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ABSTRACT: Motivated by the debate over similarities between the current and previous financial crises, logit estimates reveal significantly changed linkages between observable financial ratios and probabilities of subsequent bank failure using U.S. data from the 1980s and 2008.

Keywords: bank failure; regime shift; crisis

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1. Introduction

The recent financial crisis has stirred controversy over whether fundamental risks in the banking industry have changed. While some observers point to financial innovation and unprecedented complexity of mortgage-based derivatives (such as synthetic CDOs) as contributing to the crisis, others note strong historical parallels in pre-crisis macroeconomic patterns.[1]

Bank regulators, lacking authority over aggregate price and output indicators, are constrained to focus on within-bank indicators in promoting stability. Accordingly, it is useful – as a complement to other directions of research – to explore whether observable linkages between traditional banking risk ratios and the probability of failure are different now than in earlier crises. This note does so, comparing estimates of a standard logit model of U.S. bank failure using current data versus data from the previous peak of bank failures 20 years ago.[2] I find statistically and economically meaningful shifts, lending support to the notion that earlier perceptions of bank risk profiles are no longer adequate.

2. Model and data

A well-established empirical literature has identified several publicly available financial ratios as consistent predictors of bank failure. Table 1 lists the explanatory variables used here, together with the anticipated sign of each regression coefficient and

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[1] Reinhart and Rogoff (2008) emphasize telling trends in equity prices, housing prices, and output growth, while Reinhart and Rogoff (2009) emphasize excessive debt accumulation as potential predictors of crisis.

[2] Until the wave of bank failures in the late 1980s and early 1990s, few banks failed since the end of the Great Depression in the 1930s. I do not attempt to estimate a failure model for the 1930s due to lack of comparable bank-level financial data.

representative citations. Based on theory and prior empirical findings, risk of failure is reduced by higher profits or capital ratios. Similarly, higher expenses and nonperforming loans (credit risk) contribute to risk of failure. Larger banks exhibit lower risk of failure, perhaps due to diversification or regulatory "too-big-to-fail" status. Jumbo certificates of deposit (JCDs) and higher loan/asset ratios imply lower liquidity and higher risk of failure.

Sparse failures through 1995-2007 precluded updating such models during that period, allowing the underlying risk linkages to potentially shift unobserved.[3] Here I estimate logit models using financial data from year-end 1984, 1989, and 2008 to predict U.S. bank failures during the two years following each reporting date.[4,5] Table 2 reports summary statistics.[6]

Compared to both earlier samples, the 2008 sample shows higher ratios of JCDs and total loans, and just *half* the net income /assets, suggesting higher average risk of failure despite better capitalization. Indeed, the rate of failure was nearly twice as high in the 2008 sample versus the 1984 sample (table 3).[7] We next explore whether these

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[3] Not a single commercial bank failed in the U.S. during 2005-2006, one bank failed in 1997, and three failed in each of 1998, 2003, and 2007. The inability to update these models has been a particular problem for federal regulatory agencies that use them (Cole, 1995).

[4] 1984 is near the beginning of the earlier crisis but after major changes in financial reporting. The second period spans the 1990-91 recession and the last phase of the 1980s crisis, after the FDIC had increased its staffing to deal with the increased need for handling closures. The third period covers the early part of the 2007-2009 crisis. The choice of a two-year failure window is common in the literature.

[5] Some studies have alternately estimated a hazard (time to failure) model. Logit and hazard models have both found similar variables to be significant predictors of bank failure.

[6] I omitted banks that reported loans/assets > 1, expenses/assets < 0 or > 0.2, equity/assets > 0.4, or net income / assets > 0.1. The omitted values likely reflect either reporting errors or anomalous transactions such as major asset sales. Regression estimates on the unfiltered sample, not reported here, are very similar.

[7] Data on bank failures are from www.fdic.gov; reliance on the FDIC's failure classifications implicitly incorporates the FDIC's bank closure policies, which may vary over time with staffing and other factors.

aggregate ratios tell the whole story, or whether instead the linkages themselves changed over time.

