Systemic Funding Liquidity Risk and Bank Failures

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Motivation

- Theoretical literature has underscored the systemic nature of liquidity risk and the important role of contagion in financial crisis
- Recent empirical studies have identified systemic liquidity disruptions in multiple short-term funding markets
- Few empirical bank failure prediction models have directly linked bank failures to both systemic and idiosyncratic liquidity risks.

Research Questions

- We examine the roles of idiosyncratic and systemic funding liquidity risks in bank failures
- We propose a discrete-time hazard model of bank failure with the following features
  - We link the conditional probability of bank failure to insolvency and funding liquidity risks
  - We divide funding liquidity risk into idiosyncratic and systemic funding liquidity risks
  - The systemic funding liquidity risk is measured by the interbank interest rate spread
- We estimate this model using the call report data of U.S. commercial bank

Results and Contributions

- Main results
  - This model outperforms typical bank failure prediction models
  - We find that the systemic funding risk was the major predictor of bank failures in 2008 and 2009
- Main contributions
  - This model allows us to estimate the share of bank failures attributed to insolvency or liquidity risk
  - We are among the first to incorporate the systemic funding liquidity risk into an empirical bank failure prediction model
  - The sample period of our data spans from 1985 through 2011, longer than most existing empirical studies

Related Literature

Related Literature

- Liquidity risk and financial crisis
  - Systemic liquidity risk and financial contagion
  - Liquidity pricing
  - Financial crisis and panics in short-term-debt markets
- Bank failure prediction models
  - Accounting ratio models
  - Structural default models

Liquidity Risk and Financial Crisis: Theories

- Theoretical literature has underscored the systemic nature of liquidity risk and the important role of contagion in financial crisis
  - Diamond and Dybvig (1983)
    - Liquidity risk and bank runs
  - Diamond and Rajan (2001)
    - The inherent link between liquidity creation and financial fragility
  - Diamond and Rajan (2005)
    - How liquidity shortages and solvency problems can reinforce each other, leading to a contagion of bank failures
  - Allen and Gale (2000)
    - Financial fragility and systemic risk
  - Allen, Carletti, and Gale (2009)
    - Divide liquidity risk into idiosyncratic liquidity risk and aggregate liquidity risk

Liquidity Risk and Financial Crisis: Empirical Studies

- Empirical studies have identified systemic liquidity disruptions in multiple short-term funding markets
  - Collapse of the asset-backed commercial paper (ABCP) market in 2007 (Covitz, Liang, and Suarez, 2013)
  - The run on the repurchase agreement market and the shadow banking system (Gorton and Metrick, 2010, 2012b, 2012a)
  - Strains in the interbank market (International Monetary Fund (IMF), 2008, 2010).
  - Berger and Bouwman (2009) have found that banking crises in the United States have been preceded by periods of abnormal liquidity creation .

Bank Failure Prediction Models

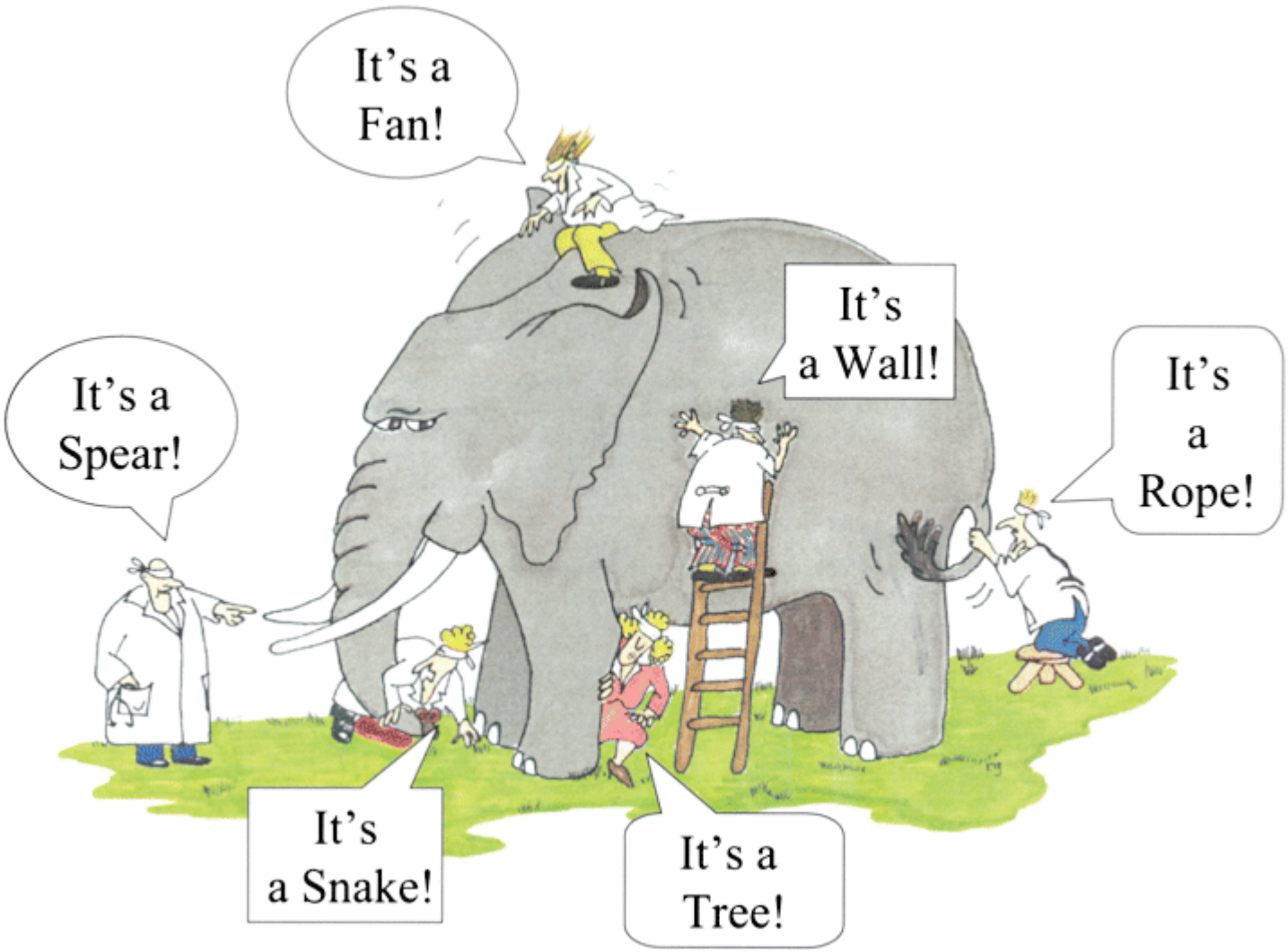
- Accounting ratio models
  - Altman's z-score model (1968), Beaver (1966)
  - Moody's RiskCalc U.S. Bank Model
- Structural default models
  - Contingent claims valuation models proposed by Black and Scholes (1973) and Merton (1974)
  - Successful commercialization by Moody's KMV
- No bank failure prediction models are based on structural default models because most banks do not have public-traded stocks

Recent Studies in Corporate Default Prediction Models

- Bharath and Shumway (2008)
  - Distance-to-default is not a sufficient statistics for default intensity
- Duffie and Lando (2001)
  - When there is measurement error in distance-to-default, other covariates can help predict default intensity
- Duffie, Saita, and Wang (2007)
  - Four explanatory variables: the firm's distance to default, the firm's trailing one-year stock return, the three-month Treasury bill rate, and the trailing one-year return on the S&P 500 index
- Das, Duffie, Kapadia, Saita (2007)
  - Defaults are correlated, reject doublly stochastic assumption
- Duffie, Eckner, Horel, Saita (2009)
  - Frailty Correlated Default: resorted to an unobservable frailty factor

