A Liquidity Index

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Abstract

The recent financial crisis re-ignites the concerns of systemic risk in the financial industry. It is the first time that systemic risk is caused by a lack of liquidity in the marketplace. To deal with this newly emerged systemic risk, researchers have been trying to develop various quantitative indicators. Despite of successful empirical results, these indicators are mainly empirically based and not capable of differentiating liquidity risk from other sources of risk such as market and credit. In this paper, we propose a liquidity index to measure the severeness of lack of liquidity in the financial market. The index is computed based upon an extension of the liquidity discount model developed by Chen (2012) where asset values are discounted when lack of demand is detected in the marketplace. We choose a comprehensive sample of Russell 1000 financial stocks from January 1997 to July 2011 to construct the liquidity index which then can be used in conjunction with the popular Russel 1000 financial index. The empirical results reveal that as of July 2011, the liquidity has not been restored to the pre-crisis level, although various sectors demonstrate very different liquidity levels.

Key words. liquidity discounts, liquidity index, asset liquidity, systemic risk

JEL Classification: G, G01, G02, G12, G21, G24, G28

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1 Introduction

The unprecedented financial crisis and the largest bankruptcy in U.S. history in 2008 prompted record awareness of systemic risk inside the financial industry. The rise of systemic risk is usually a result of a phenomenon one would expect in a bank run. Yet the 2008 crisis was not a conventional bank run but a liquidity vacuum. In other words, due to a lack of willingness to trade (buy), prices fall dramatically, and hence create a near-perfect correlation situation where diversification is impossible.

Systemic risk is not a new concept.[1] In "Systemic Risk: A Survey" by the European Central Bank in 2000, three types of systemic risk have been identified:

- bank run
- contagion
- failure in interbank systems

of which theories and empirical evidence are reviewed in details. However, the recent 2008 crisis defines a new systemic risk in our financial systems. Allen and Carletti (2013) view this new systemic risk as "banking crises due to asset price falls". They further define such a problem as "mispricing due to inefficient liquidity provision and limits to arbitrage."[2] Shin (2009) explicitly characterizes this liquidity-driven crisis as a new type of bank run. He contends that illiquidity, together with excess leverage and credit risk, ultimately affects nearly every financial institution. Also, Adrian and Shin (2010) document how financial institutions manage their leverage and the dynamics of the relationship between leverage and liquidity in the market.

Measuring this liquidity-induced systemic risk is an urgent topic. Shortly after the Lehman default, the Basel Committee has swiftly announced two liquidity ratios, LCR (liquidity coverage ratio) and NSFR (net stable funding ratio) to measure the liquidity

[1] This paper is authored by De Bandt and Hartmann (2000).
[2] Allen and Carletti (2013) define systemic risk as "it is the interactions of financial institutions and markets that determine the systemic risks that drive financial crises," and as a result, in addition to the three defined by the European Central Bank in footnote 1, they recognize a new kind of systemic risk that caused the recent crisis.

risk of a financial institution. However, researchers have critically criticized these two measures as being inappropriate and inaccurate.[3]

While Basel has been improving its liquidity ratios,[4] proposals have been provided by various regulatory bodies. Mainly they can be summarized as the following three areas. The first is to monitor correlations and price co-movements. Binici, Köksal and Orman (2013) study the Turkish banking system. They investigate the evolution of systemic risk in the Turkish banking sector over the past two decades using correlations of banks' stock returns as a systemic risk indicator. They report that the correlations between bank stock returns almost doubled in 2000s in comparison to 1990s, decreased somewhat after 2002 and increased again during the 2007-2009 financial crisis.[5] However, while equity correlations are certainly impacted by the crisis, it is not a clean measure of liquidity risk. In other words, there are too many causes for equity correlations to rise and hence the rise in equity correlations is not necessarily a signal for a lack of liquidity. In short, equity correlation is a necessary condition of the crisis, not a sufficient condition. We shall demonstrate that with our model for liquidity discounts, high equity correlations are a natural result of liquidity shortage. Furthermore, we shall demonstrate how to separate "normal" correlations from liquidity-induced correlations. Namely, with liquidity discounts, we can derive the correlations among illiquid asset values are the true indicator of systemic risk.

The second area is to observe default probabilities in the market. Combining default probabilities estimated with credit default swap (CDS) data with equity return correlations (as a proxy for asset correlations), Huang, Zhou, and Zhu (2009) create an indicator for systemic risk. They argue that their indicator for systemic risk is an ideal tool to measure a "distress insurance premium" – the theoretical price of insurance against financial distress. However, default probabilities estimated from CDS and equity correlations cannot be consistent with each other. Besides, neither measurement can gauge the magnitude of liquidity risk. Indeed, they are meant to measure credit and market risks. What we provide in this paper is to derive liquidity-implied asset

[3] See, for example, Hong, Huang, and Wu (2014) for their empirical work and a comprehensive review provided. Bučková and Reuse (2011) provide evidence on the European banks.
[4] For example, see January 6, 2013 BIS report: "Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools".
[5] In addition, they explore possible determinants of systemic risk, the knowledge of which can be a useful input into effective macroprudential policymaking. Results show that determinants of systemic risk appear to be the market share of bank pairs, the amount of nonperforming loans, herding behavior of banks, and volatilities of macro variables including the exchange rate, U.S. T-bills, EMBI+, VIX, and MSCI emerging markets index.

correlations and default probabilities. As we shall demonstrate later, we differentiate liquidity and economic defaults and compute default probabilities and correlations consistenly. This then allows us to study separately how systemic risk is decomposed into credit and liquidity components.[6]

The third kind is to use expected shortfall (ES) or conditional Value at Risk (CoVaR). Both measures are based upon the popular market risk methodology – Value at Risk (VaR). Acharya, Pedersen, Philippon, and Richardson, (2010) use the expected shortfall as an indicator for systemic risk. They test 18 banks with their CDS data. They demonstrate empirically the ability of ES to predict emerging risks during the financial crisis of 2007-2009. De Nicolò and Lucchetta (2012) use ES to measure "real" liquidity risk with GDP growth and "financial" liquidity risk with the excess return of a portfolio of a set of specifically chosen financial firms. They use a vector-auto-regressive model to estimate and forecast the two variables and find significant out-of-sample forecasting power for tail real and financial risk realizations. They also argue that stress testing provides useful early warnings on the build-up of real and financial vulnerabilities.

A similar indicator, conditional Value at Risk (CoVaR), is proposed by Adrian and Brunnermeier (2011). A CoVaR is the VaR of the financial system conditional on institutions being under distress. They compute the contribution to systemic risk as the difference between the CoVaR conditional on the institution being under distress and the CoVaR in the median state of the institution. Using the universe of publicly traded financial institutions, they estimate CoVaR and study how firm characteristics such as leverage, size, and maturity mismatch can predict systemic risk contribution. They further argue that CoVaR could predict more than half of realized covariances during the financial crisis as early as 2006Q4.

One common deficiency shared by these papers is that they lack a theoretical liquidity discount model.[7] Without a liquidity discount model, one cannot measure systemic risk

[6] Schwarz (2014) argues that widening interest rate spreads in the recent financial crisis could represent deteriorating asset liquidity and tries to separate market liquidity from credit risk so one can obtain a clean effect of liquidity risk. Her results reconfirm that market liquidity explains more than two-thirds of the widening of interest rate spreads. She concludes that the large role for market liquidity is due to the pricing of liquidity risk.

[7] The theory on systemic risk is voluminous. For example, Allen, Babus, and Carletti (2010) develop a model where institutions form connections through swaps of projects in order to diversify their individual risk. Upon the arrival of a signal about banks' future defaults, investors update their expectations of bank solvency. If their expectations are low, they do not roll over the debt and there is systemic risk in that all institutions are early liquidated. He and Krishnamurthy (2012) also derive a macroeconomic framework for quantifying systemic risk. Jobst (2012) proposes a systemic risk-adjusted liquidity model to study the

properly. For example the asset correlation implied by the Merton model is too low, as we shall show, to reflect the liquidity risk. As a result, it will lead to the under-estimation of systemic risk. Similarly, default probabilities and expected shortfalls measured without a liquidity discount model suffer the same deficiencies.

In this paper, we propose a liquidity index to measure the severeness of lack of liquidity in the financial industry. The index is computed based upon an extension of the liquidity discount model developed by Chen (2012) where asset values are discounted when lack of demand is detected in the marketplace. To evaluate a bank's assets under liquidity influence, the Chen model is built upon a capital structure model for which we choose the Geske model (1977). The Geske model is chosen in that it endogenizes both recovery and default barrier. Furthermore, the Geske model takes actual cash outflow obligations as inputs (strike prices) and hence suits seamlessly in explaining a bank's default. A brief sketch of the integration of the two models can be found in Section 2.

In a recent paper, Chen et. al. (2013) study the U.S. largest 23 banks for their liquidity resistance during the crisis period and successfully identify good banks from bad banks. This paper differs from the Chen et. al. study in the following ways. Firstly, we adopt a large data set (stocks that are constituents of Russel 1000 financial index) which allows us to form a liquidity index. This liquidity index can then be used in conjunction with the stock index to monitor the overall market health. Secondly, we improve the equity volatility estimation by replacing historical estimates with GARCH forecasts. Historical estimates of volatility have been shown to be unreliable in predicting future levels of volatility. Thirdly, due to the large number of banks in the study, a simplified capital structure is adopted. We do not use Factset that provides information of all debts but use COMPUSTAT that provides debt information up to only 5 years.[8]

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impact of liquidity risk on banks. The proposed model is based on the Black and Scholes (1973) and Merton (1974) idea that the equity is a call on assets and the total liability is a default-free debt minus a put. He continues on to model the put option with the Black-Scholes formula. He gauges the general level of liquidity risk for a portfolio of institutions based on the current regulatory proposal aimed at limiting term structure transformation – the Net Stable Funding Ratio (NSFR), a measure for liquidity. His empirical tests use 212 banks globally.

[8] We are currently using the FactSet data for the liquidity study. FactSet data contain all bonds of each bank. For example Goldman Sachs has a total of over 3,000 bonds in any particular year (with the longest maturity over 30 years). To handle this extremely large data quantity, we are using commercial database products such as Oracle or MySql to analyze such large data. We note that when these large quantity of data, the capital structure and liquidity models cannot run efficiently and hence a smaller set of banks can be analyzed. In other words, there is a tradeoff between an index that requires a wide coverage of banks and consequently cannot use all bonds of the banks and in-depth analysis of each bank with all bonds of that bank. As a first study, we only use COMPUSTAT for the index.

Our liquidity index covers the period from January 1997 to July 2011. As expected, the liquidity index shows a substantial plummet of 40% during the crisis period and then gradually recovers. However, the liquidity index, as of July 2011, has not recovered fully to the pre-crisis level. Our empirical results also demonstrate a large variation among different sectors of banks. In general, liquidity compression exists for large banks and regional banks. Furthermore, foreign banks suffer more liquidity compression than U.S. banks. Our empirical study demonstrates that our liquidity index can be used for regulatory purposes as a barometer for the liquidity health of the banking industry.

The rest of the paper is organized as follows. Section 2 describes the mail model of asset valuation, which includes the capital structure of model of Geske (1977), the accounting-based liquidity default model, and the liquidity discount model of Chen (2012). Section 3 index construction and its performance. Mainly, a liquidity index for the entire sample (Russel 1000 financial companies) is constructed and the results of breakdowns into various sectors are also reported. Section 4 explores two further results. First, we study the connectivity of the liquidity discount shocks among banking sectors. Then, we examine the predictability of these indices. Section 5 concludes.

2 Model for Asset Price – Liquid vs. Illiquid

As mentioned earlier, the recent crisis that prompted the unprecedented collapse of the banking system is due to the simultaneous falls of asset prices. These assets are owned by financial institutions in an interconnected manner (see Allen, Babus, and Carletti (2010)). As liquidity squeeze starts to surface in the market, banks are forced to sell assets in a very short period, causing prices to fall sharply, which in turn resulting in lenders (debt holders) to panic and start requesting additional collaterals. This phenomenon is known as a lack of funding liquidity. In other words, as the market values of these assets deviate drastically from their fair values, banks lose their ability to pay their short term debt obligations. Originally this could have been funded via short term borrowing. Yet, in a liquidity crisis, short term funding capacities dry up and liquidating assets becomes banks' only source of funding to repay their debts. As asset values drop rapidly, banks cannot liquidate their assets to generate enough cash to pay their debts. They then must file bankruptcy, leading to liquidity default.

This notion of default needs to be compared with the usual default that is caused by lack of profitability, which we term economic default.[9] When a firm cannot generate profits,

[9] Wu and Hong (2012) term it insolvency.

it will then gradually lose its capital. When all of its capital is depleted, the firm then must file bankruptcy. In this situation, the firm also has lost its capability to raise any equity as investors see no value of the firm. Formally, we define an economic default to be a default situation where a firm cannot raise any more capital, debt or equity. This occurs when the value of the assets falls below the total value of the debts (often called "negative equity value"). On the other hand, a liquidity default is a situation where a firm is profitable and yet lack of cash (or low liquidation value of assets) to pay for its immediate debt obligation.

Liquidity defaults have been monitored closely by accounting professionals. Annual auditing by CPA firms includes a going concern opinion as a result of the liquidity situation of a company. Liquidity here is defined as one year expected net cash flow. If there is not enough cash to pay expenses in the coming year, then the firm is deemed as illiquid and will not receive a favorable going concern audit. Note that the two new liquidity ratios by Basel III (LCR and NSFR) are quite similar to the liquidity ratios used in accounting.

In this section, we derive a model that explains this phenomenon. We use a multi-period version of the Merton model for determining banks' assets. We must use a multi-period model because there is no liquidity default in the Merton model. In a single period, all assets are liquidated at the end of the period and hence there is no differentiation of economic and liquidity defaults. In a multi-period setting, say two periods, we can differentiate if a bank defaults at time 1 due to liquidity (liquidity default) or due to profitability (economic default).

As in Merton (1974), Jobst (2012), Chen et. al. (2013), and many others, we model the equity of a bank by a call option. However, different from previous studies, we use the Geske compound option model (1979) as opposed to the Black-Scholes model in that our model of liquidity cannot be handled in a single period setting.

