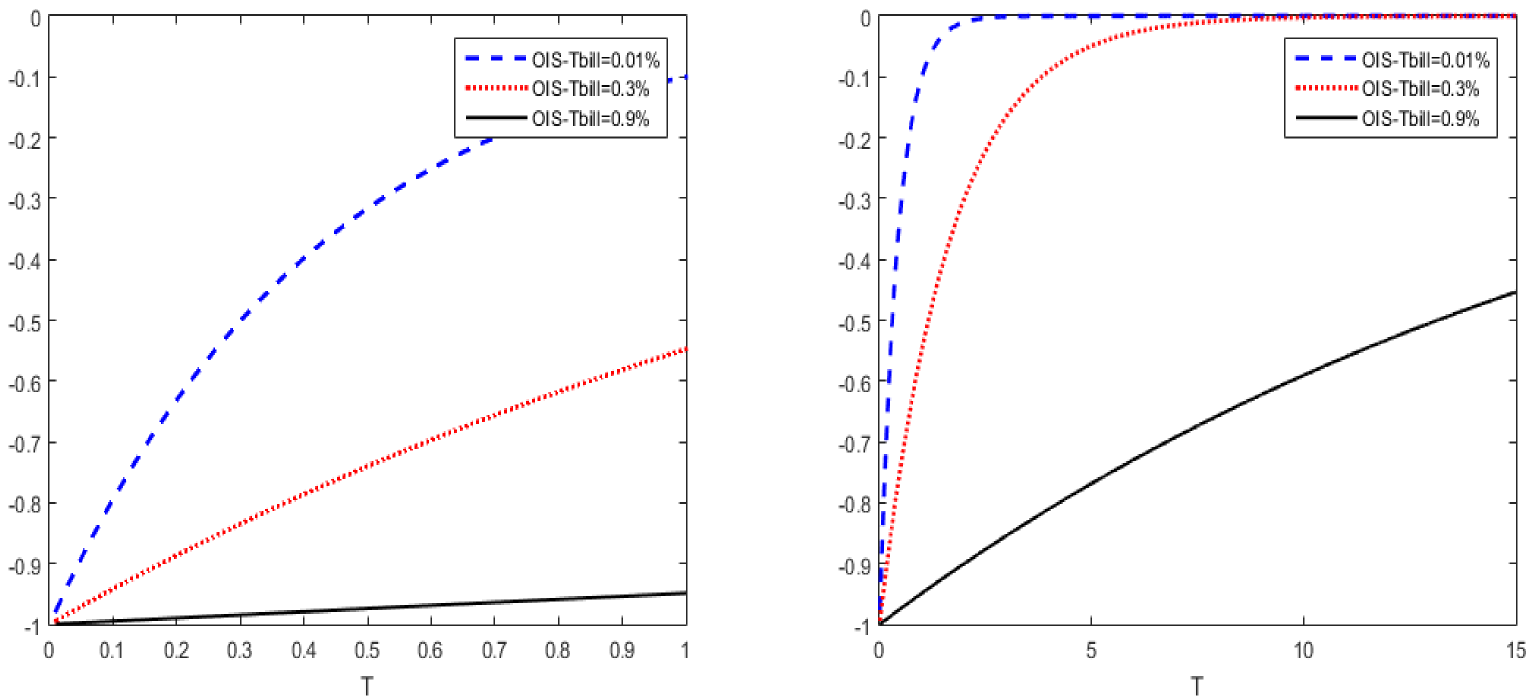


Figure 2: **Liability Liquidity Weights:** $\lambda_{L_k} = -\exp\left(\kappa \cdot \ln(OIS - Tbill)T_{k'}\right)$, **We set** $\kappa = 0.5$ **as in our calibration.**

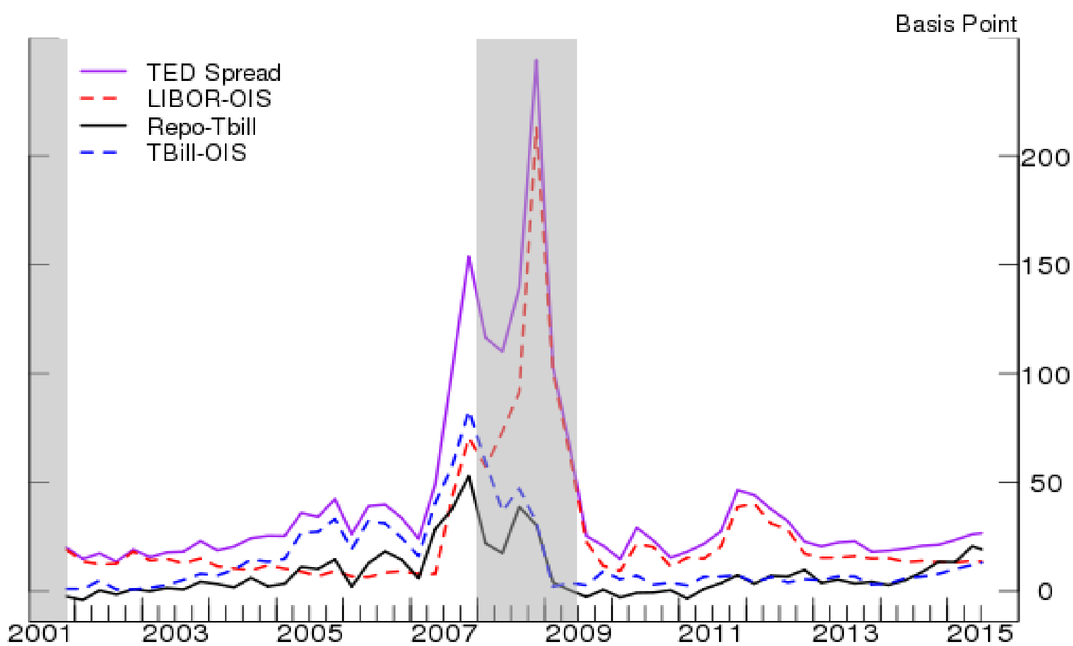


Figure 3: **Proxies for Funding Liquidity Premium**

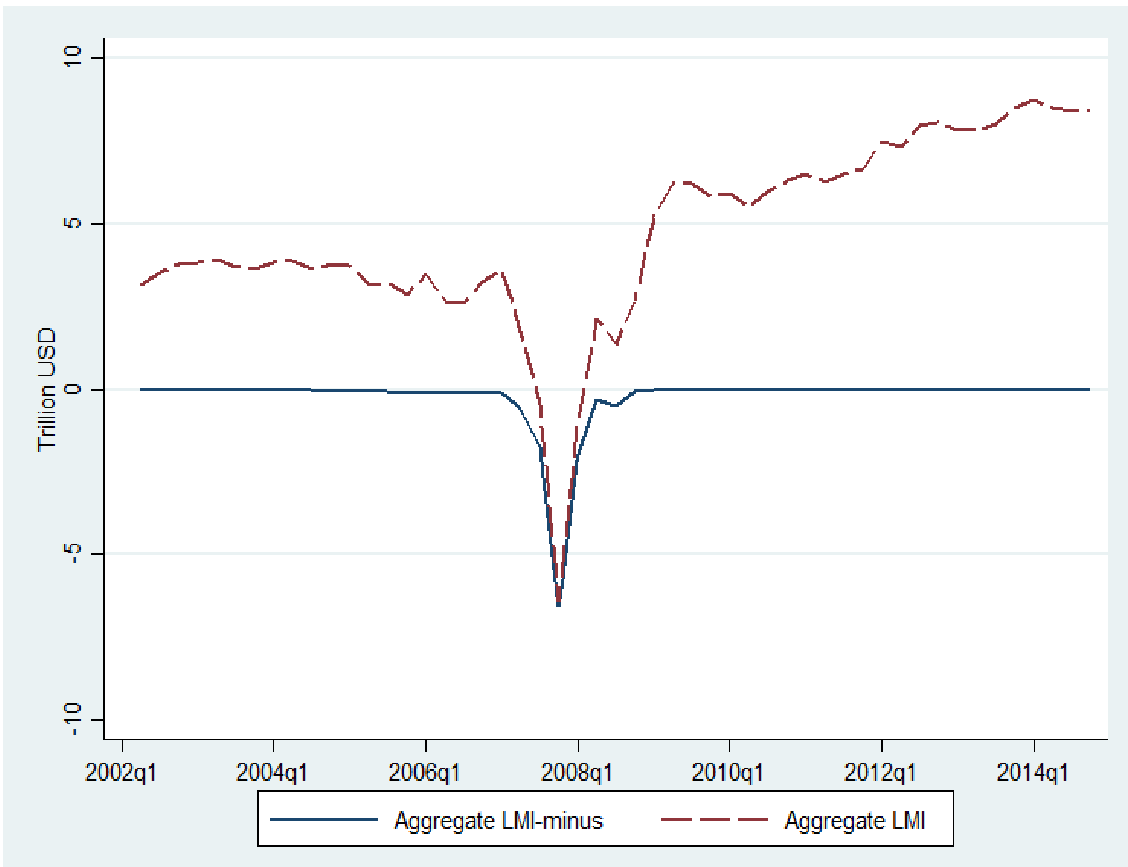
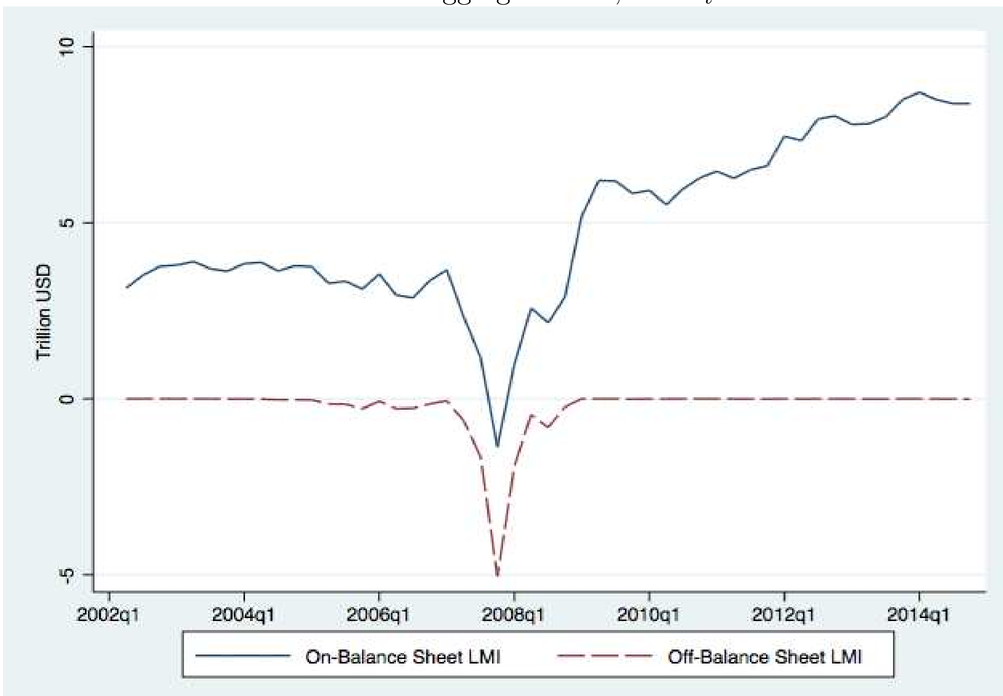