Modeling Methodology

The Blind Economists and an Elephant



Pitfalls in Econometric Modeling

- The Lucas critique (1976)
  - Reduced-form models are problematic
  - Finding the "correct" underlying structural model is an elusive task that few economists have ever achieved
  - In reality, all econometric models are reduced-form models
    - Including models with "micro-foundation"
    - All models need to be simplified to be useful
- The pragmatic approach
  - Box and Draper (1987): "Essentially, all models are wrong, but some are useful. However, the approximate nature of the model must always be borne in mind."
  - Friedman (1953): Models should be judged by their ability to predict events rather than by the realism of their assumptions

Modeling Methodology

- A discrete-time hazard model of bank failure
  - The log hazard consists of an insolvency risk component and a liquidity risk component
  - The liquidity risk component consists of an idiosyncratic component and a systemic component
  - The insolvency risk component depends on equity value
    - Combine two estimates of equity value to improve prediction: Market value and book value of equity
    - Forecast combination improve the prediction: Bates and Granger (1969), Granger and Ramanathan (1984)

Model Derivation

- Log-hazard (log of default intensity) is a function of two latent variables: the insolvency condition (U) and the liquidity condition (V)

$$h_{i,t+1} = \log(\lambda_{i,t+1}) = U_{i,t+1} + V_{i,t+1} \ ,$$

$$\widehat{V}i,t+1 = b_0 + b_1 Gov_Sec_R_{i,t} + b_2 Brokered_Deposits_R_{i,t} + b_3 TED_t \ ,$$

$$U_{i,t+1} = \frac{E_{i,t+1}}{TCE_{i,t} + ALLL_{i,t}} \ ,$$

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

The Final Econometric Model

$$\hat{h}_{i,t+1} = \beta_0 + \beta_1 Market_Valuation_Ratio_{i,t} + \beta_2 Intangible_Capital_Ratio_{i,t}$$
$$+\beta_3 Loan_Interest_Ratio_{i,t} + \beta_4 Security_Interest_Ratio_{i,t} + \beta_5 Interest_Expense_Ratio_{i,t}$$
$$+\beta_6 Net_Noninterest_Ratio_{i,t} + \beta_7 Texas_Ratio_{i,t} + \beta_8 HPI_Effects_{i,t}$$
$$+\beta_9 Unemployment_Effects_{i,t} + \beta_{10} Gov_Sec_R_{i,t} + \beta_{11} Brokered_Deposit_R_{i,t} + \beta_{12} Ted_t \ .$$

Panel A: Explanatory variables in Eq. (17)

Name	Math notation	Description
Market valuation ratio	$Market_Valuation_Ratio_{i,t}$	The product of the effective leverage ratio and the market-discounted ROA ratio
Intangible capital ratio	$Intangible_Capital_Ratio_{i,t}$	Intangible capital divided by effective capital
Loan interest ratio	$Loan_Interest_Ratio_{i,t}$	Loan interest income divided by effective capital
Security interest ratio	$Security_Interest_Ratio_{i,t}$	Security interest income divided by effective capital
Interest expense ratio	$Interest_Expense_Ratio_{i,t}$	Total interest expenses divided by effective capital
Net noninterest income ratio	$Net_Noninterest_Ratio_{i,t}$	Net noninterest income divided by effective capital
Texas ratio	$Texas_Ratio_{i,t}$	Non-performing assets divided by effective capital
HPI effects	$HPI_Effects_{i,t}$	Texas ratio multiplied by the change in state-level housing price index (HPI)
Unemployment effects	$Unemployment_Effects_{i,t}$	Texas ratio multiplied by the change in state-level unemployment ratio
Government securities ratio	$Gov_Sec_R_{i,t}$	Government securities to total assets ratio
Brokered deposits ratio	$Brokered_Deposit_R_{i,t}$	Brokered deposits to total assets ratio
TED spread	TED_t	Spread of the three-month LIBOR over the three-month Treasury rate

Empirical Results

Data

- Data source
  - Income statement and balance sheet data of U.S. commercial banks (e.g., call report) between 1984 and 2011
  - Bank failure data since 1985 from the Federal Deposit Insurance Corporation (FDIC)
- Bank failure definition: All categories of failure and assistance transactions
  - Assistance transactions
  - Purchase and assumption transactions
  - Payoff transactions
- Sample design
  - Estimation sample: 1984-2004, validation sample: 2005-2011

Table 2
Sample description

This table summarizes the sample size and the number of failed banks 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.

Sample	Period	Failed banks	Total observations (bank year)
Estimation sample	1985–2004	1,349	221,327
Validation sample	2005–2011	368	51,871
All	1985–2001	1,717	273,198

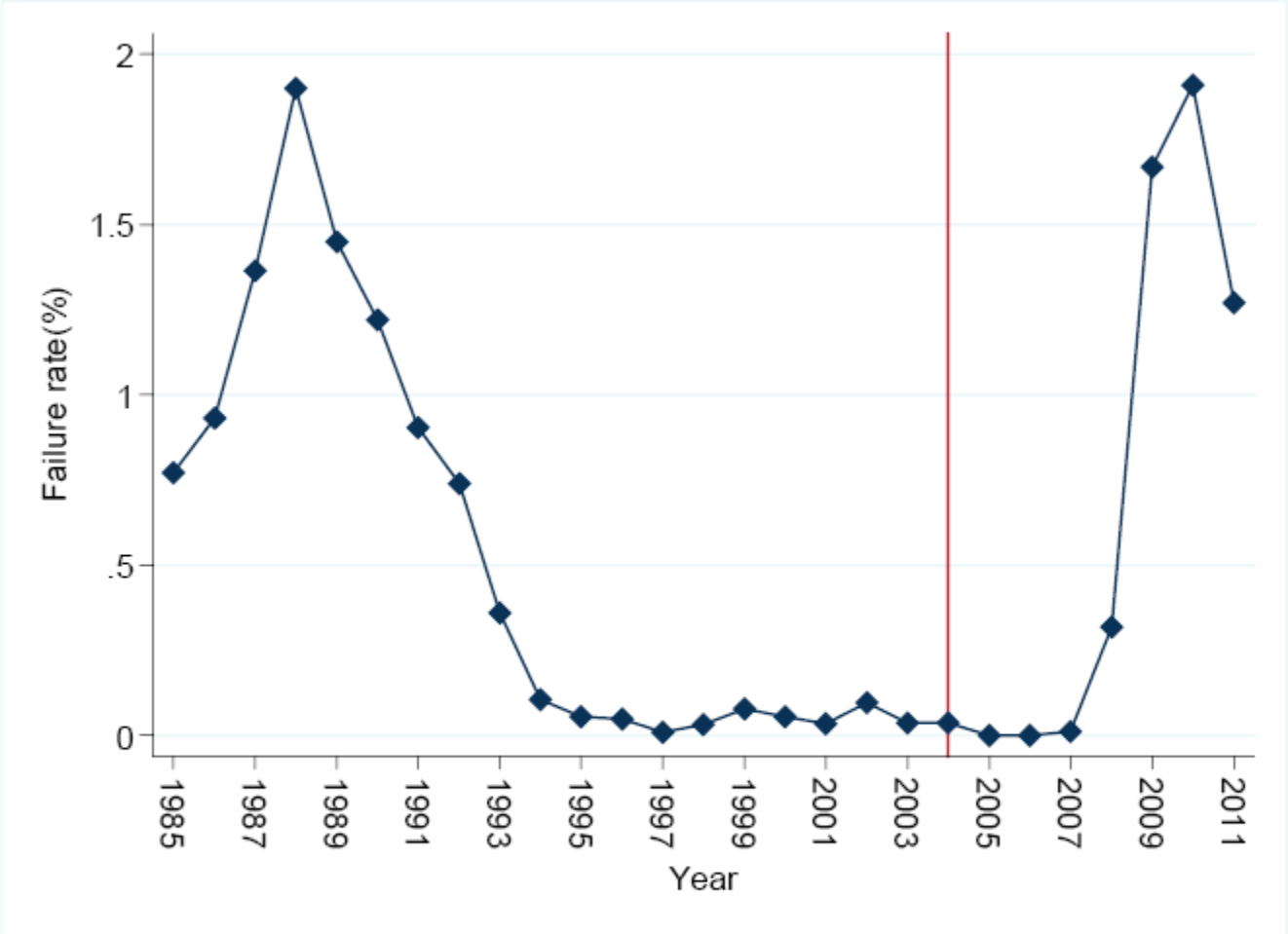


Fig. 1. The failure rate of U.S. commercial banks, 1985–2011. The U.S. bank failure rate peaked in 1988 and 2010. The former was linked to the savings and loan crisis of the 1980s and 1990s, while the latter was associated with the financial crisis of 2007–2009.

