Liquidity Risk, Market Valuation, and Bank Failures

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Abstract

We propose a model that links the conditional probability of bank failure to insolvency and liquidity risks, and show that liquidity risk affects bank failures through systematic and idiosyncratic channels. Empirical results based on U.S. bank data between 1985 and 2011 show that this model outperforms typical accounting-ratio-based models. We find that systematic liquidity risk was a major predictor of bank failures in 2008 and 2009. This finding has important implications for the new international standards on liquidity risk management.

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Recent research offers important insights into how liquidity risk causes or exacerbates financial crises (Brunnermeier (2009)). Particularly important are the works on short-term debt rollover risk, which suggest the potential predictive power of debt market liquidity risk for corporate default (He and Xiong (2012)), and underscore the systemic nature of rollover risk and the link between rollover risk and market freeze (Acharya, Gale, and Yorulmazer (2011)). Furthermore, market illiquidity can lead to the insolvency of financial firms through the market valuation channel (Allen and Carletti (2008); and Plantin, Sapra, and Shin (2008)). In spite of the theoretical advance that links liquidity risk to bank failures, little progress has been made to apply these theoretical insights in predicting bank failures. A recent survey by King, Nuxoll, and Yeager (2006) shows that the majority of existing bank failure prediction models are built through a process that searches through a large number of accounting ratios. Although bank-specific liquidity measures are generally included in this search process, whether they are included in the final model depends on the outcome of the search process. Further investigations are therefore needed to understand the mechanism of how liquidity risk affects bank failures.

The present paper bridges the gap between the theoretical literature of liquidity risk and the empirical literature of bank failure prediction. We propose a model that links bank failures to insolvency and liquidity risks. In this model, liquidity risk contributes to bank failures through two channels. The first is the idiosyncratic channel, which differentiates between banks based on the quality of their liquidity risk management. For example, a bank with more rigorous liquidity risk management has less exposure to this risk. It is widely recognized that banks with more highly liquid assets and less dependence on wholesale funding have less exposure to liquidity risk. Our model builds on this knowledge. The second is the systematic channel, which affects every bank in the market. For instance, a severe liquidity disruption in the market would cause difficulty to every bank. While banks can enhance their liquidity risk management to reduce their exposure, no bank can be completely immune to systematic liquidity risk. Our model allows us to differentiate between the contributions of these two channels to bank failures.

We estimate our model using U.S. bank data between 1985 and 2004 and test the model's out-of-sample performance between 2005 and 2011. The empirical results show that our model outperforms typical accounting-ratio-based bank failure models. We also find that systematic liquidity risk was a major predictor of bank failures in 2008 and 2009.

Our paper contributes to the literature in four aspects. First, we build on the recent theoretical literature on liquidity risk and financial crisis. Our paper is among the first to incorporate debt market liquidity risk into a bank failure model to be tested empirically. By modeling the insolvency and liquidity conditions of bank failures, we contribute to the literature of bank failure models by providing a theoretical underpinning for determining the appropriate relationship between the dependent variable and the explanatory variables for accounting-ratio-based models. Our approach allows us to estimate the predicted share of bank failures attributed to insolvency or liquidity risk. For instance, we find that more than 70% of the predicted bank failures in 2008 and more than 80% of the predicted bank failures in 2009 were attributed to liquidity risk.

Second, by explicitly modeling the idiosyncratic and systematic channels through which liquidity risk affects bank failures, we are able to estimate the contributions of these different channels in predicting bank failures. For example, we find that systematic liquidity risk was the major predictor of bank failures in 2008 and 2009, with about 70% of the predicted bank failures attributed to this channel. On the other hand, idiosyncratic risk played a very minimal role during the same period.

Third, we model the mechanism through which local economic conditions would affect a bank's insolvency. In our model, a bank's losses depend on its non-performing assets and loss severity. Local economic conditions affect a bank's losses through their impact on loss severity. We show that the well-known Texas ratio is a special case of our model.

Our last contribution is empirical in nature. The sample period of our data spans from 1985 through 2011, longer than most existing empirical studies, which typically cover a period of less than 10 years[1]. Because of the short sample periods in previous studies, there is little variation among banks in marketwide conditions, which leads to inaccuracy in estimating the effects of marketwide variables. The longer sample period in our study allows us to obtain a more robust estimate of the effects of marketwide variables.

Our results have important implications for the new international standards for liquidity risk management under the Basel III global regulatory standards (Basel Committee on Banking Supervision (2010)). The new standards aim at two complementary objectives: to promote the short-term liquidity resilience of banks by ensuring that they have sufficient high-quality liquid assets to survive a significant stress scenario over one month, and to promote resilience over a longer time horizon by forcing banks to fund their activities with more stable sources of funding. Our finding that systematic liquidity risk was a major predictor of bank failures in 2009 and 2009 underscores the importance of systematic liquidity risk management. Correspondingly, regulatory requirements that target individual banks' liquidity risk management while ignoring systematic liquidity risk could fail to enhance the safety and soundness of the banking system.

Finally, we would like to bring attention to the inextricably intertwined nature of systematic and systemic liquidity risks. While it is helpful to distinguish between them for the purpose of

[1] To the best of our knowledge, Moody's RiskCalc™ 3.1 U.S. banks model uses the longest sample period (1986-2004) among existing studies.

advancing our theoretical thinking, it is difficult to draw a hard line in practice. For this reason, our results on systematic liquidity risk can also have a systemic liquidity risk interpretation.

The remainder of the paper is organized in four sections. Section I reviews the related literature. Section II develops the model. Section III describes the data. Section IV presents and discusses the estimation results. Section V concludes.

I. Related Literature

This paper builds on two literatures: the literature on liquidity and financial crises and the literature on corporate default and bank failure models. Within the first literature, our modeling of the systematic channel of liquidity risk is inspired by He and Xiong (2012), who argue that debt market liquidity can be used as a common economic factor to predict firm default, and by Acharya, Gale, and Yorulmazer (2011), who emphasize the systemic nature of rollover risk by linking rollover risk to market freeze, and show that even a small change in the asset's fundamental value can lead to a catastrophic drop in the debt capacity. In a broad context, our modeling of the systematic channel is also inspired by the works on financial contagion and systemic risk (Allen and Gale (2000); Allen and Gale (1998); Allen and Gale (2004); Diamond and Rajan (2005); and Diamond and Rajan (2001)), and the amplification effects of the deleveraging process on liquidity destruction (Adrian and Shin (2010)). Our modeling of the market valuation component is inspired by the works on the interaction between liquidity risk and mark-to-market valuation (Allen and Carletti (2008); and Plantin, Sapra, and Shin (2008)), and on asset pricing with liquidity risk by Acharya and Pedersen (2005), and Chordia, Huh, and Subrahmanyam (2009). On the empirical side, our paper is inspired by Berger and Bouwman (2009), who show that banking crises in the United States have been preceded by periods of abnormal liquidity creation.

Liquidity is an intuitive concept that is difficult to define precisely, and is even more difficult to measure. Therefore, it is necessary to clarify the concepts we use. First, we define liquidity risk as the risk that results from a firm's inability to meet payment obligations in a timely and cost-effective manner. Liquidity risk can be the result of either funding problems or market liquidity risk. Funding liquidity risk is the inability of a firm to obtain adequate funding to meet its cash flow and collateral needs without affecting its financial condition. Market liquidity risk is the inability of a bank to liquidate assets without significant losses because of inadequate market depth or market disturbances. Therefore, this definition of market liquidity is different from that of Brunnermeier and Pedersen (2009). They focus on the market liquidity of assets, while we are concerned with a bank's ability to liquidate its assets in the market.

The second clarification is on the relation and difference between systemic risk and systematic risk. Systemic risk is generally used in reference to the risk of collapse of an entire financial system or entire market. On the other hand, systematic risk refers to the risk inherent in the aggregate market that cannot be eliminated through diversification. Systemic risk does not have a precise definition.[2] It can include the risks that stem from financial system instability or interdependency in a system or market, in which the failure of one or several institutions can cause a cascading failure. While systemic risk is a very important concept, further research is necessary to reach a consensus on how to measure it. On the other hand, systematic risk does have a widely recognized definition. Therefore, we choose to focus on systematic liquidity risk in this study. We use the TED spread—the spread between three-month Libor and three-month U.S. Treasury bills rate—as the measure of systematic liquidity risk. The TED spread is

[2] See http://macroblog.typepad.com/macroblog/2009/11/what-is-systemic-risk-anyway.html for informative reading. Discussions about systemic risk definition can be found in Bullard, Neely, and Wheelock (2009); Freixas, Parigi, Jean-Charles, and Krishnamurthy (2000); Huang, Zhou, and Zhu (2009); and Schwerter (2011).

commonly used as an indicator to gauge funding liquidity in the general market. On the other hand, the TED spread is closely associated with systemic risk, in the sense that a jump in the TED spread is indicative of elevated systemic risk. In that sense, our results on the systematic channel of liquidity risk can be interpreted as a gauge of the impacts of systemic liquidity risk.

Within the second literature, the corporate default models can be divided into two major groups. The first group of models comprises the accounting-ratio-based models pioneered by Altman (1968) and Beaver (1966). Most bank failure models fall into this group (Arena (2008); Cole and Gunther (1995); Cole and Gunther (1998); DeYoung (2003); Jin, Kanagaretnam, and Lobo (2011); Kolari, Glennon, Shin, and Caputo (2002); Lane, Looney, and Wansley (1986); Meyer and Pifer (1970); Wheelock and Wilson (1995); and Wheelock and Wilson (2000)). Commercially successful models in this category include Zeta® and Moody's RiskCalc™ U.S. banks model. These models are typically built by searching through a large number of accounting-ratio variables covering capital adequacy, asset quality, profitability, liquidity, growth, and volatility without specifying the relationship among these variables. Consequently, they lack a theoretical framework for determining the appropriate relationship between the dependent variable and the explanatory variables.

The second group of models comprises the contingent claims valuation models, first proposed by Black and Scholes (1973) and Merton (1974), and later commercialized by Moody's KMV. Despite their commercial success, these models suffer from the limitations that two key inputs of the model, the market value and the volatility of a firm's assets, are not directly observed and have to be calibrated under certain assumptions. As a result, only firms with publicly traded securities can be calibrated. Bharath and Shumway (2008) have examined the accuracy of default forecasting models based on the KMV-Merton model, and have concluded that the KMV-Merton model does not form a sufficient statistic for the probability of default. Agarwal and Taffler (2008), using a sample of UK non-financial firms during the period of 1985–2001, find that accounting-ratio-based models perform slightly better than KMV-type models.

Duffie and Lando (2001) use an information filtration argument to show that if the distance to default cannot be accurately measured, then the default intensity would depend not only on the measured distance to default, but also on other covariates that may reveal additional information about the firm's conditional default probability. Using an approach analogous to Duffie and Lando (2001), we develop a discrete-time hazard model that links the bank's conditional failure rate to its insolvency and liquidity conditions.

II. The Model

We assume that a bank may fail because of insolvency or illiquidity. The insolvency condition indicates whether a bank's liabilities exceed its assets, while the liquidity condition specifies whether a bank is unable to meet its liquidity obligation. Although most bank failures are caused by insolvency, serious liquidity problems can cause an otherwise solvent bank to fail under certain conditions (Diamond and Dybvig (1983)).

We formulate our econometric model by specifying a dynamic discrete-time hazard model such that the hazard (i.e., default intensity, or the conditional probability that bank i fails at time $t+1$ given it has not failed at time t) is defined as

$$\lambda_{i,t+1} = \exp\left(a_0 + a_1 \cdot U_{i,t+1} + a_2 \cdot V_{i,t+1}\right). \tag{1}$$

So the log-hazard can be defined as

$$h_{i,t+1} = \log(\lambda_{i,t+1}) = a_0 + a_1 \cdot U_{i,t+1} + a_2 \cdot V_{i,t+1}. \tag{2}$$

In this equation, the log-hazard comprises a latent variable for the insolvency condition ($U_{i,t+1}$) and a latent variable for the liquidity condition ($V_{i,t+1}$). We describe the derivation of these variables in subsequent sections.

