Measuring Liquidity Mismatch in the Banking Sector

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This version: July 2015

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. The aggregate banking sector liquidity worsens from +$5 trillion before the crisis to -$3 trillion in 2008, and reverses back to the pre-crisis level in 2009. We also show how a liquidity stress test can be conducted with the LMI metric, and that such a stress test as an effective macroprudential tool could have revealed the liquidity need of the banking system in the late 2007. In the cross section, we find that banks with more liquidity mismatch have a higher crash probability in the financial crisis and have a higher chance of borrowing from the government during the financial crisis. Thus our LMI measure is informative regarding both individual bank liquidity risk as well as the liquidity risk of the entire banking system. We compare our LMI measure of liquidity to other measures and show that our measure performs better on many dimensions.

JEL Classification: G21, G28.
Keywords: liquidity regulation; market liquidity; funding liquidity; macroprudential tool.

*We thank Viral Acharya, Markus Brunnermeier, Allen Berger, Christa Bouwman, Dong Beom Choi, Adam Copeland, Darrell Duffie, Michael Fleming, Stefan Nagel, Antoine Martin, Klaus Schaeck, Philipp Schnabl, Mark Seasholes, and seminar participants at WFA (2014), EFA (2014), SFS Finance Calvacade (2014), FDIC Annual Conference (2014), BIS Research Network meeting (2014), European Bank Association's Annual Financial Stability Conference (2014), Mitsui Finance Symposium (2015), New York University, Copenhagen Business School, the Federal Reserve Board, Federal Reserve Bank of New York, Bank of France, Bank of England, the Department of the Treasury's Office of Financial Research, Georgetown University, and University of Rhode Island for helpful comments. Jonathan Choi and Jay Im provided excellent research assistance. Bai is with McDonough School of Business at Georgetown University, jb2348@georgetown.edu. Krishnamurthy is with Stanford University Graduate School of Business and NBER, a-krishnamurthy@stanford.edu. Weymuller is with French Treasury, charles-henri.weymuller@dgtresor.gouv.fr .

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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. The aggregate banking sector liquidity worsens from +$5 trillion before the crisis to -$3 trillion in 2008, and reverses back to the pre-crisis level in 2009. We also show how a liquidity stress test can be conducted with the LMI metric, and that such a stress test as an effective macroprudential tool could have revealed the liquidity need of the banking system in the late 2007. In the cross section, we find that banks with more liquidity mismatch have a higher crash probability in the financial crisis and have a higher chance of borrowing from the government during the financial crisis. Thus our LMI measure is informative regarding both individual bank liquidity risk as well as the liquidity risk of the entire banking system. We compare our LMI measure of liquidity to other measures and show that our measure performs better on many dimensions.

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, building on theoretical work by Brunnermeier, Gorton, and Krishnamurthy (2011). Their "Liquidity Mismatch Index (LMI)," gauges the mismatch between the market liquidity of assets and the funding liquidity of liabilities. There are many empirical challenges that arise in implementing their theoretical approach. We take

[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)).

up these challenges, measuring the LMI from balance-sheet as well as off-balance-sheet information of a given bank and market indicators of liquidity and liquidity premia. We construct the LMI for the universe of bank holding companies (BHCs) in the U.S. and describe features of the time-series and cross-sectional properties of the bank-specific and aggregate LMI.

What makes a good liquidity measure? The measure must be theoretically founded. Brunnermeier, Gorton, and Krishnamurthy (2011) offer a number of theoretical arguments to support their LMI construction. An important theoretical point that we develop is that the LMI satisfies a recursive principle common to valuation metrics: the LMI today is the appropriately "discounted" value of the expected LMI tomorrow. The recursive construction naturally 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.

The bulk of this paper shows that the LMI performs well on empirical criteria. 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. Second, the LMI is also well suited to stress test analysis. The market liquidity of assets and funding liquidity of liabilities, which form the LMI, can be described in terms of their exposures to a set of underlying factors. In our implementation, we use repo market haircuts to extract the asset liquidity factor and the OIS-Treasury Bill spread as the funding liquidity factor. With these factor exposure representation, 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 perform a stress test on the LMI where we stress the market and funding liquidity factor by N-sigma. In 2007Q2, a 3-sigma event takes the LMI of the banking sector from +\$4 trillion to -\$1 trillion. In 2007Q3, a 2-sigma shock takes the LMI from +\$2.6 trillion to -\$5 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.

Our second set of 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. 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 TARP, and they indeed receive more liquidity injections. In addition, we find that the banks that have the worse LMI are the largest banks, perhaps suggesting a strategy of exploiting the too-big-to-fail backstop. 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 borrowings from the government. The two Basel measures have little predictive power. Thus, in both micro and macro dimensions the LMI performs better 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 theoretically-motivated liquidity measure. The principal difference between the LMI and the Berger-Bouwman measure is that the LMI incorporates information from asset market measures of liquidity which vary over time. Indeed this is central to our recursive formulation for measuring liquidity.[2] In the language of Berger and Bouwman, our liquidity weights are time-varying, while their liquidity weights are constant regardless in normal times or in stressed times, a static feature also shared by the Basel III's two measures. On the macro dimension the incorporation of time-varying weights is critical to capture liquidity stress during a financial crisis. That is, as noted by stressing the underlying market factors, we are able to perform a liquidity stress test. We also compare the Berger-Bouwman measure to our measure in explaining the cross-section of banks' liquidity risk, and their predictive power on banks' crash probability as well as borrowing decision from the government. Although the Berger-Bouwman measure does slightly better than Basel III, it does not perform as well as the LMI.

[2] There is an alternative measure in Berger and Bouwman (2009) that sets the weights on bank loans to vary with the amount of securitization. In our paper, the time-varying feature is generalized to every item on- and off-balance sheet.

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. (2014), 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 constructed from both asset and liability side of the balance sheet, and is furthermore dependent on market-wide liquidity conditions. Each asset and each liability contributes to the liquidity position of the bank. It is thus a comprehensive single measure of bank liquidity. 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 End (2012) 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, Gorton, and Krishnamurthy (2011). 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

[3] There is also a literature examining banks' hoarding of liquidity and its implications for interbank markets. See Heider, Hoerova, and Holhausen (2009), Acharya and Merrouche (2013) and Acharya and Rosa (2013).

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

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.*

Based on this, they 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, Gorton, and Krishnamurthy (2011) provide several examples of assets and liabilities, explaining why [i] and [ii] should drive the measurement of liquidity.

We go beyond Brunnermeier, Gorton, and Krishnamurthy (2011) 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 considering dynamics. 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, $\sum_{k'} \lambda_{t,l_{k'}} l_{t,k'}^i$. It is easier to explain our methodology by moving to a continuous maturity setting, although we implement the LMI based on a sum of discrete liability classes as in formula (1). We use T to denote the maturity of liability class k'. Thus, let $l_{t,T}^i$ be the liability of the bank i due at time T, where the notation $\{l_{t,T}^i\}$ 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 has issued liabilities $\{l^i_{t,T}\}$, and used the proceeds to invest in a long-term illiquid asset. We assume that this "carry trade" earns a profit 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 $V(\{l^i_{t,T}\}, t)$ as the value to a bank with a liability structure $\{l^i_{t,T}\}$ at time t in the stress event. The bank has to pay a penalty rate of θ^i in order to obtain any cash that is due to creditors. Then,

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

where μdt 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 a hypothetical Diamond-Dybvig bank which buys \$100 of illiquid assets at date 0 which pay off at date 2. The return R on the illiquid assets is 10%. The bank finances itself with debt that is demandable at date 1 and then at date 2. The interest rate on this debt, r, is zero. The relevant liquidity stress for this bank is the bank run equilibrium at date 1, in which case the bank has to borrow \$100 from the discount window at the penalty rate of 20% ($\theta^i = 0.2$). 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:

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

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 define the LMI based on (2). We rewrite,

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

where the first term on the right-hand side is the value of the profits to the carry trade and the second term is the cost of liquidity, i.e., θ^i times the liquidity position of the bank.

Then, we can write the profit function recursively as:

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

while the LMI is,

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

For the simple two-period Diamond-Dybvig bank, the LMI is -100. Consider a three-period version of the Diamond-Dybvig bank, to understand the recursive definition of the LMI. Suppose that 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 date 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 the simple Diamond-Dybvig bank funded solely by short-term debt, for which we compute that the LMI_1 is $-\$100$. At date 0, our recursive construction makes LMI_0 the "discounted value" of LMI_1. In a liquidity stress episode, all contractual claimants on the bank act to maximally extract cash from the bank. This means that overnight debt holders refuse to rollover debt and the bank has to cover the cash shortfall from this loss of funding. Thus, for the three period Diamond-Dybvig bank, if the probability that the stress episode ends is 10% then the $LMI_0 = 0.90 \times LMI_1 = -\$90$. This bank has higher LMI (less mismatch) because the bank 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 maturity. We look for an LMI function that is maturity invariant, 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 a 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

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

The liquidity weight is an exponential function of the μ and the liability's time to maturity $T-t$. A high μ 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

A key variable in the construction of the LMI is μ, which controls the expected duration of the stress event — the higher μ, the shorter duration of the stress event. We aim to map μ 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,

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

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

$$\pi_{t,T} = \psi^i\theta^i e^{-\mu_t T}. \tag{7}$$

The bank earns a liquidity premium on issuing liabilities of maturity T, but at liquidity cost governed by $e^{-\mu_t T}$. 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 term structure of OIS-TBill spreads. We assume that $\pi_{t,T}$ is proportional to OIS-TBill spread of the given maturity. This assumption says that when investors have a strong desire to own liquid assets, as reflected in the spread between OIS and T-Bill, any financial intermediary that can issue a liquid liability can earn a premium on this liquidity. 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. Under this assumption, μ_t is proportional to $ln(OIS - TBill)/\text{T}$. 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 constant function of T. In our implementation of liquidity weights, we make this assumption. However, μ itself has a term structure that reflects an uneven speed of exit from the liquidity event (i.e., μ_t is a function of T). The term structure of μ is reflected in the term structure of the liquidity premium, which is observable. It is straightforward to see that in the general case with T-dependent μ, the liquidity premium at maturity T solves:

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

While in this paper we opt for the simple approach of assuming that μ_t is a constant function of time, it should be clear that our proposed methodology is amenable to a more sophisticated implementation that uses the entire term structure.