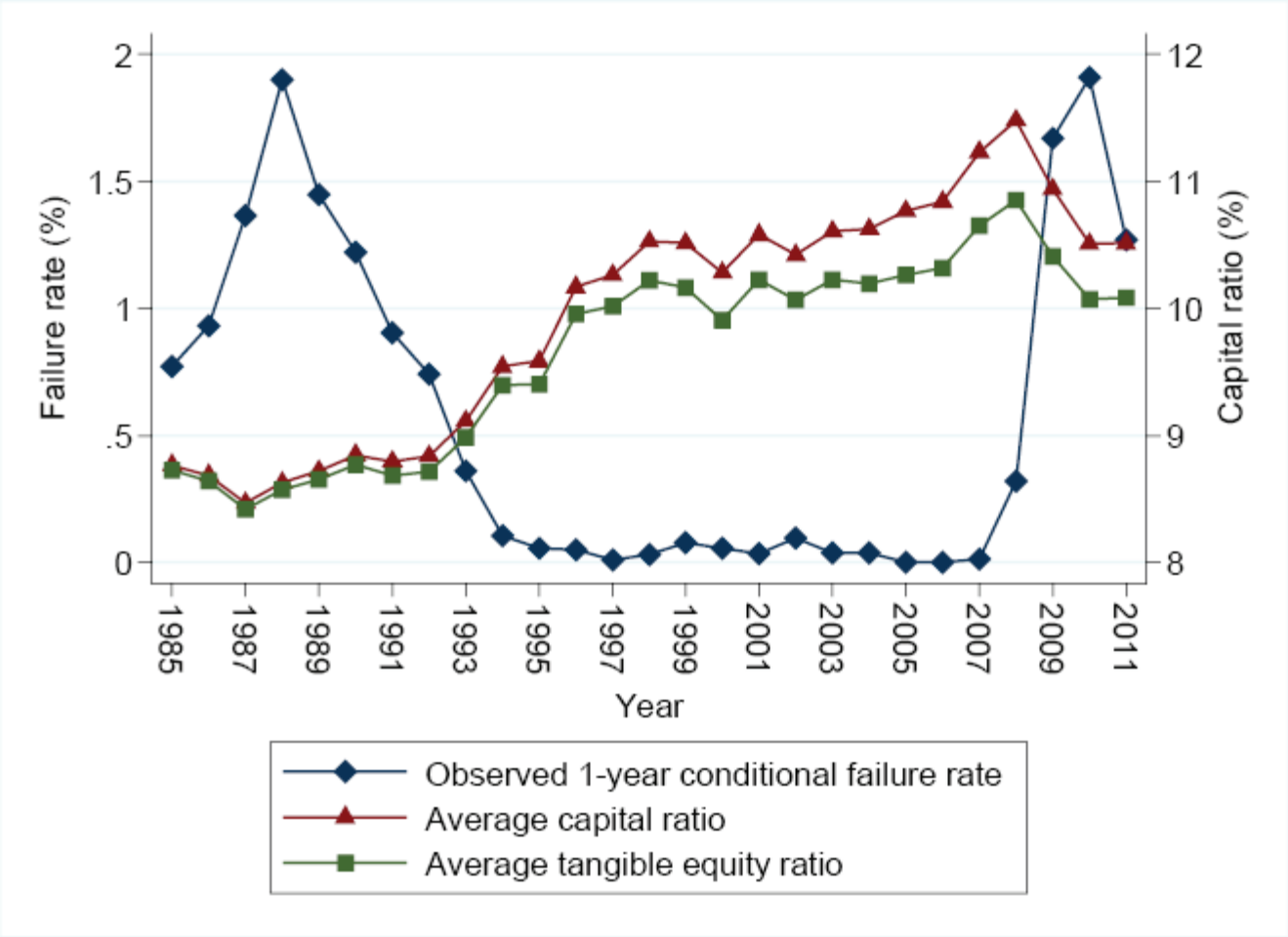


Fig. 2. The capital ratios and the failure rate of U.S. commercial banks, 1985–2011. This figure plots the one-year conditional bank failure rate against the average capital ratio and the average tangible capital ratio in the previous year. It shows that both ratios peaked in 2007, the year when the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