Figure 4: **Aggregate Liquidity Mismatch for All BHCs ($Trillion).** After calculating bank-level LMI, we aggregate them in two ways: one is to create a raw sum, $\widetilde{\boldsymbol{LMI}}_t = \sum_i LMI_t^i$, the other is sum over negative values, $[\boldsymbol{LMI}]_{\boldsymbol{t}}^- = \sum_i \min(LMI_t^i, 0)$.

Panel A: Aggregate LMI, $\widetilde{\boldsymbol{LMI}_t}$



Panel B: Snapshot of Aggregate LMI-minus, $[\boldsymbol{LMI}]_{\boldsymbol{t}}^{-}$

Figure 5: **Liquidity Mismatch On- and Off-Balance Sheet**

A: LMI post-crisis minus LMI in the crisis

B: LMI post-crisis minus LMI pre-crisis

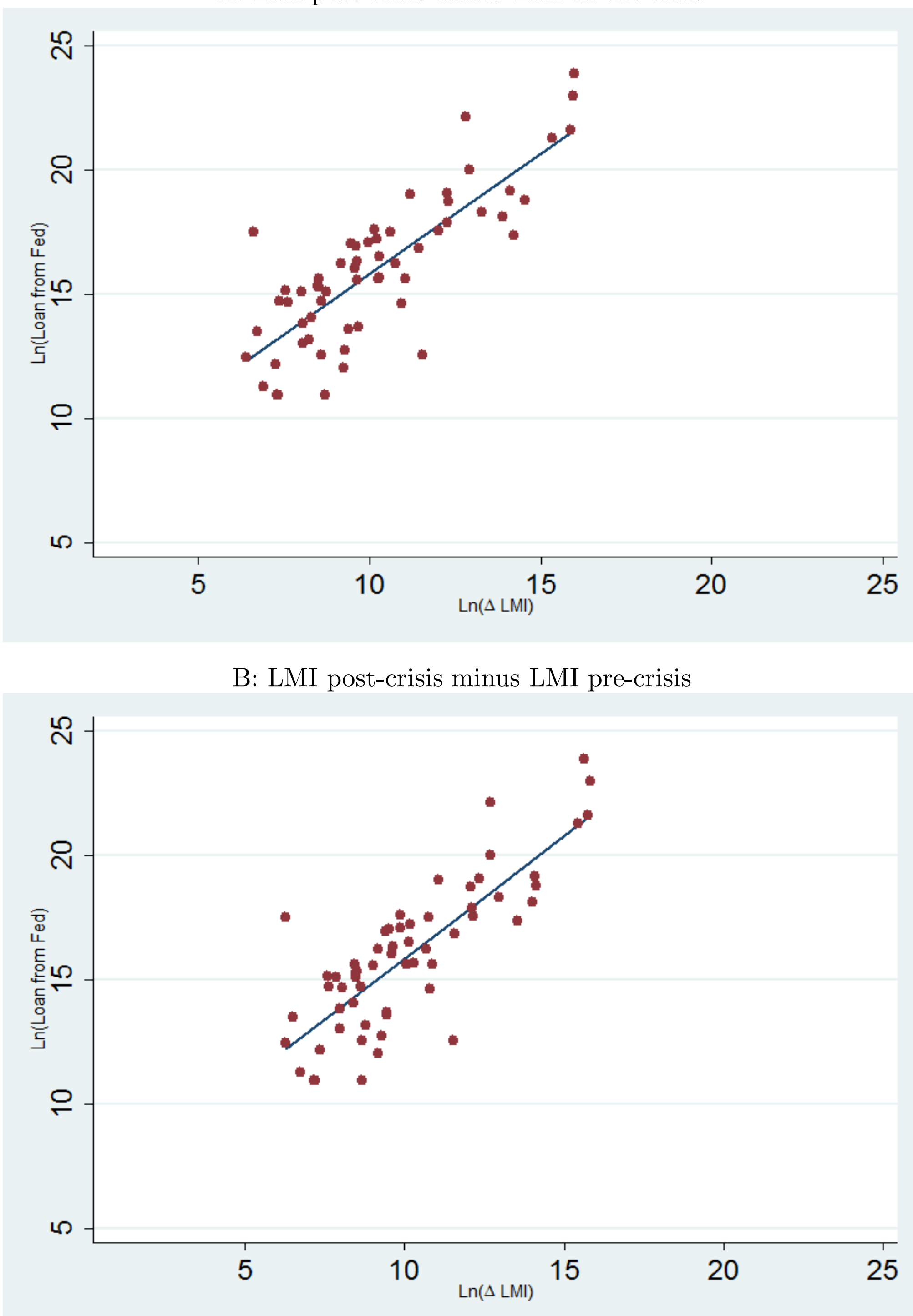


Figure 6: **Correlation between Fed Injections** ($\ln(loan)$) **and the Change of LMI** ($\ln(\Delta LMI)$)**.** The pre-crisis sample period is from 2006Q1 to 2007Q2, the crisis period is from 2007Q3 to 2009Q2 which is between the subprime crisis and the end of recession, and the post-crisis period is from 2009Q3 to 2012Q1 (the result is robust if using longer post-crisis period).