2.1 Economic Default (Geske)

Geske (1977) demonstrates that the compound call option is identical to the equity value of the firm when the firm has multiple debts. Geske adopts the usual Black-Scholes assumptions that under the risk-neutral measure the underlying asset, V, follows a log normal process under the risk-neutral measure as follows:

(1) $$\frac{dV_t}{V_t} = rdt + \sigma dW_t$$

where r and σ represent the risk-free rate and the volatility respectively that can be possibly random. Define $\underline{T} =< T_1, \cdots, T_n >$ as a series of exercise times (note that these times need not be equally apart). Define K_i (strike price in the compound option framework) where $i = 1, \cdots, n$ to represent the total cash-flow paid by the firm at time T_i.

At each exercise time, T_i, the equity holders decide if it is worthwhile to pay K_i to keep the firm alive. If the continuation value (i.e. expected present value of future uncertain cash-flows) is higher than K_i, the option is exercised and the firm is kept alive; or the option will be left unexercised and the firm defaults.

Denote E_t as the equity value at time t, then formally, at any time T_i, the comparison is made between $\mathbb{E}_{T_i}\left[\exp\left(-\int_{T_i}^{T_{i+1}} r_u du\right) E_{T_{i+1}}\right]$ (continuation value) and the cash flow K_i. In other words, the equity value must be:

$$E_{T_i} = \max\left\{\mathbb{E}_{T_i}\left[\exp\left(-\int_{T_i}^{T_{i+1}} r_u du\right) E_{T_{i+1}}\right] - K_i, 0\right\} \tag{2}$$

where $\mathbb{E}_\tau[\cdot]$ is the risk-neutral expectation conditional on time τ, K_i represents the cash-flow paid by the firm at time T_i. If the firm cannot make the K_i payment, then the firm must default.

In this section, we first demonstrate the model with a two-cash-flow example in order to show the basic modeling structure. Empirically we can carry out the analyses with any arbitrary number of periods. In the two-cash-flow model, there exist closed-form solutions to the equity value, debt values, and default probabilities.

In a two-period model, the firm has two cash-flow payments K_1 and K_2 at times T_1 and T_2. The firm liquidates at time T_2. Let the values of debts be $D_{t,T}$ where current time is t and maturity time is T. It is apparent that at time T_2, should the firm has survived at time T_1, the debt and equity values are $D_{T_2,T_2} = \min\{V_{T_2}, K_2\}$ and $E_{T_2} = \max\{V_{T_2} - K_2, 0\}$ respectively. At time T_1, the equity value before checking for default is precisely the Black-Scholes value:

$$\begin{aligned} \zeta_{T_1} &= e^{-r(T_2-T_1)}\mathbb{E}_{T_1}[\max\{V_{T_2} - K_2, 0\}] \\ &= V_{T_1}N(d^+) - e^{-r(T_2-T_1)}K_2 N(d^-) \end{aligned} \tag{3}$$

where $\mathbb{E}_\tau[\cdot]$ is the risk-neutral expectation conditional on (the information given at) time τ and

$$d^\pm = \frac{\ln V_{T_1} - \ln K_2 + (r \pm ½\sigma^2)(T_2 - T_1)}{\sigma\sqrt{T_2 - T_1}}$$

In the option literature this is called the "continuation value" which is the present value of the future payoff. In the compound option model, this value needs to be compared against the cash-flow amount at time T_1. Hence the equity value at time T_1 is:

(4) $$E_{T_1} = \max\{\zeta_{T_1} - K_1, 0\}$$

The current value of the equity is $E_t = e^{-r(T_1-t)}\mathbb{E}_t[E_{T_1}] = e^{-r(T_1-t)}\mathbb{E}_t[\max\{\zeta_{T_1} - K_1, 0\}]$. Should we know the distribution of ζ_{T_1}, the solution can be easily derived. Unfortunately, the distribution of ζ_{T_1} is unknown. As a result, the closed-form solution can only be derived if we perform the change of variable from ζ_{T_1} to V_{T_1} using (3). In doing so, we must also translate the strike price K_1 for the equity to the strike price $\bar{V}_1$ for the firm value. This implied strike for the firm value must be solved numerically as a value that makes the following equality hold:

(5) $$\zeta_{T_1} = K_1$$

Once we know the value of $\bar{V}_1$, we can then derive the closed-form solution for the equity:

(6) $$\begin{aligned} E_t &= e^{-r(T_1-t)}\mathbb{E}_t[\max\{\zeta_{T_1} - K_1, 0\}] \\ &= e^{-r(T_1-t)}\mathbb{E}_t[\max\{V_{T_1} - \bar{V}_1, 0\}] \\ &= V_t M\left(y^+, z^+; \sqrt{\tfrac{T_1-t}{T_2-t}}\right) - e^{-r(T_1-t)}K_1 N(y^-) - e^{-r(T_2-t)}K_2 M\left(y^-, z^-; \sqrt{\tfrac{T_1-t}{T_2-t}}\right) \end{aligned}$$

and the two debt values:

(7)

$$\begin{aligned} D_{t,T_1} &= V_t[1 - N(x^+)] + e^{-r(T_1-t)}K_1 N(x^-) \\ D_{t,T_2} &= V_t\left[N(x^+) - M\left(y^+, z^+; \sqrt{\tfrac{T_1-t}{T_2-t}}\right)\right] + e^{-r(T_1-t)}K_1\left[N(y^-) - N(x^-)\right] + e^{-r(T_2-t)}K_2 M\left(y^-, z^-; \sqrt{\tfrac{T_1-t}{T_2-t}}\right) \end{aligned}$$

where

$$x^{\pm} = \frac{\ln V_t - \ln K_1 + (r \pm ½\sigma^2)(T_1 - t)}{\sigma\sqrt{T_1 - t}}$$

$$y^{\pm} = \frac{\ln V_t - \ln \bar{V}_1 + (r \pm ½\sigma^2)(T_1 - t)}{\sigma\sqrt{T_1 - t}}$$

$$z^{\pm} = \frac{\ln V_t - \ln K_2 + (r \pm ½\sigma^2)(T_1 - t)}{\sigma\sqrt{T_1 - t}}$$

and $N[\cdot]$ is the uni-variate standard normal probability and $M(a,b;c)$ is the bi-variate standard normal probability with two limits *a* and *b* and the correlation *c*.

The spreads are:

$$
(8) \qquad \begin{aligned} s_{t,T_2} &= -\frac{1}{T_2 - t}\ln D_{t,T_2} - r \\ s_{t,T_1} &= -\frac{1}{T_1 - t}\ln D_{t,T_1} - r \end{aligned}
$$

The total debt value is $V_t - E_t$ which is equal to:

$$
(9) \qquad D_t = V_t\left(1 - M\left(y^+, z^+; \sqrt{\tfrac{T_1 - t}{T_2 - t}}\right)\right) + e^{-r(T_1 - t)}K_1 N(y^-) + e^{-r(T_2 - t)}K_2 M\left(y^-, z^-; \sqrt{\tfrac{T_1 - t}{T_2 - t}}\right)
$$

The first term is term is known as the expected recover value. The second and third terms are the current values of the first and second cash-flows (K_1 and K_2) respectively. Note that $N(y^-)$ and $M\left(y^-, z^-; \sqrt{\tfrac{T_1 - t}{T_2 - t}}\right)$ are T_1 and T_2 risk-neutral survival probabilities respectively. The T_1 survival probability $N(y^-)$ is the probability of $V_{T_1} > \bar{V}_1$ (or equivalently $\zeta_{T_1} > K_1$). The T_2 survival probability $M\left(y^-, z^-; \sqrt{\tfrac{T_1 - t}{T_2 - t}}\right)$ is the joint probability of $V_{T_1} > \bar{V}_1$ and $V_{T_2} > K_2$.

The total risk-neutral default probability which is $1 - M\left(y^-, z^-; \sqrt{\tfrac{T_1 - t}{T_2 - t}}\right)$ represents either default at T_1 or T_2. When the firm defaults at T_1, (i.e. $V_{T_1} < \bar{V}_1$), the firm is liquidated and V_{T_1} is the recovery value and split between the two debts. If the firm survives at T_1 but defaults at T_2 (i.e. $V_{T_1} > \bar{V}_1$ and $V_{T_2} < K_2$), then the first debt is paid in full and the recovery value for the second debt is V_{T_2}.

When the random recovery value V_{T_1} and V_{T_2} paid at T_1 or T_2 should default occur combine with the default probabilities, it gives rise to the expected recovery value as $V_t\left(1 - M\left(y^+, z^+; \sqrt{\tfrac{T_1 - t}{T_2 - t}}\right)\right)$ which is the current asset value multiplied by the default probability under the measure in which the random asset value is the numerarie.

In a multi-period setting, although the solution can be easily extended, the solutions to the default points over time (i.e. $\bar{V}_1 \cdots \bar{V}_n$ at $T_1 \cdots T_n$) become increasingly complex. For example, in a three-period model, $\bar{V}_2$ is the internal solution to $\zeta_{T_2} = K_2$ which requires a uni-variate numerical integration. But ζ_{T_1} requires a bi-variate numerical integration and hence $\bar{V}_1$ requires a bi-variate search (such that $\zeta_{T_1} = K_1$). Hence, as the number of dimensions increases (say n), the solution to $\bar{V}_1$ cannot be solved without an $n-1$ numerical algorithm.[10]

2.2 Liquidity Default (Accounting)

Accounting firms must issue going concern audits to publicly firms to reveal if these firms possess enough liquid assets to survive in the next year. Such audits do not

[10] Note that the *n*-cash-flow model in Geske (1977) carries a mistake and is later corrected by Geske and Johnson (1984).

consider economic consequences of the firms' investments but only examine the liquidity needs of these firms. Hence, for those firms that fail to acquire a passing audit, they are subject to liquidity defaults.

Here, we can formally quantify (as opposed to human audits) such a liquidity default within the consistent framework that determines economic default, as described in the previous section. We define a liquidity default as:

(10) $V_t^* < K_t$

at any time t where V_t^* is the liquid value of total assets. We can also view V_t^* as the liquidation value of the firm. In other words, at any given time, as long as the liquidation value of the firm at any given time is insufficient to pay the cash flow due, the firm must default, regardless if the firm has large accrued profits. In our discrete setting, a firm survives only if $V_{T_i}^* > K_i$ for all i.

By definition $V_t^* \leq V_t$. That is, the firm suffers some value when it sells its illiquid assets. This is reasonable in that when K_i is due and if the firm has insufficient cash to pay for it, then it must liquidate its illiquid assets and in such a circumstance the value is reduced.

To determine the liquidation value of assets, we adopt the liquidity discount model by Chen (2012), as introduced in the next section.

2.3 The Liquidity Model of Chen

This subsection provides a brief overview of the Chen (2012) model which evaluates the discount (or premium) caused by illiquidity. In the Chen model, liquidity is defined as the ability to trade. If an asset is not liquid, then it cannot be transacted easily and as a result, there exists a discount in price. The concept can be best illustrated in the context of a binomial model by Cox, Ross and Rubinstein (1979). In the binomial model, the liquid asset value is the result of recursive substitutions (known as backward induction) of the payoffs because the asset can be transacted at every node of the lattice. On the other hand, if the asset is not liquid, then there can be no transactions in the lattice and such substitutions are not possible. Expected value of the terminal payoff must be computed by one single step. If the asset is risky (i.e. payoff is convex), then Chen shows that a discount must exist. Chen also shows that the riskier is the asset (i.e. more convex is the payoff), the more severe of the discount.

In the Chen model, any financial asset is assumed to be a state contingent claim where the underlying state variable is the overall economy, symbolized as W. A financial asset

is a convex contingent claim on this state variable. For simplicity and without loss of generality, we specify the convex payoff as $V_T = \max\{W_T - K, 0\}$, where K represents the convexity (i.e. riskiness) of the asset. In Chen, the underlying state variable, W_T, is assumed to follow a lognormal distribution with mean μ_W and variance σ_W^2.[11] As Chen argues, the larger the convexity, the larger the discount. As a result, the "liquidity health" of the assets (V) is determined by K. When $K = 0$, liquidity has no impact on the asset value V. Later on, we calibrate this parameter to the firm's spreads.

According to Chen, when no trading is permitted for the asset,[12] the liquid and illiquid prices are computed by the following equations respectively:

$$(11) \qquad \begin{cases} V_{t_i} = \dfrac{1}{R(t_i, t_{i+1})}(\mathbb{E}[V_{t_{i+1}}] - \beta_i^{\$}\{\mathbb{E}[W_{t_{i+1}}] - R(t_i, t_{i+1})W_{t_i}\}) \\ V_t^* = \dfrac{1}{R(t,T)}(\mathbb{E}[V_T] - \beta^{\$}\{\mathbb{E}[W_T] - R(t,T)W_t\}) \end{cases},$$

where $R(t,T) = e^{r(T-t)}$ is the risk-free money market account and $\beta^{\$} = \mathrm{cov}[V_T, W_T]/\mathrm{var}[W_T]$ or $\beta_i^{\$} = \mathrm{cov}[V_{t_{i+1}}, W_{t_{i+1}}]/\mathrm{var}[W_{t_{i+1}}]$ is known as the dollar beta. This solution must be computed numerically. Equation (11) is known as the CAPM in a dollar form. Intuitively it indicates that the illiquid price is a one-step expectation of the terminal payoff while the liquid price is a series of repeated use of the equation. Chen (2012) proves that $V_t^* \le V_t$ with the equality holds when the payoff is linear.

As mentioned earlier, the condition of an economic default at time T_1 is $V_{T_1} < \bar{V}_{T_1}$ where $\bar{V}_{T_1} = \sum_{i=1}^{n} D_i$ (where D_i is the ith debt value and $D_1 \equiv K_1$) represents the total value of debts and the probability of survival is $N(y^-)$. On the other hand, the liquidity default probability is $V_{T_1}^* < K_1$. To compute the probability of liquidity default, we approximate $V_{T_1}^*$ as follows:

$$(12) \qquad V_{T_1}^* = V_t^* \exp\left(-\tfrac{1}{2}\sigma_A^2 + \sigma_A \int_t^{T_1} dz\right)$$

where V_t^* is computed using equation (11). The probability of liquidity default is then computed numerically by implementing $\Pr[V_{T_1}^* < K_1]$. Note that $\bar{V}_{T_1} > K_1$. In a "normal" situation when the market is liquid, $V_{T_1}^* = V_{T_1}$ and hence the economic default probability is larger than the liquidity default probability. However, in a crisis situation, $V_{T_1}^* < V_{T_1}$. Hence, while $K_1 < \sum_i^n D_i$, the liquidity squeeze can be so severe that the company is

[11] We have tried other convex functions such as quadratic and put functions and the result does not change empirically.
[12] The "*k*" parameter is set to 0.

economically solvent (i.e. $V_{T_1} > \sum_{i=1}^{n} D_i$) but liquidity insolvent (i.e. $V_{T_1}^{*} < K_1$). As we can imagine, under usual circumstances, economic default proceeds liquidity default, but in a severe situation liquidity default can proceed economic default. Figure 1 depicts the relationship between the two default probabilities.