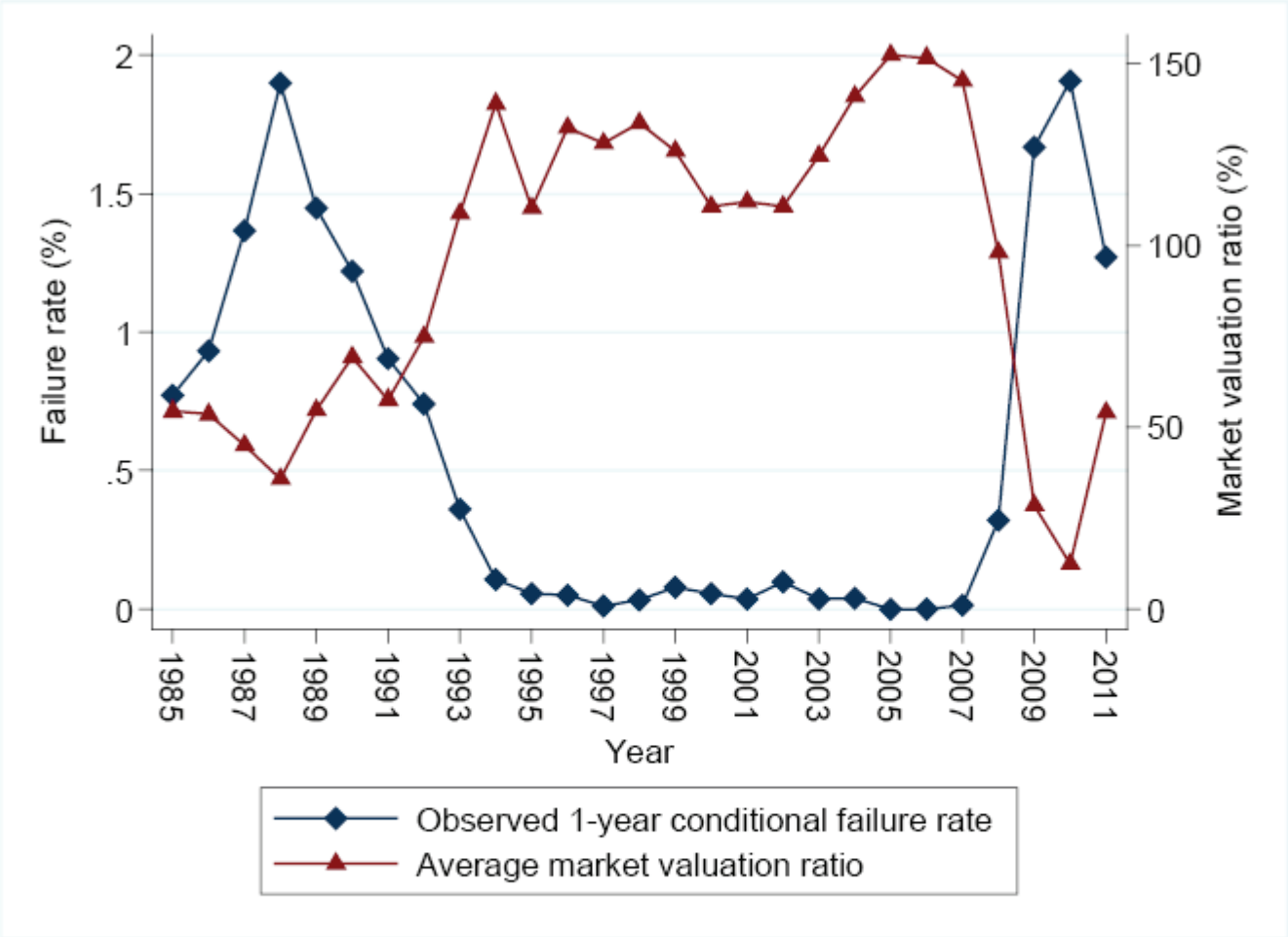


Fig. 3. The market value ratio and the failure rate of U.S. commercial banks, 1985–2011. This figure plots the one-year conditional bank failure rate against the average market valuation ratio in the previous year. It shows that the failure rate is inversely correlated to the average market valuation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

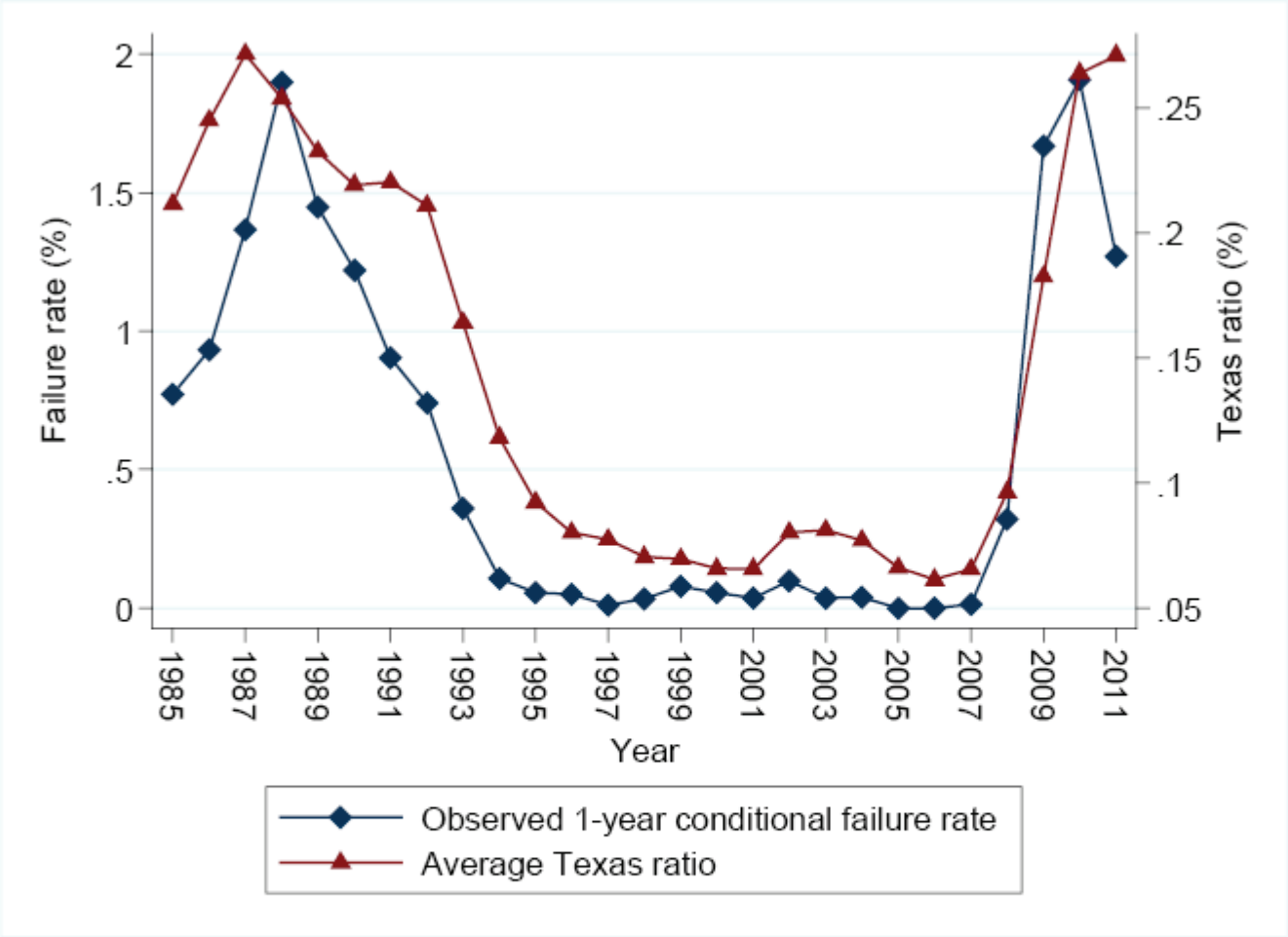


Fig. 4. The Texas ratio and the failure rate of U.S. commercial banks, 1985–2011. This figure plots the one-year conditional bank failure rate against the average Texas ratio in the preceding year, which shows that the conditional failure rate is highly positively correlated to the average Texas ratio.

