

Does a Bank's History Affect Its Risk-Taking?[†]

By CHRISTA H. S. BOUWMAN AND ULRIKE MALMENDIER*

Financial crises are challenging times for any financial institution, but some are more prepared than others. The equity ratios of US commercial banks prior to the recent financial crisis, for example, ranged from a high 16.4 percent (ninetieth percentile) to less than half the magnitude, 7.5 percent (tenth percentile). Banks also differed significantly in their risk-taking as measured by net charge-offs and nonperforming loans (NPLs).¹

The fate of banks at the two ends of the spectrum were very different. Douglass National Bank, for example, whose pre-crisis equity ratio was 3.3 percent and NPL ratio 11.4 percent, did not survive 2008. It was closed by the Office of the Comptroller of the Currency after its capital dropped to 2.2 percent in 2007. At the other end of the spectrum, Mitsubishi UFJ Trust and Banking Corp USA had 91.7 percent equity capital and an NPL ratio of 0.5 percent in 2006, and made it through the crisis without a dent.

What explains such wide heterogeneity? Much of the existing literature focuses on incentive misalignment: since regulators aim to ensure the safety and soundness of the financial system, they provide deposit insurance, which, in turn, provides incentives to take excessive risks. In this paper, we explore an alternative hypothesis,

the influence of past experiences. We examine whether a bank's capitalization and risk appetite are affected by the economic environment and outcomes it has faced, and survived, in the past.

Anecdotal evidence suggests as much. In the Federal Reserve System's *Community Banking Connections*, for example, Lemieux (2014) points to the positive example of a suburban bank that managed to adhere to strict underwriting standards during the financial crisis. She argues that "it is no coincidence that three of the bank's senior managers began their careers during the savings-and-loan and commercial property crisis" and describes the bank as "long on institutional memory," which is precisely the hypothesis we investigate in this paper.

Using Call Reports we show that past experiences of difficult times, as proxied for using under-capitalization, predict significantly more careful lending behavior and higher capitalization in the long run. We also find that witnessing other banks in crisis does not induce such behavior. If anything, bankers who see other banks fail but their own bank survive build on this (relatively) good experience to take on more risk and hold less capital.

Our evidence is suggestive in that Call Reports allow us to analyze only a fraction of banks' histories, and limit our ability to address survivorship bias or to employ matching methodologies.² Moreover, the data does not allow us to explore the micro-foundation of institutional memory.

One possible explanation for our findings is that institutional memory aggregates the individual-level experience effects documented by Malmendier and Nagel (forthcoming, 2011): Individuals overweight their personal experience

Bouwman: Mays Business School, Texas A&M University, Wehner 360H, College Station, TX 77843 (e-mail: cbouwman@mays.tamu.edu); Malmendier: Department of Economics and Haas School of Business, University of California Berkeley, 501 Evans Hall, Berkeley, CA, 94720 (e-mail: ulrike@berkeley.edu). We thank Allen Berger, Rudiger Fahlenbrach, and participants at the 2015 American Economic Association Meeting in Boston for insightful comments. Adelina Wang provided excellent research assistance.

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¹ Interdecile ranges are -0.01 – 0.28 percent for net charge-offs, and 0 – 1.4 percent for NPLs. All calculations based on December 2006 Call Reports. The ranges are similar in December 2007, with 7.7 – 16.8 percent for equity ratios, 0 – 0.42 percent for net charge-offs, and 0 – 2 percent for NPLs.

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of risky outcomes when predicting future outcomes. As a result they tend to take more risk after experiencing good outcomes, and less after bad outcomes.³ Under this hypothesis the past experiences of a bank's current management and board would be essential determinants of institutional memory. Alternatively, bad times may lead to "corporate repairs" (cf. Camerer and Malmendier 2007) which institutionalize processes to avoid the suboptimal outcomes experienced during the crisis and thus survive the tenure of individuals who experienced the crisis. Call Reports do not allow us to track this information. We will discuss at the end which data needs to be assembled to test for channels and gain identification.

I. Methodology and Data

We construct two main datasets for our analysis, one with detailed information about the performance and risk-taking of banks, and one with historical information about bank failures. Summary statistics are in online Appendix Table A1.

We obtain the information about banks from the Federal Financial Institutions Examination Council (FFIEC) Reports of Income and Condition. All regulated commercial banks have to file such Call Reports with their primary regulator. The reports provide standardized information from balance sheets and income statements. We obtain the Call Report data from 1984 to 2010 from the website of the Federal Reserve Bank of Chicago. To ensure that the sample is restricted to commercial banks, we follow Berger and Bouwman (2013) and require that the filing institution (i) has commercial real estate or has commercial and industrial loans outstanding, and (ii) has deposits outstanding. We use year-end data to match our other, annual data sources.

To examine whether banks whose institutional history includes more, or more severe, bad times operate with higher capital and take less risk going forward, we regress bank capital and bank risk-taking on various bad-times proxies and a battery of control variables, including

year and bank fixed effects. We cluster standard errors by bank.