3. Estimates and discussion

Table 3 reports logit regression estimates. [8,9] Likelihood ratio tests strongly reject equality of the coefficients between each pair of periods overall.[10] Coefficients on all six regressors show significant changes between at least one of the earlier years and 2008 (t-statistics in table 4). However, only half of these coefficients changed significantly between 1984 and 1989, despite concurrent changes in regulatory staffing and bank closure policies. The coefficient on log(assets) actually changed sign between the 1980s and 2008, likely reflecting a decline in the efficacy or application of the policy of "too-big-to-fail."[11]

Table 4 also quantifies magnitudes of these significant changes, in two forms. First is the change over time in the marginal effect of each regressor on the probability of

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Hence, any changes in empirical linkages will reflect a joint change in financial risk and in the regulatory closure policies, and available data cannot decompose those two components. For many stakeholders – including investors, depositors, and other regulatory agencies – regulatory closures (rather than other possible indicators of financial distress) are the relevant outcome.

[8] Note that, while regressions cannot prove causality, the important question here is the ability of particular ratios to predict failure, potentially without regard to causality. The analysis here therefore follows previous literature in relying on the regression estimates and remaining silent about causality, although – as noted above – theoretical arguments do predict causal links for several ratios.

[9] An alternate specification, not reported in the tables, also included fee income (as a proxy for off-balance-sheet activity) and unused commitments (which affect liquidity risk). Neither variable was significant, and the signs and significance of coefficients on the other variables were unaltered.

[10] Chi-square test statistics were 82.36 for 1984 versus 1989; 151.92 for 1984 versus 2008; and 57.22 for 1989 versus 2008, all with $p < 0.0001$.

[11] By early 2010, with three bank holding companies at or above $2 trillion each in assets (collectively over 40 percent of U.S. GDP; data from the Federal Reserve) and some with several times that amount in off-balance-sheet derivative contracts, one might conjecture that the very largest banks had grown beyond "too big to fail" into the realm of "too big to protect."

failure, starting from the earlier year's unconditional probability of failure. Second is the same item expressed as a percentage of the earlier year's marginal change in probability of failure associated with that regressor. Across each pair of years, several changes are quite large – ranging to more than double the base year's marginal impact and implying strong economic significance.

The table also indicates whether the change had the same sign as the earlier effect, reinforcing the sensitivity of failure risk to the regressor, or the opposite. Banks' risk of failure was more sensitive to nonperforming loans in 2008 than in the 1980s, a pattern consistent with some known causes of the later crisis.[12] Conversely, failure risk has become progressively less sensitive over time to loans/assets. Equity/assets affected failure risk more strongly after 1984, but more so in 1989 than in 2008. Failure risk was more sensitive to profitability but less sensitive to JCDs in 2008 than in 1989.

If the distribution of regressor values has changed over time, changes in marginal failure risk might also result from nonlinearity of failure risk with respect to regressors, a possibility not explored by previous studies. Table 5 reports logit estimates in which quadratic terms are added for each financial ratio. Increasing marginal risk is indicated for profitability in each year, since its linear and quadratic terms have the same sign. Linear and quadratic terms have opposite signs for the nonperforming loan ratio each year, implying decreasing marginal risk. Failure risk is concave with respect to capitalization in 2008, implying that small increments of equity capital are now more effective at preventing failure among thinly capitalized banks than among others. No other consistent pattern of nonlinearity emerges. Overall, the hypothesis of convexity is not adequate to explain the changes in marginal risk summarized in table 4, but suggests

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[12] The coefficient's point estimate is over 60 percent larger in 2008 than in each earlier sample

some additional structure in observable linkages between financial ratios and the probability of failure.

4. Conclusion

Empirical linkages between every financial ratio studied here and the probability of subsequent bank failiure changed between the 1980s and the more recent crisis. Some such changes materialized early in the previous crisis, while others emerged at the end. Half of those linkages also changed during the previous crisis, likely reflecting some evolution in both the banking industry and the FDIC's closure rule. Key changes were both statistically and economically significant.