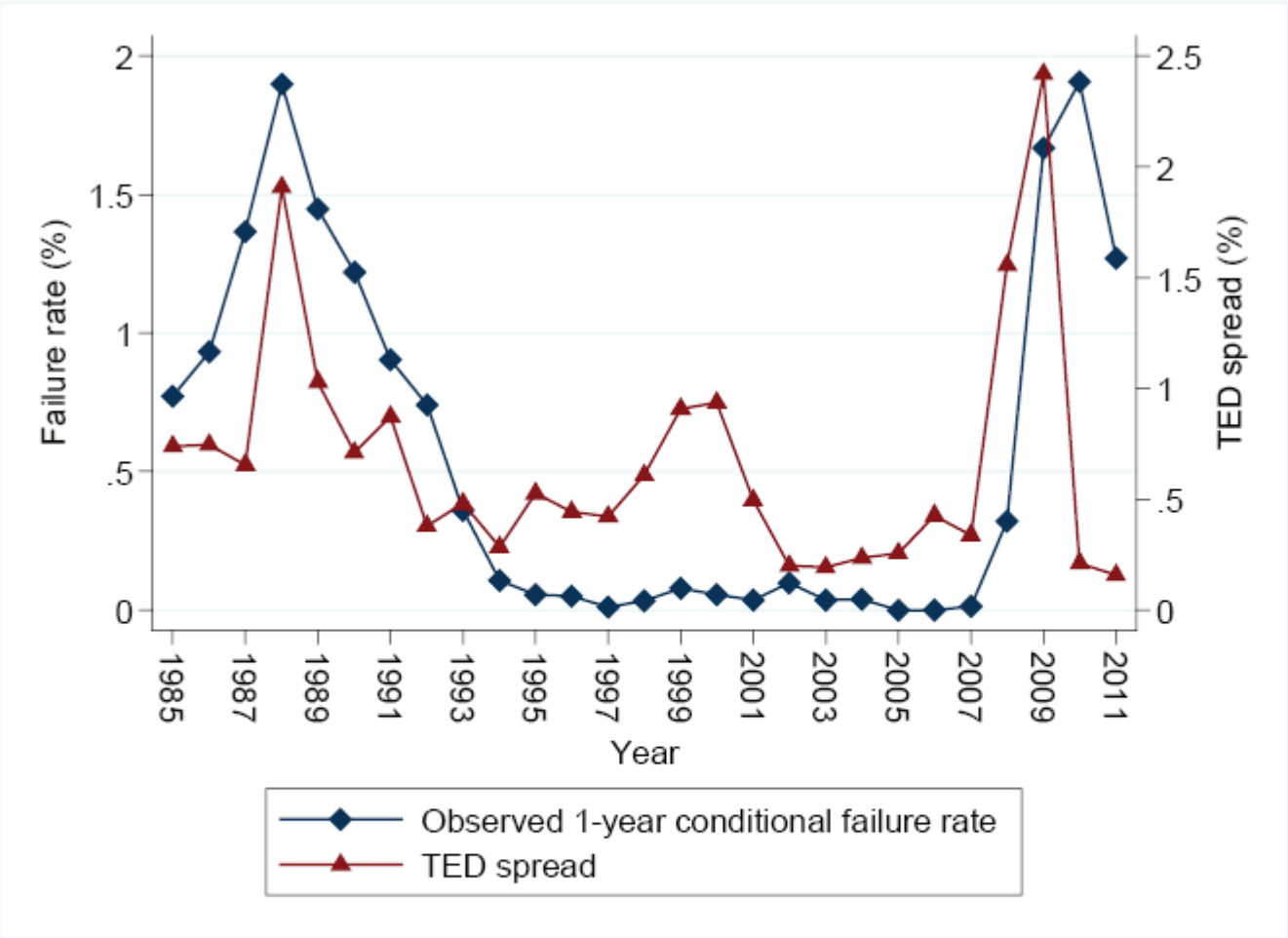


Fig. 5. The Ted spread and the failure rate of U.S. commercial banks, 1985–2011. This figure plots the one-year conditional bank failure rate against the TED spread in the preceding year. It shows that a rise in the TED spread generally precedes a rise in the bank failure rate.

Table 3

Estimation results for Models 1–4

Panel A reports in-sample (1985–2004) and out-of-sample performance statistics for Models 1-4 using annual data. Panel B reports parameter estimates for Models 1–4 on the annual data sample from 1985 to 2004. *, **, and *** indicates statistical significance at the 10%, 5%, and 1% level, respectively.

Model 1 is based on the log-hazard model specified in Eq. (17):

$$\hat{h}_{i,t+1} = E\left(h_{i,t+1} \middle| t\right) = \beta_0 + \beta_1 Market_Valuation_Ratio_{i,t} + \beta_2 Intangible_Capital_Ratio_{i,t}$$
$$+\beta_3 Loan_Interest_Ratio_{i,t} + \beta_4 Security_Interest_Ratio_{i,t} + \beta_5 Interest_Expense_Ratio_{i,t}$$
$$+\beta_6 Net_Noninterest_Ratio_{i,t} + \beta_7 Texas_Ratio_{i,t} + \beta_8 HPI_Effects_{i,t} + \beta_9 Unemployment_Effects_{i,t}$$
$$+\beta_{10} Gov_Sec_R_{i,t} + \beta_{11} Brokered_Deposit_R_{i,t} + \beta_{12} Ted_t \ .$$

Model 2 is Model 1 plus state fixed effects. Model 3 is an accounting-ratio model that includes all financial statement variables used in the Moody's RiskCalc™ U.S. banks model. Model 4 uses the Texas ratio as the only explanatory variable.

Panel A: Performance statistic

	Model 1	Model 2: State fixed effects model	Model 3: Accounting-ratio model	Model 4: Texas ratio model
Model statistics				
Observations	221,327	220,878	221,327	221,327
Pseudo R^2	0.546	0.561	0.538	0.443
AIC	7,487.785	7,337.796	7,626.925	9,168.523
BIC	7,621.781	7,976.729	7,729.999	9,189.138
Log likelihood	-3,730.892	-3,606.898	-3,803.462	-4,582.261
In-sample performance (1985–2004)				
AUC statistic	0.983	0.984	0.977	0.960
Accuracy ratio	0.966	0.968	0.954	0.920
HL statistic	81.841	54.029	144.339	114.990
HL P-value	0.000	0.000	0.000	0.000
Brier score*1000	4.391	4.308	4.337	4.911
Out-of-sample performance (2005–2011)				
AUC statistic	0.979	0.952	0.961	0.971
Accuracy ratio	0.958	0.904	0.922	0.942
HL statistic	18.274	118.939	4731.154	179.004
HL P-value	0.051	0.000	0.000	0.000
Brier score*1000	4.051	4.635	4.463	5.114

Panel B: Parameter estimates for Models 1–4

	Model 1	Model 2	Model 3	Model 4
Constant	-7.362***	-6.440***	3.481***	-7.029***
	[0.142]	[0.342]	[0.478]	[0.054]
Market valuation ratio	-0.504***	-0.499***		
	[0.024]	[0.025]		
Intangible capital ratio	-0.374	-0.182		
	[0.323]	[0.281]		
Loan interest ratio	-0.461***	-0.250		
	[0.163]	[0.171]		
Security interest ratio	-2.275***	-2.027***		
	[0.330]	[0.340]		
Interest expense ratio	2.391***	2.321***		
	[0.208]	[0.221]		
Net noninterest income ratio	0.189	0.308		
	[0.219]	[0.225]		
Texas ratio	1.820***	1.703***		3.626***
	[0.073]	[0.074]		[0.055]
HPI effects	-1.978***	-0.085		
	[0.703]	[0.826]		
Unemployment effects	3.347	2.457		
	[2.858]	[3.034]		
Government securities ratio	-2.937***	-2.955***	-4.317***	
	[0.457]	[0.445]	[0.347]	
Brokered deposits ratio	3.155***	4.546***		
	[1.108]	[1.192]		
TED spread	75.353***	69.162***		
	[9.626]	[10.568]		
Capital ratio			-74.968***	
			[3.464]	
Return on assets			-45.804***	
			[2.301]	
Net interest margin			-27.143***	
			[3.819]	
Loan mix			0.572***	
			[0.182]	
OREO ratio			24.927***	
			[1.944]	
Size			-0.271***	
			[0.034]	
Consumer loan charge-off ratio			-22.645	
			[67.917]	
Commercial loan charge-off ratio			115.595***	
			[32.067]	