A. The insolvency condition

Let $E_{i,t+1}$ refer to the real value of bank i's equity at time $t+1$. We define the latent variable for the insolvency condition ($U_{i,t+1}$) as the distance between the normalized real value of a bank's equity and zero:

$$U_{i,t+1} = \frac{E_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} - 0 = \frac{E_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}}. \qquad (3)$$

The sum of tangible common equity ($TCE_{i,t}$) and allowance of loan and lease losses ($ALLL_{i,t}$) can be viewed as the effective capital of a bank. As will become clear later, by normalizing a bank's equity using its effective capital, we can derive an insolvency condition that encompasses the well-known Texas ratio as a special case.

Since the real value of a bank's equity is unobservable, it has to be estimated using different valuation approaches. We use two commonly used valuation approaches. The first approach is the market-value-based approach, while the second approach is based on a firm's book value of equity. Market value accounting records a bank's assets and liabilities at their current market value, while book value accounting records them at their historical values (with certain adjustments). While the debate on the merits of these accounting methods is unsettled, it is fair to say that each approach has its own strength and weakness. For example, both approaches can result in distorted measures of a bank's financial condition. Book value accounting may overvalue or undervalue a bank's assets if their current market prices deviate from their historical costs. On the other hand, since current market prices of assets may not be indicative of their long-term economic values in times of market panic, market value accounting could lead to excessive and artificial volatility (Allen and Carletti (2008); and Plantin, Sapra, and Shin (2008)).

We assume there are two estimators of $E_{i,t+1}$ that are subject to measurement errors:

$$E_{i,t+1}^{MV} = E_{i,t+1} + \varepsilon_{i,t+1}^{1}, \tag{4}$$

$$E_{i,t+1}^{BV} = E_{i,t+1} + \varepsilon_{i,t+1}^{2}, \tag{5}$$

$$V = \begin{pmatrix} \mathrm{cov}(\varepsilon_{i,t+1}^{1}, \varepsilon_{i,t+1}^{1}) & \mathrm{cov}(\varepsilon_{i,t+1}^{1}, \varepsilon_{i,t+1}^{2}) \\ \mathrm{cov}(\varepsilon_{i,t+1}^{2}, \varepsilon_{i,t+1}^{1}) & \mathrm{cov}(\varepsilon_{i,t+1}^{2}, \varepsilon_{i,t+1}^{2}) \end{pmatrix}. \tag{6}$$

We use superscript "BV" or "MV" when we need to differentiate between the book value and the market value of a variable. If the covariance matrix of the measurement errors has full rank, then there exists a best linear estimator of $E_{i,t+1}$, which is a weighted average of $E_{i,t+1}^{MV}$ and $E_{i,t+1}^{BV}$, and has the minimum mean squared error among all linear estimators (Bates and Granger (1969); Newbold and Granger (1974)). The weights of the linear estimator are determined by the variance-covariance matrix of measurement errors, as specified below:

$$\hat{E}_{i,t+1} = w_1 E_{i,t+1}^{MV} + w_2 E_{i,t+1}^{BV}, \tag{7}$$

where

$$w = \begin{pmatrix} w_1 \\ w_2 \end{pmatrix} = (e^T V^{-1} e) V^{-1} e = \begin{pmatrix} 1 & 1 \end{pmatrix} V^{-1} \begin{pmatrix} 1 \\ 1 \end{pmatrix} V^{-1} \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \tag{8}$$

and

$$w^T e = \begin{pmatrix} w_1 & w_2 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \sum_{i=1}^{2} w_i = 1. \tag{9}$$

Therefore, we can use Equation (7) to estimate the real value of a bank's equity. We describe the market value and book value estimators of a bank's equity in subsequent sections.

A.1. The equity value estimator based on market value

A widely used market valuation approach is based on the contingent claim valuation models of Black and Scholes (1973) and Merton (1974). However, this approach requires firms to have publicly traded stocks. Using U.S. bank data as an example, where there have been more than 6,770 banks each year between 1985 and 2011, there have been fewer than 200 banks with publicly traded stocks for any given year. Because of this limitation, we use an alternative approach that calculates the market value of equity using a discounted cash flow model with an appropriate discount rate.

Let $NI_{i,t+k}$ denote the net income at time $t+k$, and let $r_{i,t}^{d}$ denote the market discount rate at time t. Using a discounted cash flow model with an infinite horizon, the market value of equity becomes

$$E_{i,t+1}^{MV} = \sum_{k=1}^{\infty} \frac{NI_{t+k}}{\left(1+r_{i,t}^{d}\right)^{k}} . \tag{10}$$

We define the return on assets ($ROA_{i,t+k}$) as the ratio of net income ($NI_{i,t+k}$) divided by the book value of assets ($A_{i,t+k-1}^{BV}$):

$$ROA_{i,t+k} = \frac{NI_{i,t+k}}{A_{i,t+k-1}^{BV}} . \tag{11}$$

If we assume that the market approximates all future net income using the net income at time $t+1$ ($ROA_{i,t+1}$), such that

$$NI_{i,t+k} \approx NI_{i,t+1} = A_{i,t}^{BV} ROA_{i,t+1}, \tag{12}$$

then the market value of equity can be approximated by

$$E_{i,t+1}^{MV} \approx A_{i,t}^{BV} ROA_{i,t+1} \sum_{t=1}^{\infty} \frac{1}{\left(1+r_{i,t}^{d}\right)^{t}} \approx A_{i,t}^{BV} \frac{ROA_{i,t+1}}{r_{i,t}^{d}}. \tag{13}$$

We define the market discount rate for bank i as

$$r_{i,t}^{d} = r_{t}^{Baa} + TED\_spread_{t} + Net\_CO_{i,t}. \tag{14}$$

In the above equation, the average yield on Moody's Baa-rated corporate bonds (r_t^{Aaa}) reflects the average market discount rate. The TED spread (TED_spread_t) is generally used as an indicator of market funding liquidity, so it represents the excess return required for compensating for market funding liquidity risk. The net charge-off rate ($Net\_CO_{i,t}$) represents the idiosyncratic credit quality of bank i's assets. This variable thus denotes the excess return required for compensating for the credit quality of bank i's assets.

A.2. The equity value estimator based on book value

The book value of a bank's equity at time $t+1$ equals its book value at time t, plus the net income between time t and $t+1$:

$$E_{i,t+1}^{BV} = E_{i,t}^{BV} + NI_{i,t+1}^{BV}, \tag{15}$$

where the net income ($NI_{i,t+1}^{BV}$) can be expanded as

$$\begin{aligned} NI_{i,t+1}^{BV} &= Total\_Income_{i,t+1}^{BV} - Total\_Expense_{i,t+1}^{BV} \\ &= Interest\_Income_{i,t+1}^{BV} - Interest\_Expense_{i,t+1}^{BV} \\ &\quad + Net\_Noninterest\_Income_{i,t+1}^{BV} - Unexpected\_Losses_{i,t+1}^{BV}. \end{aligned} \tag{16}$$

The interest income is the sum of interest incomes from loans and securities:

$$
\begin{aligned}
&Interest\_Income_{i,t+1} = Loans_{i,t+1} \bullet Loan\_Yields_{i,t+1} \\
&+Securities_{i,t+1} \bullet Security\_Yield_{i,t+1}
\end{aligned} \tag{17}
$$

The bank's unexpected losses equal its total losses at time $t+1$ ($Loss_{i,t+1}$), less the allowance for loan and lease losses ($ALLL_{i,t}$):

$$Unexpected\_Losses^{BV}_{i,t+1} = Loss_{i,t+1} - ALLL_{i,t}, \tag{18}$$

where the amount of total losses ($Loss_{i,t+1}$) is a function of the bank's non-performing assets ($NPA_{i,t}$) at time t and the average loss given default ($LGD_{i,t+1}$) at time $t+1$:

$$Loss_{i,t+1} = NPA_{i,t} \bullet LGD_{i,t+1}. \tag{19}$$

Therefore, the estimator of a bank's equity value based on book value can be derived as

$$
\begin{aligned}
&E^{BV}_{i,t+1} = E^{BV}_{t} + Loans_{i,t+1} \bullet Loan\_Yields_{i,t+1} \\
&+Securities_{i,t+1} \bullet Security\_Yield_{i,t+1} - Interest\_Expense^{BV}_{i,t+1} \\
&+Net\_Noninterest\_Income^{BV}_{i,t+1} - (LGD_{i,t+1} \bullet NPA_{i,t} - ALLL_{i,t})
\end{aligned} \tag{20}
$$

The amount of non-performing assets ($NPA_{i,t}$) equals the sum of the bank's non-performing loans, and other real estate owned. We assume that the average loss given default ($LGD_{i,t+1}$) is a function of the bank's own underwriting and collateral policy, as well as local economic conditions, such as the change in local housing prices ($\Delta HPI_{i,t+1}$) and the change in local unemployment rates ($\Delta Unemp_{i,t+1}$). We assume that the relationship between LGD and the economic variables has the following simple linear form:

$$LGD_{i,t+1} = \phi_0 + \phi_1 \Delta HPI_{i,t+1} + \phi_2 \Delta Unemp_{i,t+1} + \xi_{i,t+1} \tag{21}$$

A.3. The insolvency condition and the Texas ratio

Combining Equations (7), (13), and (20) and rearranging terms, we obtain the estimator of bank equity value as

$$\hat{E}_{i,t+1} = w_1 \left[A^{BV}_{i,t} \bullet \frac{ROA_{i,t+1}}{r^{d}_{i,t}} \right] + w_2 \left[\begin{array}{l} E^{BV}_{t} + ALLL_{i,t} + Loans_{i,t+1} \bullet Loan\_Yields_{i,t+1} \\ + Securities_{i,t+1} \bullet Security\_Yield_{i,t+1} - Interest\_Expense^{BV}_{i,t+1} \\ + Net\_Noninterest\_Income^{BV}_{i,t+1} - NPA_{i,t} \bullet LGD_{i,t+1} \end{array} \right]. \tag{22}$$

If we substitute Equation (22) into Equation (3), we obtain the following estimator of $U_{i,t+1}$:

$$\begin{aligned} \hat{U}_{i,t+1} = {} & w_1 \frac{A^{BV}_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet \frac{ROA_{i,t+1}}{r^{d}_{i,t}} + w_2 \frac{E^{BV}_{t} + ALLL_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \\ & + w_2 \frac{Loans_{i,t+1} \bullet Loan\_Yields_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} \\ & + w_2 \frac{Securities_{i,t+1} \bullet Security\_Yield_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} \\ & - w_2 \frac{Interest\_Expense^{BV}_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} + w_2 \frac{Net\_Noninterest\_Income^{BV}_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} \\ & - w_2 \frac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet LGD_{i,t+1} . \end{aligned} \tag{23}$$

In the above equation, the term $\frac{NPA_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}}$ is the well-known Texas ratio, a measure that Gerard Cassidy at RBC Capital developed while analyzing bank stocks during the wave of failures that hit the Texas banking industry in the 1980s. This ratio is derived by comparing a bank's non-performing assets with its capital plus loan loss reserve. If this ratio is at or above 100%, the bank is at severe risk of failure because it might not have enough capital to cover its losses.

One of the limitations of the Texas ratio is that it does not account for the potential value of collateral. If a borrower defaults on a loan and the bank seizes collateral worth only 90% of the outstanding loan amount, the ultimate loss is very different from the loss that would be realized if the bank could recover only 10% of the loan amount.

Therefore, by normalizing a bank's equity using the sum of its tangible common equity ($TCE_{i,t}$) and loan loss reserves ($ALLL_{i,t}$), we derive an insolvency condition that includes the Texas ratio as a special case.

B. The liquidity condition

A bank's liquidity condition index $V_{i,t+1}$ is assumed to consist of an idiosyncratic component and a systematic component. The idiosyncratic component differentiates between banks with strong and weak liquidity risk management, while the systematic component affects every bank.

The indirect measures for banks' idiosyncratic liquidity risk comprise measures on asset liquidity and funding stability[3]. We choose the government securities ratio as the measure for asset liquidity and the brokered deposits ratio as the measure for funding stability[4].