[Figure 1 Here]

The solid line (black) and the dotted line (red) represent economic and liquidity probabilities of default under various asset values. As the asset value increases, the default probabilities drops. When asset values are high, liquidity defaults are unlikely and hence the probabilities are low. When asset values are low, liquidity defaults more likely and the probabilities are high. The two probability curves cross somewhere in the diagram and the crossover point represents the critical asset value where the economy is under a liquidity squeeze.

2.4 Bank's Balancesheet

We now combine the two models to evaluate the balancesheets of banks. While the literature of using the structural model of Geske (1977) to evaluate a firm's assets is voluminous, it has been mostly for non-financial firms. Financial firms are highly levered and hence the structural models generally fail. Recently, Chen et. al. (2014) argue that structural models are suitable for financial companies as long as we classify their assets and liabilities by their liquidity quality. Then they successfully estimate the default probabilities using only those illiquid assets and liabilities.

Banks borrow a disproportionably large amount of very short term liabilities (overnight) for their daily operations and borrow long term debts like non-financial firms. As a result, as Chen et. al. point out, a large (short term) portion of the leverage of a bank can be waived from calculating economic default probabilities. These large amounts of short term liabilities are "rolled over" to another almost identical short term liabilities. The ability to roll over short term liabilities is known as the funding liquidity.

When a bank is healthy, lenders of the short term liabilities comfortably collect interests and let the bank roll over. When the bank becomes risky, lenders can call off their lending and then the bank must liquidate some of its assets to pay for the liabilities. If the economy is strong and the market is liquid, then the bank can sell its assets at fair prices. If not, then the bank must suffer lower than fair prices when it sells its assets. A liquidity crisis is a situation where banks are losing their funding capability rapidly and all of them

are selling assets at the same time. As a result, there is a direct connection between asset liquidity and funding liquidity.

Banks' balancesheets in general are very complex. Due to the high leverage nature of banks, regulations require banks carefully categorize their assets and liabilities in terms of liquidity. Chen et. al (2014) do a very detailed analysis of Lehman's balancesheet. In their Table 1, they demonstrate that overall Lehman has over 50% assets that are very liquid, over 40% assets that are semi-liquid, and 5% or so assets that are illiquid. In terms of liabilities, 50% of the liabilities are liquid, slightly above 25% of the liabilities are semi-liquid, and 20% or so of the liabilities are illiquid. They also survey the literature and conclude that using "net debt" is the most reasonable liability amount to estimate default probabilities. Here, without detailed bond issuance data from FactSet, we adopt the same methodology and use only data from long and short debts in CompuStat.

Similar to Chen et. al., we let the assets be classified as two classes (which can be generalized to m classes later): V_L and V_I where V_L represents the amount of liquid assets and V_I is the amount of illiquid assets. V_L (e.g. cash) is perfectly liquid and will not suffer from any liquidity discounts. On the contrary, the market value of V_I is V_I^*. Hence the market value of total assets (MVA) is $V_L + V_I^*$. Let the liabilities be also classified as two classes (n classes later) K_L and K_I where K_L is liquid like overnight funding and K_I is illiquid like bonds. The market value of debt (MVD) is $K_L + D_I$ where D_I is the market value of K_I considering liquidity discounts. Market value of equity (MVE) therefore is, by construction, $V_L + V_I - (K_L + D_I)$ in a liquid situation or $V_L + V_I^* - (K_L + D_I)$ in an illiquid situation. If $V_L = K_L$ which is the case of most banks, then MVE is $E = V_I - D_I$ or $E^* = V_I^* - D_I$. As a result, the equity value can be used to back out V_I using only K_I. Note that in our empirical work, a two-factor Geske is used and K_I consists of K_1 (one year debt) and K_2 (long term debt).

Wu and Hong (2012) have a similar recognition of the difference between the two types of default.[13] However, instead of a structural modeling approach, they use an econometrically estimated hazard rate for the risk of economic default and the TED spread[14] for the risk of liquidity default. Our approach differs from theirs in the following ways. First, we physically model default events as opposed to likelihoods of default. Second, our two default events are endogenously connected as opposed to

[13] They term economic default as insolvency.
[14] TED is an acronym formed from T-Bill and ED, the ticker symbol for the Eurodollar futures contract.

separately measured. Third, because of the endogeneity, the two types of default allow us to calculate various existing measures for systemic risk.

2.5 Index Construction

We apply the model to examine the large U.S. banks in the Russell 1000 index to investigate how their assets are affected if the market faces a liquidity squeeze. We use market information – that is, market capitalization and its volatility – to infer the implied liquid and illiquid asset values. These values differ from the book value of assets in that they reflect the evaluations of equity investors. In other words, we assume that equity investors correctly evaluate the firm's assets and credit risk (via its capital structure) and assign a value to the equity. When the market is free from a liquidity squeeze, then the equity value should reflect the perfectly liquid asset value. Similarly, when the market is under a liquidity squeeze, the asset value is compressed and the equity value is also lowered to reflect the liquidity-discounted asset value.

As a result, we adopt the following steps to calibrate the model to the market information:

- We compute, monthly, K_1 and K_2 values paid at T_1 and T_2 respectively;[15]
- We compute the bank's market capitalization E and its volatility σ_E monthly;
- We solve for V_t and σ using equation (6) and equation $\sigma = \sigma_E \frac{E}{V} \frac{1}{\partial E / \partial V}$ (two equations and two unknowns)[16] by substituting market capitalization for E_t and its volatility for σ_E.
- With the liquid asset value, we can solve for the economic state variable W by using equation (11) with K calibrated to the credit spread of the bank: $K = W \times (1 - 4(10\% - s))$ where *s* is the taken from the one-year spread of equation (8), μ_W and σ_W are set to 0.6 and 0.3 respectively, and the risk-free rate r is set to 0.
- Then, the Chen model is used to compute V_t^* using equation (11).
- Lastly, the liquidity index is calculated as $\frac{V_t - V_t^*}{V_t^*}$.

To estimate a firm's asset values, we first simplify the debt structure to have only two annual payments to fit to equation (6). The first payment, K_1, equals the first cash flow due in one year (seen in equation (6)). The second payment, K_2, equals the second cash

[15] We follow the KMV method, in which all cash flows after T_2 are aggregated and halved and then added to the T_2 cash-flow.
[16] The asset values computed with this method are the liquidity values.

flow plus half of all the remaining cash flows.[17] The market capitalization is used as the equity value in the Geske model. The volatility, σ_E, using the equally-weighted volatility or a GARCH model that is described in the next sub-section.. The volatility of stock returns is an equity volatility, σ_E, and needs to be translated to the asset volatility, σ, with the transformation formula $\sigma = \sigma_E \frac{E}{V} \frac{1}{\partial E / \partial V}$ where $\frac{\partial E}{\partial V} = M\left(y^+, z^+; \sqrt{\frac{T_1 - t}{T_2 - t}}\right)$. Now we can proceed to estimate the asset value (liquid) of a firm using the market capitalization value as the equity value. This approach (of using market cap and the volatility of market cap) to solve for the asset value and asset volatility is adopted widely in industry and academic research.[18]

After solving for the asset value and asset volatility, we compute the liquidity-constraint asset value using the Chen model. Several parameters in this model are preset: the frequency of rebalancing (symbolized by k in the original article) is set to 0; the mean and standard deviation of the underlying state variable μ_W and σ_W are set to 0.6 and 0.3, respectively; the risk-free rate r is set to 0; and finally, the number of steps for the binomial model is set to four, to conserve time.[19] The number of steps used in the lattice is 100.

Now we are left with only one parameter, K, which represents the convexity of the liquidity discount function. To minimize the calibration, we use the "implied credit spreads" from the Geske model (see the Appendix for the spread calculation). Because liquidity and credit risks are highly correlated (see, e.g., a recent study by Imbierowicz and Rauch (2012)), this calibration is reasonable.[20] Because liquidity worsens when the spread widens, we set the parameter to $K = W \times (1 - 4(10\% - s))$, where W is wealth and s is the implied spread. The two scalars, 4 and 10%, are designed to bring the level of the spread in line with the level of the convexity parameter. These two scalars only parallel-shift the illiquid values from the liquid values and do not change the relative relationship between them. One alternative method to estimate these two scalars is to use cross-sectional data, which is beyond the scope of this article.

[17] This method is proposed by KMV.
[18] This method is proposed by KMV.
[19] None of these parameter values has any material impact on the final result as we calibrate the model to the market information. Currently we use only information from equities. Should more information be available for calibration, many of these parameters can be estimated more meaningfully.
[20] We could calibrate the parameter to the CDS spreads and achieve similar results because of the extremely high correlation between the implied credit spreads and the CDS spreads. The result is available on request.

3 Preliminary Results

3.1 Data

We obtain constituent stocks in Russell 1000 financial sector index from January 1997 to July 2011, a total of 175 months. The data are collected from CRSP-CRSP/ COMPUSTAT MERGED. We list all inputs and sources as below:

- K_1: Debt in Current Liability (DLCQ from Fundamental Quarterly)
- K_2: Long-Term Debt – Total(DLTTQ) - Long-Term Debt Due in One Year (DD1Q) (in-consistent with the description in the previous part of this draft)
- Market Capitalization: The Multiplication of Price-Close-Monthly(PRCCM) and Common Shares Outstanding(CSHOQ).
- Stock vol: GARCH(1,1) or equally-weighted volatility using the method described in 3.1.2.
- K (credit spread)

The period is from January 1997 to July 2011, a total of 175 months. The sample size varies over time. The peak of the sample size (402 banks) is in December 2012 and the bottom of the sample size (189 banks) is in January 1997. The average size is 306 banks and the median is 308 banks. The banking classification information comes from Bloomberg. Then we classify the sample into 12 sectors in three broader categories as follows:

- Commercial
    - US commercial (305/129/229/236)
    - non-US commercial (90/42/64/63)
- Regional
    - eastern (71/35/55/59)
    - southern (108/35/74/75)
    - western (58/25/42/45)
    - central (70/34/56/59)
    - regional non-US (5/3/4/4)
    - super regional (10/7/7/8)

- Other
    - diversified (18/6/10/11)
    - fiduciary (7/4/5/5)
    - mortgage (2/1/1/2)
    - money center (1/1/1/1)

where the four numbers in each of the parenthesis represent max, min, mean, and median number of banks respectively.[21] The summary statistics of the input variables are presented in Figure 2. Note that the number of financial institutions in the sample varies over time. Hence, in Figure 2 we present the cross-sectional average for each year of the input variables: volatility (VOL), short-term debt (STD), long-term debt (LTD) and market capitalization (MCAP). We note that the cross-sectional average of LTD continues to go up in the sample period, even after the crisis. The average of STD peaked in 2007 and then dropped afterwards, as a result of the crisis. The average of MCAP also behaves much like STD, which is consistent with the crisis. The most interesting statistic is the volatility (VOL) that valleyed during the crisis and then increased to 2009.

[Figure 2 here]

We use these inputs to compute the liquidity discount percentage using the Chen model (2012). The liquidity discount percentage is calculated for every firm for every month. The summary statistics of these liquidity discount percentages are summarized in Table 1 where the discounts are categorized by types of banks. The means reported in Table 1 indicate that the diversified banks suffer the most liquidity discount (20.434%) while the fiduciary banks suffer the least (3.65%). We note that except for these two "extreme" groups, other groups suffer the liquidity discount by roughly the same magnitude. Finally, the Jarque-Bera test rejects normality of the distributions of the discounts for all the banking groups.

[Table 1 here]

[21] Super regional bank contains Fifth Third Bancorp; Huntington; Wells Fargo; PNC Financial; KeyCorp; SunTrust Bank; Capital One, etc. Fiduciary bank includes Bank of New York Mellon Corp; Northern Trust Corp; and State Street Corp. Diversified banks has JP Morgan Chase & CO; Citi Group Inc; Bank of America Corp; Morgan Stanley; HSBC Holding Plc; Deutsche Bank AG; Dean Witter Discover & Co; Goldman Sachs Group Inc.

3.2 Economic PD vs. Liquidity PD

Probability of default (PD) is regarded as an indicator for systemic risk. A record number of bank default cases since Lehman default is unambiguously the consequence of the liquidity crisis.[22] Huang, Zhou and Zhu (2009) propose to use default probabilities, in conjunction with correlations, as a measure for systemic risk. Wu and Hong (2012) use conditional probability of default for the measure of systemic risk. Similar to our model, Wu and Hong also differentiate liquidity and economic defaults. Yet the two defaults are measured empirically separately while in our approach the two types of default are endogenously connected. In other words, our liquidity default probability is a better measure of systemic risk that emerged in the recent crisis.

As mentioned earlier, an economic default arises when a company does not generate enough profits to sustain its business. Losses gradually consume away equity and ultimately the firm runs out of capital and must default. Liquidity defaults are a completely different matter. A liquidity default is when a company, while profitable, is short of cash. In this situation, the company must liquidate its assets and the large discrepancies between the book/fair values of the assets and the market values of the assets can lead to bankruptcy of the company. In a previous section, we formulate the economic default condition as the total liquid asset value smaller than the total debt value $V_{T_1} < \sum_{i=1}^{n} D_i$ where D_i is the ith debt value (or the market value of cash flow K_i to be paid at time T_i) and the liquidity default condition as the total illiquid asset value smaller than the first cash flow due $V_{T_1}^* < K_1$. When the market is liquid, the two values are identical $V_{T_1}^* = V_{T_1}$ but when the market is not liquid, $V_{T_1}^* < V_{T_1}$. Hence, while $K_1 < \sum_{i}^{n} D_i$, the liquidity squeeze can be so severe that the company is economically solvent (i.e. $V_{T_1} > \sum_{i=1}^{n} D_i$) but liquidity insolvent (i.e. $V_{T_1}^* < K_1$). As we can imagine, under usual circumstances, economic default proceeds liquidity default, but in a severe situation liquidity default can proceed economic default.