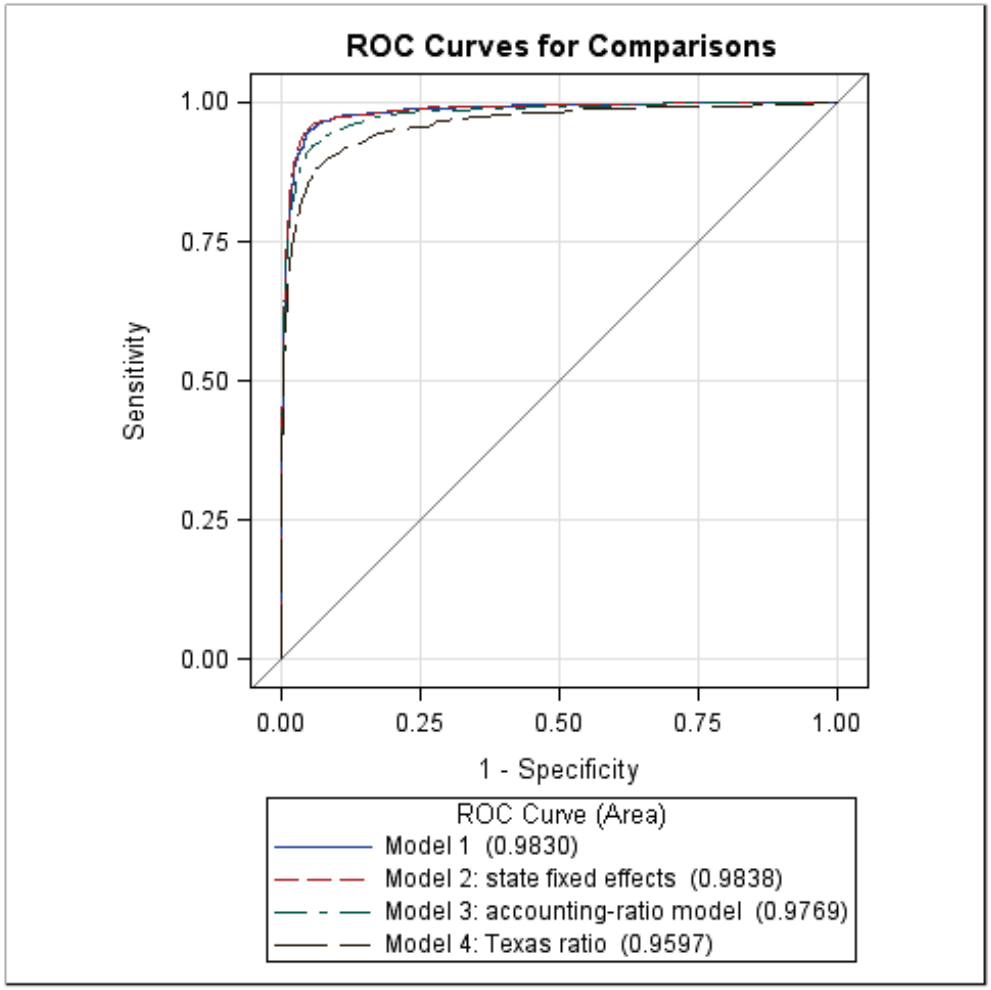


Fig. 6. In-sample ROC curves comparisons of Models 1–4 (In-sample: 1985–2004). The estimation sample covers the period of 1985–2004, and contains 221,327 observations (bank year) and 1,349 failed banks. Model 1 is based on Eq. (17). Model 2 is Model 1 plus state fixed effects. Model 3 is an accounting-ratio model that includes all financial statement variables used in the Moody's RiskCalc™ U.S. banks model. Model 4 uses the Texas ratio as the only explanatory variable. The state fixed effects model (i.e., Model 2) has the highest in-sample AUC statistic.

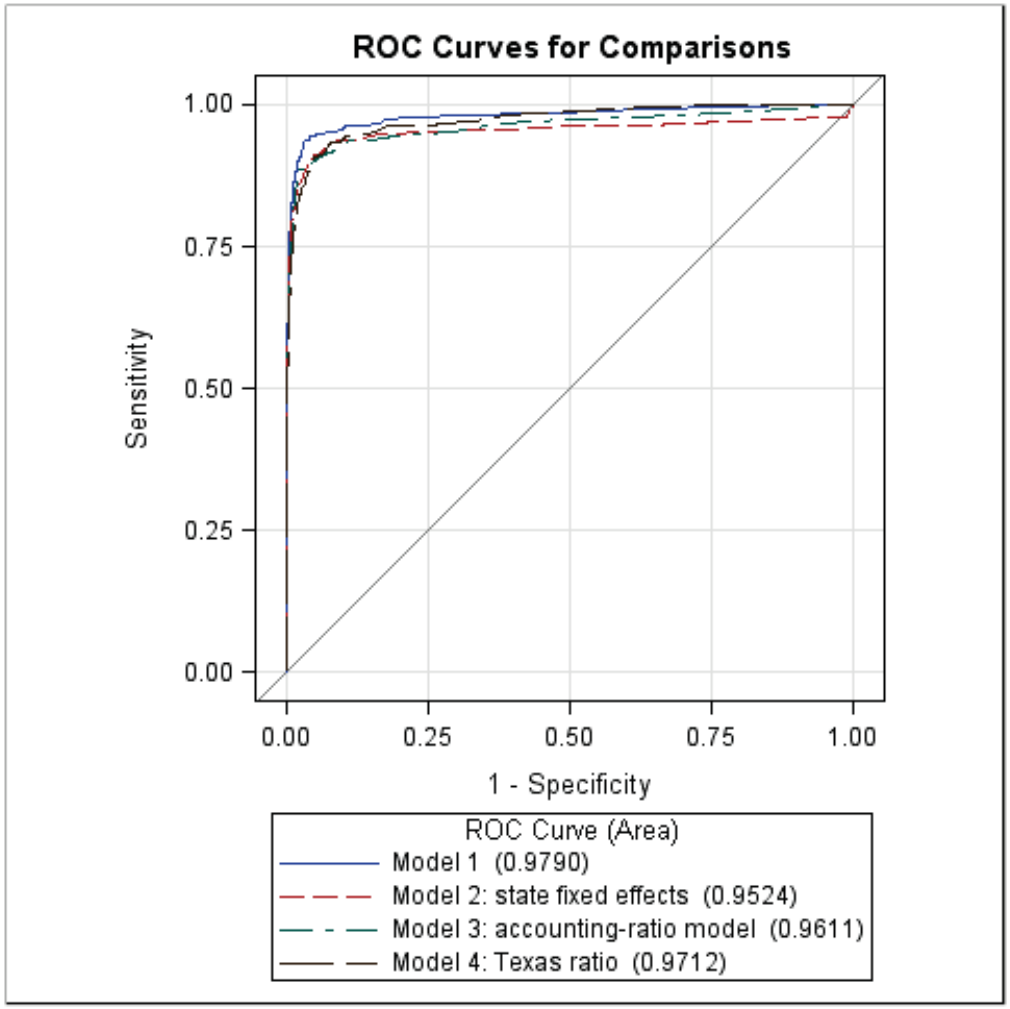


Fig. 7. Out-of-sample ROC curves comparisons for models 1–4 (Out-of-sample: 2005–2011). The validation sample covers the period of 2005–2011, and contains 51,871 observations and 368 failed banks. Model 1 is based on Eq. (17). Model 2 is Model 1 plus state fixed effects. Model 3 is an accounting-ratio model that includes all financial statement variables used in the Moody's RiskCalc™ U.S. banks model. Model 4 uses the Texas ratio as the only explanatory variable. Model 1 has the highest out-of-sample AUC statistic.