A. Asset-side and liability-side LMI (in Absolute Value)

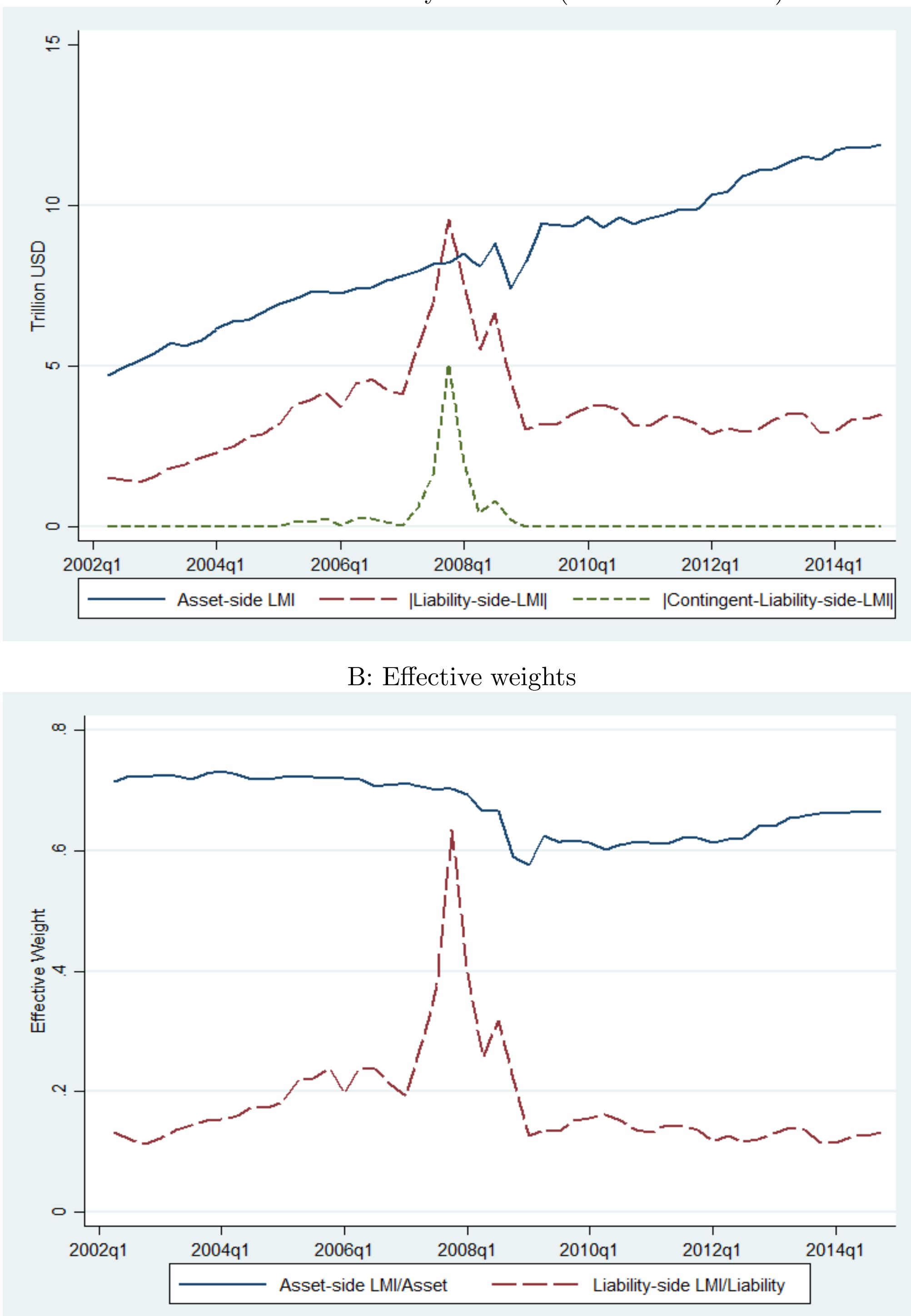
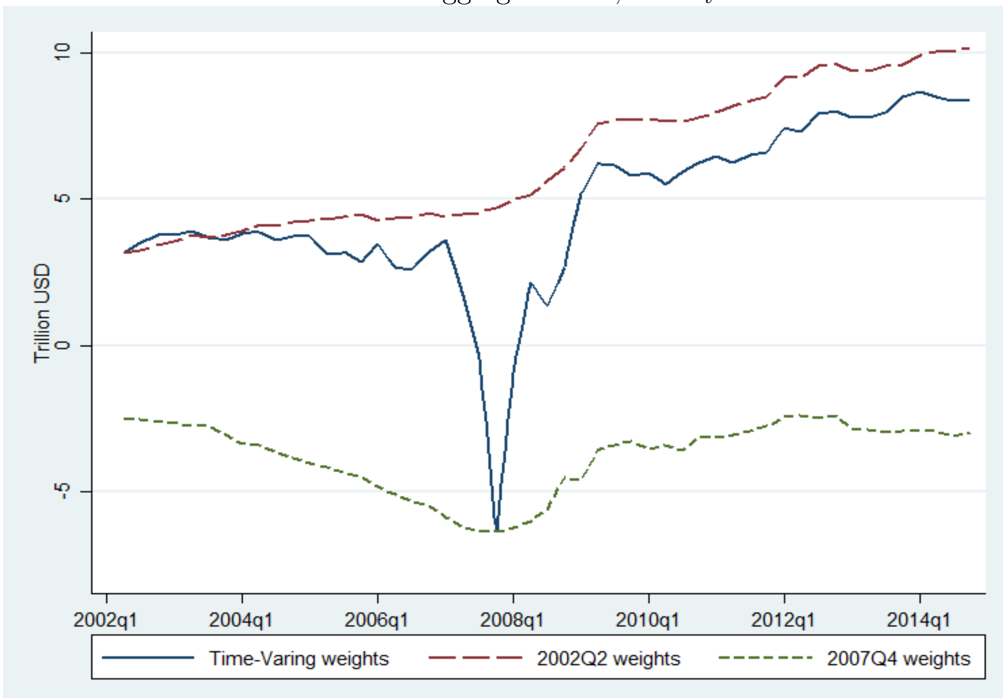


Figure 7: **Decomposition of LMI by Assets and Liabilities.** To facilitate comparison, we use the absolute value of liability-side and contingent-liability-side LMI in Panel A. Panel B depicts the average effective weights across banks, defined as the liquidity-weighted assets (or liabilities) divided by the total amount of assets (liabilities) used in the bank-level LMI calculation.

Panel A: Aggregate LMI, $\widetilde{\boldsymbol{LMI}}_t$



Panel B: Aggregate LMI-minus, $[\boldsymbol{LMI}]_{\boldsymbol{t}}^{-}$

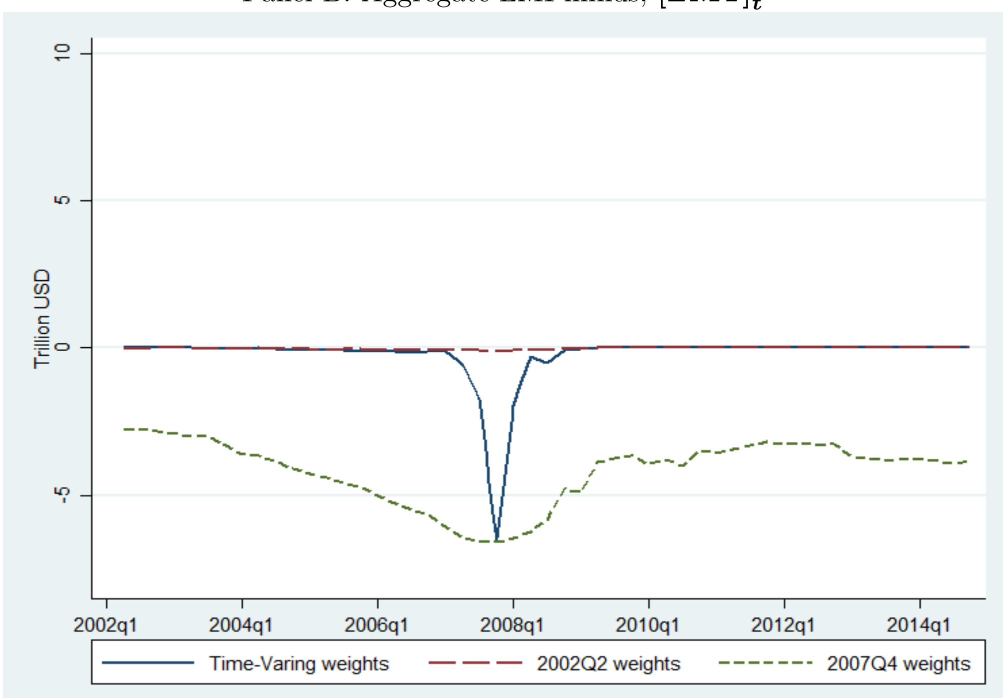
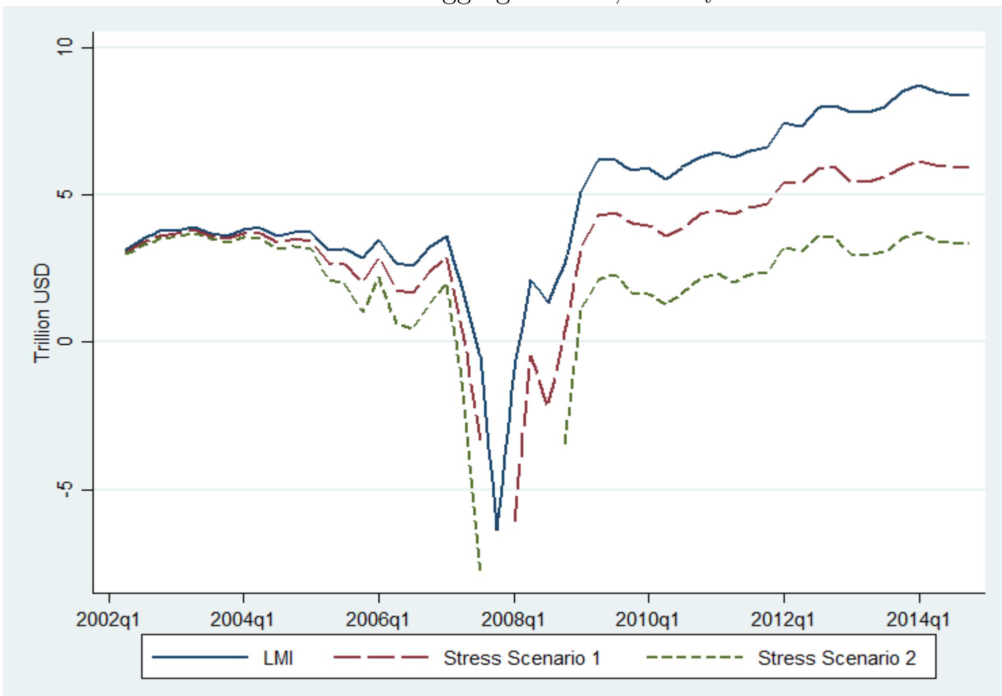