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, Gorton, and Krishnamurthy (2011).

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

$$w_t = \sum_k (1 - m_{t,k}) a^i_{t,k}. \tag{9}$$

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

$$LMI(\{l^i_{t,T}\}, w_t, t) = \max_{\Delta_t \geq 0} \left(-\max(l^i_{t,t} - \Delta_t, 0)dt + (1 - \mu dt) LMI(\{l^i_{t+dt,T}\}, w_t + dw_t, t + dt) \right), \quad (10)$$

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

$$w_t = \int_t^{T^*} l^i_{t,T} dT. \quad (11)$$

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 (11) 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

$$\lambda_{t,a_k} = 1 - m_{t,k}, \tag{12}$$

and the liability-side weights are

$$\lambda_{t,l_{k'}} = -e^{-\mu_t T_{k'}}. \tag{13}$$

To summarize, we have expanded on Brunnermeier, Gorton, and Krishnamurthy (2011) by considering an explicit dynamic optimization problem for a bank. This problem leads us to an explicit specification of the liquidity weights. We have also shown how market prices should enter into the LMI construction.

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 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.

[Table 1 about here]

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.[5] Our sample period covers from 2002:Q2 to 2014:Q3. The dataset includes 2882 BHCs throughout the sample period.[6]

[5]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.

[6]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.

Among them, there are 54 U.S. subsidiaries of foreign banks, such as Taunus corp (parent company is Deutsche Bank) and Barclays U.S. subsidiary. Table 1 lists the summary statistics for these BHCs, including total asset, risk-adjusted asset, Tier 1 leverage ratio and Tier 1 risk-based capital ratio (both ratios are Basel regulatory measures), as well as return on assets. Panel B provides a snapshot of the top 50 BHCs, ranked by their total asset values as of March 31, 2006. The top 50 BHCs together have a total asset of 11.07 trillion dollars, comprising a large fraction of gross domestic products (the U.S. real GDP is 14.55 trillion dollars in 2006:Q1).

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, $\lambda_{t,a_k} = 1 - m_{t,k}$. 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 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, so that the haircut is a natural measure of asset liquidity sensitivity. In addition, the haircuts change over market conditions and hence can reflect the 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 collect haircut data based on repo transactions reported by the Money Market Fund (MMF) sector, which is the largest provider of repo lending to banks and dealers. According to the Flow of Funds data as of September 2011, the U.S. Money Market Funds have $458 billion of holdings in repo contracts, representing 46% of the total volume of repo lending in the US. The list of the 145 largest prime institutional MMFs is obtained from Peter Crane intelligence. Our approach follows Krishnamurthy, Nagel, and Orlov (2014). For each fund, we further 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.

[Table 2 about here.]

Between the extremes of liquid (cash) and illiquid (intangible) assets, there are a number of asset classes. These include Treasuries, agencies, commercial paper, municipals, corporate debt, structured finance, and equity. Table 2 shows the distribution of triparty 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 two percent. Municipal bonds and commercial papers have higher haircuts with an average of three percent. Corporate debt, structured finance products and equities have much lower collateral quality, hence even higher haircuts around five, six, seven percent.

Bank loans are probably the most important asset in a bank's balance sheet. In the financial crisis, bank loans suffered from fire sales, which will have a significant influence on asset-side liquidity. We measure the loan haircuts based on the bid price as a percentage of par in the secondary loan market,[7] and report haircut summary statistics in Table 2. The loan haircut in the secondary market is flat and remains less than 5% in normal times, while it fell 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%.

[Figure 1 about here]

Given all haircut data, we take the following approach to define the asset-side liquidity weight. Instead of using individual time series for each asset class, we extract the first principal component, $m_{PC1,t}$, from the panel of haircut series. 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 security k. Thus we measure the asset weight as

$$\lambda_{t,a_k} = \exp\left(-(\overline{m}_k + \beta_k m_{PC1,t})\right), \tag{14}$$

where $\overline{m}_k$ is the average haircut for asset k. Figure 1 plots the time series of cross-collateral haircut values, m_{PC1}.

There are three principal advantages of this approach over that of using individual haircut series.

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

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 where we have incomplete haircut information, requiring only knowledge of β_k and $m_{PC1,t}$. 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's worth noting that while we adopt a one-factor structure for simplicity, our approach can be readily expanded to account for multiple factors.

One caveat on the data is that haircut prices are based on the triparty repo market, except for the loan haircut. It is well known that the haircuts in the triparty market were much more stable than in the bilateral repo market (see Copeland, Martin, and Walker (2010) and Gorton and Metrick (2012)), hence they may not accurately capture liquidity conditions. To accommodate this concern, we assume that β_k in our final implementation is five times the one estimated from the principal components analysis. Appendix A reports the original beta values for each asset. Loans and equity sectors are the most sensitive to the principal component of cross-collateral haircuts whereas Treasury and agency bonds are the least sensitive to the factor.

3.2 Liability-side liquidity weights

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

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

The parameter μ_t captures the expected stress duration which is proxied by using a market measure of liquidity premium.

[Figure 2 and 3 about here]

The literature has considered many proxies to measure the liquidity premium. Figure 2 plots a number of common spreads, including the Libor-OIS spread, the TED spread (Libor-TBill), the Repo-TBill spread on the OIS-TBill spread. We note that the Libor-OIS and the TED spread both rise in late 2007, fall, 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 though 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 2 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 value of 0.90. All our empirical results (magnitude and significance) remain unchanged if using the Repo-TBill spread as the proxy of liquidity premium.[8]

The parameter $T_{k'}$ indicates the maturity of a liability. Figure 3 simulates the liability-side liquidity weight as a function of the maturity parameter $T_{k'}$, under various scenarios of market liquidity premium. The left panel focuses on $T_{k'} \in [0, 1]$ 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 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. For our calibration, we set overnight financing (federal funds and repo) to have a maturity of zero, 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.[9] 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 liquidity features.

Clearly, this calibration is subjective, although this is a general feature of this type of exercise (e.g., the liquidity measures in Basel III and Berger-Bouwman measure are also based on judgment). We have conduct sensitivity analysis to different calibrations of the maturity parameter $T_{k'}$. The performance of LMI in Sections 4 and 5 remain similar across these different calibrations.

[8] 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.

[9] The off-balance-sheet securities are based on Schedule HC-L (Derivatives and Off-Balance-Sheet Items) and HC-S (Servicing, Securitization, and Asset Sales Activities) in Y-9C report.

4 Macro variation in the LMI

4.1 LMI as a macroprudential barometer

The LMI can be aggregated across firms and sectors. This is a property that is not shared by Basel's liquidity measures which are ratios and hence cannot be meaningfully aggregated. Summed across all BHCs, the aggregate LMI equals the overall liquidity mismatch in the banking system. We suggest that this aggregate LMI 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 LMI is low, the banking sector is more susceptible to a liquidity stress ("runs").

[Figure 4 about here.]

Figure 4 plots the aggregate liquidity mismatch over the 2002–2014 period. Recall that a lower value of LMI at the firm level indicates a balance sheet that is more vulnerable to liquidity stress. The magnitude of the LMI is important as it indicates whether our calibration of the liquidity weights are in the right ballpark. The LMI in the crisis is about [negative] 3 trillion dollars which is of the same magnitude as the Fed and other government liquidity provision actions. The liquidity mismatch reversed with the Fed's liquidity injections. As the crisis faded, the aggregate LMI recovered to the pre-crisis level by 2009:Q1. The trough of the liquidity mismatch occurred three quarters before the Lehman Brothers' bankruptcy and six quarters before the stock market reaching its nadir.

Figure 4 also plots the time-series of aggregate LMI summed over top 50 BHCs. These BHCs were the primary users of the Fed's liquidity facilities from 2007 to 2009. The aggregate LMI of top 50 BHCs is close to that of the universe of BHCs, in terms of both the pattern and the magnitude, especially during the crisis period. This evidence suggests that in dollar amount, the US banking sector's liquidity condition is overwhelmingly determined by large banks represented by top 50 BHCs.

[Figure 5 about here.]

To understand further the composition of aggregate LMI, we present in Figure 5 the liquidity mismatch on- and off-balance sheet. Clearly, the off-balance-sheet liquidity pressure is minimal in normal times, but increased to 2.76 trillion dollars in the crisis period.