He and Xiong (2012) suggest that debt market liquidity can be used as an economic factor for predicting firm default, so we use the TED spread as the debt market liquidity indicator. Therefore, we define the estimator on the latent variable of liquidity condition as

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[3] Asset liquidity measures include the net liquid asset ratio, the current ratio, the acid test ratio, and the government securities ratio. The liquidity coverage ratio under the new Basel III liquidity framework also belongs to this group. Funding stability measures include the brokered deposit ratio, the core deposit ratio, the non-core funding ratio, and the net stable funding ratio under the Basel III standards.

[4] We didn't use the liquidity coverage ratio (LCR) and net stable funding ratio (NSFR) in our analysis for the following reasons. First, there are some ambiguities in the Basel III liquidity standards. Second, the U.S. bank data we collected through call report data have some limitations. Therefore it is difficult to calculate LCR and NSFR with a reasonable level of accuracy, especially for data before 2001.

$$\hat{V}_{i,t+1} = b_0 + b_1 TED\_Spread_{t+1} + b_2 Gov\_Sec\_R_{i,t+1} + b_3 Brokered\_Deposit\_R_{i,t+1} \quad (24)$$

C. The final model

We substitute Equation (23) and Equation (24) into Equation (2) to obtain the following equation:

$$\hat{h}_{i,t+1} = a_0 + a_1 \cdot \hat{U}_{i,t+1} + a_2 \cdot \hat{V}_{i,t+1}$$

$$= a_0 + a_1 \left[\begin{array}{l} w_1 \dfrac{A^{BV}_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet \dfrac{ROA_{i,t+1}}{r^d_{i,t}} + w_2 \dfrac{E^{BV}_t + ALLL_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \\ + w_2 \dfrac{Loans_{i,t+1} \bullet Loan\_Yields_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} \\ + w_2 \dfrac{Securities_{i,t+1} \bullet Security\_Yield_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} \\ - w_2 \dfrac{Interest\_Expense^{BV}_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} + w_2 \dfrac{Net\_Noninterest\_Income^{BV}_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} \\ - w_2 \dfrac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet LGD_{i,t+1} \end{array} \right]$$

$$+ a_2 \left[\begin{array}{l} b_0 + b_1 TED\_Spread_{t+1} + b_2 Gov\_Sec\_R_{i,t+1} \\ + b_3 Brokered\_Deposit\_R_{i,t+1} \end{array} \right] \quad (25)$$

We next substitute Equation (21) into Equation (25), and take the conditional expectation of $\hat{h}_{i,t+1}$ at time t. We obtain the following estimator of $h_{i,t+1}$ after reparameterization:

$$
\begin{aligned}
\tilde{h}_{i,t+1} = E\left(\hat{h}_{i,t+1}\middle|t\right) &= \beta_0 + \beta_1 \frac{A_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} \bullet \frac{ROA_{i,t}}{r_{i,t}^{d}} + \beta_2 \frac{E_t^{BV} - TCE_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \\
&+ \beta_3 \frac{Loans_{i,t} \bullet Loan\_Yields_{i,t}}{TCE_{i,t} + ALLL_{i,t}} + \beta_4 \frac{Securities_{i,t} \bullet Security\_Yield_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \\
&+ \beta_5 \frac{Interest\_Expense_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} + \beta_6 \frac{Net\_Noninterest\_Income_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} \\
&+ \beta_7 \frac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} + \beta_8 \frac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet \Delta HPI_{i,t} \\
&+ \beta_9 \frac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet \Delta Unemp_{i,t} \\
&+ \beta_{10} Ted\_Spread_t + \beta_{11} Gov\_Sec\_R_{i,t} + \beta_{12} Brokered\_Deposit\_R_{i,t}
\end{aligned} \quad . \qquad (26)
$$

Therefore, Equation (26) specifies the discrete-time hazard model that links the conditional bank failure probability to bank-specific and marketwide variables through the insolvency and liquidity conditions. We briefly explain each component of this model in subsequent paragraphs.

The first component is the market valuation component ($\frac{A_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} \bullet \frac{ROA_{i,t}}{r_{i,t}^{d}}$), which consists of two terms (i.e., $\frac{A_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}}$ and $\frac{ROA_{i,t}}{r_{i,t}^{d}}$). Since the sum of tangible common equity and allowance for loan and lease losses ($TCE_{i,t} + ALLL_{i,t}$) can be viewed as the effective capital, the first term ($\frac{A_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}}$) is a measure of leverage. The second term is the ratio of return on assets to market discount rate. We expect the coefficient on the market valuation component (β_1) to be negative, so an increase in the return on assets reduces the hazard, while an increase in the market discount rate increases the hazard. The leverage term ($\frac{A_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}}$)

serves as an amplifier for the effects of changes in the return on assets and in the market discount rate. In other words, this amplifier can make a good thing better and a bad thing worse.

The market valuation component can also be expanded as

$$\frac{A_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} * \frac{ROA_{i,t+1}}{r_t^{Baa} + TED\_spread_t + Net\_CO_{i,t}}.$$

Therefore, changes in the market interest rate (r_t^{Baa}), the funding liquidity risk (TED_spread_t), and the idiosyncratic asset quality of individual banks ($Net\_CO_{i,t}$) can affect the hazard through the market valuation component.

The second component ($\frac{E_t^{BV} - TCE_{i,t}}{TCE_{i,t} + ALLL_{i,t}}$) is the ratio of intangible capital ($E_t^{BV} - TCE_{i,t}$) to effective capital. We have no a priori expectation about the sign on the coefficient of this component. On one hand, intangible capital increases the capital buffer, so one would expect it to reduce the hazard. On the other hand, intangible capital could overinflate the reported capital, which could lead to a positive sign on this coefficient.

The coefficients on the third and fourth components measure the effects of interest incomes from loans and securities on the hazard. We expect their coefficients (β_3 and β_4) to have negative signs. We expect the coefficient on interest expense (β_5) to have a positive sign. We do not have any a priori expectation about the sign on the coefficient on the net noninterest income (β_6). On the one hand, an income would reduce the hazard. On the other hand, if this income is associated with taking additional risk, it would increase the hazard.

The seventh component is the Texas ratio ($\frac{NPA_{i,t}}{TCE_{i,t}+ALLL_{i,t}}$). We expect its coefficient (β_7) to be positive. The eighth component is the interaction term between the Texas ratio and the change in housing price indices. We expect its coefficient (β_8) to be negative, as rising housing prices would reduce the loss severity. We expect the coefficient on the ninth component (β_9), the interaction term between the Texas ratio and the change in unemployment rates, to be positive, because a high unemployment rate would increase the loss severity.

The 10th, 11th, and 12th components come from the liquidity conditions. We expect the coefficient on the TED spread (β_{10}) to be positive, as a rise in the TED spread would increase the market funding liquidity risk. We expect the coefficient on the government securities ratio (β_{11}) to be negative, as banks with more liquid assets are less likely to encounter liquidity difficulties. Finally, the coefficient on the brokered deposit ratio (β_{12}) is expected to be positive, as banks with excessive reliance on unstable funding are more likely to run into funding problems.

III. Data description

Our sample spans the period from 1985 to 2011. We obtain commercial banks' income statement and balance sheet data (e.g., call reports) between 1985 and 2011 from the Federal Reserve Bank of Chicago. Bank failure data since 1985 are obtained from the Federal Deposit Insurance Corporation (FDIC) and are matched with the call reports. We use annual data for this study, based on the fourth quarter of each year. The data are adjusted for bank mergers. Tables I summarizes the sample size and the number of defaults in the estimation and validation samples. As can be seen from Table 1, the entire sample consists of 262,838 observations (bank year) with

1,719 failures. Table II lists the definitions of variables used in this study. Table III reports the summary statistics of bank-specific and economic variables. To reduce the effect of possibly spurious outliers, bank-specific variables are winsorized at the first and 99th percentiles.

Figure 1 plots the U.S bank failure rate from 1985 to 2011, showing that the bank failure rate peaked twice through the entire period. The first peak occurred in 1988 and was associated with the savings and loan crisis of the 1980s and 1990s. The second peak occurred between 2009 and 2010 and was associated with the 2007-2009 financial crisis. As can be seen, the bank failure rate had risen steadily since 1985 and peaked in 1988, when it reached 2% with 262 bank failures. Although the failure rate began to decline in 1989, it remained relatively high before 1992. Bank failures became rare from 1995 to 2007. In particular, there were no bank failures in 2005 and 2006. However, the bank failure rate has shot up rapidly since 2008, exceeding 1.74% in 2009 and peaking at 1.95% in 2010.

Figures 2 through 5 plot the one-year conditional bank failure rate against the averages of four key variables in the preceding year. Figure 2 underscores the pitfalls of overreliance on capital ratios to measure risk. As can be seen, both the average capital and tangible capital ratios were lower at the beginning of the sample period and rose steadily from 1986 to 2007. For example, the lowest average capital ratio of 8.6% occurred in 1986, while the highest average capital ratio of 11.6% occurred in 2007. Therefore, an observer looking only at capital ratios would have mistakenly concluded that U.S. banks were well positioned in 2007.

Figure 3 reveals that the bank failure rate in the current year is inversely related to the average market valuation component in the preceding year. As can be seen, there was a steep fall in the average market valuation component from 2007 to 2009, which preceded a sharp rise in bank failure rates from 2008-2010. Therefore, the market valuation component is highly predictive of bank failures.

Especially interesting is Figure 4, which shows that the average Texas ratio in the preceding year is positively correlated with the bank failure rate in the current year. A rise in the average Texas ratio is generally followed by a rise in the bank failure rate.

Figure 5 reveals the strong predictive power of the TED spread on bank failures. As can be seen, a rise in the TED spread precedes a rise in the bank failure rate. In particular, the TED spread peaked in 1987 and 2008, followed by the peaks of bank failure rate in 1988, 2009 and 2010. In subsequent analysis, we show that the systematic liquidity risk, as reflected by the TED spread, was a major predictor of bank failures in 2008 and 2009.

IV. Estimation results

Because of the longer sample period of our study compared with existing studies, we can afford a validation sample design that minimizes the correlation between estimation sample and validation sample. We divide our data into two samples. The first sample is the estimation sample, which covers the period of 1985-2004, while the second sample is the out-of-time validation sample, which covers the period of 2005-2011. As a result, the estimation sample includes 212,361 observations with 1,350 failures, while the prediction sample includes 50,477 observations with 369 failures. We estimate all models using the estimation sample, and validate their out-of-sample performance using the validation sample. By devoting the entire period of 2005-2011 to out-of-sample performance validation, we can obtain more robust validation results by minimizing the correlation between estimation sample and validation sample.

We choose the time interval to be one year in our discrete-time hazard model. There are several reasons for this choice. First, the time interval should be consistent with the practical usage of the model. For capital calculation purpose, banks typically use credit risk models to predict default in the next 12 months.[5] Second, while one can estimate the hazard model using a shorter interval such as a quarter, doing so would introduce a substantial serial correlation among explanatory variables because of the way these variables are constructed. For instance, variables such as return on assets, loan yields, security yields, and interest expense are constructed using the trailing 12-month data. Even though one could model the time series property of these explanatory variables, it is not clear whether such an approach would introduce misspecification errors in addition to the complexity. On the other hand, if we construct these variables using a shorter interval, it would subject them to seasonal effects. Finally, using quarterly data to predict the conditional failure rate over a longer interval would also subject the dependent variable to serial correlation because of the overlapping of time intervals over consecutive quarters.

We divide our analysis into two stages. We compare the performance of our model to existing bank failure models in the first stage, while studying the contribution of liquidity risk to predicting bank failures in the second stage.