We measure capitalization (EQRAT) as the ratio of total equity capital to GTA, where GTA is total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve (if applicable due to country risk). We measure bank risk-taking in three ways. Our main measure (shown in the tables) is Net charge-offs/GTA, where Net charge-offs are the value of loans and leases removed from the books and charged against loss reserves, minus recoveries on delinquent debt. We obtain similar results using the non-performing loan ratio, NPL/GTA, where NPLs are loans that are past due 90 days or more and still accruing interest, plus loans in non-accrual status. We also obtain comparable results using earnings volatility, defined as the standard deviation of ROA over the past four quarters.

Our key independent variables are various proxies for "bad times." We use three macroeconomic variables for nationwide and statewide bad times. The first proxy, "Failed banks (fraction)," is the average fraction of banks that failed over the life of a bank. For example, if 1 percent of all banks failed last year and 11 percent two years ago, then the "Failed banks (fraction)" experienced by a bank that is two years old is $(0.01 + 0.11)/2 = 0.06$

³There is also evidence of past experiences affecting the behavior of executives (e.g., Graham and Narasimhan 2004; Malmendier, Tate, and Yan 2011; Schoar and Zuo 2011) and loan officers (Berger and Udell 2004).

Combining both sources of data, we are able to construct “Failed banks (fraction)” at the national level since 1864, and at the state level since 1921. Values range from 0 to 0.04 at the national level, and from 0 to 0.31 at the state level.

The second and third macro-level proxies capture the severity of nationwide and statewide bad times. “Failed banks > 1 percent” is the frequency with which a bank has experienced failure of more than 1 percent of all banks in a year, and “Failed banks (assets) > 1 percent” is the frequency of witnessing failure involving more than 1 percent of the banking sector’s assets. Both variables are normalized by bank age. We obtain data on the assets of commercial and savings banks that failed in 1921–1931 from Goldenweiser (1933), and for 1934 and later from the FDIC’s website. Surprisingly, data on the assets of banks that failed in 1932 and 1933, the height of the Great Depression, are not available. There is, however, data on the total deposits of those institutions, and we use the ratio of deposits/assets of failed banks in other years to approximate total assets of the institutions that failed in 1932–1933.

To measure bank-specific bad experiences, we focus on the bank having been undercapitalized in the recent or more distant past. We use four indicator variables for undercapitalization during different time periods (1–3, 4–6, 7–9, or 10–25 years ago), and four variables that capture the number of times the bank was undercapitalized during those four time periods.⁴ A bank is deemed undercapitalized in a particular year if its EQRAT < 4 percent (before 1991), or its Basel tier1 risk-based capital ratio < 4 percent or its Basel total risk-based capital ratio < 8 percent (from 1991 onward).

For the regressions estimating the effect of bank-specific bad times, the institutional-memory hypothesis predicts that past experiences of bad times induce banks to be particularly careful in the future. Hence, in the long-run, we expect capitalization to be high and risk-taking to be low. Mechanistically, however, a previously

⁴Distinguishing between different time periods helps to ensure that our results do not merely capture a mechanical effect: If a bank was undercapitalized in the recent past, it will likely continue to operate with low capital for a few, maybe one to three years, despite increasing its capital over this period.

undercapitalized bank will be *below* average in capital and *above* average in bad loans in the year of undercapitalization and the following years. It is an interesting empirical question when the experience effect starts to dominate and becomes measurable in the data.

All regressions, whether they estimate the effect of economy-wide bad times or bank-specific bad times, control for the following explanatory variables: $\ln(\text{GTA})$ as a control for bank size; bank holding company status (BHCD), which is a dummy variable that equals one if the bank has been part of a BHC in any of the past three years, to control for BHC-internal capital markets; bank age, to control for age-specific differences in capital ratios and risk-taking; and finally control for a bank’s local market power as well as local market conditions. Local market power affects credit availability (e.g., Petersen and Rajan 1995), and may affect risk-taking. For each bank, we establish the Herfindahl indices of the local markets in which a bank has deposits and then weight the indices by the proportion of the bank’s deposits in each market.⁵ We control for local market economic conditions using Bureau of Economic Analysis data and construct $\ln(\text{population})$, where population is the weighted average population in all markets in which a bank has deposits, and income growth, the market-level weighted average of the growth in personal income, again using bank deposits as weights.

Finally, the regressions control for lagged values of the alternative outcome variables. That is, in the regressions predicting risk-taking we control for lagged EQRAT, reflecting that capital expands banks risk-bearing capacity (e.g., Thakor 2014), and hence, banks with higher capital may take more risk. Similarly,

⁵Deposits are from the Federal Deposit Insurance Corporation’s Summary of Deposits, and are the only variable for which geographic location is available. Note that, from 1984–2004, we define the local market as the Metropolitan Statistical Area (MSA) or non-MSA county in which the bank’s offices are located. After 2004, we use the Core Based Statistical Area (CBSA) and non-CBSA county, for which areas were announced in June 2003. The term CBSA collectively refers to Metropolitan Statistical Areas and newly created Micropolitan Statistical Areas. For recent years, the Summary of Deposits data needed to construct HHI is available on the FDIC’s website only based on the new definition. It is not possible to use the new definition for our entire sample period.