4.2 LMI and Federal Reserve liquidity injection

We next discuss the impact of the government's liquidity injection on the U.S. banking sector's liquidity during the crisis. The Fed launched a range of new programs to the banking sector in order to support overall market liquidity. Appendix B provides the background on these programs. The liquidity support began in 2007:Q4 with the Term Auction Facility and continued with other programs. 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 has played a role in the increase of the aggregate LMI.

We study the effect of the Fed injections on the cross-section of LMI. There are 559 financial institutions receiving liquidity from the Fed,[10] 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 Bank's US subsidiary, Taunus.

[Figure 6 about here.]

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 and the pre-crisis period (panel A) and between the post-crisis and the crisis 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 on improving the banking sector liquidity.[11]

[10] 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.

[11] Berger et al. (2013) shows that capital injections and regulatory interventions have a costly persistent effect on reducing liquidity creation.

4.3 LMI decomposition: asset, liability, and liquidity weights

The calculation of LMI depends on assets, liabilities, and liquidity weights. Panels A in Figure 7 show the dollar amount of asset- and liability-side liquidity for the universe of BHCs. Both asset-side and liability-side liquidity contribute to the movement in the LMI, yet the liability side plays a larger role in stressed times, whereas, asset-side liquidity dominates the movement of LMI in normal times. The finding is intuitive since most assets on bank balance sheet can be easily converted to cash when liquidity constraint does not bind, while assets suffer fire sale and short-term debt enforce intense liquidity pressure when funding liquidity freezes.

Panel B of the figure plots the effective liquidity weights of assets and liabilities. These liquidity weights are defined as the liquidity-weighted asset (or liability) divided by the total amount of asset (liability) used in the LMI calculation. The figure provides some sense of how much the variation in haircuts, as captured by m_{PC1}, and liabilities, as captured by the OIS-TBill spread drives the determination of the LMI.

[Figure 7 about here.]

Asset liquidity and liability liquidity can be related. 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 et al. (2014) 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. The table below verifies the prediction of their model. We run a panel regression using all top 50 BHCs (ranked by total asset within each quarter) during 2002Q2 - 2014Q3, regressing asset-side LMI on liability-side LMI. Regardless of having time or bank dummies, we see that the absolute value on liability LMI has a significant positive relation with asset-side LMI. With both time and bank dummies, we find that a one-dollar increase in liability LMI is correlated with a roughly 0.35 dollars increase in asset LMI. The last two columns includes bank dummies, in which case the coefficient shrinks from 1.60 to 0.35, indicating that the relation we document comes primarily from cross-sectional variation across banks. Note that Hanson, Shleifer, Stein, and Vishny (2014) present an empirical analysis that is similar in spirit but using far less data and a less refined measure of liquidity.

$$Asset\_LMI_{it} = \alpha + \beta|Liab\_LMI_{it}| + \varepsilon_{it}$$

	(1)	(2)	(3)	(4)
|Liab_LMI|	1.54***	1.60***	0.34***	0.35***
	(0.02)	(0.02)	(0.03)	(0.03)
Constant	66.06	62.26	137.60	52.99
	(3.55)	(3.35)	(2.45)	(12.67)
Time FE	N	Y	N	Y
Bank FE	N	N	Y	Y
N	2500	2500	2500	2500
R-squared	0.67	0.71	0.89	0.91

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

We next turn to explaining how the changing liquidity weights contribute to movements in the LMI. Panel A in Figure 8 plots the LMI under three weighting schemes: 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); and the green dashed line uses weights as of 2007Q4 (the trough of the LMI). All three lines use the same contemporaneous balance sheet information. The three variations show that the time-varying weights contribute to a difference in liquidity of approximately 9.20 trillion dollars in the trough of 2007Q4, compared with using the weight as of 2002Q2. This figure also highlights the importance of adopting a time-varying weight linked to market conditions in terms of accurately measuring the banking sector liquidity.

[Figure 8 about here.]

Our LMI setup can be used to evaluate the liquidity risk of the banking system to market or funding liquidity shocks. In particular, we can rely on LMI as a macroprudential tool in stress test. Panel B of Figure 8 depicts the LMI and its variations under stress scenarios. Stress scenario 1 refers to the situation when both market liquidity shock (m_{PC1}) and funding liquidity shock (TOIS spread) are one-sigma away from their current 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. 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 five trillion level. Dashed lines under stress scenarios 1 and 2 thus are not visible during the most extreme period. We next elaborate on stress tests.

4.4 Liquidity stress test

After the financial crisis, the Federal Reserve has engaged in liquidity stress tests under the Dodd-Frank rules which are designed to examine banks' ability to withstand a given liquidity 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 panel A of 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.

[Table 3 about here.]

We run a liquidity stress test at three time points: 2007Q2 (two quarters before liquidity trough), 2007Q3 (one quarter before liquidity trough) and 2012Q4 (Fed's first liquidity stress test). Table 3 reports the results. Consider the first column corresponding to 2007Q2. The first row in the benchmark, denoted as "T", corresponds to the LMI value as of 2007Q2. The next line, denoted as "[0,T]", reports the historical average LMI up to this time point. We then compute the LMI under three stress scenarios: both cross-collateral haircuts and funding liquidity factor (TBill-OIS) deviate 1-, 2-, 3-sigma away from the time-T market value. Here sigma is calculated as the historical standard deviation from 2002Q2 to time T.

Recall that the aggregate liquidity mismatch was -3.14 trillion in the liquidity trough of 2007Q4. Given the stress test table, this severe liquidity dryup is about a 2-sigma event in 2007Q3, one quarter in advance, and a more than 3-sigma event in 2007Q2, two quarters ahead. Standing at 2007Q3, the liquidity shortage under 2-sigma scenario will be the difference between the aggregate LMI value under 2-σ and the value under contemporaneous market value, that is 7.67 trillion dollars (=2.58 – (-5.09)). This difference is quite close in magnitude to the liquidity injection from the Federal Reserve system.

4.5 Liquidity risk

We define the liquidity risk of a bank based on the stress test methodology:

$$\text{Liquidity risk} = LMI^i - LMI^i_{1\sigma}.$$

The liquidity risk of a bank is the exposure of that bank to a one-sigma change in market and funding liquidity conditions. The aggregate of this liquidity risk also corresponds to the liquidity risk of the banking system to a one-sigma stress event.

5 LMI and the Cross-Section of Banks

The previous section presented one benchmark for evaluating the LMI, namely its utility from a macroprudential viewpoint. We now consider another benchmark for evaluating the LMI. If the LMI contains information regarding the liquidity risk of a given bank, then changes in market liquidity conditions will affect the stock returns of banks differentially depending on their LMIs. That is, as market liquidity conditions deteriorate, a firm with a worse liquidity position (lower LMI) should experience a more negative stock return. 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 show how the LMI of different banks varies over time, and what characteristics of banks correlate with their LMIs. We then examine the informativeness of the LMI in a number of dimensions.

5.1 Cross-sectional LMI and liquidity risk

We plot the time-series LMI (in million dollars) for twelve representative banks in Figure 9. The bank-level LMIs follow the same pattern going from positive to negative in the financial crisis.[12] The absolute level of the LMI may be useful as an indicator of systemic importance (i.e. "SIFI" status). Banks like JP Morgan Chase, Bank of America, and Citigroup have large liquidity shortfall during the crisis whereas banks like State Street, Northern Trust have a far smaller liquidity shortfall.

[Figure 9, 10, and Table 4 about here.]

We investigate the relationship between the LMI and bank characteristics for the universe of BHCs. Table 4 shows the results of regressing LMI and the LMI risk exposure metric, both scaled by total assets, on a set of bank characteristics, which are collected from the Y-9C reports. Banks have a larger liquidity mismatch when risk-adjusted assets are high (large banks), when capital positions are low, when leverage ratios are high, and when the ROA is high. These results confirm our expectations.

[12] The data for Goldman Sachs and Morgan Stanley begin in 2009Q1 given that these investment banks converted to bank holding companies after the Lehman event in September 2008.

The ROA correlation could be because ROA measures the riskiness of a bank portfolio. The LMI risk exposure metric follows exactly the same pattern, albeit with the opposite sign. That means a higher liquidity risk (i.e., higher LMI exposure), related to a lower liquidity level (i.e., lower LMI), is a bank characteristic that indicates fragility.

Figure 10 presents the relationship between liquidity level and liquidity risk. Within each quarter, we run the following cross-sectional regression

$$\frac{LMI - LMI_{1\sigma}}{Asset} = \alpha + \beta \frac{LMI}{Asset} + \epsilon, \tag{16}$$

where $LMI_{1\sigma}$ is the LMI value under the one-sigma stress scenario. Panel A shows the time-series of β and its (+/− 1) standard error, and Panel B depicts the R-squared value.

There are two findings from this analysis. First, the liquidity level-risk relation changes over time. In normal times, liquidity level is marginally related to liquidity risk, with a low R-squared value of less than 10%. However in the liquidity trough, the liquidity level and risk are highly correlated with an R-squared value of 74%. Second, liquidity risk is significantly negatively related to liquidity level, indicating that a high liquidity level condition is correlated with lower liquidity risk. The shade in the figure covers the two-standard error bands, suggesting highly significant estimates. The beta estimate is 0.82 in 2007Q4.