A. Model Performance

In the first stage, we estimate four models. The first model is our benchmark model (Model 1). In this model, we include every variable on the right side of equation (26). To validate the performance of Model 1, we compare it with three additional models. In Model 2, we add state-level fixed effects to Model 1. The next two models are accounting-ratio-based models. Model 3 is very similar to the Moody's RiskCalc™ 3.1 U.S. Banks model (Dwyer, Guo, and Hood (2006); and Dwyer and Eggleton (2009)). Moody's RiskCalc™ 3.1 U.S. Banks model consists

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[5] We acknowledge that shorter prediction intervals could be useful for stress testing or other purposes; however, it is not directly relevant to the scope and purpose of this paper.

of two components: the Financial Statement Only (FSO) component and the Credit Cycle Adjustment (CCA) component. The FSO component uses eight accounting ratios as its inputs: capital ratio, return on assets, net interest margin, loan mix, commercial loan charge-off ratio, consumer loan charge-off ratio, other real estate owned ratio, and government securities ratio. Model 3 includes all these variables. We also add the brokered deposits ratio as a variable for funding stability, and include the TED spread as a proxy for the credit cycle adjustment. Finally, we build Model 4 using the Texas ratio as the only predictive variable.

We use three performance measures to compare the in-sample and out-of-sample performance. First, we use the receiver operating characteristic (ROC) curve and the associated AUC statistic to measure a model's ability to rank order firms by default risk. The AUC statistic is the area under ROC curves, which is also called c-statistic. A related measure is the accuracy ratio (AR), which is also called the Gini coefficient. The accuracy ratio is related to the AUC statistic by the following simple relationship:

$$AR = 2AUC - 1. \tag{27}$$

The AUC statistic ranges between 0.5 and 1. A value of 0.5 indicates no rank-ordering power, while a value of 1 indicates perfect rank-ordering power.

The second measure is the Hosmer-Lemeshow (H-L) statistic (Hosmer, Taber, and Lemeshow (1991)), a prediction accuracy measure that assesses whether or not the observed default rates match predicted default rates in subgroups of the population. The H-L test specifically identifies subgroups as the deciles of fitted risk values. In general, high prediction accuracy is associated with low H-L statistic.

The last measure is the Brier score (Brier (1950)), which measures the predictive accuracy at firm level, and is defined as

$$BS = \frac{\sum_{i=1}^{n}(D_i - \hat{p}_i)^2}{n}, \qquad (28)$$

where $\hat{p}_i$ is the predicted default probability of firm i, and D_i is the default indicator. A smaller Brier score is associated with better prediction accuracy at the firm level.

Table IV reports the estimation results of Model 1 through 4. Panel A compares the performance statistics, such as model fit statistics, in-sample and out-of-sample performance measures. Overall, these performance measures demonstrate that Model 1 outperforms other three models by a considerable margin.

As can be seen in Panel A, while all four models perform relatively well, Model 1 and Model 2 provide better fits than other two models. For example, the pseudo R-squared for Model 1 and Model 2 are 0.557 and 0.572, which are better than that of the accounting ratio model (0.553) and the Texas ratio model (0.449). The same conclusion can be drawn by looking at other statistics such as AIC, BIC and Log Likelihood.

Because Model 2 includes state fixed effects, it has 50 more parameters than Model 1. Therefore, it is not surprising that it is slightly better in terms of Pseudo R-squared, AIC, BIC and Log Likelihood. The in-sample performances of Model 1 and Model 2 are also similar. However, Model 1 has significantly better out-of-sample performance. Model 1 outperforms Model 2 in terms of H-L statistic, accuracy ratio, and Brier score. The performance lift of Model 1 over the other three models is further confirmed in the out-of-sample ROC curve comparisons in Figure 7.

Furthermore, Table V and Figure 8 report the observed aggregate bank failure rate along with its predicted values from Models 1 through 4, which reveal that the out-of-sample predicted value of Model 1 is more accurate than those of the other three models. Overall, these results show that Model 1 has the best performance of the four models.

Panel B of Table IV reports the parameter estimates. Overall, most parameters in Model 1 are statistically significant and are consistent with our expectation For instance, the coefficient on the market valuation channel variable (β_1) is negative and statistically significant (-0.514), implying that banks with higher market valuation are less likely to fail. The coefficient on the TED Spread is significantly positive (79.452), suggesting that high systematic liquidity risk leads to more bank failures. The coefficient on the government securities ratio is significantly negative (-2.869), which implies banks with more asset liquidity are less likely to fail. The coefficient on the brokered deposits ratio is significantly positive (2.917), which suggests that banks with higher dependence on unstable funding are more likely to fail. The coefficient on the Texas ratio is significantly positive (1.830). The coefficient on the interaction term between the Texas ratio and the change in housing price indices is significantly negative (-2.160). It implies that banks are less likely to fail when housing prices are increasing, and are more likely to fail when housing prices decline. The coefficient on the interaction term between the Texas ratio and the change in unemployment rates is positive (3.738), which implies that higher unemployment rates are associated with higher bank failures. However, this coefficient is not statistically significant. Overall, these results provide strong empirical support for our model.

For the state fixed-effects in Model 2, Wyoming is randomly chosen as the reference state because it is the last in alphabetical order. Given the fact that Arizona, California, Florida, Georgia, Illinois, and Texas have been frequently linked to bank failure in media coverage[6], one

[6] These states were prominent in that they experienced large number in bank failures during certain periods. For example, Texas was famous for the savings and loan failure that led to the

would have thought that banks in these states would have higher propensity to fail. Surprisingly, all of these states have negative coefficients, suggesting that banks in these states are less likely to fail than banks in Wyoming. We interpret this finding by arguing that bank-specific conditions and local economic conditions, as specified in Model 1, have strong explanatory power for bank failures. As a result, the covariates can explain very well the high bank failure rates in these states, in spite of the fact that banks in these states have lower propensity to fail. This result provides another justification for our choice of Model 1 as the benchmark model. Finally, we note that there were no bank failures in Nevada between 1985 and 2004. Because of this, the state fixed-effects model cannot estimate the coefficient for Nevada and has to drop all 655 observations from Nevada.

B. The role of liquidity risk

In the second stage, we examine the contributions of different liquidity risk channels in predicting bank failures. We estimate the marginal contributions of each liquidity risk channel in three steps. In the first step, we exclude the effects of systematic liquidity risk by removing the TED spread from Model 1. In the second step, we exclude the effects of the idiosyncratic liquidity risk by removing government securities and brokered deposits ratios. In the final step, we exclude the effects of both channels from Model 1.

Table VI and Figure 9 report the observed aggregate bank failure rate along with its predicted value from Model 1, as well as the predicted values when excluding different liquidity risk channels from Model 1. Figures 10, 11, and 12 graphically illustrate the marginal contributions of the systematic channel, the idiosyncratic channel, and the combined contributions of both

creation of the Texas ratio, and Georgia has experienced the largest number of bank failures in recent years.

channels. As can be seen, the systematic liquidity risk channel was the most important channel in 2008 and 2009. For example, the actual bank failure rate in 2009 is 1.74%, while the predicted failure rate of Model 1 is 1.71%. If we exclude the systematic liquidity risk, the predicted failure rate is reduced to 0.45%. On the other hand, if we exclude the idiosyncratic risk, the predicted failure rate is reduced to 1.62%.

Finally, Table VII summarizes the contribution of each liquidity risk channel in predicting bank failures by year. As can be seen, as many as 69.6% of the predicted bank failures in 2008 and 74.2% of the predicted bank failures in 2009 can be attributed to the systematic liquidity risk. In comparison, only 3.9% of the predicted bank failures in 2008 and 7.9% of the predicted bank failures in 2009 can be attributed to the idiosyncratic liquidity risk. These results reveal that systematic liquidity risk was the major predictor of bank failures in 2008 and 2009, while idiosyncratic liquidity risk played an inconsequential role during the same period. Furthermore, we note that the share of the predicted bank failures attributable to liquidity risk dropped sharply in 2010 and 2011, when only 8% of the predicted bank failures in 2010 and 7.9% of the predicted bank failures in 2011 are attributable to liquidity risk.

V. Conclusion

In this paper, we propose a bank failure model in which liquidity risk affects a bank through the systematic and idiosyncratic channels. This model bridges the gap between recent theoretical advances in the literature of liquidity risk and financial crisis, and the empirical literature of bank failure prediction. By explicitly developing the insolvency and liquidity risk conditions for bank failures, our model reflects a major enhancement over the existing accounting-ratio-based models. We test this model using U.S. bank data from 1985 to 2011. The out-of-sample prediction performances show that our model outperforms typical accounting-ratio-based models, such as a model that is similar to Moody's RiskCalc™ 3.1 U.S. Bank Model, and a model based on the Texas ratio.

We also find that systematic liquidity risk was the major predictor of bank failures in 2008 and 2009, while idiosyncratic liquidity risk played only a minimal role. This finding has important implications for the current discussion of the new Basel III liquidity risk standards. To enhance the safety and soundness of the banking system, an effective liquidity risk management framework needs to target liquidity risk at both the idiosyncratic and the systematic levels.

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Table I

Sample Description

This table summarizes the sample size and the number of defaults in the estimation and validation samples. The estimation sample covers the period of 1985-2004, while the validation sample covers the period of 2005-2011.

Period	Failed Bank	Total Banks
1985-2004	1,350	212,361
2005-2011	369	50,477
All	1,719	262,838

Table II

Variable Description

This table summarizes the main variables used in this study.

Variable	Description
$A_{i,t}^{BV}$	Total assets
E_t^{BV}	Total equity
$TCE_{i,t}$	Tangible common equity
$ALLL_{i,t}$	Allowance for loan and lease losses
$Loans_{i,t}$	Total performing loans
$Securities_{i,t}$	Total securities
$Interest\_Expense_{i,t}^{BV}$	Interest expense
$Net\_Noninterest\_Income_{i,t}^{BV}$	Net noninterest income
$NPA_{i,t}$	Non-performing assets
$ROA_{i,t}$	Return on assets
$Loan\_Yields_{i,t}$	Loan yields
$Security\_Yield_{i,t}$	Security yields
$Gov\_Sec\_R_{i,t}$	Government securities ratio: government securities to total assets ratio
$Brokered\_Deposit\_R_{i,t}$	Brokered deposits ratio: brokered deposits to total assets ratio

r_t^{Baa}	Yield on Moody's seasoned Baa-rated corporate bond
$Net\_CO_{i,t}$	Net charge-off to total asset ratio
Ted_Spread_t	The TED spread
$r_{i,t}^{d}$	Discount rate: $r_t^{Baa} + Ted\_Spread_t + Net\_CO_{i,t}$
$\Delta HPI_{i,t}$	Change in housing price index
$\Delta Unemp_{i,t}$	Change in unemployment rate
Capital ratio	Capital to total asset ratio
Tangible common equity ratio	Tangible common equity to total assets ratio
Texas ratio	The Texas ratio
Net interest margin	Net interest income to total asset ratio
Consumer loan charge-off ratio	Consumer loan charge-offs to total assets ratio
Commercial loan charge-off ratio	Commercial loan charge-offs to total assets ratio
Other real estate owned ratio	Other real estate owned to total assets ratio
Loan mix	Sum of commercial and industry loans, and commercial real estate loans to total assets ratio
Construction loan ratio	Construction loans to total assets ratio
Residential loan ratio	Residential loans to total assets ratio
Size	Natural logarithm of total assets

Table III

Summary of Statistics

This table presents the summary statistics of main variables.