Figure 8: **LMI under various liquidity weights.** The blue line is our baseline case with time-varying weights; the red dashed line uses a fixed set of weights as of 2002Q2 (beginning of the sample), which captures a good liquidity condition; and the green dashed line uses weights as of 2007Q4 (the trough of the funding liquidity condition), which captures a stressed liquidity condition. All three lines use the same contemporaneous balance sheet information.

Panel A: Aggregate LMI, $\widetilde{\boldsymbol{LMI}}_t$



Panel B: Aggregate LMI-minus, $[\boldsymbol{LMI}]_{\boldsymbol{t}}^{-}$

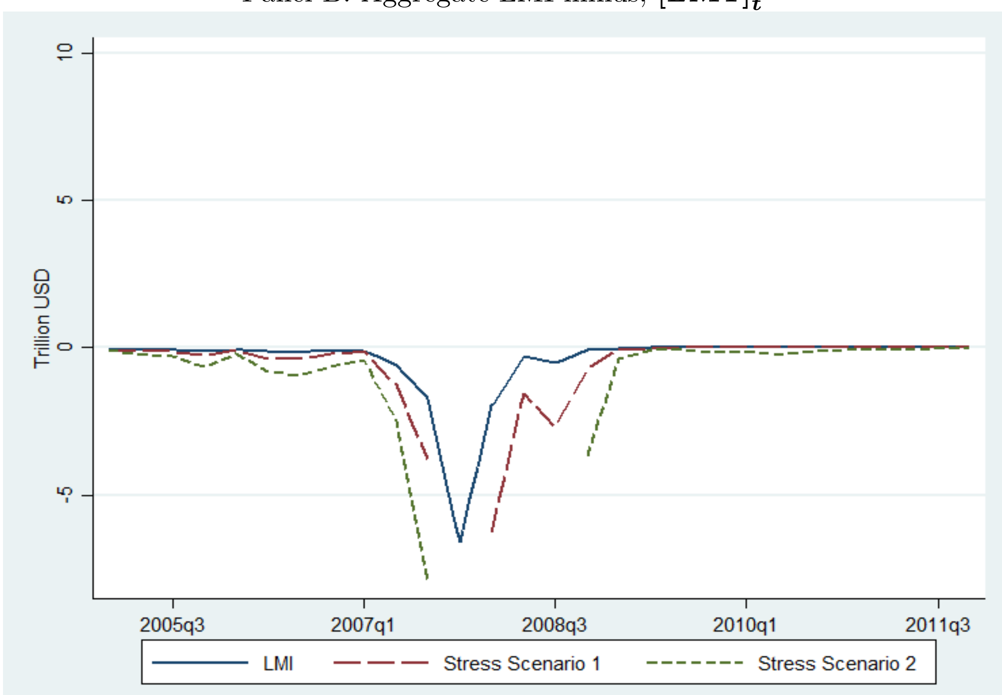


Figure 9: **LMI under $1\sigma, 2\sigma$ stress scenarios.** Stress scenario 1 refers to the situation when both market liquidity shock (m_{PC1}) and funding liquidity shock (OIS-Tbill spread) are one-sigma away from their time t market value, where the sigma is calculated as the historical standard error up to time t. Stress scenario 2 refers to the two-sigma situation. To make the figure visually readable, we truncate the y-axis at negative eight trillion level. Dashed lines under stress scenarios 1 and 2 thus are not visible during the most extreme period.

Measuring Liquidity Mismatch in the Banking Sector
Online Appendix

In the appendix we first provide a step-by-step manual for the calculation of LMI in Section A. We then test the robustness of LMI in various scenarios for the two free parameters in liquidity weights introduced in Section B. Section C presents a series of facilities utilized by the Federal Reserve System in order to support overall market liquidity. Section D calculates three benchmark liquidity measures in comparison with our LMI measure: (1) Berger and Bouwman (2009) liquidity creation, (2) Basel III's liquidity coverage ratio (LCR), and (3) the net stable funding ratio (NSFR). Tables A.1 and A.2 describe the asset-side and liability-side liquidity weights. Table A.3 shows the performance of LMI which are calculated under various sets of parameters. Table A.4 introduces a series of Fed liquidity injection facilities. Table A.5 shows the implementation of Basel III's Net Stable Funding Ratio. Table A.6 presents the results of the relationship between bank ex ante liquidity and bank's dollar borrowing amount from Fed loans or from TARP.

A Computing LMI

The LMI is the mismatch between the market liquidity of assets and the funding liquidity of liabilities. The LMI for bank i at a given time t is computed as in equation (1):

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

where $a_{t,k}^i$ and $l_{t,k'}^i$ are assets and liabilities in balance sheet, varying over time and across classes (k, k'); $\lambda_{t,a_k} > 0$ and $\lambda_{t,l_{k'}} < 0$ are the liquidity weights. We propose the following step-by-step manual for the calculation of LMI.

1. Identify the asset and liability classes, a_k and $l_{k'}$, in the FR Y-9C report.

   All balance sheet information are collected from FR Y-9C report Schedule HC and its sub-schedules. Under each category (k, k') in assets (Table A.1) and in liabilities (Table A.2), we list the corresponding schedule used in Y-9C report. The detailed item numbers are summarized in the last column, 'Source', in both tables.

2. Calculate asset liquidity weights, $\lambda_{t,a_k} = \exp\left(-(\overline{m}_k + 5 \times \beta_k m_{PC1,t})\right)$.

   - Collect tri-party repo transactions reported by the Money Market Fund from the SEC Edgar website, and calculate the haircuts, $m_{k,t}$, for each collateral asset such as Treasury and agency securities, corporate bonds, etc. Calculate the average haircuts as in Table 2.
   - Collect loan haircuts from the secondary loan market offered by the Loan Syndications & Trading Association, `www.lsta.org`.
   - Using the whole sample, conduct the principal component analysis across all asset classes and construct the first principal component, $m_{PC1,t}$.
   - Compute the loading, β_k, from the regression of individual haircut series $m_{k,t}$ to $m_{PC1,t}$, and use the absolute value of beta, see Table A.1.

3. Calculate liability liquidity weights, $\lambda_{t,l'_k} = -\exp(-\mu_t T_{k'})$.

   - Download funding liquidity proxy, the three-month OIS-Tbill spread (unit: percentage) from Bloomberg. μ_t is then the negative logarithm of the funding liquidity proxy.
   - Consult banking experts and bankers for reasonable values of $T_{k'}$, see Table A.2.

4. Multiply each asset and liability category to its matching liquidity weights for each BHC at time t, and the net value is LMI_t^i.

B Robustness of LMI

The construction of LMI has two open parameters. One parameter balances the gap between bilateral repo haircuts and tri-party repo haricuts, δ, as in the asset liquidity weight $\lambda_{t,a_k} = \exp\left(-(\overline{m}_k + \boldsymbol{\delta} \times \beta_k m_{PC1,t})\right)$; we use $\delta = 5$ in the current measure. The other parameter scales the market funding liquidity condition, κ, as in the liability liquidity weight $\lambda_{t,l'_k} = -\exp(-\boldsymbol{\kappa} \times \mu_t T_{k'})$; we use $\kappa = 0.5$ in the current measure.