5.2 The informativeness of LMI on bank borrowing decision

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 the liquidity stress, and hence a useful indicator on banks reliance on government liquidity backstop? Table 5 presents the results using all public BHCs. We estimate,

$$Pr[Y = 1 | LIQ_{i,t}] = \alpha + \beta LIQ_{i,s} + Controls_{i,s} + \varepsilon_{i,t}, \tag{17}$$

where Y is a future borrowing indicator which takes on a value of 1 if a bank has ever borrowed from Federal Reserve facilities (for details, see Section 4.2 and Appendix B) 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 asset), calculated as of 2006Q1, 2007Q1, and 2008Q1. We also include controls for standard bank characteristics, including capital and leverage which may indicate a need to borrow from the government.[13]

[Table 5 about here.]

The results indicate that the LMI is indeed informative regarding predicting a bank's decision in government borrowing, 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, between 3.11% and 5.14% for the Fed loans. For TARP, the magnitude ranges from 1.86% to 2.27%. 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 are broadly in line with those presented in the table. 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. The exposure variable is also highly informative regarding bank borrowing decisions in both cases of Fed loans and TARP, suggesting a significant positive predicting power between a bank's pre-crisis liquidity risk and banks decision to borrow during the crisis.

The last three sets of 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 C provides the details of how we replicate three liquidity measures using our sample of the universe of BHCs. The Berger-Bouwman measure has little explanatory power except in explaining the borrowing from Fed loans using their measure as of 2008Q1. 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 is weaker than our LMI measure. The use of time-varying liquidity weights in LMI has proved to provide a significant improvement over all other liquidity measures.

[13] 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.

5.3 The informativeness of LMI on bank crash risk

We next ask whether bank illiquidity can predict banks' stock market crash risk, and is thus informative regarding the market's perception of bank tail risk. We estimate the following probit model, which predicts future equity crashes during the financial crisis using bank ex-ante (il)liquidity condition, controlling for standard bank characteristics:

$$Pr[Crash = 1|LIQ_{i,t}] = \alpha + \beta LIQ_{i,s} + Controls_{i,s} + \varepsilon_{i,t}, \tag{18}$$

where "Crash" is a future 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 of 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 5.2, we use the bank (il)liquidity measure in three ex-ante time points: $s =$(2006Q1, 2007Q1, and 2008Q1).

[Table 6 about here.]

Table 6 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 4.23% and 6.88% 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 liquidity when liquidity is assessed based on its relation to time-varying market-implied economic outcomes. 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 under a liquidity stress event that is parameterized by time-varying market-implied liquidity weights.

Relative to the net stable funding ratio (NSFR) of Basel III (which is conceptually closer to our liquidity measurement exercise than the liquidity coverage ratio), the LMI has three principal advantages. First, the LMI, unlike the NSFR, can be aggregated across banks and thereby provide a macroprudential liquidity parameter. Second, the NSFR uses an arbitrary liquidity horizon of 30 days. Our implementation of the LMI links the liquidity horizon to market based measures of liquidity premium. Thus our measurement has the desirable feature that during a financial crisis when liquidity premium is high, the LMI is computed under a longer-lasting liquidity scenario. Third, the LMI framework provides a natural methodology to implement liquidity stress tests.

The LMI has a close precedent, the Berger-Bouwman liquidity creation measure. The primary change relative to the Berger-Bouwman measure is that the LMI is based on time-varying market-implied liquidity weights. We offer theory and methodology for 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 performs well relative to our macroprudential benchmarks. 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.

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 security 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 template for developing a better liquidity measure.

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Table 1: **Summary statistics of bank holding companies during 2002-2014**

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	Std	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 aggregate LMI (in $trillion) over all BHCs under stress scenarios when both funding liquidity factor (OIS-TBill) and the cross-collateral haircut deviate 1-, 2-, 3-σ away, where σ is calculated based on historical standard error from 2002Q2 to time T.

T=2007Q2		T=2007Q3		T=2012Q4	
	LMI		LMI		LMI
Benchmark		Benchmark		Benchmark	
T	4.15	T	2.58	T	9.49
$[0, T]$	4.68	$[0, T]$	4.59	$[0, T]$	5.44
Stress Scenarios		Stress Scenarios		Stress Scenarios	
1-σ	3.10	1-σ	0.03	1-σ	7.74
2-σ	1.52	2-σ	-5.09	2-σ	5.88
3-σ	-1.11	3-σ	-16.37	3-σ	3.23

Table 4: **The relationship of LMI with bank characteristics**

This table presents the results of pooled cross-sectional regression for the universe of public bank holding companies during 2002Q2 to 2014Q3. The standard errors are robust and clustered by bank. All variables are unidimensional (ratios) except risk-adjusted assets are in billion dollars. Panel A tests the scaled LMI, and panel B tests the 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).

	Panel A: Dependent variable = scaled LMI				
	(1)	(2)	(3)	(4)	(5)
Risk_adj asset	-0.25***				-0.24***
	(0.03)				(0.04)
Tier1 capital ratio		0.03			0.61***
		(0.06)			(0.17)
Tier1 leverage ratio			-0.02		-0.69***
			(0.04)		(0.19)
ROA (annualized)				-0.12**	-0.11**
				(0.05)	(0.04)
Constant	0.59***	0.58***	0.59***	0.58***	0.57***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
N	12281	12282	12282	11978	11409
R-squared	0.05	0.00	.00	0.00	0.07

	Panel B: Dependent variable = scaled (LMI – $LMI_{1\sigma}$)				
	(1)	(2)	(3)	(4)	(5)
Risk_adj asset	0.03***				0.03***
	(0.01)				(0.01)
Tier1 capital ratio		-0.04			-0.64***
		(0.06)			(0.09)
Tier1 leverage ratio			0.02		0.69***
			(0.04)		(0.12)
ROA (annualized)				0.15**	0.25**
				(0.04)	(0.04)
Constant	0.12***	0.12***	0.12***	0.12***	0.14***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
N	12281	12282	12282	11978	11409
R-squared	0.00	0.00	.00	0.00	0.03

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

Table 5: **The relationship of bank ex ante liquidity (risk) and bank's borrowing decision**

This table tests whether a BHC's decision to borrow or not from regulatory institutions during the crisis is related to bank's liquidity or liquidity risk measures:

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

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). Fed Loans refer to a series of capital and liquidity injection 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), 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 deviated 1-σ away), Basel III's two measures: liquidity coverage ratio (LCR) and net stable funding ratio (NSFR). We also include the liquidity creation measure by Berger and Bouwman (2009) as a third benchmark. The five liquidity(risk) 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. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

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

	Scaled LMI			Scaled (LMI – $\text{LMI}_{1\sigma}$)			Scaled BB			LCR			NSFR		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
In 2006Q1	-5.14***			15.88***			-1.83			-0.02			0.49		
	(0.86)			(5.63)			(1.03)			(0.05)			(0.33)		
In 2007Q1		-5.33***			13.89**			-1.31			0.00			0.00	
		(0.96)			(6.94)			(1.02)			(0.01)			(0.00)	
In 2008Q1			-3.11***			2.88***			-2.40**			0.01			0.44
			(0.61)			(0.78)			(1.04)			(0.02)			(0.30)
Tier1 cap ratio	-0.07	-0.12*	-0.04	-0.07	-0.12*	-0.04	-0.07	-0.12*	-0.04	-0.07	-0.12*	-0.04	-0.07	-0.12*	-0.04
	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
Return on asset	0.10	0.33**	-0.03	0.10	0.33**	-0.03	0.10	0.33**	-0.03	0.10	0.33**	-0.03	0.10	0.33**	-0.03
	(0.07)	(0.13)	(0.07)	(0.07)	(0.13)	(0.07)	(0.07)	(0.13)	(0.07)	(0.07)	(0.13)	(0.07)	(0.07)	(0.13)	(0.07)
Tier1 lev ratio	-0.11	-0.03	-0.14	-0.11	-0.03	-0.14	-0.11	-0.03	-0.14	-0.11	-0.03	-0.14	-0.11	-0.03	-0.14
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Intercept	2.34***	2.50***	0.53	2.34***	2.50***	0.53	2.34***	2.50***	0.53	2.34***	2.50***	0.53	2.34***	2.50***	0.53
	(0.76)	(0.80)	(0.57)	(0.76)	(0.80)	(0.57)	(0.76)	(0.80)	(0.57)	(0.76)	(0.80)	(0.57)	(0.76)	(0.80)	(0.57)
N	991	985	975	991	985	975	991	985	975	991	985	975	991	985	975
Adj R^2	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04	0.05	0.04	0.04

Table 5 (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	-2.17***			7.19*			0.83			-0.02			-1.87***		
	(0.69)			(3.68)			(0.66)			(0.03)			(0.62)		
In 2007Q1		-2.27***			4.94			0.81			0.01			0.00	
		(0.78)			(4.17)			(0.68)			(0.01)			(0.00)	
In 2008Q1			-1.86***			1.72**			0.14			0.01			-2.33***
			(0.60)			(0.77)			(0.70)			(0.01)			(0.64)
Tier1 cap ratio	-0.23***	-0.27***	-0.35***	-0.23***	-0.27***	-0.35***	-0.23***	-0.27***	-0.35***	-0.23***	-0.27***	-0.35***	-0.23***	-0.27***	-0.35***
	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)
Return on asset	0.00	0.15	0.12*	0.00	0.15	0.12*	0.00	0.15	0.12*	0.00	0.15	0.12*	0.00	0.15	0.12*
	(0.04)	(0.11)	(0.07)	(0.04)	(0.11)	(0.07)	(0.04)	(0.11)	(0.07)	(0.04)	(0.11)	(0.07)	(0.04)	(0.11)	(0.07)
Tier1 lev ratio	0.16***	0.20***	0.26***	0.16***	0.20***	0.26***	0.16***	0.20***	0.26***	0.16***	0.20***	0.26***	0.16***	0.20***	0.26***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Intercept	1.66***	1.82***	1.44***	1.66***	1.82***	1.44***	1.66***	1.82***	1.44***	1.66***	1.82***	1.44***	1.66***	1.82***	1.44***
	(0.56)	(0.63)	(0.42)	(0.56)	(0.63)	(0.42)	(0.56)	(0.63)	(0.42)	(0.56)	(0.63)	(0.42)	(0.56)	(0.63)	(0.42)
N	991	985	975	991	985	975	991	985	975	991	985	975	991	985	975
Adj R^2	0.06	0.06	0.09	0.06	0.06	0.09	0.06	0.06	0.09	0.06	0.06	0.09	0.06	0.06	0.09

Table 6: Bank Liquidity (Risk) and Crash Probability

This table tests how a bank's *ex ante* liquidity (risk) can predict their crash probability during the crisis.