	1985-2004				2005-2011			
Variable	Non-failed banks		Failed banks		Non-failed banks		Failed banks	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Capital ratio	0.0960	0.0871	0.0443	0.0364	0.1103	0.0987	0.0521	0.0373
Tangible capital ratio	0.0943	0.0855	0.0425	0.0343	0.1054	0.0938	0.0487	0.0359
Allowance for loan and lease losses ratio	0.0085	0.0075	0.0213	0.0215	0.0094	0.0085	0.0242	0.0261
Texas ratio	0.1511	0.0751	1.3747	1.5438	0.1308	0.0628	1.3429	1.4815
Non-performing assets ratio	0.0133	0.0073	0.0827	0.0971	0.0136	0.0066	0.0911	0.1126
Net charge off ratio	0.0033	0.0012	0.0248	0.0270	0.0029	0.0009	0.0245	0.0271
Return on assets	0.0085	0.0103	-0.0306	-0.0360	0.0068	0.0090	-0.0351	-0.0444
Net interest margin	0.0408	0.0404	0.0336	0.0329	0.0368	0.0365	0.0266	0.0258
Interest income ratio	0.0825	0.0821	0.0923	0.0906	0.0562	0.0556	0.0525	0.0503
Interest expense ratio	0.0415	0.0404	0.0586	0.0577	0.0192	0.0183	0.0261	0.0253
Net noninterest income ratio	-0.0253	-0.0238	-0.0394	-0.0376	-0.0240	-0.0228	-0.0332	-0.0320
Securities gains ratio	0.0004	0.0000	0.0006	0.0000	0.0002	0.0000	0.0005	0.0000
Government securities ratio	0.2048	0.1802	0.0805	0.0495	0.1405	0.1109	0.0409	0.0228
Brokered deposits ratio	0.0040	0.0000	0.0156	0.0000	0.0271	0.0000	0.0934	0.0732
Loan yields	0.1042	0.1046	0.1240	0.1223	0.0711	0.0704	0.0693	0.0661
Securities yields	0.0702	0.0688	0.0787	0.0810	0.0386	0.0399	0.0411	0.0424
Rate on liabilities	0.0457	0.0447	0.0603	0.0595	0.0216	0.0206	0.0280	0.0272
Rate on deposits	0.0451	0.0443	0.0605	0.0599	0.0208	0.0196	0.0273	0.0268
TED spread	0.0068	0.0066	0.0096	0.0075	0.0077	0.0034	0.0103	0.0021
Yield on Moody's Baa-rated bond	0.0941	0.0921	0.1071	0.1051	0.0663	0.0633	0.0710	0.0633
Aaa-Baa spread	0.0099	0.0095	0.0115	0.0117	0.0124	0.0098	0.0174	0.0113
Change in housing price index	0.0402	0.0409	-0.0082	-0.0018	0.0220	0.0167	-0.0571	-0.0512
Change in unemployment	-0.0016	-0.0020	-0.0012	-0.0053	0.0040	-0.0003	0.0189	0.0253

Variable	1985-2004				2005-2011			
	Non-failed banks		Failed banks		Non-failed banks		Failed banks	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Other real estate owned ratio	0.0038	0.0006	0.0271	0.0263	0.0034	0.0003	0.0260	0.0239
Charge off ratio	0.0042	0.0019	0.0277	0.0296	0.0034	0.0013	0.0261	0.0279
Consumer loan charge off ratio	0.0002	0.0000	0.0002	0.0000	0.0005	0.0002	0.0007	0.0002
Commercial loan charge off ratio	0.0002	0.0000	0.0006	0.0000	0.0008	0.0001	0.0032	0.0023
Performing loans ratio	0.5480	0.5620	0.5616	0.5706	0.6388	0.6629	0.6291	0.6264
Loan concentration mix ratio	0.3661	0.3344	0.4786	0.4818	0.4932	0.4851	0.7177	0.7391
Construction loans ratio	0.0366	0.0144	0.0482	0.0213	0.0902	0.0582	0.2160	0.2198
Residential loans ratio	0.2725	0.2445	0.1918	0.1629	0.2695	0.2403	0.2022	0.1878
Securities ratio, fair value	0.2818	0.2669	0.1287	0.1089	0.2128	0.1856	0.1022	0.0927
Securities ratio, book value	0.2835	0.2682	0.1275	0.1086	0.2129	0.1857	0.1003	0.0907
Liabilities ratio	0.9040	0.9129	0.9556	0.9635	0.8897	0.9012	0.9478	0.9624
Deposits ratio	0.8663	0.8858	0.9270	0.9475	0.8221	0.8405	0.8686	0.8893
Other borrowed money ratio	0.0130	0.0000	0.0089	0.0000	0.0439	0.0207	0.0658	0.0537
REPO ratio	0.0136	0.0000	0.0080	0.0000	0.0154	0.0000	0.0155	0.0000
Core deposits ratio	0.6716	0.6914	0.7098	0.7341	0.5681	0.5855	0.5696	0.5780
Money market deposits ratio	0.1099	0.0966	0.1103	0.0983	0.1257	0.0977	0.1164	0.0900
Unused commitments ratio	0.0601	0.0380	0.0351	0.0140	0.1063	0.0896	0.0799	0.0545
3-month Treasury rate	0.0547	0.0544	0.0667	0.0721	0.0220	0.0204	0.0039	0.0014
3-month Libor rate	0.0615	0.0614	0.0763	0.0809	0.0296	0.0272	0.0142	0.0029
3-month Eurodollar rate	0.0603	0.0602	0.0751	0.0799	0.0313	0.0363	0.0182	0.0046
Yield on Moody's Aaa-rated bond	0.0841	0.0845	0.0955	0.0951	0.0539	0.0539	0.0536	0.0520
Change in commercial real estate price	-0.0152	-0.0061	-0.0715	-0.0783	-0.0266	0.0211	-0.1797	-0.1956

Table IV

Estimation Results for Model 1-4

This table reports estimation and validation results of discrete-time hazard models using annual data. Panel A shows in-sample (1985-2004) and out-of-sample (2005-2011) performance statistics. Panel B shows the parameter estimates based on the 1985-2004 period. *, **, and *** indicates statistical significance at the 10%, 5%, and 1%, respectively. Model 1 is based on the log-hazard model specified in Equation (26):

$$
\begin{aligned}
\tilde{h}_{i,t+1} = {} & \beta_0 + \beta_1 \frac{A_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} \bullet \frac{ROA_{i,t}}{r_{i,t}^{d}} + \beta_2 \frac{E_t^{BV} - TCE_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \\
& + \beta_3 \frac{Loans_{i,t} \bullet Loan\_Yields_{i,t}}{TCE_{i,t} + ALLL_{i,t}} + \beta_4 \frac{Securities_{i,t} \bullet Security\_Yield_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \\
& + \beta_5 \frac{Interest\_Expense_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} + \beta_6 \frac{Net\_Noninterest\_Income_{i,t}^{BV}}{TCE_{i,t} + ALLL_{i,t}} \\
& + \beta_7 \frac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} + \beta_8 \frac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet \Delta HPI_{i,t} \\
& + \beta_9 \frac{NPA_{i,t}}{TCE_{i,t} + ALLL_{i,t}} \bullet \Delta Unemp_{i,t} \\
& + \beta_{10} Ted\_Spread_t + \beta_{11} Gov\_Sec\_R_{i,t} + \beta_{12} Brokered\_Deposit\_R_{i,t}
\end{aligned}
$$

Model 2 adds state-level fixed effects to Model 1; Model 3 is a typical accounting-ratio-based model similar to Moody's RiskCalc™; Model 4 has the Texas ratio and constant as the only right-hand-side variables.

	Model 1 Benchmark	Model 2 State-level fixed effects	Model 3 Accounting-ratio model	Model 4 Texas ratio
Panel A: Performance Statistics				
Model Statistics				
Observations	212361	211924	212361	212361
Pseudo R^2	0.557	0.572	0.553	0.449
AIC	7272.291	7119.927	7326.330	9019.370
BIC	7405.750	7756.294	7449.522	9039.902
Log Likelihood	-3623.146	-3497.964	-3651.165	-4507.685
In-sample Performance (1985-2004)				
AUC Statistic	0.9833	0.9844	0.9787	0.9605
Accuracy Ratio	0.9666	0.9688	0.9574	0.9210
HL Statistic	75.662	52.331	68.009	116.019
HL P-value	0.000	0.000	0.000	0.000
Brier Score*1000	4.4498	4.3629	4.3996	5.0499
Out-of-sample Performance (2005-2011)				
AUC Statistic	0.9781	0.9468	0.9604	0.9654

Accuracy Ratio	0.9562	0.8936	0.9208	0.9308
HL Statistic	14.097	85.474	2237.109	154.768
HL P-value	0.169	0.000	0.000	0.000
Brier Score*1000	4.0977	4.611	4.2249	5.2051
Panel B: Parameter Estimates				
β_0 (Constant)	-7.309*** [0.144]	-6.451*** [0.352]	3.304*** [0.496]	-6.993*** [0.055]
β_1 (Market valuation component)	-0.514*** [0.024]	-0.505*** [0.025]		
β_2 (Intangible capital)	-0.229 [0.267]	-0.076 [0.229]		
β_3 (Loan interest income)	-0.687*** [0.152]	-0.515*** [0.164]		
β_4 (Security interest income)	-2.540*** [0.328]	-2.344*** [0.342]		
β_5 (Interest expense)	2.629*** [0.197]	2.610*** [0.217]		
β_6 (Net noninterest income)	0.141 [0.225]	0.232 [0.233]		
β_7 (Texas ratio)	1.830*** [0.075]	1.717*** [0.076]		3.645*** [0.056]
β_8 (Texas ratio*HPI change)	-2.160*** [0.717]	-0.280 [0.844]		
β_9 (Texas ratio*Unemployment change)	3.738 [2.916]	3.648 [3.115]		
β_{10} (TED spread)	79.452*** [9.681]	74.146*** [10.608]	53.570*** [8.036]	
β_{11} (Government securities ratio)	-2.869*** [0.456]	-2.880*** [0.444]	-4.798*** [0.385]	
β_{12} (Brokered deposits ratio)	2.917*** [1.131]	4.298*** [1.241]	4.806*** [0.993]	
Return on assets			-43.756*** [2.308]	
Net interest margin			-32.144*** [3.902]	
Capital ratio			-74.294*** [3.687]	
Loan mix			0.494*** [0.186]	
Other real estate owned			24.586*** [1.963]	
Size			-0.269*** [0.034]	
Consumer loan charge off ratio			-6.624 [69.161]	
Commercial loan charge off ratio			108.347*** [29.584]	
AK		-0.652 [0.806]		

AL	-0.666
	[0.547]
AR	-1.258**
	[0.566]
AZ	-0.875**
	[0.434]
CA	-1.006***
	[0.361]
CO	-0.897**
	[0.360]
CT	-1.195***
	[0.364]
DC	-0.577
	[0.794]
DE	-1.425
	[1.100]
FL	-0.982***
	[0.373]
GA	-2.700***
	[0.742]
HI	0.213
	[0.592]
IA	-0.821**
	[0.388]
ID	-2.590**
	[1.178]
IL	-2.190***
	[0.462]
IN	-2.270***
	[0.607]
KS	-0.440
	[0.370]
KY	-1.481***
	[0.519]
LA	-1.162***
	[0.352]
MA	-1.617***
	[0.383]
MD	-2.569**
	[1.098]
ME	-1.673*
	[0.915]
MI	-2.057***
	[0.577]
MN	-1.581***
	[0.409]
MO	-0.643*
	[0.367]
MS	-1.502**
	[0.763]
MT	-1.599***

	[0.518]
NC	-1.039
	[0.791]
ND	-0.813
	[0.532]
NE	-0.494
	[0.403]
NH	-1.516***
	[0.467]
NJ	-1.115***
	[0.403]
NM	-1.297*
	[0.695]
NV	0.000
	NA
NY	-0.831*
	[0.448]
OH	-1.385***
	[0.498]
OK	-0.439
	[0.337]
OR	-2.072***
	[0.623]
PA	-1.494***
	[0.522]
RI	-1.867
	[1.872]
SC	-0.541
	[0.661]
SD	-0.758
	[0.623]
TN	-2.341***
	[0.746]
TX	-0.272
	[0.323]
UT	-0.586
	[0.540]
VA	-1.817**
	[0.737]
VT	-2.283***
	[0.838]
WA	-1.756**
	[0.731]
WI	-2.507***
	[0.710]
WV	-1.170**
	[0.582]
WY	0.000
	NA

Table V

Observed and Predicted Conditional Failure Rate for Model 1-4 (2005-2011)

This table reported the observed aggregate bank failure rate along with its predicted values from Models 1-4.

Year	Observed conditional failure rate	Prediction of Model 1	Prediction of Model 2	Prediction of Model 3	Prediction of Model 4
2005	0	0.000392	0.000327	0.000445	0.001266
2006	0	0.000584	0.000471	0.000515	0.001249
2007	0.000136	0.000557	0.000488	0.000421	0.001272
2008	0.003174	0.002823	0.002228	0.001464	0.001723
2009	0.017429	0.017137	0.011216	0.012537	0.004674
2010	0.019457	0.019929	0.012691	0.017681	0.0121
2011	0.012703	0.012716	0.007616	0.013976	0.01319
Average	0.00731	0.007491	0.004857	0.006483	0.004892

Table VI

Effects of Liquidity Risk on the Predicted Conditional Failure Rate (2005-2011)

This table reported the observed aggregate bank failure rate along with its predicted value from Model 1, and the predicted values when excluding different liquidity risk channels from Model 1.