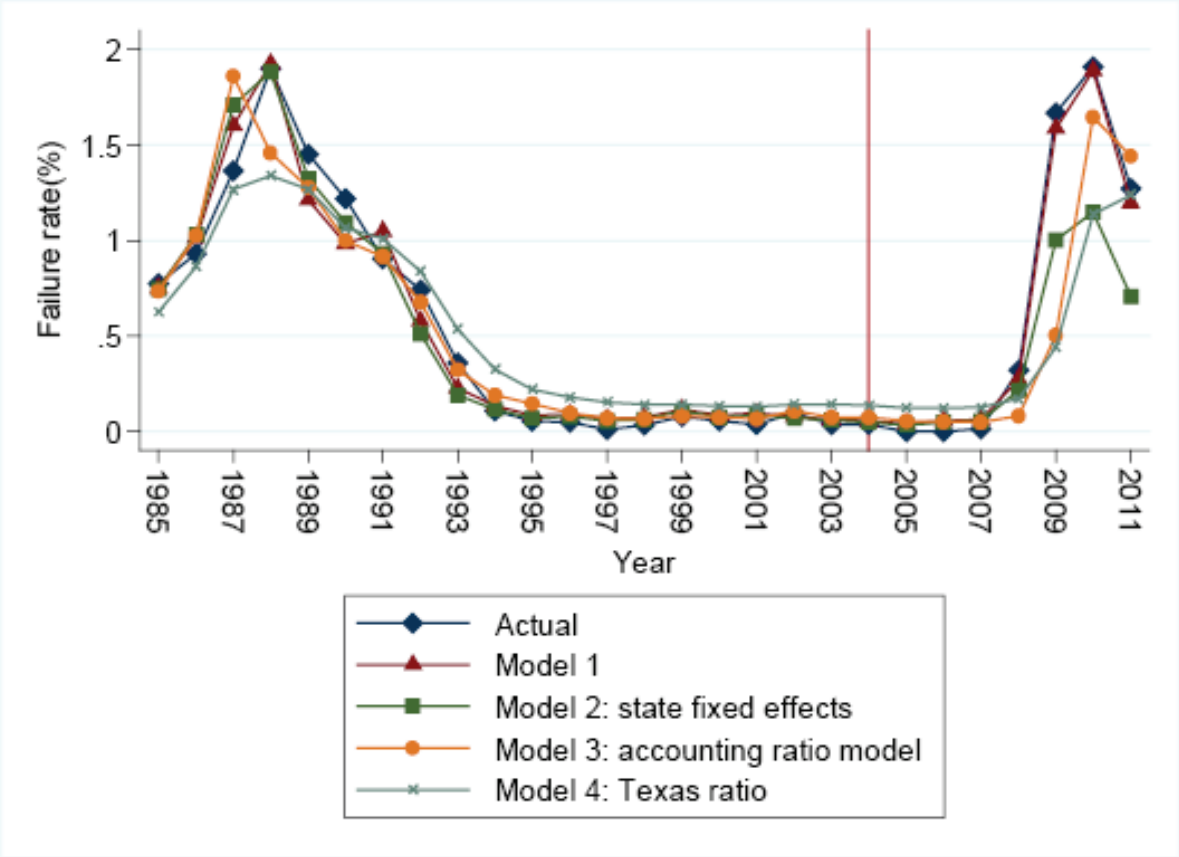


Fig. 8. Prediction performances of Models 1–4 (in-sample: 1985–2004; out-of-sample: 2005–2011). The estimation sample covers the period of 1985-2004, and contains 221,327 observations (bank year) and 1,349 failed banks. The validation sample covers the period of 2005–2011, and contains 51,871 observations and 368 failed banks. This figure plots the actual one-year conditional bank failure rate against the predictions from Models 1-4. Model 1 is based on Eq. (17). Model 2 is Model 1 plus state fixed effects. Model 3 is an accounting-ratio model that includes all financial statement variables used in the Moody's RiskCalc™ U.S. banks model. Model 4 uses the Texas ratio as the only explanatory variable. The out-of-sample predictions of Model 1 are more accurate than predictions from other models.

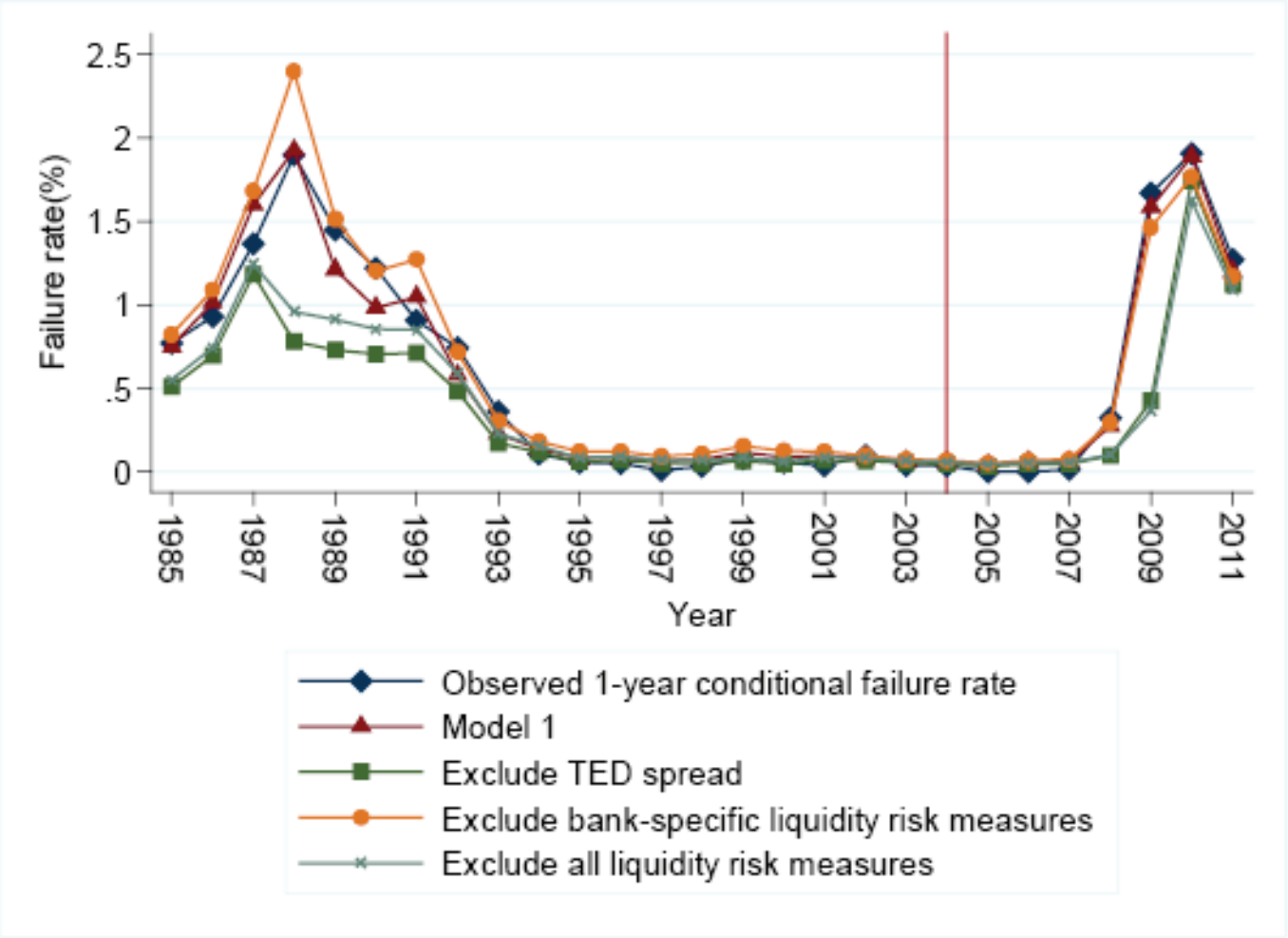


Fig. 9. Summary of liquidity risk effects on bank failures (in-sample: 1985–2004, out-of-sample: 2005–2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Model 1, and the predictions when excluding different funding liquidity risk measures from Model 1. The TED spread is a measure of systemic funding liquidity risk. It shows a significant shift when the TED spread is excluded.