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

where crash is identified if a bank's stock return ever has 25% loss in one quarter or 35% loss in two quarters (t and $t-1$) during the peak of financial crisis, 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 deviated 1-σ away), Basel III's two measures: liquidity coverage ratio (LCR) and net stable funding ratio (NSFR). We also include the liquidity creation measure by Berger and Bouwman (2009) as a third benchmark. The five liquidity(risk) measures are calculated as of 2006Q1, 2007Q1, and 2008Q1. The sample is only for public U.S. BHCs with valid stock returns in CRSP. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	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	-6.88***			8.39			-0.93			0.21			1.02		
	(1.76)			(8.61)			(1.13)			(0.16)			(0.72)		
In 2007Q1		-5.90***			-1.28			-2.23			0.09			1.00	
		(1.81)			(9.56)			(1.39)			(0.13)			(0.74)	
In 2008Q1			-4.23***			0.07			-0.68			-0.01			0.56
			(1.29)			(1.31)			(1.20)			(0.07)			(0.63)
Tier1 cap ratio	-0.24***	-0.31***	-0.24***	-0.24***	-0.31***	-0.24***	-0.24***	-0.31***	-0.24***	-0.24***	-0.31***	-0.24***	-0.24***	-0.31***	-0.24***
	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
Return on asset	-0.10	0.13	-0.18	-0.10	0.13	-0.18	-0.10	0.13	-0.18	-0.10	0.13	-0.18	-0.10	0.13	-0.18
	(0.08)	(0.18)	(0.15)	(0.08)	(0.18)	(0.15)	(0.08)	(0.18)	(0.15)	(0.08)	(0.18)	(0.15)	(0.08)	(0.18)	(0.15)
Tier1 lev ratio	0.38***	0.42***	0.35***	0.38***	0.42***	0.35***	0.38***	0.42***	0.35***	0.38***	0.42***	0.35***	0.38***	0.42***	0.35***
	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)
Intercept	5.09***	4.74***	2.51***	5.09***	4.74***	2.51***	5.09***	4.74***	2.51***	5.09***	4.74***	2.51***	5.09***	4.74***	2.51***
	(1.20)	(1.30)	(0.66)	(1.20)	(1.30)	(0.66)	(1.20)	(1.30)	(0.66)	(1.20)	(1.30)	(0.66)	(1.20)	(1.30)	(0.66)
N	340	345	349	340	345	349	340	345	349	340	345	349	340	345	349
Adj R^2	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10

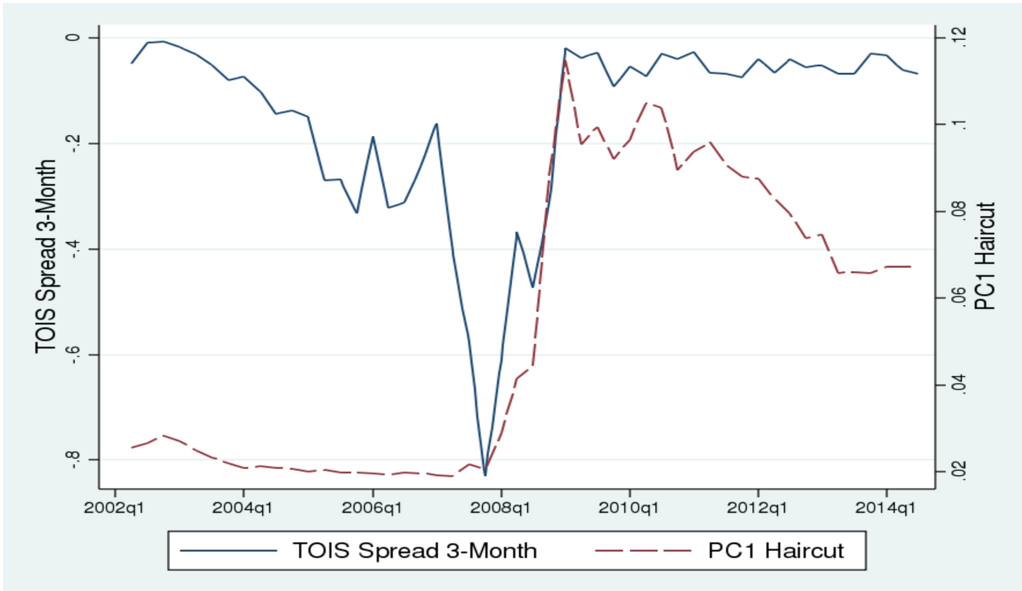


Figure 1: **Market factors for asset and liability liquidity weights: cross-collateral haircuts (m_{PC1}) and funding liquidity factor**