Year	Observed average conditional failure rate	Prediction of Model 1	Prediction when excluding systematic channel	Prediction when excluding idiosyncratic channel	Prediction when excluding all channels
2005	0	0.000392	0.0003205	0.000516	0.0004217
2006	0	0.0005837	0.0004441	0.0007217	0.0005409
2007	0.000136	0.0005573	0.0004262	0.0006852	0.0005241
2008	0.0031737	0.0028231	0.0009661	0.0030488	0.0010125
2009	0.0174289	0.0171371	0.004502	0.0161564	0.0039549
2010	0.0194569	0.0199288	0.0183915	0.0189668	0.0174332
2011	0.0127031	0.0127159	0.0118869	0.0125206	0.0116722
Average	0.0073103	0.0074911	0.0050578	0.0072844	0.004871

Table VII

Contribution of Liquidity Risk in Predicting Bank Failures (2005-2011)

This table summarizes the contribution of each liquidity risk channel in predicting bank failures by year.

Year	Systematic Channel	Idiosyncratic Channel	Total Contribution
2008	69.6%	3.9%	73.5%
2009	74.2%	7.3%	81.5%
2010	5.5%	2.5%	8.0%
2011	6.4%	1.4%	7.9%

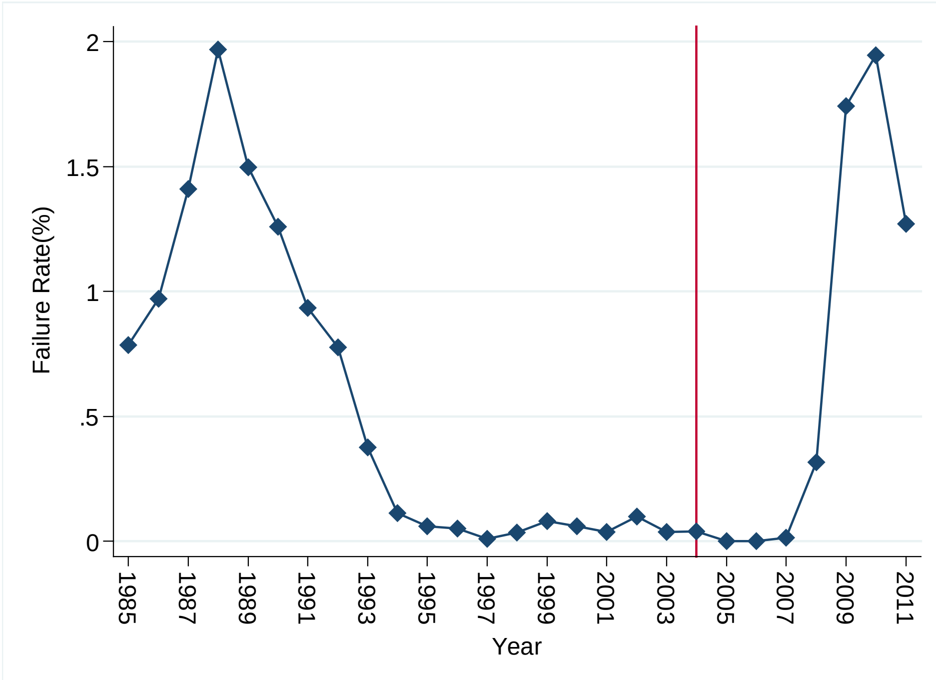

Figure 1. The U.S. banks failure rate, 1985-2011. This figure plots the one-year conditional bank failure rate from 1985 to 2011. U.S. bank failure rate peaked in 1988 and 2010; the former was linked to the savings and loan crisis of the 1980s and 1990s, while the latter was associated with the financial crisis of 2007-2009.

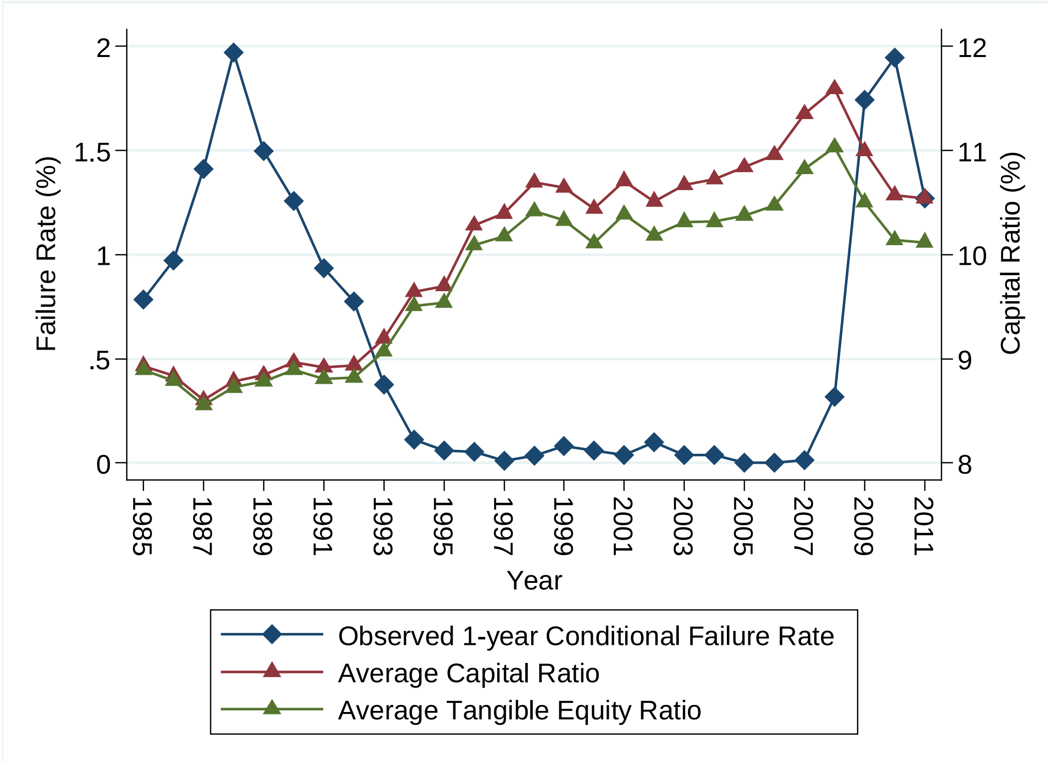

Figure 2. The U.S. banks failure rate and the capital ratios, 1985-2011. This figure plots the one-year conditional bank failure rate against the average capital ratio and the average tangible capital ratio in the preceding year. It shows that both ratios peaked in 2007, the year when the recent financial crisis started.

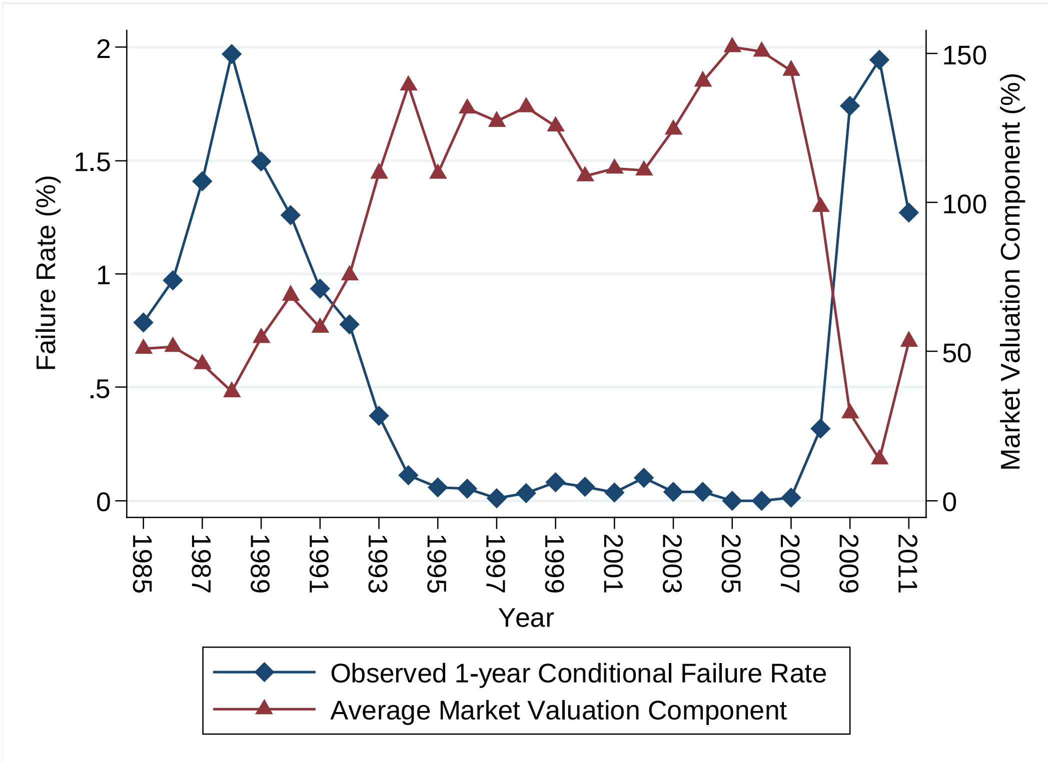

Figure 3. The U.S. banks failure rate and the market valuation component, 1985-2011. This figure plots the one-year conditional bank failure rate against the average market valuation component in the previous year. It shows that the failure rate is inversely correlated to the average market valuation component in the preceding year.

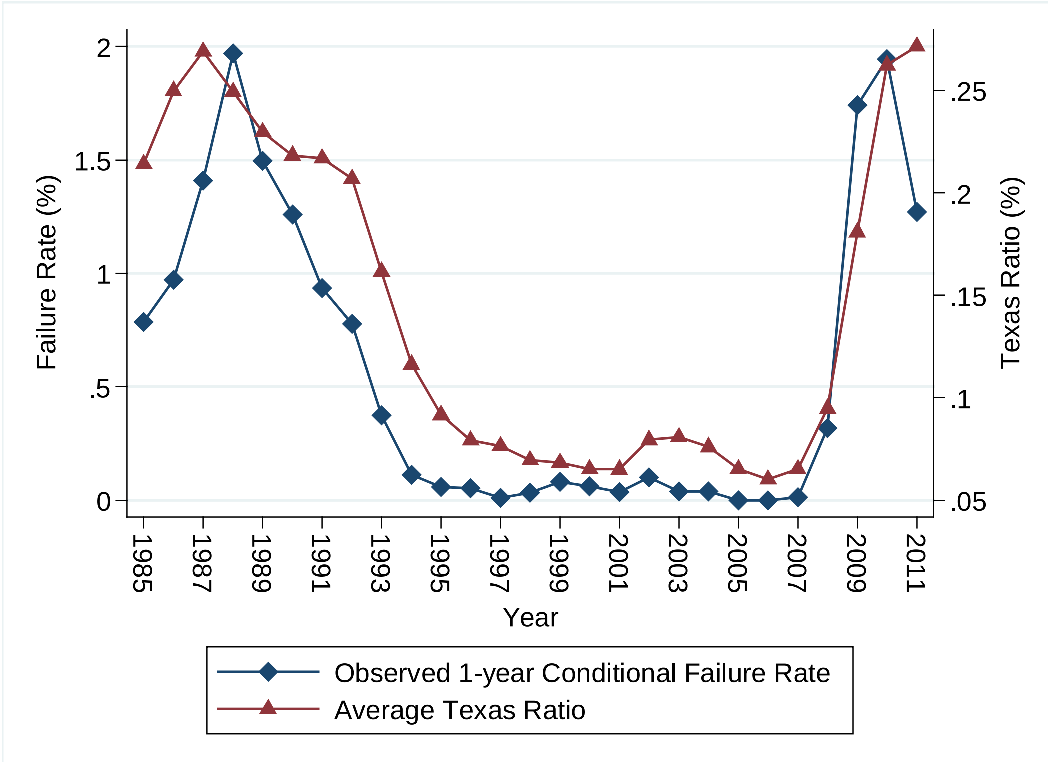

Figure 4. The U.S. banks failure rate and the Texas ratio, 1985-2011. This figure plots the one-year conditional bank failure rate against the average Texas ratio in the preceding year, which shows that the conditional failure rate is highly positively correlated to the average Texas ratio.