There does not exist a perfect way to pin down the two open parameters. However, as the conventional exercise in macroecnomics, we can test the robustness of the effective performance of

LMI under various sets of parameters. For each set of parameters, we report in Table A.3 two types of LMI performance: (i) aggregate performance such as the average asset liquidity weights, $\bar{\lambda}_{A_k}$, the average liability liquidity weights, $\bar{\lambda}_{L'_k}$, the average aggregate LMI value across BHCs, $\overline{LMI}$, and the minimum value of aggregate LMI, MIN; and (ii) cross-sectional bank-level performance which examines the relationship between bank ex ante liquidity and bank's borrowing decision or crash probability during the financial crisis, by replicating the experiments in Tables 6 and 7. For aggregate performance, we use the average value over the sample period of 2007Q4 to 2009Q2 when the financial market is under severe stress, a crucial time period to test the effectiveness of liquidity measures.

Before the robustness check, we first examine the possible and rational range for parameters.

- **Delta,** δ

  The ideal data for haircut should be those based on transactions in the bilateral market, which offers more accurate information on the asset liquidity. However, it's almost impossible to collect market-wide bilateral repo data. We thus use the tri-party repo data but rely on the parameter δ to bridge the gap between bilateral repo haircuts and tri-party repo haricuts. To get a reasonable calibration for δ, we endeavor in two ways.

  First, we get the bilateral repo data at the generosity of Adam Copeland and compare them to the tri-party data for each asset class. The difference of bilateral data and tri-party data for selected asset classes is plotted in Figure 2 in Copeland, Martin, and Walker (2014) for the period of July 2008 to February 2010. We regress the time-series bilateral repo haircuts on the tri-party repo haircuts under the matching asset class, and calculate the exposure. Ranging from Treasury securities to structured product, the regression coefficient values from 3.5 to 7.9, which provides the lower and upper boundary for δ. We mainly rely on these boundaries for our robustness test in Table A.3. It's worth noting that though the difference of haircuts between bilateral and tri-party is small in absolute value for safe assets such as Treasuries and agency securities (about 2 basis points), the difference in proportion is not trivial, still a value of 3.5.

  Second, we use the real bilateral haircut values to calculate asset liquidity weights and compare them to our current measure which relies on $\{\bar{m}_k, \beta_k, m_{PC1}\}$ and $\delta = 5$. We do this only for the sample period when bilateral repo data is available, say from August 2007 to February 2010. Row 1 of Table A.3 presents the results.

  In sum, we consider four values in the reasonable range of the delta values, (i) real value based on bilateral haircuts, (ii) lower boundary of the exposure of tri-party repo haircut to bilateral repo haircut, say $\delta = 3.5$, (iii) upper boundary of the exposure, say $\delta = 7.9$, and (iv) our current measure $\delta = 5$. The larger the delta value is, the more liquidity weights in assets. That is, assets are more cashable, hence the better liquidity condition.

- **Kappa**, κ

  The parameter kappa scales the market funding liquidity condition in the liability liquidity weights. Like the asset side, there does not exist a perfect way to pin down the extent to which market funding liquidity proxy affects the liability liquidity pressure. Currently, we set $\kappa = 1$. Then we consider four alternative proxies, $\kappa = \{0.25, 0.50, 1.50, 2.00\}$. The larger the kappa value is, the less liquidity weight (in absolute value) in liabilities. That is, liabilities generate less liquidity pressure.

Table A.3 presents the effective performance of LMI under various sets of $\{\delta, \kappa\}$ as discussed above. For the cross-sectional bank-level performance, if the predictive power of candidate LMI measure is positive and significant at 1% or below, we denote '+'; if the predictive power is negative and significant at 1% or below, we denote '-'; if the predictive power is statistically insignificant at 10% and above, we denote '\'. Following Tables 6 and 7 in the main text, we consider two candidate LMI measures: (a) Scaled LMI, denote 'SLMI', which is LMI scaled by total asset, and (b) Scaled ($\text{LMI} - \text{LMI}_{1\sigma}$), denote 'DLMI'. We test the predictive power of candidate LMI measures at ex ante time t to ex post bank borrowing decisions in Fed Loan, or TARP, as in Table 6, and the predictive power of candidate LMI measures at ex ante time t to ex post bank's crash probability as in Table 7, where t_1 refers to the time point of 2006Q1, t_2 refers to 2007Q1, and t_3 refers to 2008Q1.

There are three main findings worth attention. First and foremost, LMIs under various sets of parameters overall generate robust results, especially in the cross-sectional bank-level performance. The Scaled LMI, SLMI, calculated under all sets of parameters continues to have robust predictive power i) on a bank's decision whether or not to borrow a Fed loan or to borrow in TARP; and ii) on a bank's crash probability during the financial crisis. Banks with more liquidity mismatch, that is lower LMI before the crisis, will be more likely to borrow from the government and to crash in the crisis. The performance for the liquidity risk, Scaled ($\text{LMI} - \text{LMI}_{1\sigma}$), DLMI, is mixed: DLMI under lower κ, say 0.5 or 0.25, has better predictive power.

Second, the LMI performance using the real bilateral haircut data is similar to its performance using our current setup, $\delta = 5$, see Rows (1) and (2). Although 5 seems an arbitrary number which oversimplifies the unequal relationship of bilateral and tri-party data across various asset classes, in reality, this rule-of-thumb measure is well aligned with the real world data. Given the data constraint that most researchers and market participants cannot access the bilateral data (even the bilateral data used in Copeland et al. (2014) reflects only partial information in the bilateral repo market, which is based on a survey on selected banks and only for a very limited time period), such an assumption is a helpful necessity after this justification.

Third, when κ deviates to either very large or small values, the minimum LMI values become unreasonable. If κ is too small, say 0.25, the LMI is in the range of -9.24 to -9.88; that means, the regulatory institutions need at least \$9 trillion dollars to inject into the banking industry at the worst scenario, which is exceedingly large compared with the real injection during the financial crisis. If κ is too large, say 2.00, the LMI is in the range of 0.64 to 1.29; that means, the asset-side liquidity can fully cover the liability-side liquidity shortage, which is not the case neither in the real world. Overall, $\kappa = 0.5$ seems a reasonable choice.

In sum, higher δ or lower κ leads to more liquidity mismatch, that is, the lower LMI value. When checking the p-value, LMI under both lower δ and lower κ tends to have more significance in the cross-sectional performance, that is the lower p-value. However, a very low or high value of κ results in unreasonable aggregate performance. Overall, our current choice of ($\delta = 5, \kappa = 0.5$) is reasonable.

C Background on Federal Liquidity Injection

The Federal Reserve System (Fed) undertook numerous measures to restore economic stability from the financial crisis of 2007 - 2009. Beyond its conventional monetary policy tools, the central bank, citing "unusual and exigent circumstances," launched a range of new programs to the banking sector in order to support overall market liquidity.

Conventionally, the Fed uses open market operations and the discount window as its principal tools to manage reserves in the banking sector. During the crisis, however, the effectiveness of the discount window was limited because of a sigma effect. Banks were reluctant to approach the discount window since such action could cause market participants to draw adverse inference about the bank's financial condition (see, for example, Peristiani (1998), Furfine (2003), Armantier, Ghysels, Sarkar, and Shrader (2011)).Given the borrowing stigma and inflexibility of open market operations, the Fed proceeded to introduce additional facilities increase liquidity, including the Term Auction Facility (TAF), Term Securities Lending Facility (TSLF), Primary Dealer Credit Facility (PDCF), Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF), Commercial Paper Funding Facility (CPFF), Money Market Investor Funding Facility (MMIFF), and Term Asset-Backed Securities (TALF). Fleming (2012) provides a summary on these lending facilities. We summarize their key features in Table A.4.

The Fed announced the first facility, Term Auction Facility (TAF) on December 12, 2007 to address the funding pressure in short-term lending markets. Through the TAF, the Fed auctioned loans to depository institutions, typically for terms of 28 or 84 days. Later, to address liquidity pressures in the term funding markets, the Feds introduced the Term Securities Lending Facility (TSLF) on March 11, 2008. Through TSLF, the Fed auctioned loans of Treasury securities to primary dealers for terms of 28 days. Another related facility, the Primary Dealer Credit Facility (PDCF), was announced on March 16, through which the Fed made overnight loans to primary dealers. The bankruptcy of Lehman Brothers on September 15, 2008 led to unparalleled disruptions of the money market. On September 19, the Fed announced created the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF). It provided loans to U.S. bank holding companies, and U.S. branches and agencies of foreign banks to purchase eligible asset-backed commercial paper from money market mutual funds. On October 7, the Fed further announced the creation of the Commercial Paper Funding Facility (CPFF), through which the Fed provided credit to a special-purpose vehicle (SPV) that, in turn, bought newly issued three-month commercial paper. Two weeks later on October 21, the Fed established the Money Market Investor Funding Facility (MMIFF). All three money market-related facilities expired on February 1, 2010. Lastly, the Fed introduced the Term Asset-Backed Securities (TALF) on November 25, 2008, through which the Fed made loans to borrowers with eligible asset-backed securities as collateral.