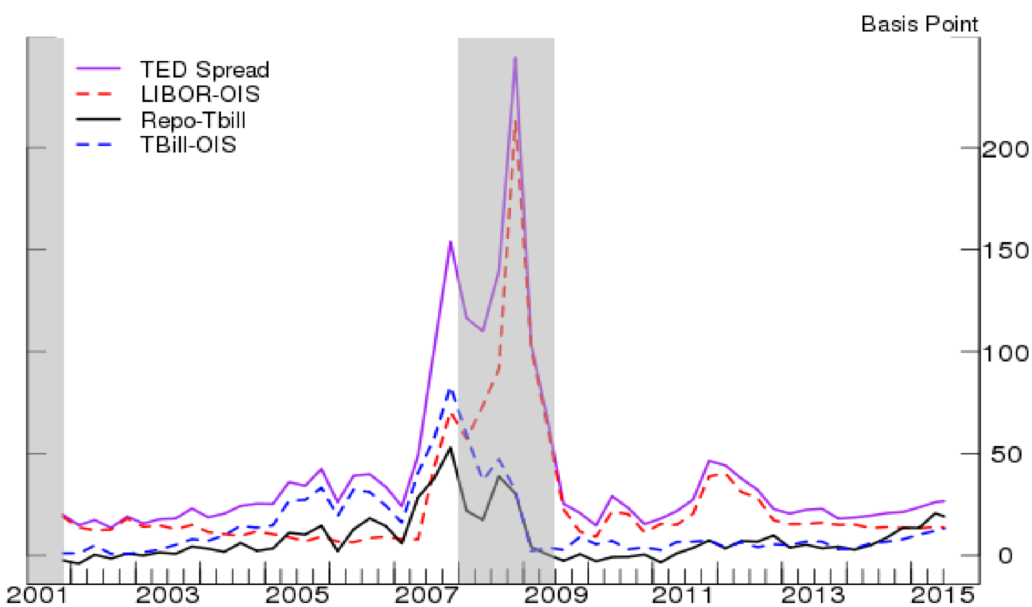


Figure 2: **Proxies for funding liquidity premium**

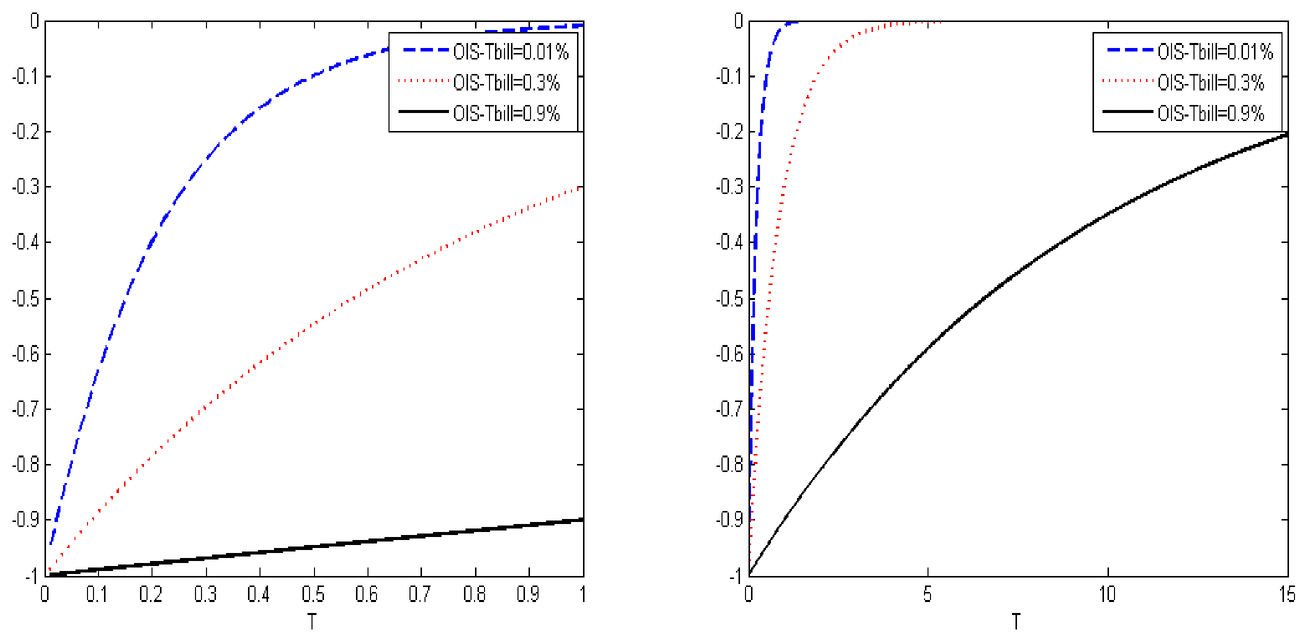


Figure 3: **Liability liquidity weights:** $\lambda_{L_k} = -\exp(\ln(OIS - Tbill)T_{k'})$.

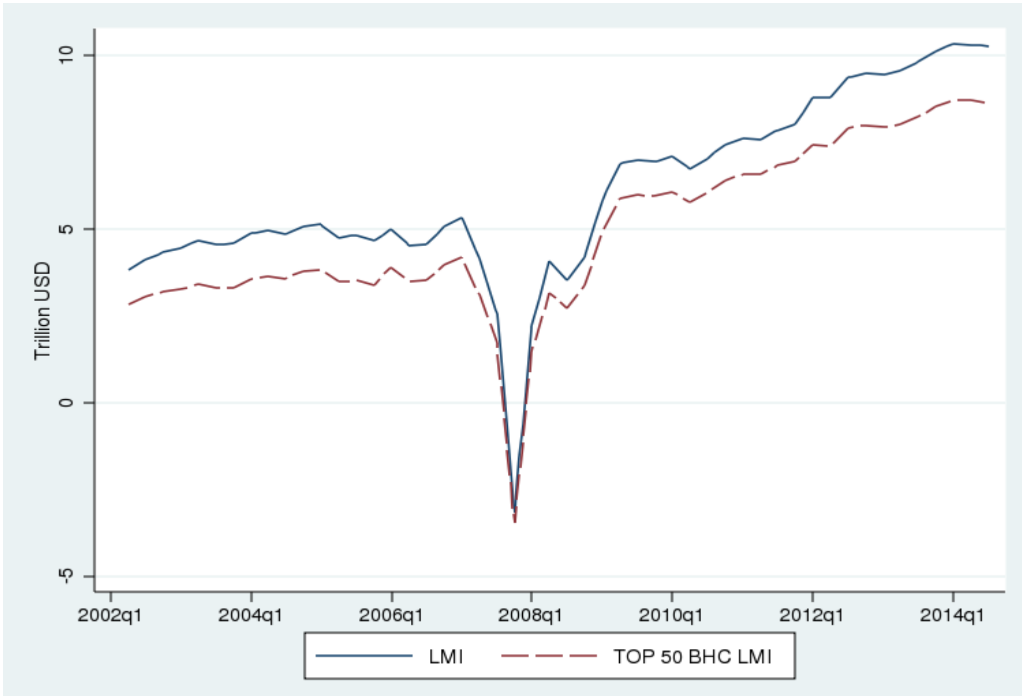


Figure 4: **Aggregate liquidity mismatch ($trillion) for top 50 and all BHCs**

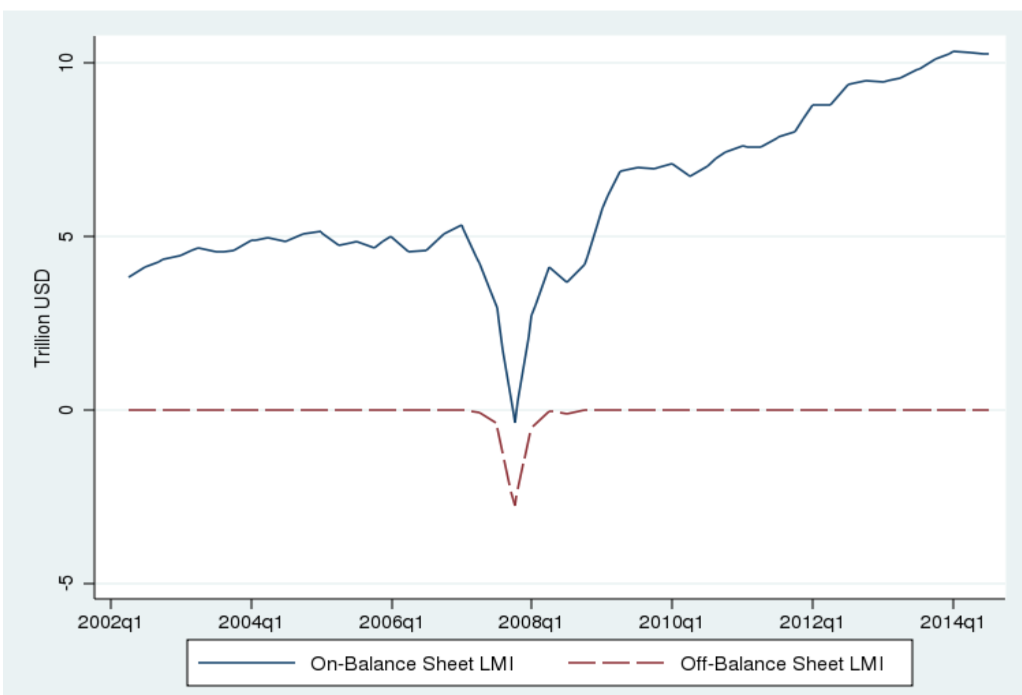
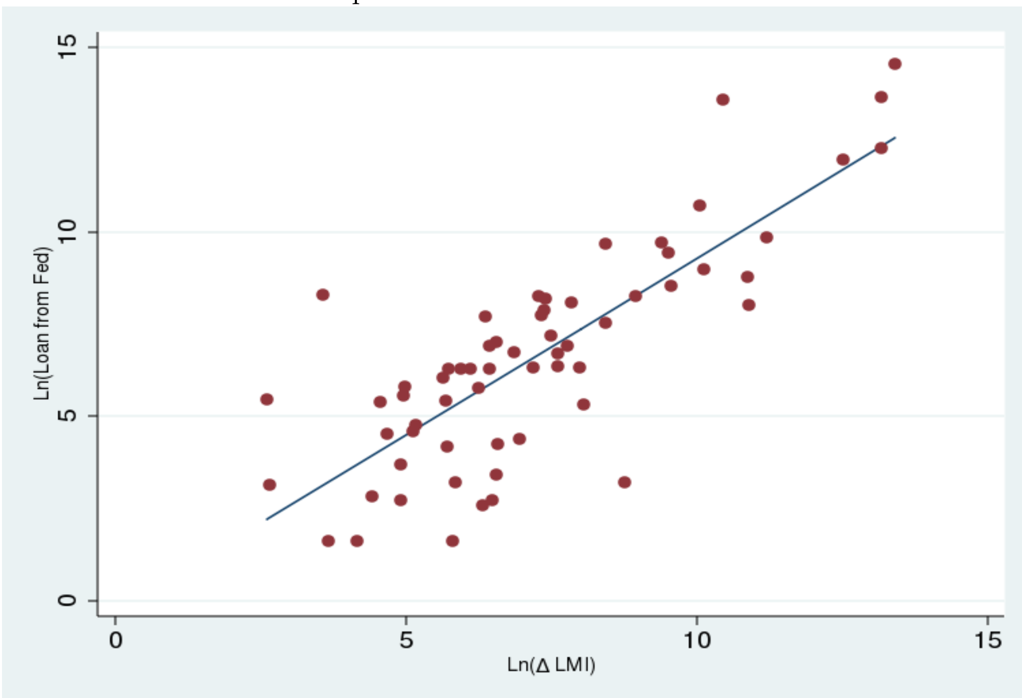