In an example, we illustrate how a company's probabilities of default due to liquidity and economics differ. In a good economy, both default probabilities are small (near 0) and hence we observe no differences. However, when the profitability of the company deteriorates, the credit risk of the company increases, the economic default probability increases. If the company remains liquid (either the company has enough cash or there is

[22] Anecdotal evidence shown in "A History of Bank Failures in the United States," on DaveManuel.com (http://www.davemanuel.com/history-of-bank-failures-in-the-united-states.php) indicates that 508 banks have defaulted since 2008.

no liquidity squeeze in the market), then the liquidity default probability is small. In this case, the difference is positive. As liquidity risk rises, the likelihood of default due to illiquidity rises. The default probability of liquidity becomes more dominant. Hence, the difference is negative.

[Figure 4 Here]

Figure 4 takes the Bank of America (BAC) as an example. In the case of BAC, we see that prior to the crisis, the difference of economic default probability and liquidity default probability is positive, indicating that economic default is more likely liquidity default. However, the situations reverse during the crisis. Liquidity default becomes more likely and the difference becomes negative.

Using the entire sample, we can see for the whole banking industry if liquidity default is more threatening than economic default during the period of crisis. This is presented in Figure 5.

[Figure 5 Here]

Figure 5 presents the time series plots of average economic probabilities of default (Econ PD) and average liquidity probabilities of default (Liq PD). It can be seen that during "normal" economic conditions economic PDs are higher than liquidity PDs, verifying the theory given above. Starting end of 2008, liquidity PDs become higher than economic PDs. This phenomenon lasts more than 1 year until end of 2010. We also observe that both economic PD and liquidity PD are low now, especially liquidity PD which is near 0.

3.3 The Index

We calculate liquidity discount ratios for all the banks in the sample period and for each month, we calculate cross-sectional market-value weighted average, equal-value weighted average, and median. Hence 13 times series plots are provided (whole sample and 12 sectors). We have the following several observations:

- liquidity is never back to where it was (from all banks)
- worst sector is non-US regional banks (bad liquidity all the time)
- compressed most are (1) diversified, (2) super regional, (3) non-US regional
- from all banks, it is clear that large banks suffer more badly from liquidity crisis thanks smaller banks (because median is fine but weighted averages are not)
- US banks are in general more healthy than non US banks

- in terms of value weight, fiduciary banks are the best– consistent with common sense.

We separate the commercial banks into different sub-indexes as stated above. Figure 6 presents three liquidity indices for the entire sample (Wilshire 1000) from January 1997 till July 2011 which are (1) market value weighted, (2) equal weighted, and (3) median of the entire sample. We observe that all three indices deviate from 100% (i.e. showing liquidity discounts) in two periods: internet bubble burst in late 1990s and early 2000s and the Lehman crisis. During the Lehman crisis, all indices start to decline at the beginning of 2008, two months earlier than Bear Sterns' default (March, 2008) and eight months before Lehman's default (September, 2008). The indices also demonstrate that the discounts in the Lehman crisis were so much more severe than those in the internet bubble burst (post 2000). Also interesting is that all three indices showed weakness in liquidity for the industry when the internet bubble was at its peak.

[Figure 6 here]

Figure 7 through Figure 9 present liquidity indices for sub-sectors of Wilshire 1000. Figure 7 divides the whole sample into US (top panel) and non-US commercial (bottom panel) banks. Overall, the two sub-sectors behave similarly. However, it is noted that half of the non-US banks were not impacted by the Lehman crisis (as the median index stays at 100% throughout the Lehman crisis). And the large non-US banks suffer the most from the Lehman crisis (as the market value weighted index lies below the equal value weighted index). This phenomenon is reversed for the US banks. The equal weighted index suffers more from the Lehman crisis than the market value weighted index, which indicates that smaller banks suffer more from Lehman's default.

[Figure 7 here]

Figure 8 presents the results for regional banks in six different regions – eastern, southern, western, central, non-US, and super regional. Out of the six regions, eastern, southern, western, and central present a similar pattern to national average. Super regional banks do show a somewhat similar patter as well and yet they suffer tremendously during the Lehman crisis. The magnitude of their liquidity discount reached as low as 0%. Interestingly, on the contrary, one group of regional banks that present a totally different result is the non-US banks that suffered tremendously in the internet bubble burst period and only very mildly during the Lehman crisis period.

[Figure 8 here]

Figure 9 presents the last sub-sector of the banks that do not belong to any of the previous sub-sectors. These are mortgage banks, fiduciary banks, and diversified banks. Mortgage banks are in bad shape throughout the entire sample period. Except for two very short periods 1999 and 2006. In other times, these banks suffer massively from liquidity discounts. The median index being sharply lower than the other two indicates that most banks suffer badly. In the entire sample, this is apparently the least healthy sub-sector of the banking industry. On the complete contrary to mortgage banks, fiduciary banks are the most healthy ones. Not only the discount in liquidity is the mildest, but the discount period is the shortest. The median index staying at 100% indicating that half of these banks are at all impacted by the Lehman crisis. Lastly diversified banks present a similar pattern than most of the banks but their liquidity indices are the most volatile. This could be due to that fact these banks are usually quite heterogeneous.

[Figure 9 here]

4 Transmission of Liquidity Shocks Among Banking Sectors

We separate the commercial banks into different sub-indexes as stated above. Our goal is to study whether the liquidity discounts are systemic risks, how many systemic components drive the liquidity risks in the banking systems, and how the banking systems adjust to the liquidity shocks. Our study also includes the identification of major source center of liquidity risks. To facilitate our study, we use the unit root tests and cointegration tests and apply the Error Correction Model (ECM) to model short-term dynamics of adjustments to the long-term relationship. The connectivity is measured by Granger Causality in ECM.

4.1 Common Factors in Liquidity Discounts

Figure 3 indicates how liquidity discount evolves over time and tends to be extremely large during the financial crisis time period and move together. We use the PCA (Principle Component Analysis) to extract the common factors in liquidity discount of eight commercial bank's sectors from January 1997 to July 2011. We use a rolling 3-year PCA to get the first principal component (PC) that explains the largest portion of variations of liquidity discounts to the eighth PC that explains the smallest portion of variations in variance. Table 2 reports the distribution of portions of these PCs in explaining variations of liquidity discounts. The first PC explains on average 83.5% and

the second PC explains on average 11.7%. The two together explain at least 95%. During the two crisis periods, the behavior of common factors is quite different. For the 3-year period ending June 2003, the first PC explains at least 81% and the second PC explain 10%. For the 3-year period ending July 2011, the first PC explains at least 90% and the second PC contributes to 5%. It shows that the common factor contributes more to explain the variations during the 2008 financial crisis than during the TMT (technology, media, and telecommunication) meltdown.

Panel B of Table 2 reports to what extent each banking sector contributes to the first PC and the combination of the first and the second PCs. The largest contributor is the diversified bank sector.

[Figure 3 here]

[Table 2 here]

4.2 Persistence of Liquid Discounts

In this section, we examine whether liquid discount is persistent and exhibit a unit root. If the liquidity shock is persistent, then our liquidity index should present a unit root since after a shock, the index never returns to its initial level (there is a unit root). We perform the augmented Dickey Fuller test and Phillips-Perron test. The lag selection in Dickey Fuller test is automatic based on the BIC criterion; and so is bandwidth selection in Phillips-Perron test. The results in Table 3 show that the null hypothesis of the unit root tests can be rejected only in super regional and fiduciary banking sectors. This indicates that the liquid shocks can be persistent.

[Table 3 here]

In Table 4 and Table 5, we investigate whether these liquidity discounts have common trends and are cointegrated. We conduct Johansen's cointegration tests. Johansen's test is based on the following Vector Autoregressive Process (VAR):

(13) $$\Delta X_t = \Phi_0 + \Pi X_{t-1} + \Phi_1 \Delta X_{t-1} + \varepsilon_t$$

where $X_t = \ln A_t^* - \ln A_t$ is an 8x1 vector that contains all the values of liquidity discounts, Φ_0 is an 8x1 vector, and Φ_1 is an 8x8 matrix. We perform the rank tests on the coefficient matrix Π. The rank is based on trace or maximum eigenvalues of Π. Judging from the curves in Figure 6 through Figure 9, we also assume that the level data have no deterministic trends and the cointergrating equations have intercepts. The four sets of Johansen's cointegration tests indicate one cointegration equation, which

represents the long-run equilibrium relationship of liquidity discounts among the commercial bank's sectors.

[Table 4 and Table 5 here]

4.3 Connectivity of Liquidity Discounts

Inter-connectivity is regarded as the main vulnerability in the banking industry. Co-integration and causality examination are the typical tools to gauge the magnitude of inter-connectivity. With our liquidity measure, we are able to for the first time see how liquidity contributes to the inter-connectivity among banks.

To do so, we estimate a vector error correction model (VEC) assuming the lag order of one as follows:

(14) $$\Delta X_t = \alpha(\beta' X_{t-1} + c) + \Phi_1 \Delta X_{t-1} + \varepsilon_t$$

where $X_t = \ln A_t^* - \ln A_t$ is an 8x1 vector, Φ_1 is an 8x8 matrix, c is a constant, and α and β are 8x1 vectors.

Panel A of Table 6 reports the estimated cointegrated vector and estimated vector error correction model (VEC) by assuming the lag order of one. The lag order is selected based on Schwarz's BIC criteria. We found that all the banking sectors, with an exception of non-US, significantly adjust to the long-run equilibrium condition as described in the cointegrated vector. The banking sectors also significantly respond to the liquidity shock in the other banking sector with a lag. The one exception is the diversified banking sector, which does not respond to any other sector's liquidity shocks.

In the Panel B of Table 6, we examine whether all lag liquidity discounts have no impact on the current liquidity discount. The tests show that five out of 8 banking sectors have a lag responsive to liquidity shocks, showing that it will takes time for banking sectors to adjust for liquidity shocks.

[Table 6 here]

In Table 7, we propose the simple measure of the interconnectivity and influence. The interconnectivity is a count measure to measure whether a liquidity shock in a banking sector can significantly Granger cause or be Granger caused by the liquidity shock in another banking sector. The influence is a count measure of the Granger cause minus the being Granger caused. Results show that Southern and Super-regional have the highest interconnectivity measure. Southern, super-regional, and diversified has the highest influence measure.

[Table 7 here]

5 Liquidity Discount and Macroeconomic Variables

5.1 Macro Economic Variables

This section shows the data summary of macroeconomic variables (such as industry production, CPI inflation, and civilian unemployment rate); financial indicators (VIX, term premiums, default premiums, St. Louis Fed's financial stress indicator, University of Michigan consumer sentiment indicator). All variables are computed as the log differences except for three interest-rate related variables. The term premium is the slope of the yield curve defined as the 10-year constant maturity Treasury yields minus the 3-month constant maturity Treasury yield while the default premium is the Moody's BAA minus AAA bond yields. The effective Federal fund rate is used. These variables are used in Gilchrist and Jakrajsek (2012). This study allows to compare the predictive power of our liquidity discount variables with that of credit spreads variables used in Gilchrist and Jakrajsek (2012). We choose two liquidity discounts variables—equally-weighted discounts and cross-sectional deviations of liquidity discounts across all banks in a given time period. The higher diversion shows more heterogeneity in liquidity of financial systems and thus less confidence in health and soundness of financial systems, which induce higher future economic growth.

5.2 Predictability

We conducted monthly and quarterly regression analyses. The quarterly regressions are rolling 3-month growth rates of macro variables with respect to 3-month changes in explanatory variables. Our explanatory variables include term premium, default premium, Federal fund rate, liquidity discount, variability of liquidity discount, VIX, FSI, Sentiment. We conduct various regressions in order to assess the predictability of our liquidity discount variables with the other financial indicators that may have predictability power on future economic growth. Our model specification is:

$$\nabla^h(X_t) = c + \alpha_1 \text{ Yield Slope} + \alpha_2 \text{ Default Premium} + \alpha_3 \text{ Fund Rate} + \beta \text{ Liq All} + \gamma Z_t + \varepsilon_t$$

where $\nabla^h(X_t) = X_{t+h} - X_t$ and

Yield Slope = slope of the yield cruve (10-yr - 3-month)

Default Premium = default premium (AAA spread - BBB spread)

Fund Rate = federal fund rate

Liq All = Our liquidity index

Regarding variable *Z*, we choose the variables that present the distress of economy and are demonstrated their predictability in the literature. They include: VIX index return (VIX_Ret); percentage change in St. Louis Fed Financial Stress Index (FSI), percentage change in Uni Michigan consumer sentiment (Sen), and cross-sectional standard deviation of individual bank's liquidity discounts (Liq_std). The last one is to capture whether the heterogeneity of liquidity discounts in the banking sectors can affect the state of economy. More heterogeneity can reflect the uncertainty of such liquidity shocks in the banking sectors. Higher uncertainty can hurt the growth of economy because the risks premium will be imposed to compensate for liquidity demands. Finally, We have three dependent variables that represent the state of economics: industrial production (IND); core CPI inflation (CPI); or unemployment rate (UMR).

We present our results in Table 7 for monthly regressions and Table 8 for quarterly regressions. For each set of monthly or quarterly regression results, we highlight the one with highest adjusted R Squared. There are several silent findings emerged from Table 7 and Table 8.

- We find that quarterly perditions are better than monthly predictions. In other words, our indices can predict three months ahead better than immediately next month. Both R-squares and t statistics are higher for the quarterly predictions than for monthly predictions.
- In quarterly predictions, the most influential explanatory variables (i.e. significant t statistics) are St. Louis Fed Financial Stress Index (FSI), our liquidity discount measure (Liq_All), and our liquidity discount standard deviations (Liq_Std). In almost all regressions, these variables remain significant.
- There is some substitution effect between FSI and Liq_All and between Liq_All and Liq_Std. The substitution effect is most obvious in predicting unemployment rate (UMR) where FSI substitutes for Liq_All in a substantial way. However, the result is reversed when predicting inflation (CPI).
- Throughout the regression tests, the "fear factor" VIX index shows no prediction power at all on the three macro variables: industrial production (IND); core CPI inflation (CPI); or unemployment rate (UMR).

To predict individual economic variables, we found that in general, the following variables have predictable power.