D Benchmark: Alternative Liquidity Measures

We consider three benchmark liquidity measures in comparison with our LMI measure: (1) Berger and Bouwman (2009) liquidity creation (BB), (2) Basel III's liquidity coverage ratio (LCR), and (3) the net stable funding ratio (NSFR). To make a fair comparison, all benchmark measures are constructed for bank holding companies (BHCs) applying to the same Y-9C data which are used in this paper.

Berger and Bouwman (2009) propose the liquidity creation measure. We follow Table 1 in their paper as the main procedure. Before applying the procedure to BHCs, we first conduct the experiment to commercial banks using the call report, which is the identical data source and study object in their paper. In so doing, we confirm our replication exercise to get the same result as the dataset provided in the author's website.[17] We then repeat the exercise to Y-9C data for the universe of BHCs.

The Basel committee on bank supervision has proposed a series of reforms known as Basel III to increase the resilience of the banking sector since July 2009 (BCBS (2014) BCBS (2013)). Our implementation is based on the final version of the release. In particular, the LCR formula and timetable is based on the final rule issued collectively by the Office of the Comptroller of the Currency (OCC), the Board of Governors of the Federal Reserve System (Federal Reserve Board), and the Federal Deposit Insurance Corporation on October 10, 2014. The LCR is defined as the ratio of the stock of high-quality liquid assets to the total net cash outflows over the next 30 calendar

[17] http://faculty.weatherhead.case.edu/bouwman/data.html

days under a significantly severe liquidity stress condition:

$$LCR = \frac{\text{High-quality liquid asset amount}}{\text{Total net cash outflow amount}}.$$

The detailed definition on high-quality liquid asset and net cash outflow can be found on the OCC website.[18]

The NSFR formula and implementation is based on the Basel release in October 2014, which we detail in Table A.5. The NSFR is the ratio of available stable funding to required stable funding:

$$NSFR = \frac{\text{Available stable funding}}{\text{Required stable funding}}.$$

Our implementation is also inspired by Dietricha et al. (2014) and Hong et al. (2014), who derive their NSFR time series in a comparable way.

[18] http://www.occ.gov/news-issuances/bulletins/2014/bulletin-2014-51.html

Table A.1: **ASSET Weight:** $\lambda_{t,a_k} = \exp\left(-(\overline{m}_k + \delta \cdot \times \beta_k m_{PC1,t})\right), \;\; \delta = 5$

Note: 1. $\overline{m}_k$ is the average haircut for asset k which is reported in Table 2.
($\overline{m}_k$ is set to be 0 for cash , and ∞ for fixed, intangible and other assets, thus $\lambda_{cash} = 1$, $\lambda_{fixed} = 0$.)
2. $m_{PC1,t}$ is the time-series of the first principal component of haircuts across all asset categories in Figure 1,
3. β_k is the absolute value of risk exposure from: $m_{k,t} = constant + \beta_k m_{PC1,t} + \varepsilon_t$.
4. In Category, we list the original source for each variable used in LMI calculation.
For example, CASH is from Schedule HC, Item 1a, 1b, 3a, 3b, in FRY-9C Report.

Category	a_k	β_k	Source
Cash (HC)	cash and balances due from depository institutions	-	1a, 1b
	federal funds sold	-	3a
	securities purchased under agreements to resell	-	3b
Trading Assets (HC-D Col A)	Treasury securities	0.059	1
	agency securities	0.059	2, 4a, 4b, 4d
	securities issued by states and political subdivisions	0.558	3
	structured product including non-agency MBS	0.303	4c, 4e, 5a
	corporate debt	0.508	5b
Available for Sale (HC-B Col D)	Treasury securities	0.059	1
	agency securities	0.059	2, 4a(1)-(2), 4b(1)-(2), 4c(1)(a), 4c(2)(a)
	securities issued by states and political subdivisions	0.558	3, 4a(3), 4b(3), 4c(1)(b), 4c(2)(b)
	structured product including non-agency MBS	0.303	5a, 5b
	corporate debt	0.508	6
	equity securities	0.652	7
Held for Maturity (HC-B Col B)	Treasury securities	0.059	1
	agency securities	0.059	2, 4a(1)-(2), 4b(1)-(2), 4c(1)(a), 4c(2)(a)
	securities issued by states and political subdivisions	0.558	3, 4a(3), 4b(3), 4c(1)(b), 4c(2)(b)
	structured product including non-agency MBS	0.303	5a, 5b
	corporate debt	0.508	6
Loans (HC-C Col A)	loans secured by real estates	1.004	1a
	commercial & industry loans	1.004	4a, 4b
	other loans	1.004	
	lease financing receivables	1.004	10
Fixed Assets (HC)	premises and fixed assets	-	6
	other real estate owned	-	7
	investment in unconsolidated subsidiaries	-	8, 9
Intangible Assets	goodwill and other intangible assets	-	10
Other Assets		-	11

Table A.2: **LIABILITY Weight:** $\lambda_{t,l'_k} = -\exp(-\kappa \cdot \mu_t T_{k'}),\ \ \kappa = 0.5$

Note: 1. μ_t is the negative logarithm of the three-month OIS-Tbill spread.
2. In Category, we list the original source for each variable used in LMI calculation.
For example, OVERNIGHT DEBT is from Schedule HC, Item 14a and 14b, in FRY-9C Report.

Category	$l_{k'}$	$T_{k'}$	Source
Overnight Debt	overnight federal funds purchased	0	14a
(HC)	securities sold under repo	0	14b
Deposits[1]	insured	10	1a, 1b
(RC-O Memo)	uninsured	1	
Trading Liabilities[2]	trading liabilities	-	13a
(HC-D)			
Other Borrowed Money	commercial paper	1/12	14a
(HC-M)	with maturity <= 1 year	1	14b
	with maturity > 1 year	5	14c
Other Liabilities	subordinated notes and debenture	10	19a, 19b
(HC)	other liabilities	10	20
Total Equity Capital	equity	30	28
(HC)			
Contingent Liabilities[3]	unused commitments	5	
(HC-L)	(revolving, open-end loans,		1a
	unused credit card lines,		1b
	to fund commercial-real-estate-related loans,		1c
(HC-S Memo)	to provide liquidity to ABCP conduit structures,		3a
	to provide liquidity to securitization structures,		3a
(HC-L)	other unused commitments)		1e
	Credit Lines	10	
(HC-L)	(financial standby letters of credits,		2
	performance standby letters of credits,		3
	commercial and similar letters of credits)		4
(HC-L)	Securities Lent	5	6, 8, 9
(HC-D)	Collateral Values[5]	10	11, 14

Notes:

1. A bank's deposit can be decomposed into multiple categories: insured and uninsured deposits, interest-bearing and non-interest-bearing deposits, domestic and foreign deposits, time deposits and broker deposits, and so on. Among them, insured and uninsured category directly relates to a bank's liquidity condition. The Federal Deposit Insurance Corporation (FDIC) provides deposit insurance in order to guarantee the safety of deposits in member banks. Such deposits, since fully guaranteed by the FDIC, should have little influence on a bank's liquidity. However, the insured and uninsured category are not clearly broken down in the Y-9C report. We collect such data instead from the Call Report FFIEC 031 Schedule RC-O – Other Data for Deposit Insurance and FICO. The Call Report data are for banks that are subsidiaries of the BHCs which file the Y9C. Therefore we manually merge the call reports data back to their highest holding company. The deposits at the BHC level is thus the sum of deposits of all its subsidiary commercial banks.

Based on the FDIC insurance limits and the call report decomposition data, we calculate the insured deposit as the combination of i) all deposit lower than the FDIC limit K and ii) the first K dollar amount in the accounts above the limit multiplying the number of such deposit accounts. There are two insurance coverage changes in our sample period. First, the FDIC increased insurance limits from \$100,000 to \$250,000 per depositor on October 3, 2008. Yet this change is not reflected in the Call Report RC-O until 2009:Q3. We follow the data availability and change our definition for insured/uninsured deposit beginning in 2009:Q3. Second, the FDIC increased the insurance for retirement accounts from \$100,000 to \$250,000 on March 14, 2006. This change is reflected in the 2006:Q2 call reports and our definition reflects this change beginning in 2006:Q2.

2. Trading liabilities is the counterpart of trading assets. Therefore we use the negative value of the trading asset liquidity weight: $-\lambda_{t,a_{k'}}$. In Y-9C report Schedule HC-D – Trading Assets and Liabilities, however, trading liabilities are not categorized to asset classes such as Treasury, agency, etc. Without knowing the detailed classes, we use the mixed haircut rate across all assets excluding the loans. The average haircut for the mixed asset is 0.040 and the risk exposure to m_{PC_1}, β is equal to 0.055.