Figure 5: **Liquidity mismatch on- and off-balance sheet**

A: LMI post-crisis minus LMI in the crisis



B: LMI post-crisis minus LMI pre-crisis

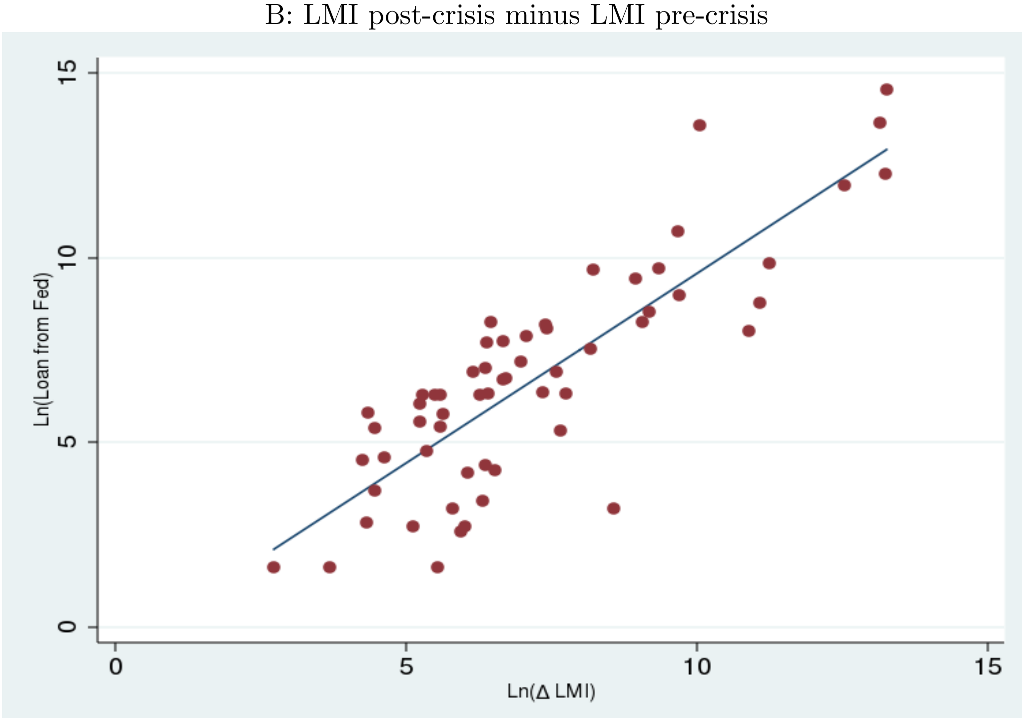
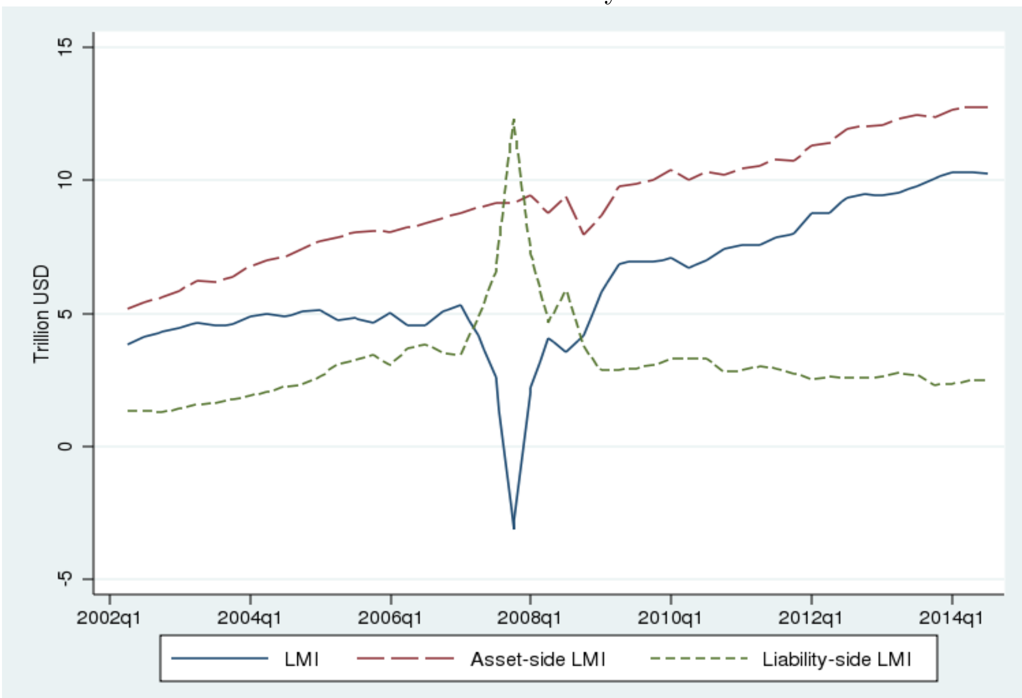


Figure 6: **Correlation between Fed injections and the change of LMI (in dollar amount)**

A. Asset-side and liability-side LMI



B: Effective weights

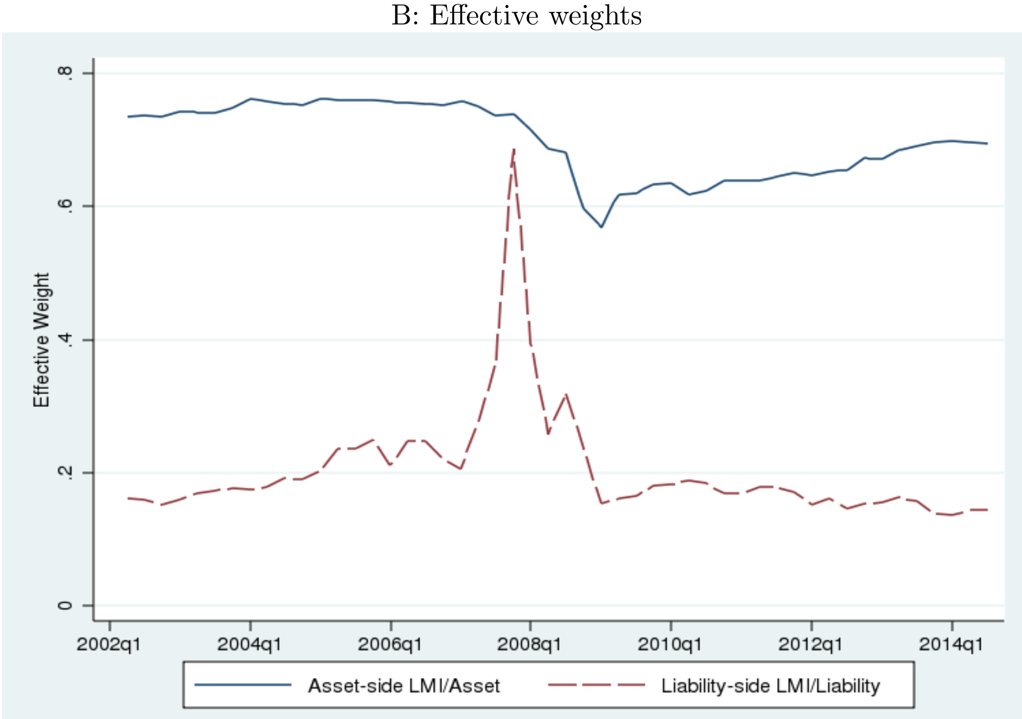
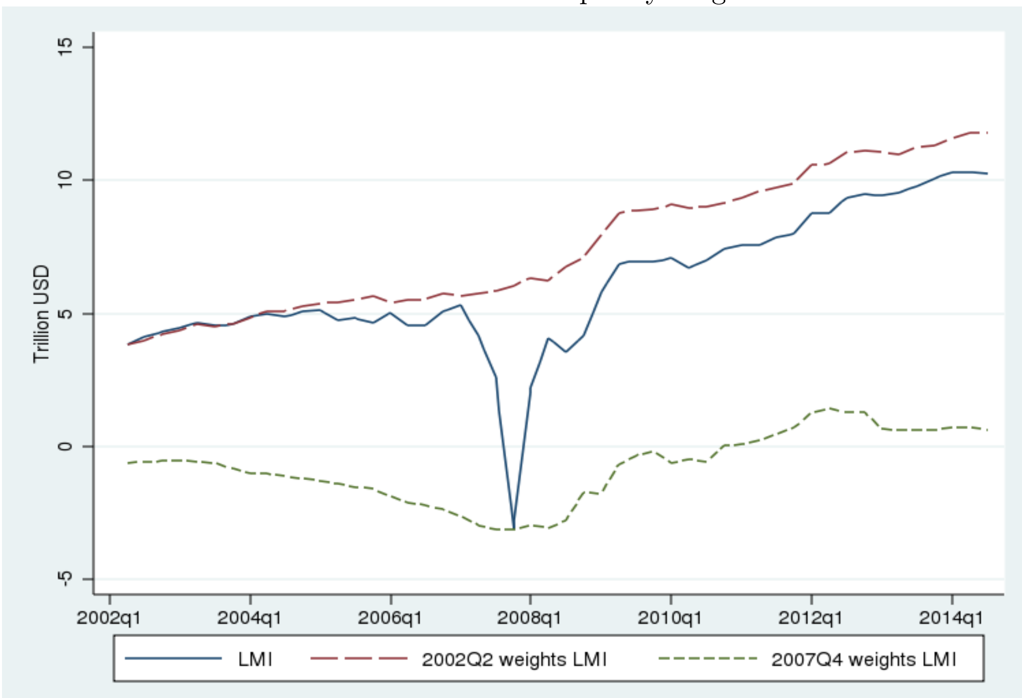


Figure 7: **Decomposition of LMI by assets and liabilities.** Effective liquidity weights are defined as the liquidity-weighted asset (or liability) divided by the total amount of asset (liability) used in the LMI calculation.