- Industry production growth: the slope of yield curves, changes in Federal Fund Rates, Default premium, Liquidity discount, and Changes in FSI stress.
- CPI inflation: the slope of yield curves, changes in Federal Fund Rates, Liquidity discount, and Changes in Michigan consumer sentiment.
- Changes in unemployment rate: liquidity discount and St. deviation of liquidity discount.

Our liquidity discount index has predictive power on all the three economic variables. Among them, it is interesting to see the FSI distress index predict the industrial production, the Michigan Consumer Sentiment predict CPI, and cross sectional standard deviation of liquidity discounts predicts unemployment rate. Our explanation is that during financial distress period as reflected in FSI, the firms cannot have easy access to capital and as the inventory piles up, it affects the incentive for production and investment. If Michigan consumer sentiment is low, then consumers do not have incentives to consume. The demand for goods becomes lower. Cross sectional standard deviation of liquidity discount reflects uncertainty in the state of liquidity conditions in the banking system, such uncertainty may impact the firms' desires for hiring and increase the future production

[Table 8 and Table 9 here]

6 Conclusion

In this paper, we propose a theoretical framework where the systemic risk risen in the recent crisis can be analyzed in a consistent manner. The theoretical framework is built upon a liquidity discount model that can explain large price falls due to the arrival of a liquidity distress. We use a large sample to construct a liquidity index for banks' assets and use it to gauge the liquidity health of the financial market. We test it on the Russel 1000 financial stocks for the period January 1997 to July 2011 (monthly) and discover that the index demonstrates a substantial plummet during the crisis period and as of July 2011 recovers to two-thirds of the pre-crisis level. We also discover that there is a large variation among banks in their liquidity health. U.S. banks are more superior to foreign banks and national banks are more superior to regional banks. At the very surface, large banks suffer more than smaller banks.

Empirical evidence of regressions indicates that these liquidity indices have striking predicative powers. For the three chosen important macro-economic variables, industry production growth, CPI inflation, and unemployment rate, our indices have predicative

powers three months ahead of time. The popular VIX index on the other hand presents no predicative power in these variables.

The model for the liquidity index is built upon the liquidity discount model by Chen (2012) and the capital structure model by Geske (1977). The two models together allow us to compute the implied liquidity asset value and illiquid asset value of a bank and the index is the ratio between the two. The model can be extended to evaluate various classes of assets a bank owns. In other words, our model can be used to compute liquidity risk weights called for by Basel III, which remains to be future work.

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8 Appendix: GARCH

We use the historical equity volatility as inputs for asset volatility. It is well-known that the volatilities of financial data are time varying and tend to be clustered so that large changes are followed by large changes. Accordingly, financial data tends to have fatter tail than the normal distribution, which may result from large price changes in the rare events. (See seminar paper by Engle (1982), Bollerslev (1987), a survey by Bollerslev, Chou, and Kroner for applications of GARCH in Finance and Economics). The use of GARCH models can better capture the dynamics of time-varying volatility. In this paper, we show the liquidity indexes built from a daily GARCH(1,1) model to forecast equity volatility using 1-year data to estimate the underlying model parameters as a robust check. The main reason for choosing equally-weighted variance is because the stock return volatility is a proxy for asset volatility, which reflects the long-term and fundamental variations in assets. We then forecast 1-day ahead and annualize by using square root of 252. The GARCH(1,1) specification is as follows:

(15) $$R_t = c + \varepsilon_t ,$$

where

(16) $$\begin{cases} \varepsilon_t \mid I_{t-1} = \sqrt{h_t} z_t \\ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \end{cases},$$

and z_t has an independent identical distribution with a zero mean and a variance of one; and I_{t-1} is the past information containing all R_t and ε_t. The one step forecast is:

(17) $$h_{T+1|T} = \omega_T + \alpha_T \varepsilon_T^2 + \beta_T h_T ,$$

where ω_T, α_T, and β_T are estimates of ω, α, and β using the 1-year data up to time T. We also compute the equally-weighted daily volatility using the same 1-year data for comparison. To estimate GARCH(1,1), we obtain the price data from CRSP-CRSP/COMPUSTAT MERGED and then calculate the adjusted daily stock prices for each firm. One convenient way to do it is to divide daily close price by Adjustment Factor- Cumulative by Ex-Date offered by CRSP which takes splits, dividend etc. into consideration. We then calculate the daily return by taking the difference between two days' logarithm of adjusted daily price. We use these daily price returns to estimate GARCH(1,1).

For the comparison, we also use the equally-weighted equity volatility by assuming zero mean daily returns and computing the mean of the past 252 days' square returns to represent the equity volatility at that day. Finally, we scale the volatility to an annually volatility by multiplying square root of 252. Since the frequency of our final outputs is monthly, we simply take the average of daily historical volatility for each month and use that as the volatility for the month for both GARCH(1,1) and equally-weighted volatility. We believe this would cause less bias compared with just using the last day's volatility as the volatility of this month.

9 Tables and Figures

Table 1: Liquidity Discount Index

	Liquidity Discount By Commerical Bank Type							
	central	eastern	non us	southern	western	supper regional	diversified	fiduciary
Mean	8.706	6.310	6.709	8.716	11.495	10.863	20.434	3.650
Median	2.935	3.952	6.478	2.167	5.171	0.117	14.122	0.126
Maximum	45.853	25.064	18.309	45.657	54.725	96.541	66.947	27.452
Minimum	0.073	0.067	0.197	0.070	0.076	0.065	0.199	0.066
Std. Dev.	13.427	6.248	4.590	14.077	15.881	25.280	20.572	7.496
Skewness	1.673	1.271	0.459	1.618	1.546	2.284	1.027	1.933
Kurtosis	4.191	3.991	2.320	3.905	4.174	6.768	2.827	5.321
Jarque-Bera	91.997	54.251	9.515	82.361	79.782	255.637	30.994	148.304
Probability	0	0	0.009	0	0	0	0	0

Table 2

A: Proportion of Variations Explained by Principal Components

Using Rolling 3-Year PCA Analysis from Janauary 1997 to July 2011

Number	Mean	Std Dev	Max	Min	P75	P50	P25
1	0.835	0.131	0.975	0.465	0.951	0.858	0.744
2	0.117	0.101	0.404	0.014	0.190	0.071	0.033
3	0.029	0.030	0.168	0.003	0.033	0.017	0.008
4	0.010	0.007	0.028	0.001	0.015	0.009	0.004
5	0.006	0.006	0.027	0.001	0.008	0.004	0.002
6	0.002	0.002	0.010	0.000	0.004	0.002	0.001
7	0.001	0.001	0.003	0.000	0.001	0.000	0.000
8	0.000	0.000	0.000	0.000	0.000	0.000	0.000

B: Marginal Contribution to Variations of 1st PC and Combined 1st and 2nd PCs

	1st PC						
	Mean	Std Dev	Max	Min	P75	P50	P25
central	0.065	0.109	0.917	-0.350	0.113	0.096	0.022
eastern	0.032	0.146	0.200	-0.651	0.124	0.071	0.029
non us	**0.075**	**0.370**	**1.253**	**-3.428**	**0.162**	**0.058**	**0.043**
southern	0.010	0.167	1.267	-0.508	0.101	0.031	-0.059
western	-0.027	0.353	0.320	-2.221	0.157	0.107	-0.009
supper regional	0.068	0.117	0.371	-0.101	0.081	0.006	0.000
diversified	**0.750**	**0.778**	**5.924**	**0.043**	**0.731**	**0.563**	**0.308**
fiduciary	0.027	0.051	0.261	-0.003	0.049	0.001	0.001

	Combined 1st PC and 2nd PC						
	Mean	Std Dev	Max	Min	P75	P50	P25
central	0.079	0.058	0.286	-0.082	0.117	0.103	0.036
eastern	0.069	0.086	0.217	-0.174	0.140	0.078	0.035
non us	**0.136**	**0.136**	**0.854**	**-0.269**	**0.172**	**0.099**	**0.048**
southern	0.042	0.099	0.188	-0.315	0.115	0.064	-0.024
western	0.053	0.214	0.367	-0.577	0.163	0.122	-0.002
supper regional	0.067	0.109	0.347	-0.012	0.081	0.009	0.002
diversified	**0.529**	**0.362**	**1.603**	**0.126**	**0.700**	**0.471**	**0.220**
fiduciary	0.026	0.051	0.264	-0.001	0.049	0.001	0.001

Table 3: Unit root Test

	Null Hypothesis: A unit root					
	Augmented Dickey-Fuller			Phillips-Perron		
	t-Statistic	Prob.*	Lag	Adj. t-Stat	Prob.*	Bandwidth
central	-1.268	0.188	3	-0.660	0.430	9
eastern	-1.070	0.257	1	-1.198	0.211	7
non us	-0.980	0.292	0	-0.970	0.296	3
southern	-0.677	0.423	3	-0.175	0.622	8
western	-1.328	0.170	3	-1.062	0.260	8
supper regional	**-1.988**	**0.045**	2	**-1.777**	**0.072**	8
diversified	-0.598	0.457	0	-0.613	0.451	3
fiduciary	**-3.125**	**0.002**	11	-1.519	0.121	2

*MacKinnon (1996) one-sided p-values.

Table 4: Cointegration Rank Test (Trace)

VAR equation: $\Delta X_t = \Phi_0 + \Pi X_{t-1} + \Phi_1 \Delta X_{t-1} + \varepsilon_t$
where $X_t = \ln A_t^* - \ln A_t$ is an 8x1 vector that contains all the values of liquidity discounts, Φ_0 is an 8x1 vector, and Φ_1 is an 8x8 matrix. We perform the rank tests on the coefficient matrix Π. The rank is based on trace or maximum eigenvalues of Π.

A: Unrestricted Cointegration Rank Test (Trace)
Lags interval: 0

No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.549	262.317	169.599	0
At most 1	0.201	123.824	134.678	0.181
At most 2	0.145	84.735	103.847	0.454
At most 3	0.134	57.470	76.973	0.581
At most 4	0.081	32.382	54.079	0.835
At most 5	0.046	17.697	35.193	0.855
At most 6	0.042	9.443	20.262	0.694
At most 7	0.011	1.950	9.165	0.788

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

B: Unrestricted Cointegration Rank Test (Trace)
Lags interval: 1

No. of CE(s)	Eigen value	Statistic	Critical Value	Prob.**
None *	0.402	232.589	169.599	0.000
At most 1 *	0.231	143.538	134.678	0.014
At most 2	0.173	98.083	103.847	0.113
At most 3	0.142	65.155	76.973	0.282
At most 4	0.118	38.631	54.079	0.540
At most 5	0.053	16.817	35.193	0.894
At most 6	0.036	7.428	20.262	0.868
At most 7	0.006	1.008	9.165	0.951

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 5: Cointegration Rank Test (Maximum Eigenvalue)

VAR equation: $\Delta X_t = \Phi_0 + \Pi X_{t-1} + \Phi_1 \Delta X_{t-1} + \varepsilon_t$
where $X_t = \ln A_t^* - \ln A_t$ is an 8x1 vector that contains all the values of liquidity discounts, Φ_0 is an 8x1 vector, and Φ_1 is an 8x8 matrix. We perform the rank tests on the coefficient matrix Π. The rank is based on trace or maximum eigenvalues of Π.

A: Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.549	138.494	53.188	0.000
At most 1	0.201	39.089	47.079	0.275
At most 2	0.145	27.265	40.957	0.673
At most 3	0.134	25.088	34.806	0.441
At most 4	0.081	14.684	28.588	0.838
At most 5	0.046	8.254	22.300	0.942
At most 6	0.042	7.493	15.892	0.609
At most 7	0.011	1.950	9.165	0.788

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

B: Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

No. of CE(s)	Eigen value	Statistic	Critical Value	Prob.**
None *	0.402	89.051	53.188	0.000
At most 1	0.231	45.454	47.079	0.074
At most 2	0.173	32.929	40.957	0.299
At most 3	0.142	26.524	34.806	0.344
At most 4	0.118	21.814	28.588	0.286
At most 5	0.053	9.389	22.300	0.879
At most 6	0.036	6.420	15.892	0.740
At most 7	0.006	1.008	9.165	0.951

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Table 6: Error Correction Model

$\Delta X_t = \alpha(\beta' X_{t-1} + c) + \Phi_1 \Delta X_{t-1} + \varepsilon_t$

where X_t is an 8x1 vector, Φ_1 is an 8x8 matrix, c is a constant, α and β are 8x1 vectors

		central	eastern	non us	southern	western	supper regional	diversified	fiduciary
Panel A: CointEq (α') vector									
	Coeff	**-0.050**	**-0.046**	-0.014	**-0.068**	**-0.062**	**-0.263**	**-0.076**	**-0.031**
	St error	**-0.010**	**-0.011**	-0.011	**-0.009**	**-0.018**	**-0.032**	**-0.037**	**-0.015**
Panel B: Matrix Φ_1									
central (-1)	Coeff	0.078	0.037	0.043	0.115	0.264	**0.672**	0.053	0.277
	St error	-0.095	-0.102	-0.111	-0.084	-0.169	**-0.311**	-0.358	-0.144
eastern (-1)	Coeff	0.082	0.124	-0.023	**0.179**	0.062	**0.628**	-0.085	0.158
	St error	-0.082	-0.088	-0.096	**-0.073**	-0.146	**-0.270**	-0.311	-0.125
non us (-1)	Coeff	-0.048	-0.056	-0.001	***0.113***	**0.397**	0.047	0.129	0.047
	St error	-0.074	-0.079	-0.086	***-0.065***	**-0.131**	-0.242	-0.279	-0.112
southern (-1)	Coeff	-0.103	***-0.188***	-0.067	**-0.211**	***-0.329***	**-0.765**	-0.502	**-0.585**
	St error	-0.102	***-0.110***	-0.120	**-0.091**	***-0.182***	**-0.336**	-0.387	**-0.155**
western (-1)	Coeff	-0.020	-0.059	-0.036	**-0.097**	***-0.162***	**-0.410**	-0.033	0.075
	St error	-0.055	-0.059	-0.064	**-0.049**	***-0.098***	**-0.181**	-0.208	-0.083
supper regional (-1)	Coeff	**0.064**	***0.052***	**0.071**	0.035	***0.089***	-0.013	0.150	***-0.075***
	St error	**-0.026**	***-0.028***	**-0.031**	-0.024	***-0.047***	-0.087	-0.100	***-0.040***
diversified (-1)	Coeff	0.022	-0.003	0.013	**0.040**	0.058	-0.019	-0.038	0.039
	St error	-0.022	-0.024	-0.026	**-0.020**	-0.039	-0.073	-0.084	-0.033
fiduciary (-1)	Coeff	0.053	0.037	**-0.132**	0.045	0.085	-0.270	0.095	***0.150***
	St error	-0.054	-0.057	**-0.063**	-0.048	-0.095	-0.176	-0.202	***-0.081***
R-squared		0.372	0.200	0.081	0.493	0.293	0.396	0.068	0.177
Adj. R-squared		0.342	0.161	0.036	0.469	0.259	0.367	0.022	0.137
F-statistic		12.155	5.141	1.798	19.959	8.496	13.462	1.490	4.414
Log likelihood		-260.855	-272.684	-287.579	-240.239	-360.682	-466.446	-490.837	-332.720
Schwarz SC		3.284	3.421	3.593	3.045	4.438	5.661	5.943	4.115