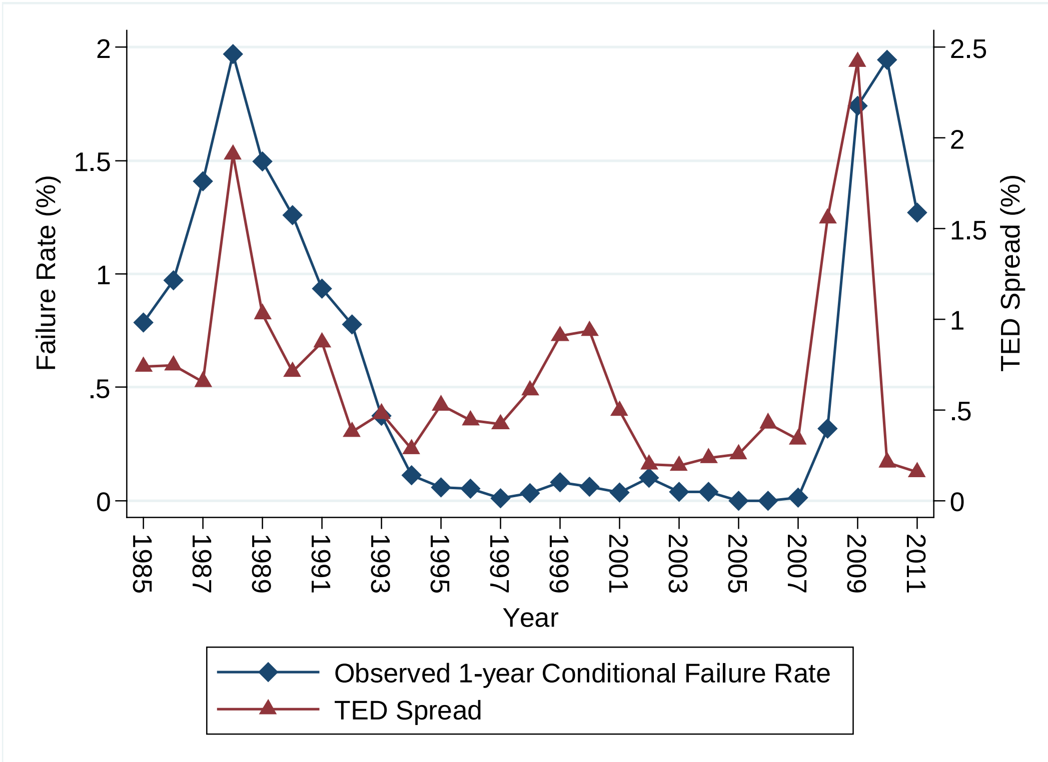

Figure 5. The U.S. banks failure rate and the TED spread, 1985-2011. This figure plots the one-year conditional bank failure rate against the TED spread. It shows that both variables are highly positively correlated, where a rise in the TED spread generally precedes a rise in the bank failure rate.

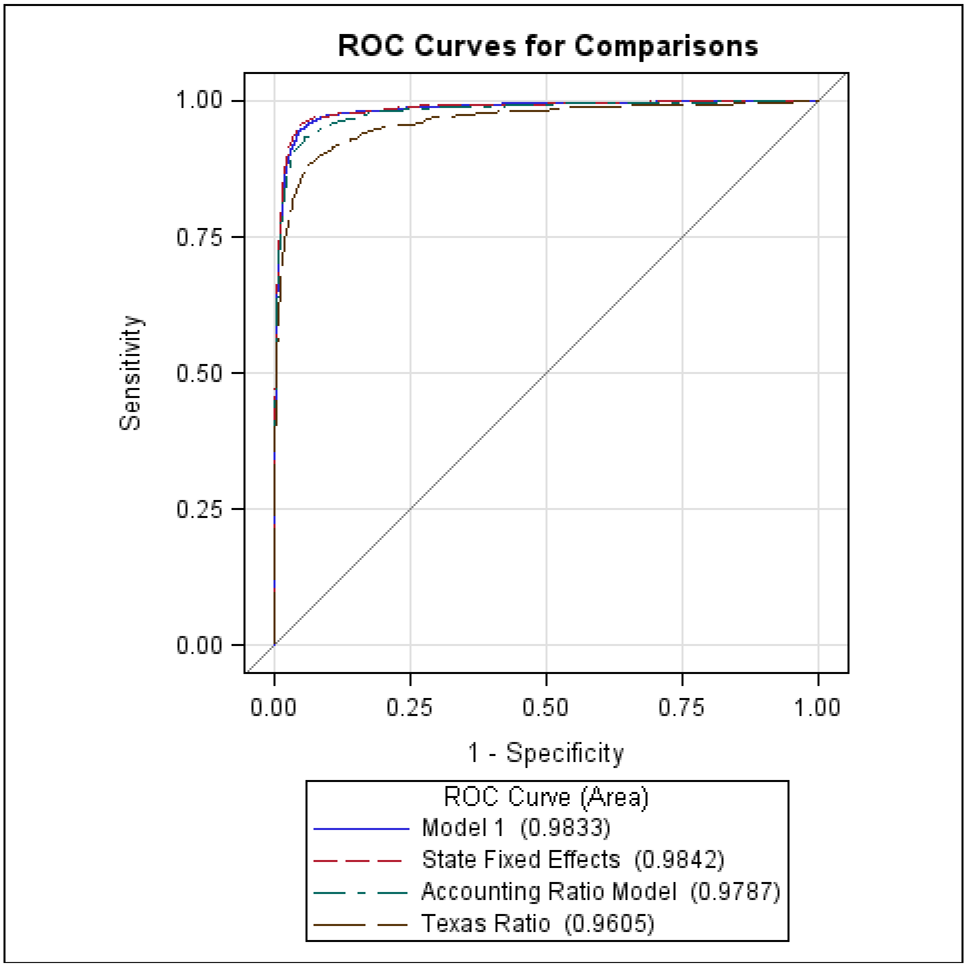

Figure 6. In-sample ROC curves comparisons of Models 1-4 (1985-2004). This figure displays the in-sample ROC curves, which shows that the state fixed effects model (i.e., Model 2) has the highest in-sample AUC statistic.

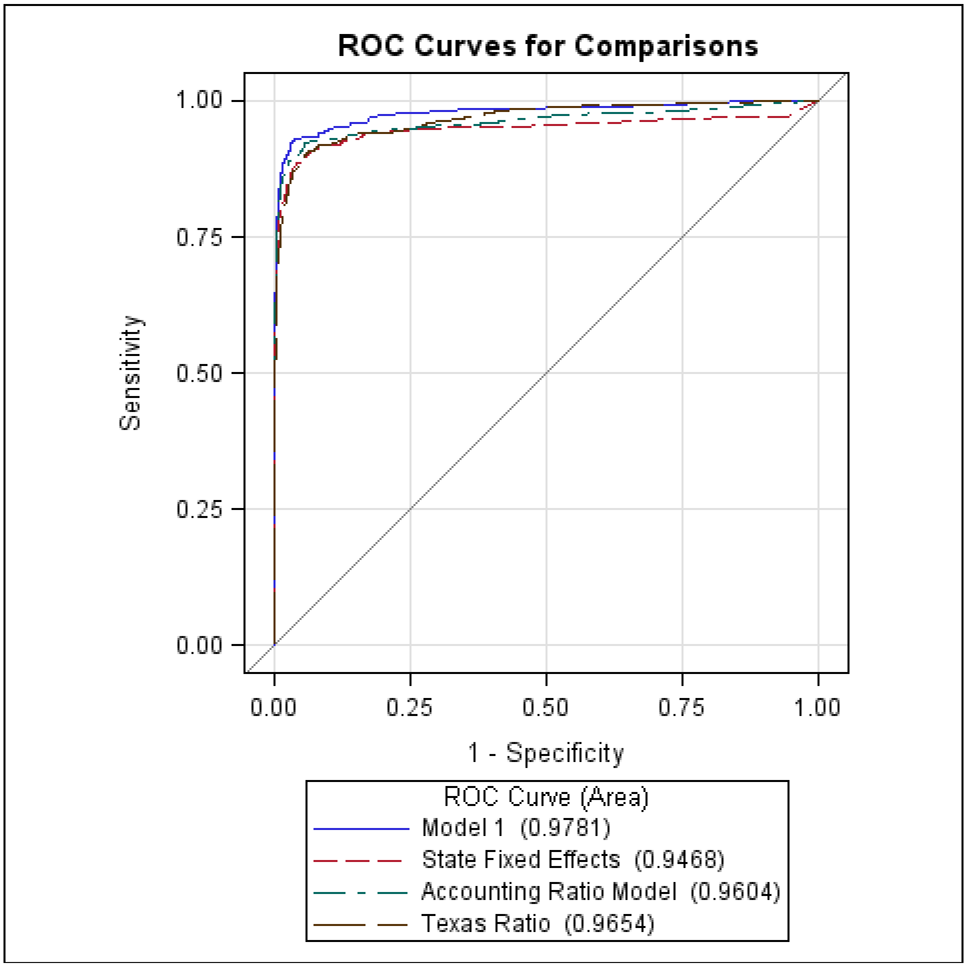

Figure 7. Out-of-sample ROC curves comparisons for models 1-4 (2005-2011). This figure displays the out-of-sample ROC curves, which shows that Model 1 has the highest out-of-sample AUC statistic.

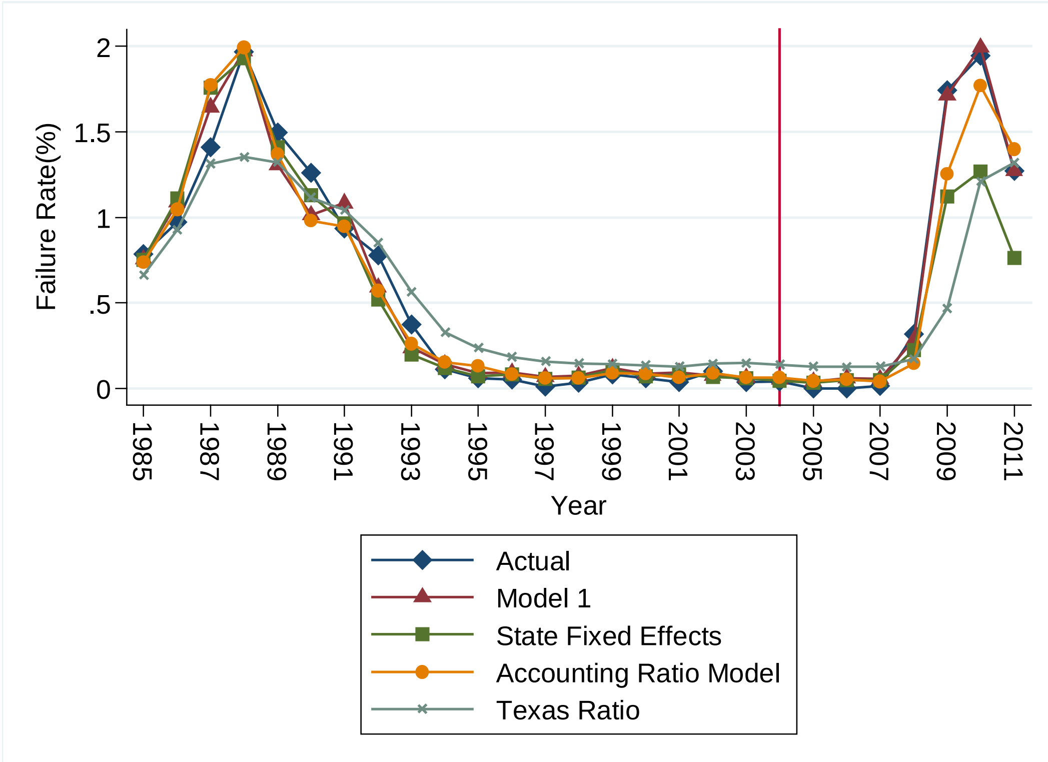

Figure 8. Prediction performances of models 1-4 (in-sample: 1985-2004; out-of-sample: 2005-2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Models 1-4. It shows that the predicted values of Model 1 are more accurate than the predictions from other models.