A. LMI under various liquidity weights



B. LMI under $1\sigma, 2\sigma$ stress scenarios (truncated at -5 trillion)

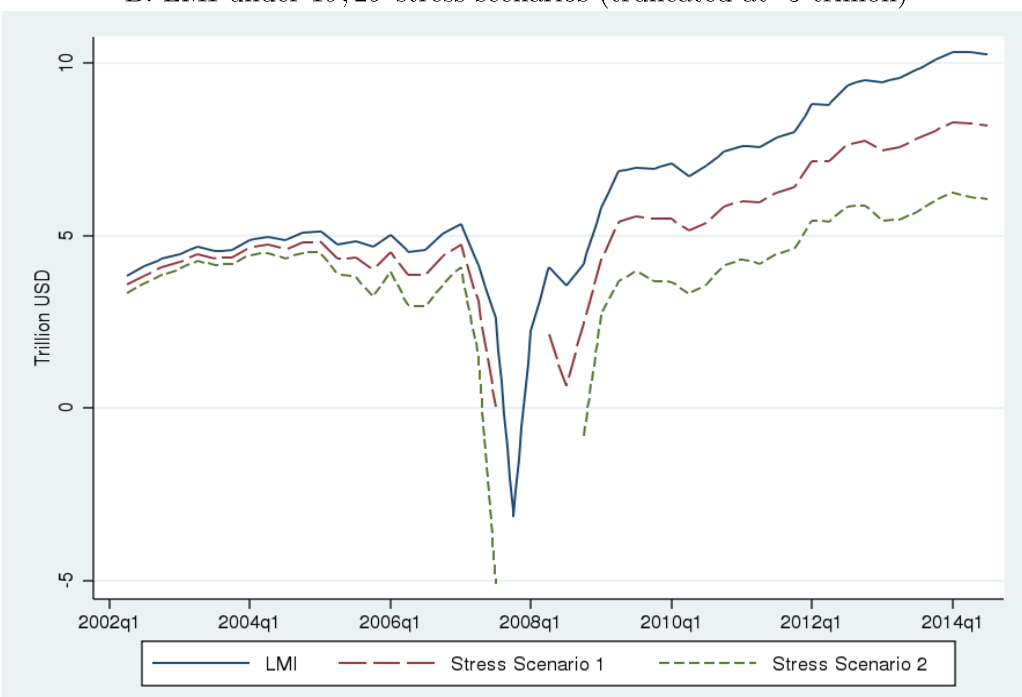


Figure 8: **LMI as a macroprudential tool**

Figure 9: **Selected bank-level liquidity mismatch (in $million)**

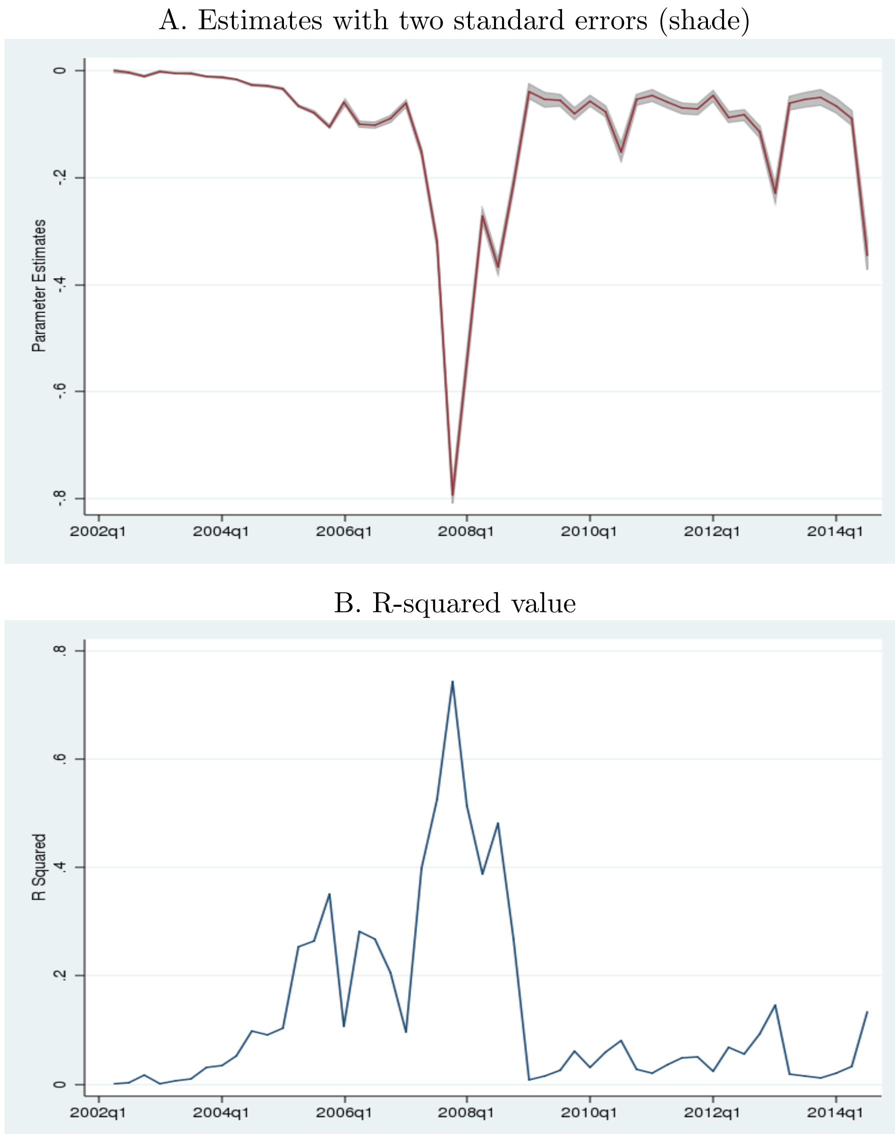


Figure 10: **The relationship between liquidity level and liquidity risk.** Within each quarter, we run the cross-sectional regression of $\frac{LMI - LMI_{1\sigma}}{Asset} = \alpha + \beta \frac{LMI}{Asset} + \epsilon$ and present the time-series of β and its (+/− 1) standard error in panel A, and the R-squared value in panel B. $LMI_{1\sigma}$ is the LMI value under 1-σ stress scenario.

Appendix

A Computing the LMI

ASSET Weight: $\lambda_{t,a_k} = \exp\left(-(\overline{m}_k + 5 \times \beta_k m_{PC1,t})\right)$

Note: 1. $\overline{m}_k$ is the average haircut for asset k.
($\overline{m}_k$ is set to be 0 for Cash, and 99 for Fixed, Intangible and other Assets.)
2. $m_{PC1,t}$ is the time-series of the first principal component of haircuts across all asset categories.
3. β_k is the absolute value of risk exposure from: $m_{k,t} = constant + \beta_k m_{PC1,t} + \varepsilon_t$

Category	A_k	β_k
Cash	cash and balances due from depository institutions	-
	federal funds sold	-
	securities purchased under agreements to resell	-
Trading Assets	Treasury securities	0.059
	agency securities	0.059
	securities Issued by States and U.S. Pol. Subdivisions	0.558
	non-agency MBS	0.303
	structured product	0.303
	corporate debt	0.508
Available for Sale	Treasury securities	0.059
	agency securities	0.059
	securities Issued by States and U.S. Pol. Subdivisions	0.558
	non-agency MBS	0.303
	structured product	0.303
	corporate debt	0.508
	equity securities	0.652
Held for Maturity	Treasury securities	0.059
	agency securities	0.059
	securities Issued by States and U.S. Pol. Subdivisions	0.558
	non-agency MBS	0.303
	structured product	0.303
	corporate debt	0.508
Loans	loans secured by real estates	1.004
	commercial & Industry Loans	1.004
	other Loans	1.004
	lease financing receivables	1.004
Fixed Assets	premises and fixed assets	-
	other real estate owned	-
	investment in unconsolidated subsidiaries	-
Intangible Assets	goodwill and other intangible assets	-
Other Assets		-

LIABILITY Weight: $\lambda_{t,l'_k} = -\exp(-\mu_t T_{k'})$

Note: μ_t is the negative logarithm of the 3-month OIS-TBill spread.

Category	$L_{k'}$	$T_{k'}$
Fed Funds	overnight federal funds purchased	0
Repo	securities sold under repo	0
Deposits[1]	insured	10
	uninsured	1
Trading Liabilities	trading liabilities	$-\lambda_{t,a_{k'}}$
Other Borrowed Money	commercial paper	1/12
	with maturity <= 1 year	1
	with maturity > 1 year	5
Other Liabilities	subordinated notes and debenture	10
	other liabilities	10
Total Equity Capital	equity	30
Contingent Liabilities[2]	unused commitments (revolving, open-end loans, unused credit card lines, to fund commercial-real-estate-related loans, to provide liquidity to ABCP conduit structures, to provide liquidity to securitization structures, other unused commitments)	5
	Credit Lines (financial standby letters of credits, performance standby letters of credits, commercial and similar letters of credits)	10
	Securities Lent	5
	Collateral Values	10

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. 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 use Item 15 to collect the fair value of collateral posted for over-the-counter derivatives.

B 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 the following table.

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.

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.

C Liquidity Benchmark Measures

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

Berger and Bouwman (2009) proposed 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.[14] 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 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.[15]

The NSFR formula and implementation is based on the Basel release in October 2014. 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.

[14] http://faculty.weatherhead.case.edu/bouwman/data.html
[15] http://www.occ.gov/news-issuances/bulletins/2014/bulletin-2014-51.html

Available Stable Funding		Required Stable Funding	
Item	Factor	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 ≥ 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¡comma¿ maturity ≥ 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).