Panel C Cointegration Equation—coefficient of β' vector and C (constant)

		central	eastern	non us	southern	western	supper regional	diversified	fiduciary	Constant C
CointEq	Coeff	1	**3.255**	**-0.847**	**1.039**	**-2.439**	**0.454**	-0.158	-1.885	-0.778
	St error		**-0.388**	**-0.329**	**-0.229**	**-0.275**	**-0.109**	-0.119	-0.303	-1.718

Bold: 5% significance. Bold and Italic: 10% significance

Table 7: Causality Test

	central		eastern		non us		southern		western		supper regional		diversified		fiduciary	
Excluded	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.	Chi-sq	Prob.
central (-1)			0.130	0.719	0.154	0.695	1.876	0.171	2.446	0.118	**4.660**	0.031	0.022	0.882	3.717	0.054
eastern (-1)	0.996	0.318			0.057	0.812	**6.000**	0.014	0.178	0.673	**5.419**	0.020	0.076	0.783	1.606	0.205
non us (-1)	0.417	0.518	0.507	0.476			2.997	0.083	**9.111**	0.003	0.037	0.847	0.215	0.643	0.176	0.675
southern (-1)	1.015	0.314	2.925	0.087	0.310	0.578			***3.259***	0.071	**5.179**	0.023	1.680	0.195	**14.211**	0.000
western (-1)	0.126	0.722	0.988	0.320	0.320	0.572	3.972	0.046			**5.156**	0.023	0.025	0.874	0.813	0.367
supper regional (-1)	**5.761**	0.016	***3.312***	0.069	**5.307**	0.021	2.270	0.132	***3.534***	0.060			2.235	0.135	***3.516***	0.061
diversified (-1)	0.963	0.326	0.020	0.888	0.265	0.607	**4.177**	0.041	2.165	0.141	0.071	0.790			1.325	0.250
fiduciary (-1)	0.968	0.325	0.421	0.516	4.468	0.035	0.911	0.340	0.798	0.372	2.356	0.125	0.221	0.638		
All	10.646	0.155	6.521	0.480	10.367	0.169	**32.881**	0.000	**29.053**	0.000	**19.686**	0.006	3.589	0.826	**31.222**	0.000
Chi-squared test statistics for lag exclusion (DF=8)																
Chi-Squared test	16.545		8.122		10.371		33.064		29.125		21.072		3.747		32.103	
P-Value	0.035		0.422		0.240		0.000		0.000		0.007		0.879		0.000	

	central	eastern	non us	southern	western	supper regional	diversified	fiduciary
Granger Caused by the others	1	2	2	4	3	4	0	2
Granger Cause the others	1	2	2	5	3	5	1	2
Interconnect	2	4	4	9	6	9	1	4
Influence	0	0	0	1	0	1	1	0

Table 8: Monthly Regressions

Panel A: IND

	yield_slope	fund_rate	default_premium	liq_all	vix_ret	fsi	sen	liq_std	R Square	Adjusted R Square	F test
Coefficient	0.0904154	0.052511	-0.008659	-0.00683					0.0892	0.0678	0.0423
T-Statitics	1.6	1.41	-0.11	-1.68							
Coefficient	0.0893999	0.052175	-0.0076739	-0.00691	-0.07676				0.0574	0.0295	0.0729
T-Statitics	1.58	1.4	-0.1	-1.69	-0.47						
Coefficient	0.2049197	0.136806	0.477695	-0.00373		-0.22034			0.111	0.0847	0.0012
T-Statitics	3.13	3.07	0.1684553	-0.91		-3.23					
Coefficient	0.086702	0.050352	-0.0095633	-0.00713			0.008921		0.068	0.0404	0.0348
T-Statitics	1.54	1.36	-0.12	-1.75			1.46				
Coefficient	0.1194942	0.054744	0.0041998	0.016644				-0.02574	0.0939	0.0671	0.0049
T-Statitics	2.11	1.5	0.06	1.71				-2.65			

Panel B: CPI

	yield_slope	fund_rate	default_premium	liq_all	vix_ret	fsi	sen	liq_std	R Square	Adjusted R Square	F test
Coefficient	-0.0439728	-0.02557	-0.081403	-0.01048					0.0892	0.0678	0.003
T-Statitics	-0.77	-0.68	-1.04	-2.55							
Coefficient	-0.0457666	-0.02616	-0.0796629	-0.01062	-0.13558				0.0928	0.0659	0.0053
T-Statitics	-0.8	-0.7	-1.02	-2.57	-0.81						
Coefficient	-0.0006327	0.006338	0.1026831	-0.00931		-0.0834			0.0966	0.0699	0.0039
T-Statitics	-0.01	0.14	0.59	-2.2		-1.18					
Coefficient	-0.0436218	-0.02536	-0.0813175	-0.01046			-0.00084		0.0893	0.0624	0.007
T-Statitics	-0.76	-0.67	-1.04	-2.53			-0.14				
Coefficient	-0.0560749	-0.0265	-0.0867546	-0.02025				0.010712	0.0954	0.0686	0.0043
T-Statitics	-0.96	-0.71	-1.11	-2.03				1.07			

Panel C: UMR

	yield_slope	fund_rate	default_premium	liq_all	vix_ret	fsi	sen	liq_std	R Square	Adjusted R Square	F test
Coefficient	0.0048797	0.004241	0.0065572	0.00094					0.0086	-0.0147	0.8302
T-Statitics	0.35	0.46	0.34	0.92							
Coefficient	0.0046085	0.004152	0.0068203	0.00092	-0.0205				0.0101	-0.0192	0.886
T-Statitics	0.33	0.44	0.35	0.9	-0.5						
Coefficient	-0.0157085	-0.01092	0.0003816			0.039618			0.0383	0.0098	0.2478
T-Statitics	-0.94	-0.96	0.37			2.28					
Coefficient	0.0054066	0.004548	0.0066855	0.000983			-0.00127		0.0126	-0.0166	0.8271
T-Statitics	0.38	0.49	0.34	0.96			-0.82				
Coefficient	-0.0015554	0.003747	0.0037116	-0.00425				0.005696	0.0395	0.0111	0.2302
T-Statitics	-0.11	0.41	0.19	-1.74				2.33			

Table 9: Quarterly Regressions

Panel A: IND

	yield_slope	fund_rate	default_premium	liq_all	vix_ret	fsi	sen	liq_std	R Square	Adjusted R Square	F test
Coefficient	0.3065651	0.155533	-0.0593088	-0.02129					0.1455	0.1254	0
T-Statitics	3.04	2.34	-0.43	-2.92							
Coefficient	0.304479	0.154842	0.1387964	-0.02144	-0.15768				0.1469	0.1217	0.0001
T-Statitics	3.01	2.32	0.68	-2.93	-0.53						
Coefficient	0.6176181	0.384521	1.261881	-0.01285		-0.59857			0.2598	0.2379	0
T-Statitics	5.5	5.02	4.37	-1.84		-5.11					
Coefficient	0.3028181	0.153354	-0.0602213	-0.02159			0.009002		0.1489	0.1237	0
T-Statitics	2.99	2.3	-0.43	-2.96			0.82				
Coefficient	0.3938164	0.162234	-0.0207257	0.04915				-0.07723	0.2415	0.219	0
T-Statitics	4.05	2.58	-0.16	2.94				-4.62			

Panel B: CPI

	yield_slope	fund_rate	default_premium	liq_all	vix_ret	fsi	sen	liq_std	R Square	Adjusted R Square	F test
Coefficient	-0.1936406	-0.11591	-0.23444	-0.03318					0.1902	0.1711	0
T-Statitics	-1.72	-1.56	-1.52	-4.08							
Coefficient	-0.1975865	-0.11722	-0.2306121	-0.03347	-0.29825				0.1941	0.1703	0
T-Statitics	-1.75	-1.58	-1.49	-4.11	-0.91						
Coefficient	-0.0383779	-0.00161	0.4250341	-0.02897		-0.29878			0.2118	0.1885	0
T-Statitics	-0.29	-0.02	1.24	-3.49		-2.15					
Coefficient	-0.2047387	-0.12236	-0.2371426	-0.03408			0.026661		0.2127	0.1894	0
T-Statitics	-1.83	-1.66	-1.55	-4.23			2.2				
Coefficient	-0.2231845	-0.11818	-0.2475045	-0.05703				0.026151	0.1986	0.1748	0
T-Statitics	-1.95	-1.59	-1.6	-2.89				1.33			

Panel C: UMR

	yield_slope	fund_rate	default_premium	liq_all	vix_ret	fsi	sen	liq_std	R Square	Adjusted R Square	F test
Coefficient	0.0018799	0.010142	0.0170411	0.003274					0.0263	0.0034	0.3358
T-Statitics	0.08	0.63	0.51	1.87							
Coefficient	0.0020677	0.010204	0.0168589	0.003288	0.014194				0.0265	-0.0023	0.4686
T-Statitics	0.08	0.64	0.5	1.87	0.2						
Coefficient	-0.0600884	-0.03548	-0.2461679	0.001593		0.119247			0.1158	0.0896	0.0008
T-Statitics	-2.18	-1.88	-3.46	0.92		4.14					
Coefficient	0.0033074	0.010972	0.0173887	0.00339			-0.00343		0.036	0.0075	0.283
T-Statitics	0.14	0.69	0.52	1.94			-1.3				
Coefficient	-0.0183114	0.008591	0.0081124	-0.01303				0.017872	0.1277	0.1018	0.0003
T-Statitics	-0.78	0.57	0.26	-3.23				4.43			

Figure 1 – Simulated Default Probabilities (Economic versus Liquidity)

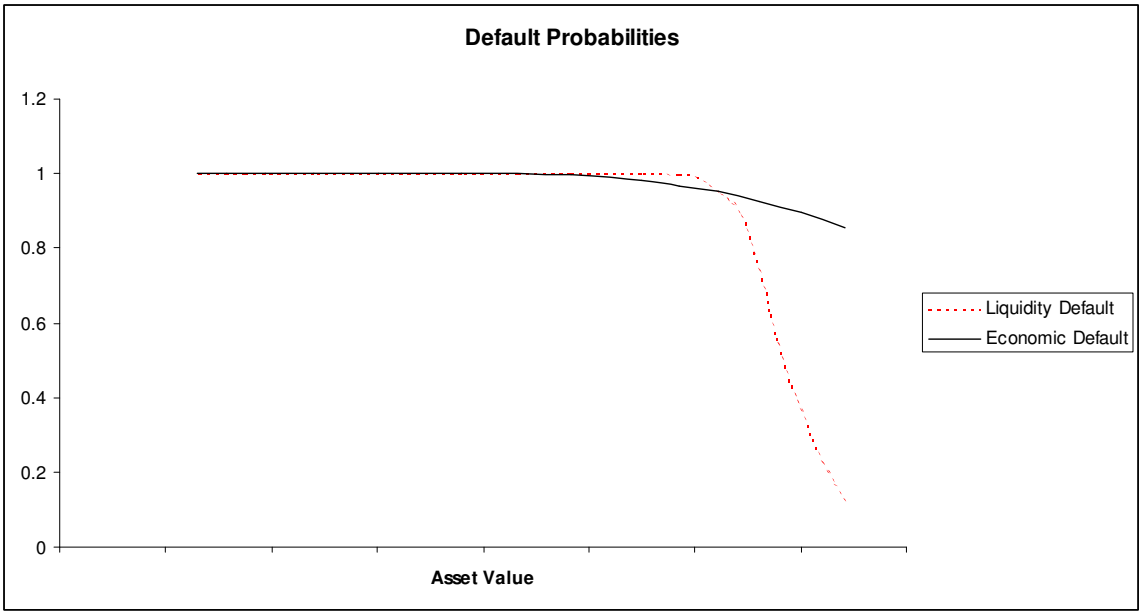
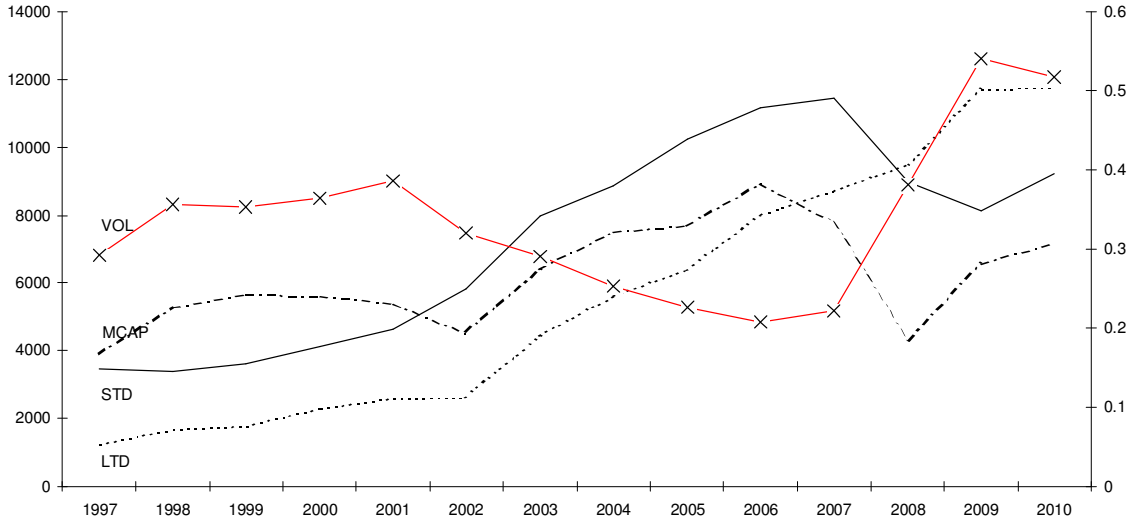


Figure 2 – Cross-sectional Summary Statistics



STD: Short-term debt; LTD: Long-term debt; MCAP: Market capitalization; VOL: volatility. The first three are plotted on the left axis ($) and the volatility is plotted on the right axis (decimal). These are end-of-year cross-sectional averages across all firms in the sample (note that the number of firms in each year varies.)