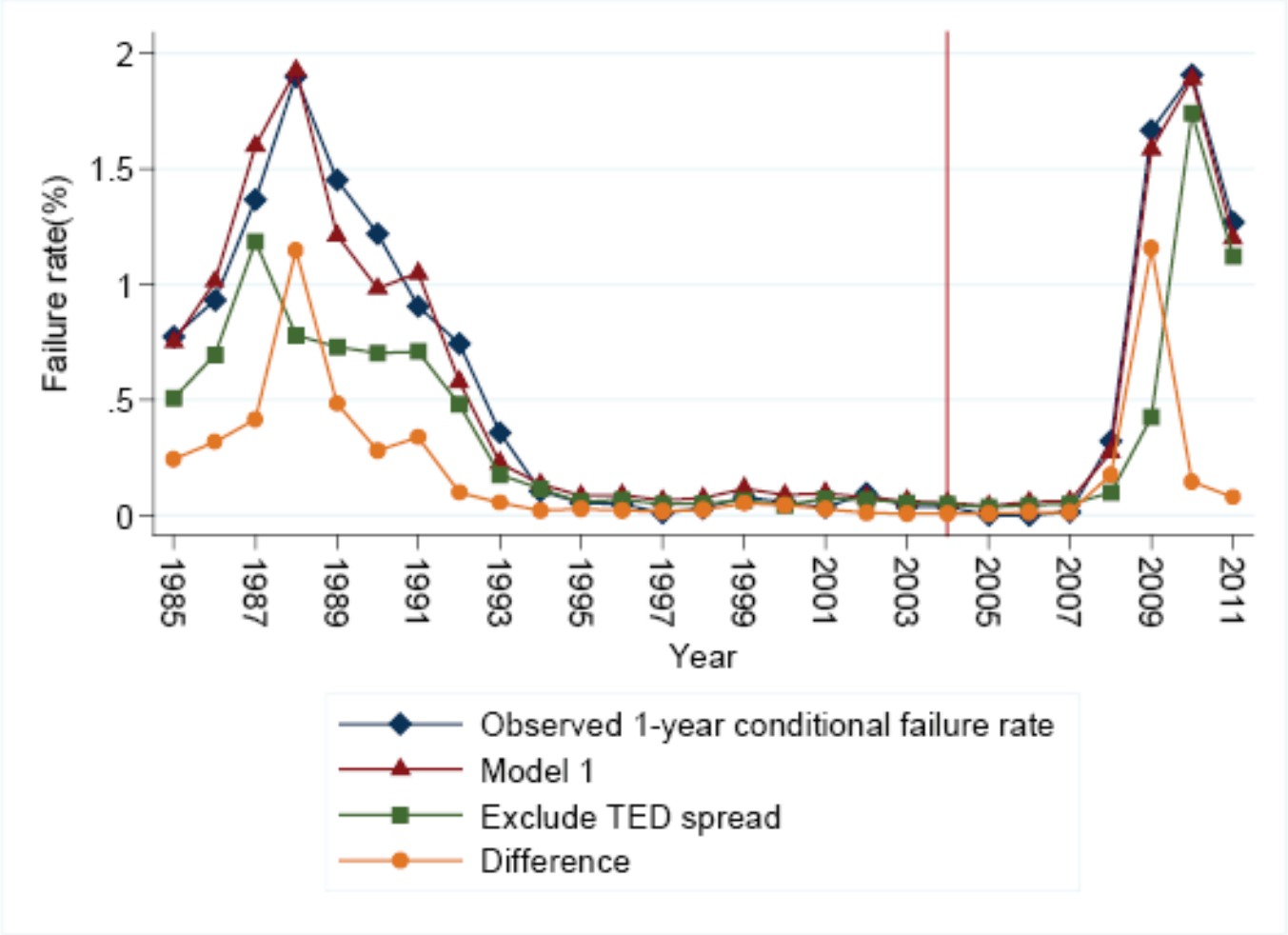


Fig. 10. The effects of systemic funding liquidity risk (in-sample: 1985–2004, out-of-sample: 2005–2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Model 1, and the predictions when excluding the TED spread. The TED spread is a measure of systemic funding liquidity risk. The differences between the predictions of Model 1 and the predictions without the TED spread were large in 1988 and 2009.

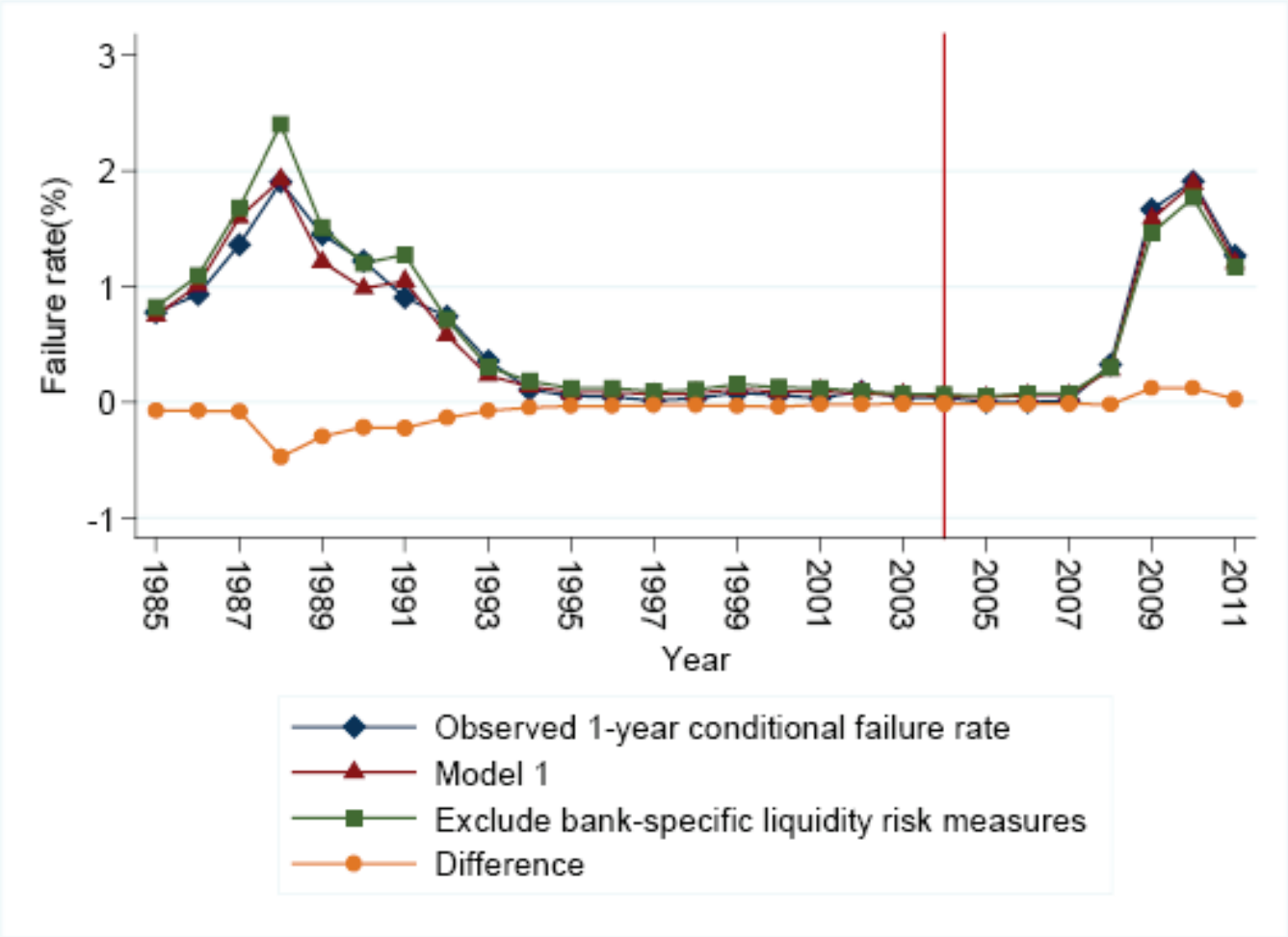


Fig. 11. The effects of bank-specific funding liquidity risk (in-sample: 1985–2004, out-of-sample: 2005–2011). This figure plots the actual one-year conditional bank failure rate against the predicted values from Models 1, and the predictions when excluding the bank-specific funding liquidity risk measures.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

Conclusions

- Our model outperforms typical bank failure prediction models
  - Link bank failures to both idiosyncratic and systemic liquidity risk
  - Combine market value accounting and book value accounting to improve the estimation of equity value
- We find that the systemic funding risk was the major predictor of bank failures in 2008 and 2009

The End