One policy implication of these findings is that regulatory capital requirements alone may not be the most effective means of promoting systemic stability in the current environment, but may usefully be augmented by additional regulatory instruments. For instance, risk-based pricing of deposit insurance may benefit from incorporating loan quality and profitability more precisely than through regulatory examination ratings alone, though this interpretation may be somewhat tempered by the FDIC's ability to adjust its closure rule. Another implication is that statistical models predicting bank failures should indeed be re-estimated periodically, as the Federal Reserve has intended for its own internal models (Cole, 1995). Extended periods of sparse failures, by hindering such re-estimation, can permit underlying risk linkages to shift unobserved or aggregate risk to rise undetected. This problem poses a fundamental obstacle to any prospect of eliminating the possibility of future banking crises.

References

Arena, M., 2008, Bank failures and bank fundamentals: A comparative analysis of Latin America and East Asia during the nineties using bank-level data, Journal of Banking and Finance 32, 299-310.

Cole, R.A., 1995, FIMS: A new monitoring system for banking institutions, Federal Reserve Bulletin 81, 1-15.

Cole, R.A. and J. Gunther, 1995, Separating the likelihood and timing of bank failure, Journal of Banking and Finance 19, 1073-1089.

DeYoung, R., 2003, De novo bank exit, Journal of Money, Credit, and Banking 35, 711-728.

Reinhart, C.M. and K.S. Rogoff, 2008, Is the 2007 U.S. sub-prime financial crisis so different? An international historical comparison, NBER Working Paper No. 13761.

Reinhart, C.M. and K.S. Rogoff, 2009, This Time is Different: Eight Centuries of Financial Folly. (Princeton University Press, Princeton, NJ).

Whalen, G., 1991, A proportional hazards model of bank failure: An examination of its usefulness as an early warning tool, Economic Review, Federal Reserve Bank of Cleveland, First Quarter, 21–31.

Wheelock, D.C. and P.W. Wilson, 2000, Why do banks disappear? The determinants of U.S. bank Failures and acquisitions, Review of Economics and Statistics 82, 127-138.

Table 1: Explanatory Variables

Explanatory Variable	Illustrative References
Log (Assets) (-)[a]	Cole and Gunther (1995), Wheelock and Wilson (2000), DeYoung (2003), Arena (2008)
Equity/Assets (-)	Whalen (1991), Cole and Gunther (1995), Wheelock and Wilson (2000), DeYoung (2003), Arena (2008)
Nonperforming Loans/ Assets[b] (+)	Cole and Gunther (1995), Wheelock and Wilson (2000)[c]
Net Income/Assets (-)	Whalen (1991), Cole and Gunther (1995), Arena (2008)
Jumbo Certificates of Deposits (JCDs)/Assets (+)	Whalen (1991), Cole and Gunther (1995), DeYoung (2003)
Loans/Assets (+)	Whalen (1991), Wheelock and Wilson (2000), DeYoung (2003), Arena (2008)

[a]Anticipated sign of regression coefficient in parentheses.

[b]Nonperforming loans equal loans past due 90+ days plus nonaccruing loans.

[c]Similarly, Whalen (1991) included the difference between primary capital / average total assets and nonperforming loans / average total assets.

Table 2: Summary Statistics

Variable	1984 Sample		1989 Sample		2008 Sample	
	Mean	*Std.Dev.*	*Mean*	*Std.Dev.*	*Mean*	*Std.Dev.*
Log (Assets)	10.565	1.199	10.893	1.290	11.928	1.209
Equity/Assets	0.0882	0.0360	0.0879	0.0376	0.1097	0.0419
Nonperforming Loans / Assets	0.0141	0.0176	0.0117	0.0155	0.0147	0.0216
Net Income / Assets	0.0065	0.0129	0.0064	0.0132	0.0032	0.0160
JCDs / Assets	0.1094	0.0989	0.1056	0.0780	0.1618	0.0839
Total Loans / Assets	0.5305	0.1350	0.5424	0.1555	0.6730	0.1589