Figure 3 – First Two Principle Components

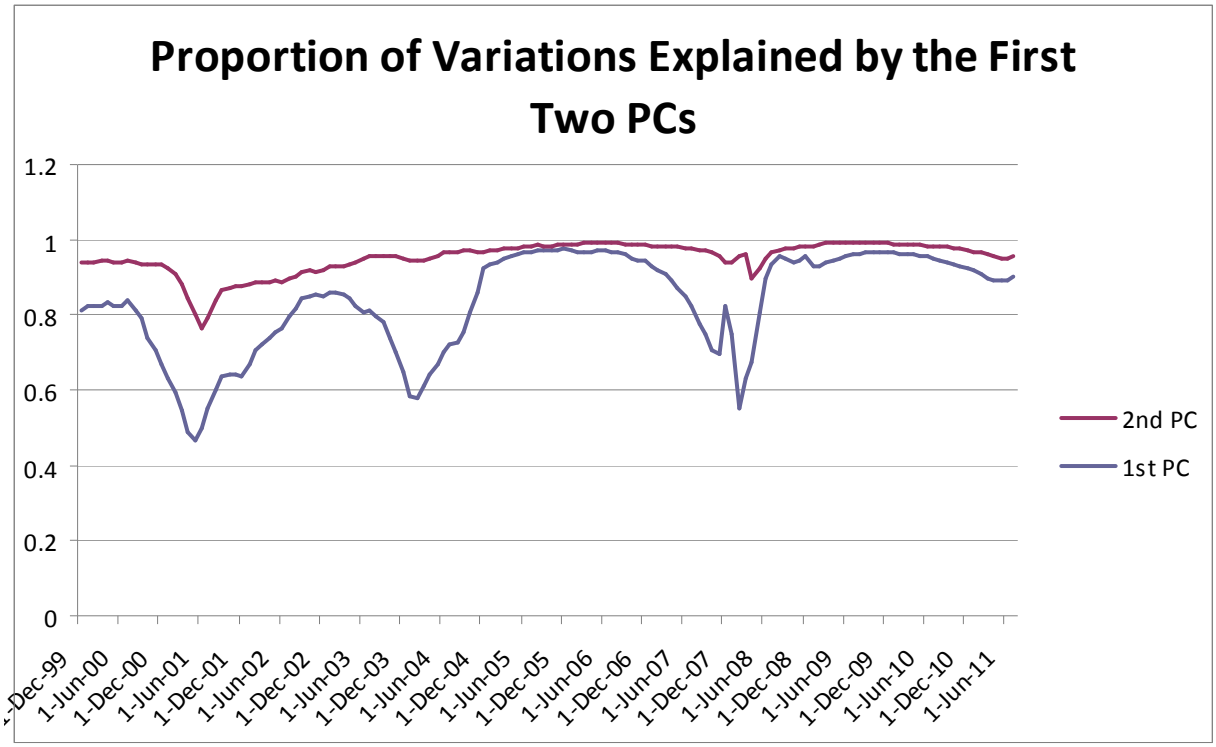
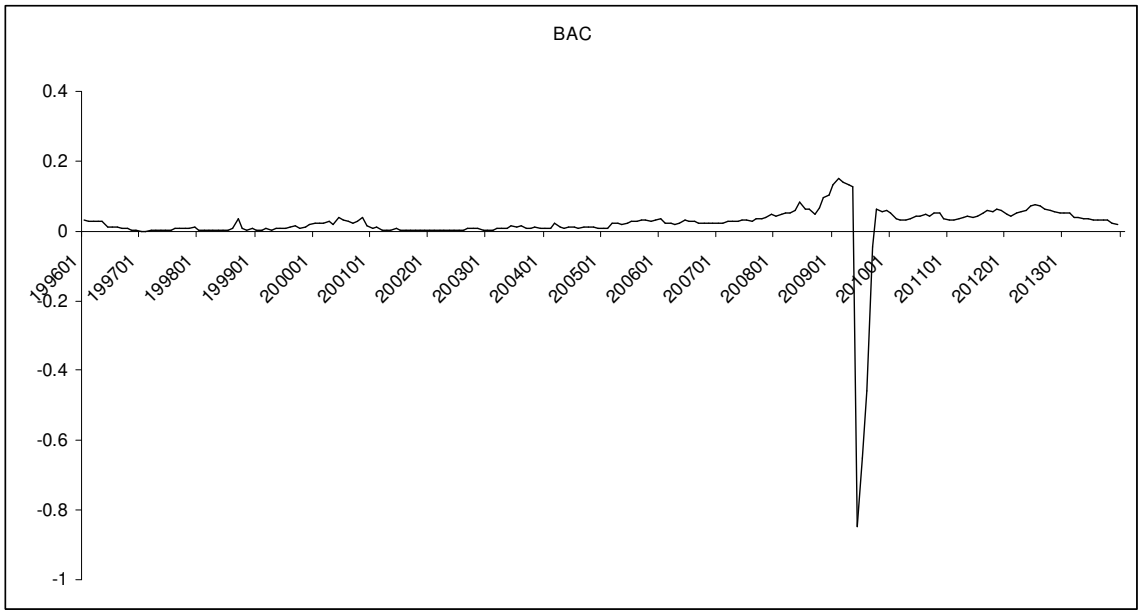


Figure 4: Difference in Economic and Liquidity Default Probabilities (former minus latter)



This is an example of Bank of America (BAC). Before the first quarter of 2009, the economic default probability of BAC is higher than the default probability and the difference is positive. Afterwards, the liquidity default probability becomes higher and

the difference becomes negative. After the fourth quarter of 2009, economic default probabilities are higher again. During the period where the liquidity probabilities are higher, BAC is more likely to default due to liquidity than to economics.

Figure 5 – Economic PD versus Liquidity PD

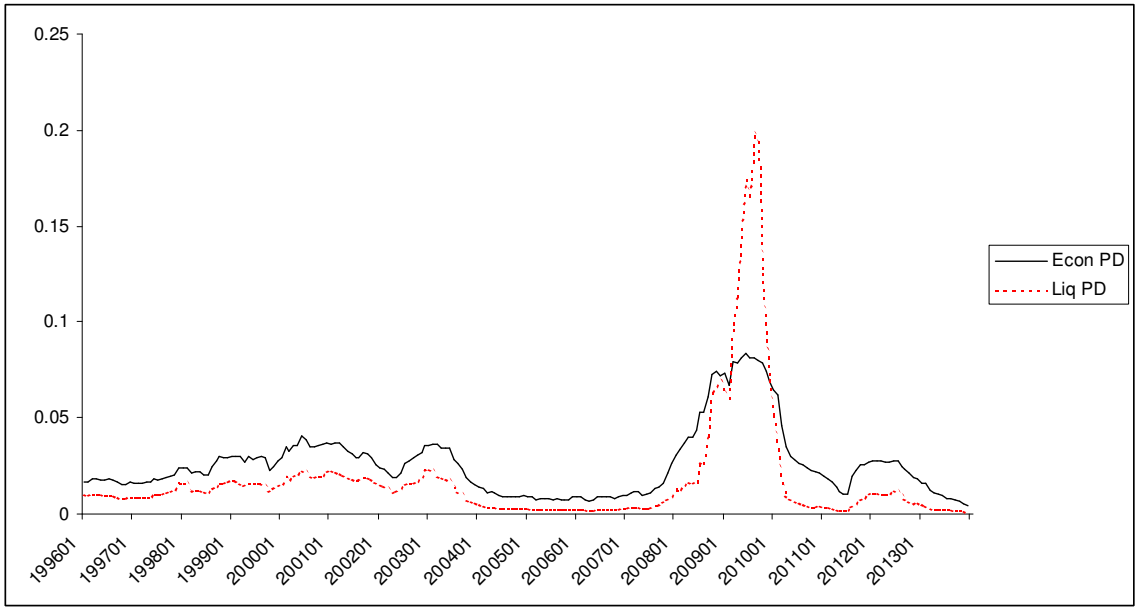


Figure 6 – All Banks

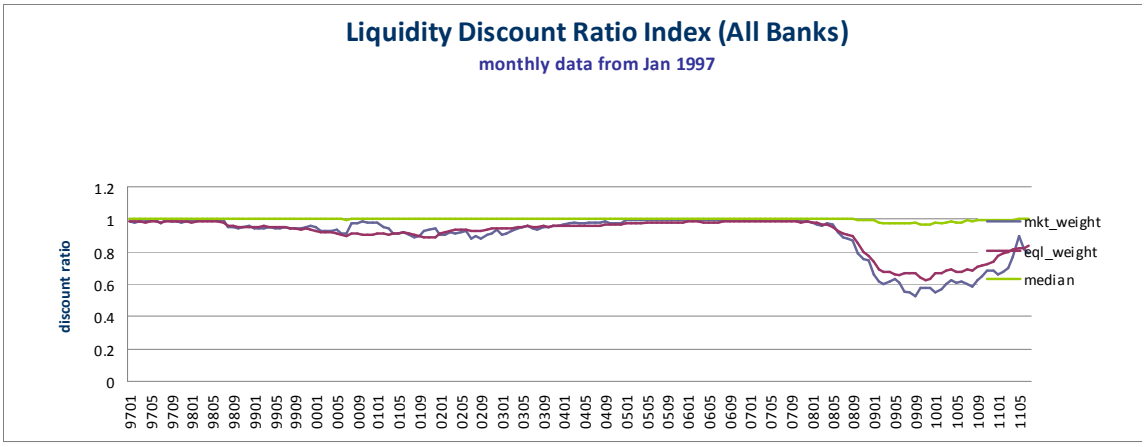
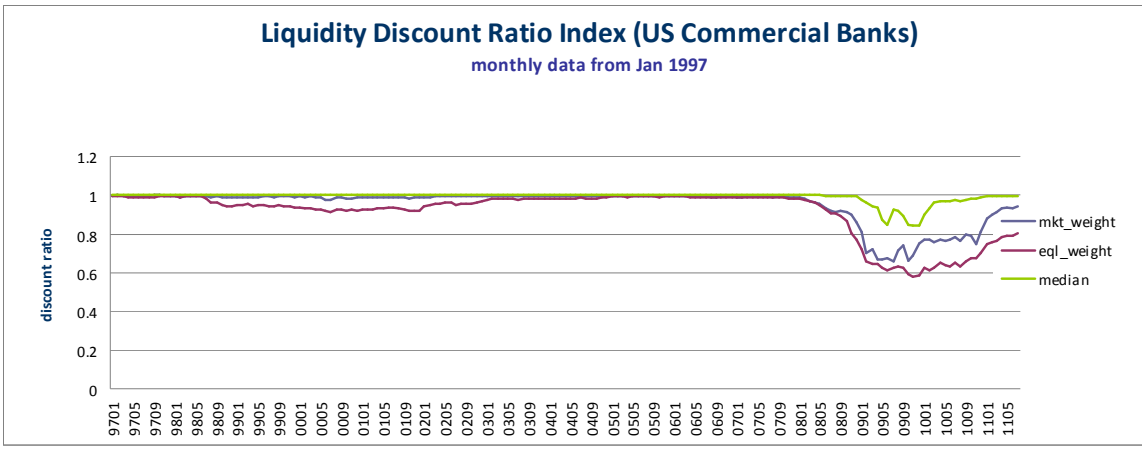