TABLE 1—EFFECT OF NATIONWIDE, STATEWIDE, AND BANK-SPECIFIC BAD TIMES ON BANK CAPITAL AND RISK-TAKING

	EQRAT	Net chargeoffs/ GTA	EQRAT	Net chargeoffs/ GTA
Control variables	Yes	Yes	Yes	Yes
Year and bank fixed effects	Yes	Yes	Yes	Yes
<i>Panel A. Bad times measured</i>	Nationwide		Statewide	
Failed banks (fraction)	−0.25738*** (−2.93)	0.18052*** (12.22)	−0.20714*** (−4.60)	0.01035 (1.39)
Observations	220,020	220,020	116,715	116,715
Adjusted R^2	0.659	0.365	0.623	0.376
Failed banks > 1 percent	−0.01006*** (−4.53)	0.00455*** (12.09)	−0.01561*** (−7.55)	0.00349*** (7.06)
Observations	220,020	220,020	116,715	116,715
Adjusted R^2	0.659	0.365	0.623	0.377
Failed banks (assets) > 1 percent	−0.00735*** (−3.22)	0.00343*** (8.22)	−0.01849*** (−8.97)	0.00427*** (8.54)
Observations	116,883	116,883	116,715	116,715
Adjusted R^2	0.623	0.377	0.624	0.377
<i>Panel B. Bad times measured</i>	Undercapitalization dummies		Number of times undercapitalized	
Undercapitalized 1–3 years ago	−0.00690** (−2.29)	0.00245*** (3.33)	0.00030 (0.09)	0.00099 (1.28)
Undercapitalized 4–6 years ago	−0.00164 (−0.76)	−0.00123*** (−3.69)	0.00400 (1.07)	−0.00171** (−2.31)
Undercapitalized 7–9 years ago	−0.00086 (−0.51)	−0.00053* (−1.93)	0.00535 (1.42)	−0.00115 (−1.53)
Undercapitalized 10–25 years ago	0.00578*** (2.82)	−0.00122*** (−3.31)	0.00825** (2.23)	−0.00136* (−1.81)
Observations	110,681	110,681	100,752	100,752
Adjusted R^2	0.711	0.312	0.721	0.309

Notes: Panel A shows how the average fraction of banks that failed over a bank's life, and the number of years in which the number (or assets) of failed banks exceeded 1 percent of the number (or assets) of banks at the nationwide and statewide level affect bank capital (EQRAT) and risk-taking (Net chargeoffs/GTA). Panel B shows how bank-specific bad times (indicator variable for undercapitalization 1–3/4–6/7–9/10–25 years ago, or the number of undercapitalization episodes during those time periods) affect bank capital and risk-taking. All regressions include all the control variables mentioned in online Appendix Table A1 and year and bank fixed effects. All variables are defined in the main text. t -statistics based on robust standard errors clustered by bank are in parentheses.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

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the regressions predicting EQRAT control for banks' past risk-taking.⁶

⁶We note that the fixed effect regressions might be affected by dynamic panel bias, though the magnitude will be small, especially once we consider longer time periods.

II. Results

Panel A in Table 1 shows the effects of banks successfully living through times of bank failure, whether they are nationwide or statewide. We estimate a significantly negative effect on capitalization, and a significantly positive effect on risk-taking.

If, however, the bank itself is affected, the effect reverses. Banks that were undercapitalized and hence underwent the threat of failure slowly recover and ultimately operate with higher capital and take less risk, as shown in panel B in Table 1. The results are similar using indicator variables (first two columns) and count variables (last two columns). While the effects are not always significant, they generally have the expected signs. Consistent with mechanic autocorrelation and, hence, slow reversal, the effects are strongest relative to undercapitalization 10–25 years ago. If a bank was undercapitalized 10–25 years ago, it currently operates with 0.578 percent higher capital and 0.122 percent fewer net charge-offs, which seems sizable relative to the sample means of 10 percent and 0.0 percent, respectively.

We also note that the effect is strongest for small banks with GTA below \$1 billion (untabulated for brevity). This definition of small banks conforms to the usual notion of “community banks” that primarily operate by transforming locally generated deposits into local loans. The effects are generally not significant for large banks, possibly reflecting an expectation that regulators will come to their rescue, even if they are not “officially” too-big-to-fail.

III. Conclusion

Past macroeconomic and bank-specific shocks experienced (and survived) by a financial institution appear to affect its capitalization and risk-taking, suggesting that experiences propagate into the future and generate some form of institutional memory.

Several data limitations of the Call Reports hamper the analysis. First, while we were able to measure nationwide and statewide bank failure over long horizons, financial statement information on bank capital and risk-taking are publicly available only from the early 1980s onward. Second, the available data does not allow us to test whether experience effects are CEO- or director-specific, nor does it provide governance information. We are hand-collecting financial statement and corporate governance data from Moody’s Corporate Manuals for the top 100 banks in 1930–2013, and will address these limitations in future research.

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