3. We study four types of contingent liabilities that may exert a pressure on bank's liquidity. Many banks carry *unused commitments*, including revolving loans secured by residential properties, unused credit card lines, commitments to fund commercial real estate, construction, and land development loans, securities underwriting, commitments to commercial and industrial loans, and commitments to provide liquidity to asset-backed commercial paper conduits and other securitization structures. The second type are *credit lines*, including financial standby letters of credit and foreign office guarantees, performance standby letters of credit and foreign office guarantees, commercial and similar letters of credit. A third type of contingent liability is *securities lent.* The last type of contingent liability in our study is the *derivative* contract. Item 7 in Schedule HC-L lists the gross notional amount of credit derivative contracts, including credit default swaps, total return swaps, credit options and other credit derivatives. However, such gross notional amount does not reflect the contracts' liquidity. What matters in a credit derivative contract in terms of liquidity impact is the additional collateral or margin required in a stress event. We therefore focus on trading assets and liabilities in Schedule HC-D and use the net value of derivatives since it is those in the trading category who most likely require margins.

Table A.3: **LMI Performance under Various Sets of Parameters** $\{\delta, \kappa\}$

This table examines the effective performance of LMI under various sets of parameters. For each set of parameters, we report two types of LMI performance: (i) aggregate performance over the period of 2007Q4 to 2009Q2 when the financial market is under severe stress, including the average asset liquidity weights, $\bar{\lambda}_{a_k}$, the average liability liquidity weights, $\bar{\lambda}_{l_{k'}}$, the average aggregate LMI value across BHCs, $\overline{LMI}$, and the minimum value of aggregate LMI, MIN; and (ii) cross-sectional bank-level performance which examines the relationship between bank ex ante liquidity at three time points, 2006Q1 (t_1), 2007Q1 (t_2), and 2008Q1 (t_3), and bank's borrowing decision in Fed loan or TARP, and bank's crash probability during the financial crisis, which replicate the experiments in Table 6 and Table 7. Row (1) uses the real bilateral repo data which is available from August 2007 to February 2010, based on which we examine the aggregate performance over 2007Q4 to 2009Q2 and the cross-sectional performance only at 2008Q1 (t_3). We consider two candidate LMI measures: (a) Scaled LMI, denote 'SLMI', which is LMI scaled by total asset, and (b) Scaled (LMI – $\text{LMI}_{1\sigma}$), denote 'DLMI'. Panel A reports the performance with abstract illustrations, $\{+, -, /\}$. If the predictive power of candidate LMI measure is positive and significant at 1% or below, we denote '+'; if the predictive power is negative and significant at 1% or below, we denote '-'; if the predictive power is statistically insignificant at 10% and above, we denote '\'. Panel B reports the p-value of the predictive power of LMI in the cross-sectional bank performance regressions.

Panel A: Illustration with $\{+, -, /\}$

Row	Scenario		$\bar{\lambda}_{A_k}$	$\bar{\lambda}_{L'_k}$	$\overline{LMI}$	MIN	Fed Loan						TARP						Crash					
							SLMI			DLMI			SLMI			DLMI			SLMI			DLMI		
	δ	κ					t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3
(1)	Real	0.50	0.75	-0.45	1.40	-6.43			-			+			-			+			-			/
(2)	5.0	0.50	0.78	-0.45	1.46	-6.41	-	-	-	+	+	+	-	-	-	+	+	+	-	-	-	/	/	/
(3)	3.5	0.50	0.80	-0.45	1.90	-6.18	-	-	-	+	+	+	-	-	-	+	+	+	-	-	-	/	/	/
(4)	7.9	0.50	0.73	-0.45	0.71	-6.82	-	-	-	+	+	+	-	-	-	+	+	+	-	-	-	/	/	/
(5)	5.0	1.00	0.78	-0.38	3.43	-2.52	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(6)	3.5	1.00	0.80	-0.38	3.88	-2.29	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(7)	7.9	1.00	0.73	-0.38	2.69	-3.04	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(8)	5.0	1.50	0.78	-0.34	4.27	-0.30	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(9)	3.5	1.50	0.80	-0.34	4.71	-0.07	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(10)	7.9	1.50	0.73	-0.34	3.53	-0.72	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(11)	5.0	0.25	0.78	-0.53	-1.19	-9.47	-	-	-	+	+	+	-	-	-	+	+	+	-	-	-	/	/	/
(12)	3.5	0.25	0.80	-0.53	-0.75	-9.24	-	-	-	+	+	+	-	-	-	+	+	+	-	-	-	/	/	/
(13)	7.9	0.25	0.73	-0.53	-1.94	-9.88	-	-	-	+	+	+	-	-	-	+	+	+	-	-	-	/	/	/
(14)	5.0	2.00	0.78	-0.32	4.74	1.06	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(15)	3.5	2.00	0.80	-0.32	5.19	1.29	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/
(16)	7.9	2.00	0.73	-0.32	4.00	0.64	-	-	-	+	+	+	-	-	-	/	/	+	-	-	-	/	/	/

Panel B: Illustration with p-values

Row	Scenario		$\bar{\lambda}_{A_k}$	$\bar{\lambda}_{L'_k}$	$\overline{LMI}$	MIN	Fed Loan						TARP						Crash					
							SLMI			DLMI			SLMI			DLMI			SLMI			DLMI		
	δ	κ					t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3	t_1	t_2	t_3
(1)	Real	0.50	0.75	-0.45	1.40	-6.43			0.00			0.00			0.00			0.01			0.00			0.93
(2)	5.0	0.50	0.78	-0.45	1.46	-6.41	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.03	0.03	0.01	0.00	0.00	0.02	0.62	0.75	0.83
(3)	3.5	0.50	0.80	-0.45	1.90	-6.18	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.03	0.03	0.01	0.00	0.00	0.02	0.62	0.76	0.83
(4)	7.9	0.50	0.73	-0.45	0.71	-6.82	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.03	0.03	0.01	0.00	0.00	0.02	0.62	0.74	0.83
(5)	5.0	1.00	0.78	-0.38	3.43	-2.52	0.00	0.00	0.00	0.04	0.04	0.00	0.01	0.00	0.00	0.15	0.13	0.01	0.00	0.00	0.00	0.32	0.96	0.93
(6)	3.5	1.00	0.80	-0.38	3.88	-2.29	0.00	0.00	0.00	0.04	0.03	0.00	0.01	0.00	0.00	0.15	0.13	0.01	0.00	0.00	0.00	0.32	0.96	0.93
(7)	7.9	1.00	0.73	-0.38	2.69	-3.04	0.00	0.00	0.00	0.05	0.04	0.00	0.01	0.00	0.00	0.15	0.14	0.01	0.00	0.00	0.00	0.32	0.98	0.93
(8)	5.0	1.50	0.78	-0.34	4.27	-0.30	0.00	0.00	0.00	0.05	0.05	0.00	0.01	0.01	0.00	0.18	0.16	0.02	0.00	0.00	0.00	0.29	0.93	0.93
(9)	3.5	1.50	0.80	-0.34	4.71	-0.07	0.00	0.00	0.00	0.05	0.04	0.00	0.01	0.01	0.00	0.18	0.16	0.02	0.00	0.00	0.00	0.29	0.92	0.93
(10)	7.9	1.50	0.73	-0.34	3.53	-0.72	0.00	0.00	0.00	0.06	0.06	0.00	0.01	0.01	0.00	0.19	0.16	0.02	0.00	0.00	0.00	0.29	0.95	0.94
(11)	5.0	0.25	0.78	-0.53	-1.19	-9.47	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.03	0.10	0.99	0.61	0.72
(12)	3.5	0.25	0.80	-0.53	-0.75	-9.24	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.03	0.10	0.99	0.61	0.72
(13)	7.9	0.25	0.73	-0.53	-1.94	-9.88	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.03	0.10	0.99	0.60	0.72
(14)	5.0	2.00	0.78	-0.32	4.74	1.06	0.00	0.00	0.00	0.05	0.06	0.00	0.02	0.01	0.00	0.21	0.18	0.02	0.00	0.00	0.00	0.27	0.90	0.88
(15)	3.5	2.00	0.80	-0.32	5.19	1.29	0.00	0.00	0.00	0.05	0.05	0.00	0.01	0.01	0.00	0.20	0.18	0.02	0.00	0.00	0.00	0.27	0.89	0.88
(16)	7.9	2.00	0.73	-0.32	4.00	0.64	0.00	0.00	0.00	0.07	0.08	0.00	0.02	0.01	0.00	0.22	0.18	0.02	0.00	0.00	0.00	0.27	0.93	0.88

Table A.4: **Fed Liquidity Injection Facilities**

Facility	Announcement	Expiration	Participants	Term
TAF	Dec12, 2007	Mar08, 2010	Depository Inst.	28 or 84 days
TSLF	Mar11, 2008	Feb01, 2010	Primary dealers	28 days
PDCF	Mar17, 2008	Feb01, 2010	Primary dealers	overnight
AMLF	Sep19, 2008	Feb01, 2010	BHCs and branches of foreign banks	<120 days for D* <270 days for non-D
CPFF	Oct07, 2008	Feb01, 2010	U.S. CP issuers	3 months
MMIFF	Oct21, 2008	Oct30, 2009	Money Mkt Funds	90 days or less
TALF	Nov25, 2008	Jun30, 2010	U.S. eligible banks	<5 years

*: D denotes depository institutions; non-D is non-depository institutions.