Figure 7 – Commercial Banks



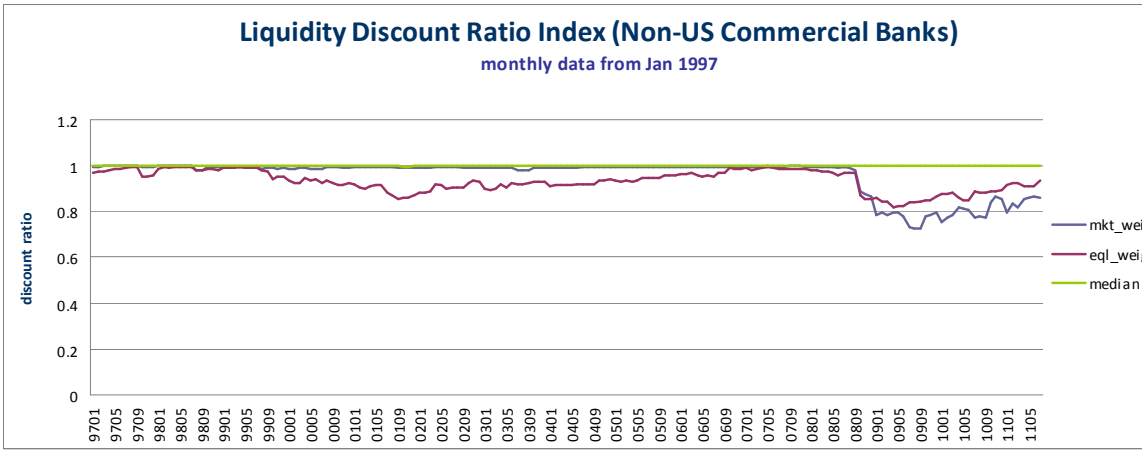
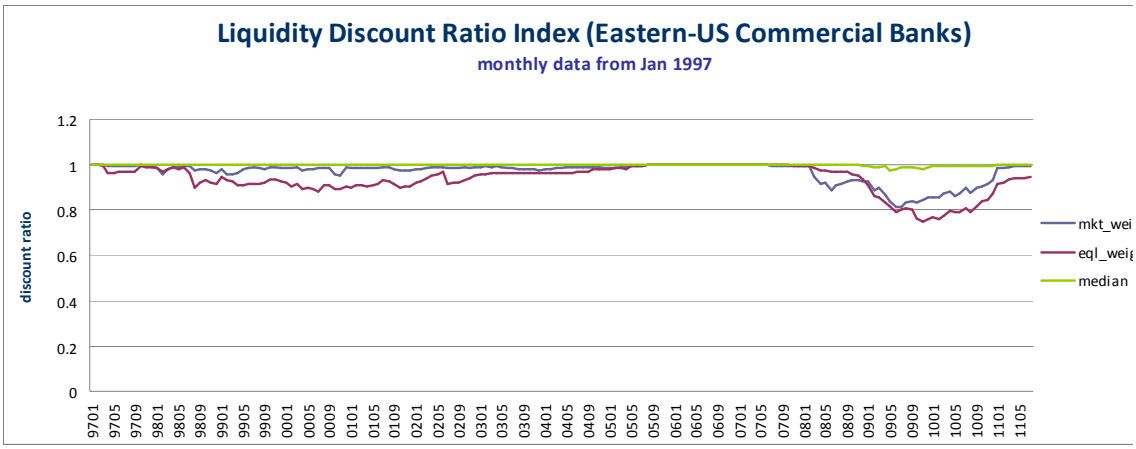
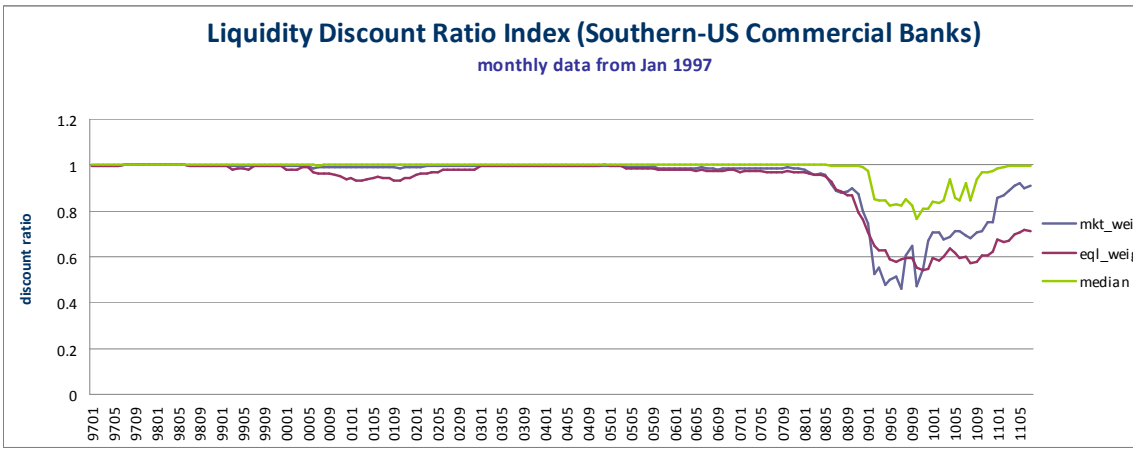
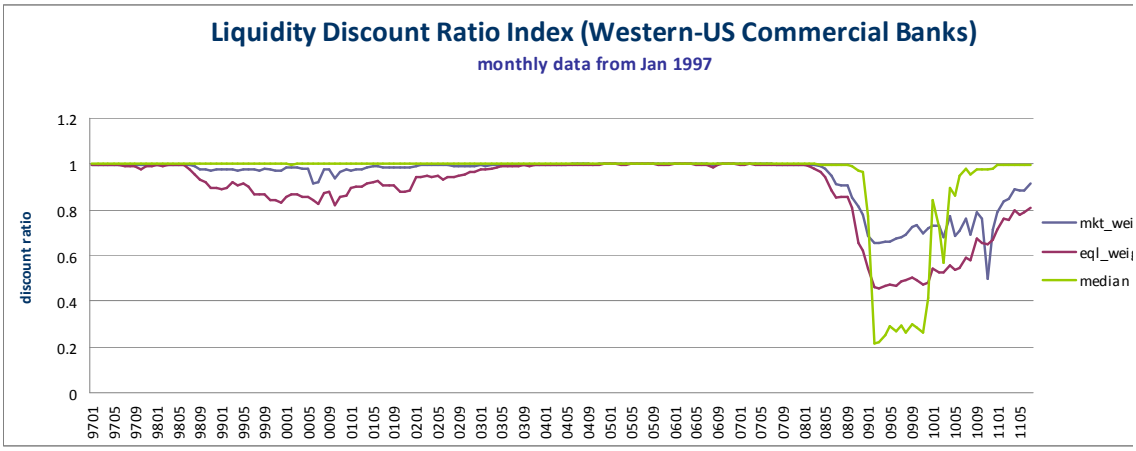
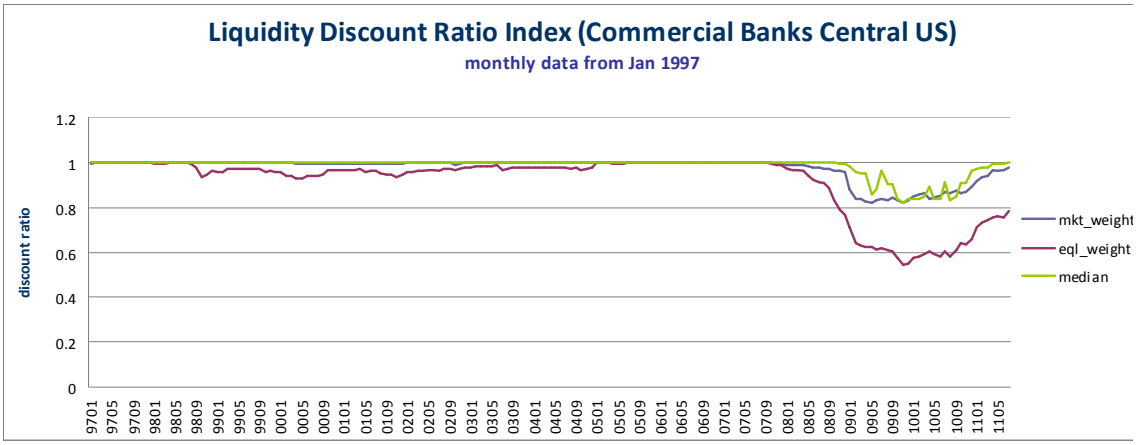


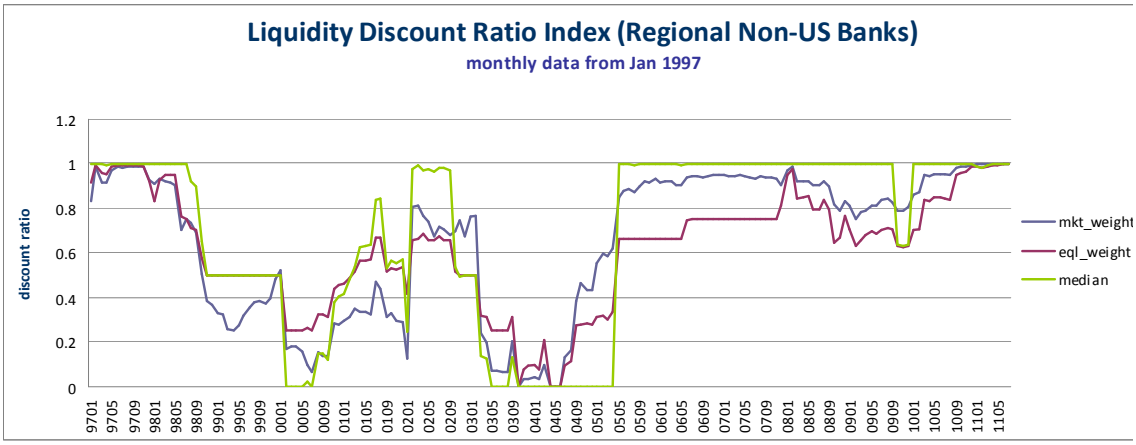
Figure 8 – Regional Banks

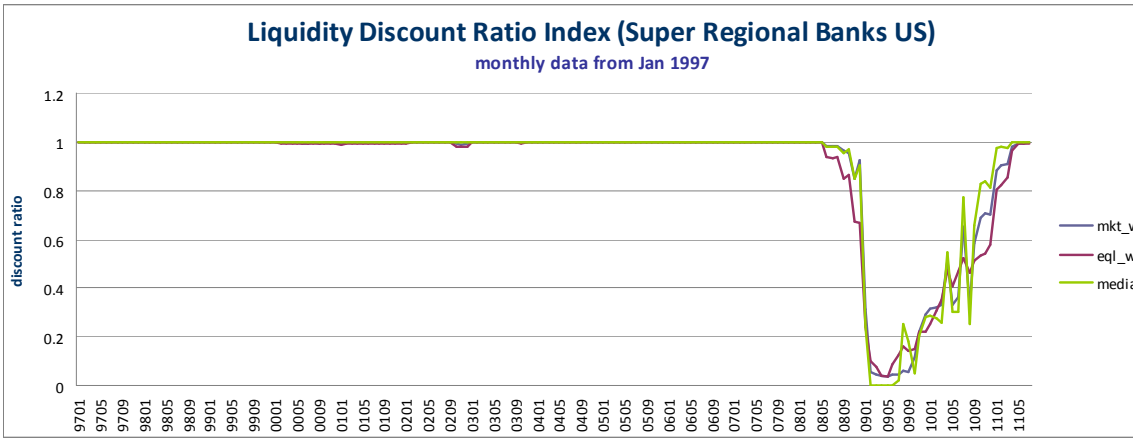







Liquidity Discount Ratio Index (Commercial Banks Central US)
monthly data from Jan 1997
discount ratio
1.2
1
0.8
0.6
0.4
0.2
0
9701 9705 9709 9801 9805 9809 9901 9905 9909 0001 0005 0009 0101 0105 0109 0201 0205 0209 0301 0305 0309 0401 0405 0409 0501 0505 0509 0601 0605 0609 0701 0705 0709 0801 0805 0809 0901 0905 0909 1001 1005 1009 1101 1105
mkt_weight
eql_weight
median


Liquidity Discount Ratio Index (Regional Non-US Banks)
monthly data from Jan 1997
discount ratio
1.2
1
0.8
0.6
0.4
0.2
0
9701 9705 9709 9801 9805 9809 9901 9905 9909 0001 0005 0009 0101 0105 0109 0201 0205 0209 0301 0305 0309 0401 0405 0409 0501 0505 0509 0601 0605 0609 0701 0705 0709 0801 0805 0809 0901 0905 0909 1001 1005 1009 1101 1105
mkt_weight
eql_weight
median


Liquidity Discount Ratio Index (Super Regional Banks US)
monthly data from Jan 1997
discount ratio
1.2
1
0.8
0.6
0.4
0.2
0
9701 9705 9709 9801 9805 9809 9901 9905 9909 0001 0005 0009 0101 0105 0109 0201 0205 0209 0301 0305 0309 0401 0405 0409 0501 0505 0509 0601 0605 0609 0701 0705 0709 0801 0805 0809 0901 0905 0909 1001 1005 1009 1101 1105

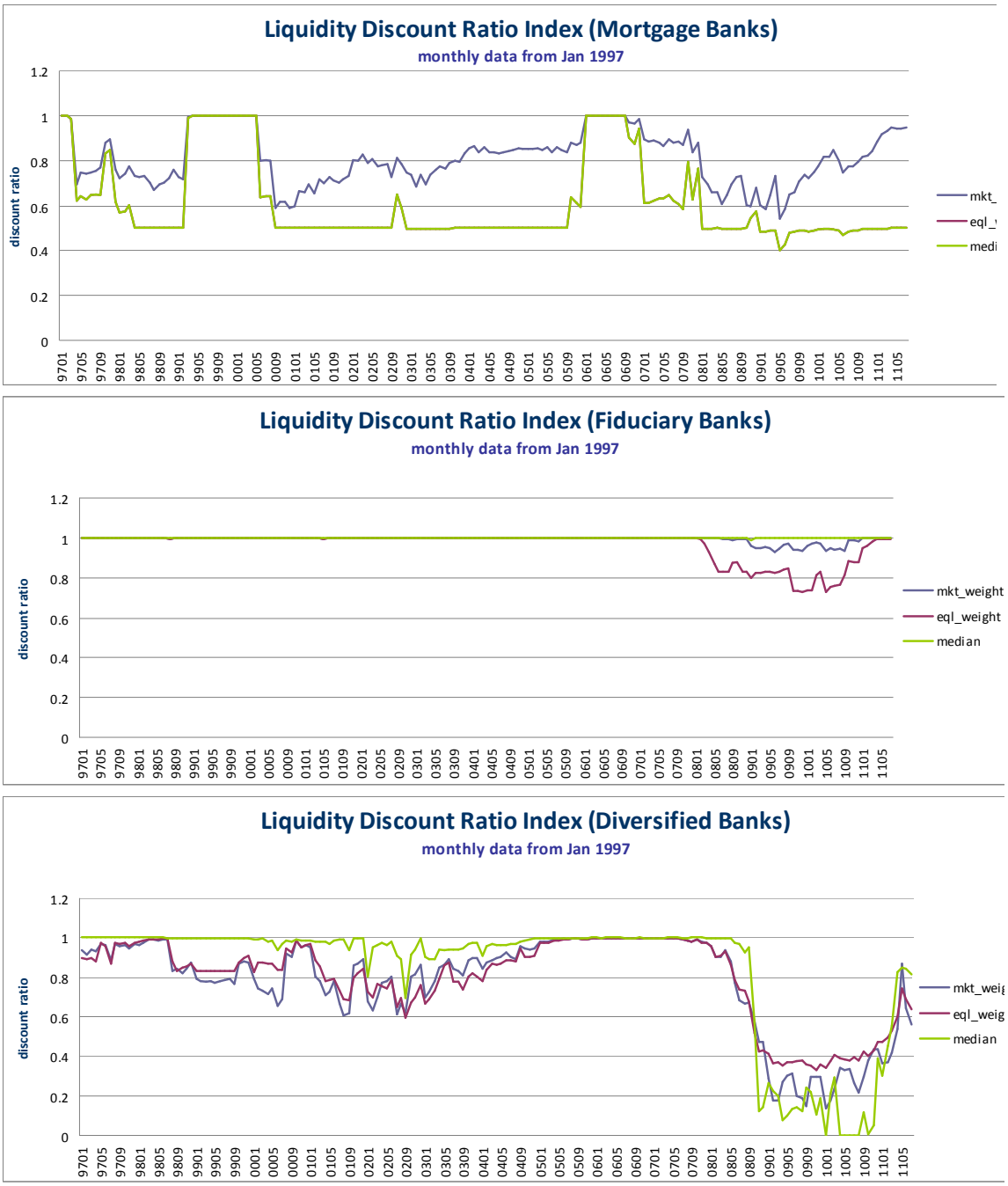



Figure 9 – Other Banks