Source: Regulatory Call Reports at

http://www.chicagofed.org/webpages/banking/financial_institution_reports/commercial_

bank_data.cfm

Table 3: Logit Regression Results

Variable	1984 Sample		1989 Sample		2008 Sample	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*	*Coefficient*	*t-statistic*
Intercept	-1.75	-1.64	-2.36	-3.28*	-8.26	-7.38*
Log (Assets)	-0.548	-6.69*	-0.195	-3.17*	0.364	5.28*
Equity/Assets	-23.42	-6.87*	-52.87	-14.02*	-40.83	-9.32*
Nonperforming Loans /Assets	24.11	9.94*	23.67	7.26*	39.27	13.88*
Net Income /Assets	-14.31	-3.99*	-22.72	-5.13*	-24.09	-6.27*
JCDs/Assets	3.93	6.88*	2.95	3.09*	2.96	3.33*
Loans/Assets	6.60	8.54*	4.67	6.79*	3.07	3.71*
Number of observations	14,295		13,034		7,280	
Number (fraction) of failed banks in sample	252 (0.01763)		269 (0.02064)		239 (0.03283)	
Log likelihood	-839.75		-609.94		-575.18	

Significant at the *0.01 level. Dependent variable equals 1 for each bank that failed within two years after the respective year-end financial data.

Table 4: Significant Changes to Failure Linkages

Variable	1984-89	1984-2008	1989-2008
Log(Assets)	3.52* 0.0044 165.5% opp.	8.40* 0.0138 263.7% opp.	
Equity/Assets	-6.44* -0.3887 134.6% same	-3.31* -0.2804 78.0% same	2.56** 0.2022 27.3% opp.
Nonperforming Loans/Assets		4.42* 0.2498 67.6% same	4.91* 0.2928 90.1% same
Loans/Assets	-2.31** -0.0291 35.8% opp.	-3.26* -0.0561 55.4% opp.	
Net Income /Assets			-2.33** -0.1646 77.1% same
JCDs /Assets			-1.68*** -0.0290 51.1% opp.

Top entry in each cell is the t-value of the change in the coefficient on the indicated regressor across the indicated years, significant at the *0.01, **0.05, or ***0.10 level. Second entry in each cell is the change in dP/dx_i from earlier year to later year, starting from the earlier year's unconditional probability of failure, where P = probability of failure and x_i is each successive regressor. Bottom entry is the same item expressed as a percentage of the earlier year's dP/dx_i where "same" (respectively, "opp.") indicates that the change has the same (respectively, opposite) sign as the earlier year's dP/dx_i.

Table 5: Logit Regression Estimates with Quadratic Terms

Variable	1984 Sample		1989 Sample		2008 Sample	
	Coefficient	*t-statistic*	*Coefficient*	*t-statistic*	*Coefficient*	*t-statistic*
Intercept	-6.63	-2.43**	-3.76	-2.39**	-5.38	-3.00*
Log of Assets	-0.494	-5.99*	-0.160	-2.67*	0.369	5.33*
Equity /Assets	-26.67	-6.61*	-41.76	-7.37*	-61.07	-6.68*
(Equity /Assets)^2	38.71	1.26	-69.23	-1.08	121.14	3.50*
Nonperforming Loans / Assets	40.83	7.27*	47.91	7.29*	51.84	10.57*
(Nonperforming Loans /Assets)^2	-156.12	-4.29*	-207.42	-5.31*	-117.69	-5.02*
Net Income /Assets	-42.65	-6.74*	-48.34	-6.39*	-40.65	-6.87*
(Net Income /Assets)^2	-365.28	-5.12*	-373.43	-4.58*	-145.75	-3.95*
JCDs /Assets	5.39	3.55*	4.49	1.62	2.85	0.98
(JCDs /Assets)^2	-2.91	-1.02	-4.97	-0.71	-0.41	-0.07
Total Loans /Assets	19.75	2.41**	5.23	1.16	-4.11	-0.97
(Total Loans /Assets)^2	-10.56	-1.64	-0.51	-0.14	5.24	1.70***
Number of observations	14,295		13,034		7,280	
Log likelihood	-800.87		-578.48		-549.86	

Significant at the *0.01, **0.05, or ***0.10 level. Dependent variable equals 1 for each bank that failed within two years after the respective year-end financial data.