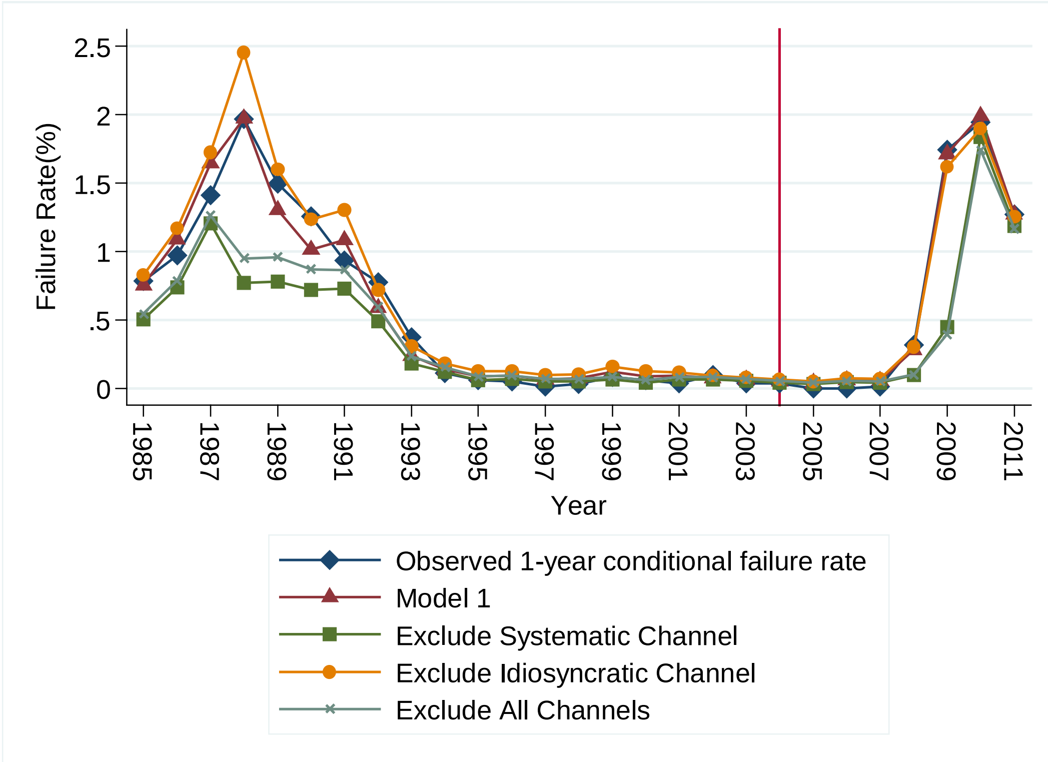

Figure 9. Summary of liquidity risk effects on bank failures (in-sample: 1985-2004, out-of-sample: 2005-2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Models 1, and the predicted values when excluding different liquidity risk channels from Model 1. It shows a significant shift when the systematic liquidity risk channel is excluded.

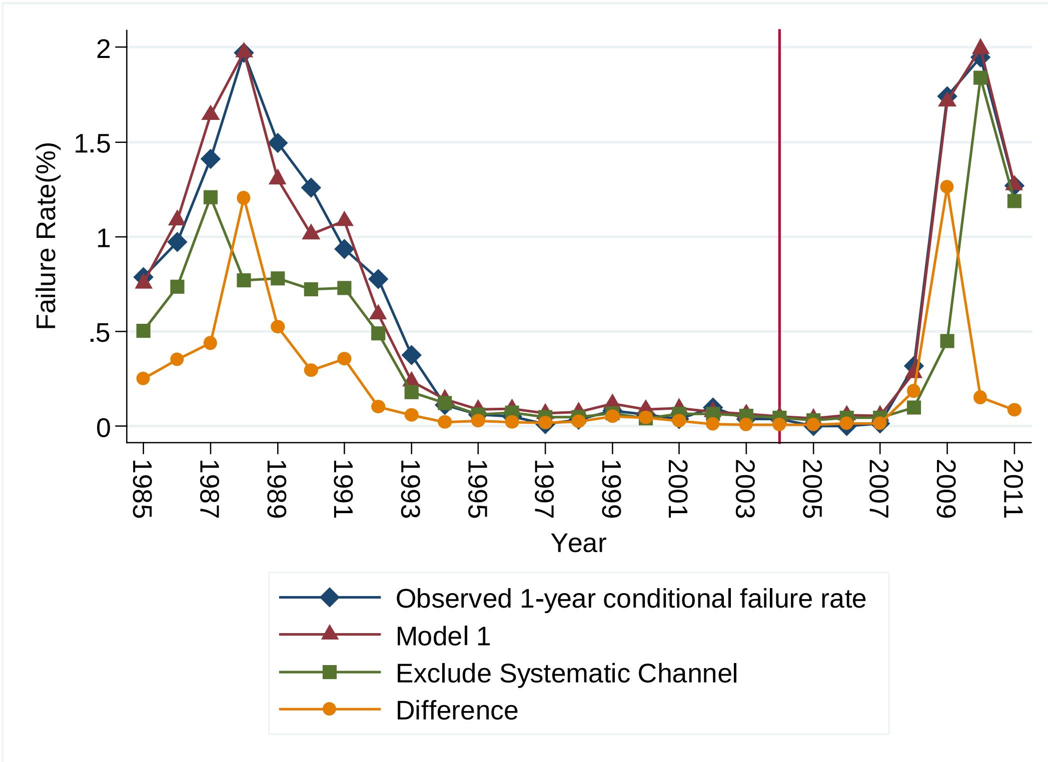

Figure 10. The effects of systematic channel of liquidity risk (in-sample: 1985-2004, out-of-sample: 2005-2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Models 1, and the predicted values when excluding the systematic liquidity risk channel. The differences between the prediction of Model 1 and the prediction without the systematic liquidity risk were large in 1988 and 2009.

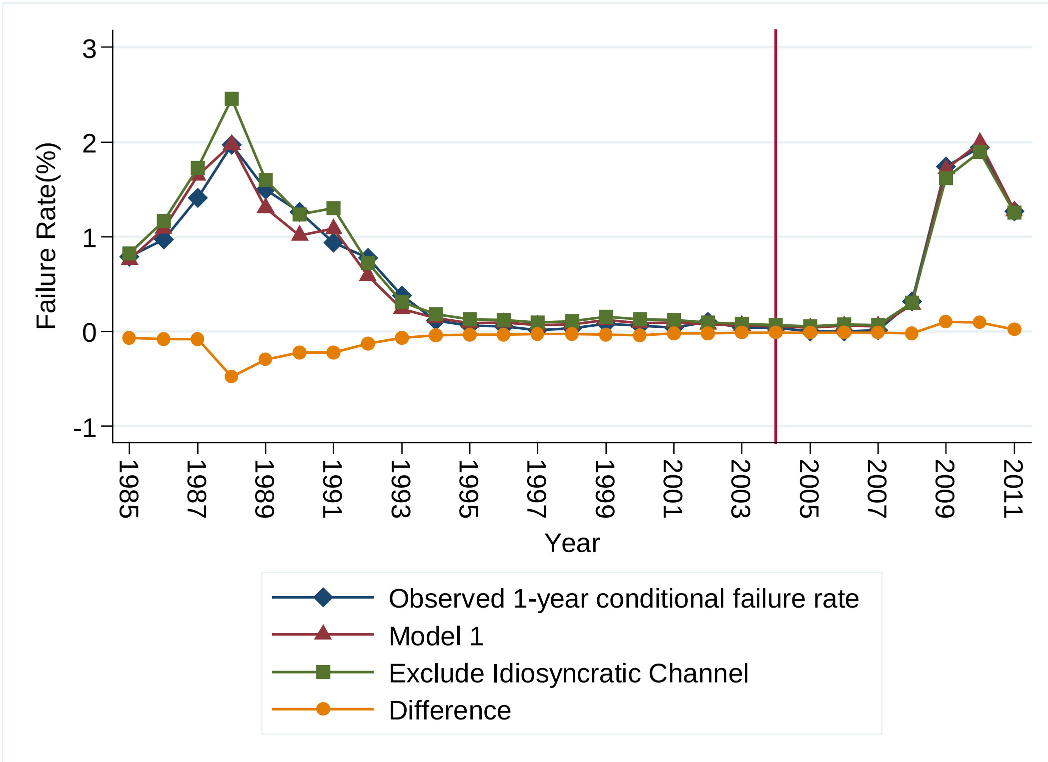

Figure 11. The effects of idiosyncratic channel of liquidity risk (in-sample: 1985-2004, out-of-sample: 2005-2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Models 1, and the predicted values when excluding the idiosyncratic liquidity risk channel. The differences between the prediction of Model 1 and the prediction without the idiosyncratic liquidity risk were generally small.

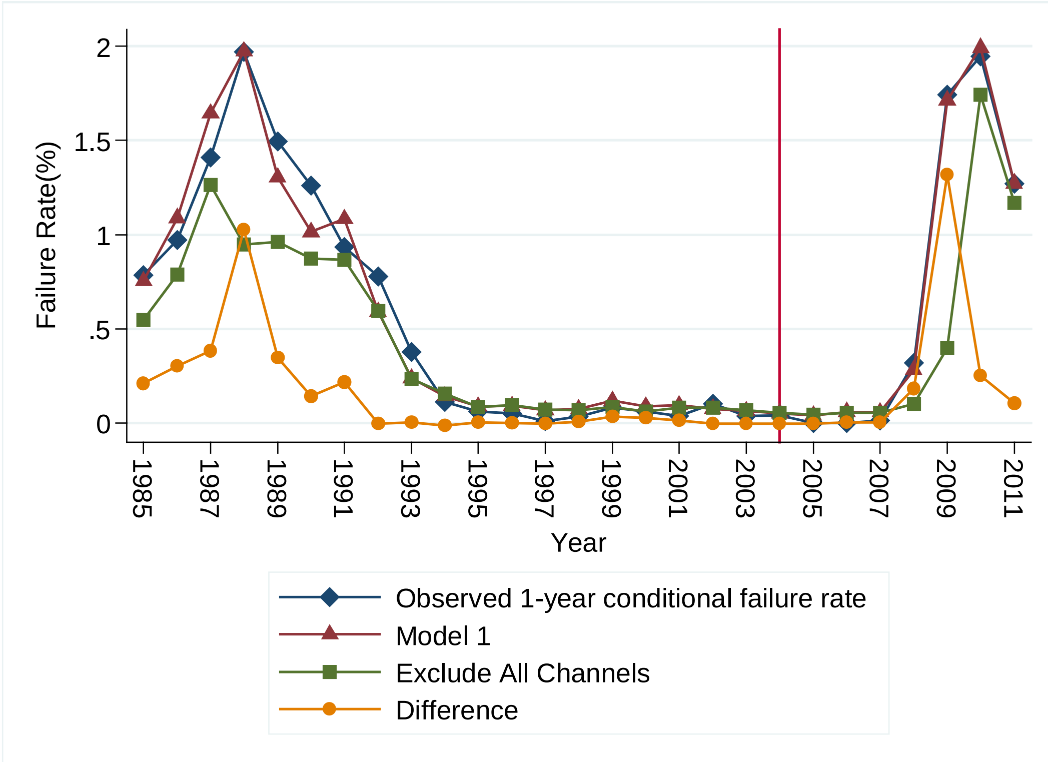

Figure 12. The combined effects of both channels of liquidity risk (in-sample: 1985-2004, out-of-sample: 2005-2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Models 1, and the predicted values when excluding both the systematic and the idiosyncratic channels of liquidity risk. The differences between the prediction of Model 1 and the prediction without liquidity risk were large in 1988 and 2009.