Table A.5: **Implementation of Net Stable Funding Ratio**

Available Stable Funding: Item	Factor	Required Stable Funding: Item	Factor
Tier 1 & 2 capital instruments Other preferred shares and capital instruments having an effective maturity of 1 year or greater Other liabilities with an effective maturity of 1 year or greater	100	Cash Short-term unsecured actively-traded instruments (<1 yr.) Securities with exactly offsetting reverse repo Securities with maturity <1 yr Interbank claims with maturity <1 yr	0
Stable deposits of retail and small business customers (non-maturity or residual maturity < 1 yr)	90	Government debt with a 0% risk weight under Basel II Debt issued or guaranteed by sovereigns, central banks, BIS, IMF, EC, non-central government, multilateral development banks with a 0% risk weight under Basel II approach	5
Less stable deposits of retail and small business customers (non-maturity or residual maturity < 1yr)	80	Unencumbered non-financial senior unsecured corporate bonds and covered bonds rated at least AA-, and debt that is issued by sovereigns, central banks, and public sector entities with a risk-weighting of 20%; maturity $\geq$ 1 yr.	20
Wholesale funding provided by non-financial corporate customers, sovereign central banks, multilateral development banks and public sector entities (non-maturity or residual maturity < 1yr)	50	Unencumbered listed equity securities or non-financial senior unsecured corporate bonds (or covered bonds) rated from A+ to A with a maturity $\geq$ 1 yr Gold Loans to non-financial corporate clients, sovereigns, central banks, and public sector entities with a maturity < 1 yr.	50
All other liabilities and equity not included above (including interbank lending)	0	Unencumbered residential mortgages of any maturity that would qualify for the 35% or lower risk weight under Basel II standardized approach. Other unencumbered loans (excluding loans to financial institutions) with a remaining maturity of 1 year or greater that would qualify for the 35 or lower risk weight under Basel II standardized approach	65
		Other loans to retail clients and small businesses having a	85
		All other assets	100
		Undrawn amount of committed credit and liquidity facilities Other contingent funding obligations	5

Source: BCBC (2014).

Table A.6: **The Relationship of Bank ex ante Liquidity and Bank's Borrowing Amount**

This table tests whether the total amount of loans a BHC has borrowed from regulatory institutions during the crisis is related to bank's liquidity or liquidity risk measures.

$$\log(Loan)_{i,t} = \alpha + \beta\ LIQ_{i,s} + Controls_{i,s} + \varepsilon_{i,t},$$

where $\log(Loan)_{i,t}$ is the log of borrowing amount by bank i from Fed loans (panel A) or from TARP (panel B) in the financial crisis. Fed Loans refer to a series of capital and liquidity injections by the Federal reserve system during December 2007 - November 2008. TARP, the Troubled Asset Relief Program allows the U.S. Treasury to purchase illiquid assets from financial institutions between October 2008 to June 2009. Proxies for liquidity risk include scaled LMI (scaling by total asset), Basel III's two measures: liquidity coverage ratio (LCR) and net stable funding ratio (NSFR), and the liquidity creation measure by Berger and Bouwman (2009). All liquidity measures are calculated as of 2006Q1, 2007Q1, and 2008Q1. **N** refers to the total number of BHCs in each dataset where corresponding liquidity (risk) measure and all control variables are available in a given quarter. In parentheses, we report the p-value for the estimation of regression coefficients.

Panel A: $Y = 1$ if borrowing from Fed loans

	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)
In 2006Q1	-6.25***			-3.10			-0.08			-0.31			0.14	
	(0.00)			(0.59)			(0.96)			(0.29)			(-0.67)	
In 2007Q1		-7.46***			-7.35			0.93			-0.29			0.11
		(0.00)			(0.38)			(0.63)			(0.33)			(-0.72)
In 2008Q1			-3.07**			1.09			-1.24			0.06		
			(-0.02)			(0.53)			(0.61)			(0.81)		
Tier 1 Cap Ratio	0.07	-0.02	0.09	0.08	0.06	0.10	0.08	0.10	0.02	-0.04	-0.06	0.03	-0.08	-0.11
	(0.43)	(0.81)	(0.50)	(0.37)	(0.52)	(0.49)	(0.47)	(0.36)	(0.91)	(0.82)	(0.72)	(0.87)	(-0.65)	(-0.50)
Tier 1 Lev Ratio	-0.72***	-0.62**	-0.60**	-1.25***	-1.24***	-0.77***	-1.23***	-1.32***	-0.69**	-1.13***	-1.14***	-0.83***	-1.14***	-1.13***
	(0.01)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Return on Asset	0.54**	1.92***	-0.26	0.80***	3.03***	-0.09	0.78***	2.89***	-0.03	0.61***	2.36***	0.09	0.69***	2.57***
	(0.01)	(0.01)	(0.52)	(0.00)	(0.00)	(0.83)	(0.00)	(0.00)	(0.94)	(0.01)	(0.00)	(0.83)	(0.00)	(0.00)
Intercept	19.66***	20.67***	18.03***	20.44***	20.34***	18.36***	20.17***	19.71***	19.35***	21.49***	21.38***	19.65***	21.29***	21.17***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	72	71	69	72	71	69	71	70	69	69	68	67	69	68
R-squared	0.50	0.55	0.29	0.44	0.50	0.23	0.43	0.49	0.23	0.44	0.49	0.22	0.43	0.49

* p<0.10, ** p<0.05, *** p<0.01

Table A.6 (Cont'd) The Relationship of Bank ex ante Liquidity and Bank's Borrowing Amount

Panel A: $Y = 1$ if borrowing from Fed loans

	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)
In 2006Q1	-7.07***			27.08***			-0.18			-0.20*			-1.31*	
	(0.00)			(0.00)			(-0.87)			(-0.09)			(-0.09)	
In 2007Q1		-9.56***			55.74***			-1.25			0.01			0
		0			(0.00)			(-0.30)			(-0.28)			(-0.24)
In 2008Q1			-4.14***			6.77***			-3.17***			-0.06		
			(0.00)			(0.00)			(-0.01)			(-0.50)		
Tier 1 Cap Ratio	-0.01	-0.10*	-0.25***	-0.02	-0.12*	-0.26***	-0.07	-0.27**	-0.54***	-0.04	-0.20***	-0.28***	0	-0.20***
	(-0.93)	(-0.08)	(0.00)	(0.76)	(0.07)	(0.00)	(-0.47)	(-0.01)	(0.00)	(-0.55)	(-0.01)	(0.00)	(-1.00)	(-0.01)
Tier 1 Lev Ratio	-0.22***	-0.08	-0.02	-0.35***	-0.23***	-0.09	-0.30**	-0.07	0.15	-0.31***	-0.14	-0.19**	-0.36***	-0.14
	(0.00)	(-0.25)	(-0.83)	(0.00)	(0.01)	(0.27)	(-0.02)	(-0.58)	(-0.25)	(0.00)	(-0.11)	(-0.05)	(0.00)	(-0.11)
Return on Asset	0.40***	0.79***	0.12	0.49***	1.05***	0.13	0.49***	1.04***	0.23*	0.57***	1.15***	0.2	0.57***	1.15***
	(0.00)	(0.00)	(-0.29)	(0.00)	(0.00)	(0.28)	(0.00)	(0.00)	(-0.07)	(0.00)	(0.00)	(-0.11)	(0.00)	(0.00)
Intercept	15.16***	17.49***	14.49***	11.88***	12.30***	13.05***	12.81***	14.15***	16.68***	12.50***	13.23***	15.24***	13.31***	13.23***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	266	273	286	266	273	286	265	272	286	253	261	274	253	261
R-squared	0.46	0.5	0.35	0.28	0.27	0.22	0.25	0.22	0.18	0.27	0.23	0.18	0.27	0.23

* p<0.10, ** p<0.05, *** p<0.01