Is This Time Different?

Do Bank CEOs Learn from Crisis Experiences?

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Abstract

This paper studies how the early-career exposure of bank holding company (BHC) CEOs to the 1980s savings and loans (S&L) crisis affects corporate policies and survival of the BHCs they subsequently manage. I measure the "Intensity" of crisis exposure by the bank failure rate in the states where CEOs worked during the S&L crisis. First, I identify the characteristics of BHCs managed by high-Intensity ("experienced") CEOs and find that such BHCs exhibit lower systemic risk and are less likely to fail: a one-unit increase in Intensity is associated with 0.39% lower systemic risk and an 0.5% lower failure rate. Second, I identify the type of banking policies that account for these results; in particular, experienced CEOs adopt a BHC business model that is less affected by interest rate shocks, they exert more effective control over credit risk. Their BHCs have relatively larger holdings of liquid assets on the balance sheet. At the same time, there are no significant differences between experienced and other CEOs with respect to asset growth and diversification strategies. Finally, I use the exogenous turnover of CEOs to establish that these findings are not driven by bank–CEO matching.

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"I know we have crises every five or ten years."

Jamie Dimon, J.P. Morgan's chairman and chief executive, January 2010

1 Introduction

Do economic agents learn from past experience? Does experiencing a crisis in the past affect how CEOs manage their banks and hence the survival of those banks? The existing evidence is inconclusive.

On one hand, there is evidence to suggest that past crises do not matter. As Reinhart and Rogoff 2010 state, we suffer from a "this time is different" syndrome. Thus we firmly believe "financial crises are things that happen to other people in other countries at other times"—even as we continue to engage in risky activities.

On the other hand, there is anecdotal evidence to suggest that past crises *do* affect individuals' future behavior. In a Federal Reserve System publication, for example, Lemieux[1] cites the positive example of a suburban bank that managed to survive 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." It remains unclear whether these claims are true and applicable to the financial sector as a whole.[2]

This paper undertakes an empirical assessment of whether and how banking crisis experiences matter for BHCs and their CEOs. The question is especially relevant to the financial services sector in the current era, which is characterized by economic, political, and technological uncertainties. Understanding the impact of past experiences helps us understand the dynamics of banker and banking behavior over normal times and times of crisis—and, thereby, the financial crisis mechanism. In normal times, past experience can shed light on the time variation and heterogeneity in banking models and policies. With respect to particular crises, this paper helps explain mechanisms driving the substantial differences in bank outcomes observed during the 2007–2008 global financial crisis (a.k.a. the Great Recession), which is of great interest to scholars and practitioners alike.

To investigate empirically whether crisis experiences matter for the banking sector, I examine the early-career banking crisis experiences of BHC CEOs. Given the evidence from medical studies (e.g., Lyoo et al. 2011), I expect an inverse relationship between the intensity of crisis experiences and future BHC systemic risk. As compared with bank managers who assess risks conventionally and neglect

[1] https://communitybankingconnections.org/articles/2014/Q1/bank-strategies-in-the-new-year

[2] Medical studies show that traumatic events—such as crises—have direct effects on an individual's psyche, neurobiology, and decision making. Trauma-exposed individuals exhibit different brain-use patterns and epigenetic mechanisms.

low-probability events (Gennaioli et al. 2012), bank CEOs who have witnessed banking crises, liquidity evaporation, and the wholesale shuttering of financial institutions should be more aware of these tail risks and hence should follow business models that are more resilient to systemic risks and market fluctuations. It follows that BHCs managed by such CEOs will better withstand liquidity shocks and, during a financial crisis, be more likely to survive. This hypothesis accords with mounting evidence in the finance literature that the past experience of executives and investors affects their subsequent behavior and performance (Bertrand et al. 2003, Malmendier and Nagel 2011, Schoar and Zuo 2011, Custódio et al. 2013, Malmendier and Nagel 2016). In particular, Bernile et al. 2015 shows that there is a non-monotonic relation between the intensity of CEOs' early-career exposure to natural disasters and subsequent corporate risk taking. The effect of exposure to trauma on subsequent decision making has also been widely documented in the psychology and medical literatures.

To test my conjecture, I focus on the CEOs of BHCs from 1999 to 2009. For the 301 bank CEOs during this period, I identify the institutions they worked for during 1985–1990 as well as where they were employed during the S&L crisis. I also use Federal Deposit Insurance Corporation (FDIC) records to assemble a data set of US state–level bank failure events from 1985 to 1990. I then combine these two data sets to draw conclusions about the possible exposure of CEOs to the banking crisis and associated financial institution failures during the 1980s.

I employ several measures to quantify CEOs' experiences. I report my main findings based on the "Intensity" measure, as described next. For each state–year pair, I scale the total amount of deposits associated with failed financial institutions by the sum of deposits in the entire state; I then take the maximum of this ratio for each CEO over the years for which I have information on that individual's employment location from 1985 to 1990. The resulting variable is hereafter called *Intensity*.[3]

There are two reasons why I construct CEOs' exposure to banking crises by using bank failure rates of the states in which they worked during the 1980s. The first is that thrifts, S&Ls, banks, and other depository institutions in the 1980s operated locally (i.e., within the states they were headquartered) because interstate branches and acquisitions were not allowed until 1995. Therefore, state-level bank failure rates best summarize the bank failure cases to which CEOs were exposed through their banking business connections and practices. Second, CEOs' mobility across states in anticipation of state-level bank failure rates in the 1980s is less of an endogeneity concern than is CEO mobility due to expecting their *own* firms to fail. Unlike firm-level shocks, state-level shocks are largely unexpected by—and certainly beyond the control of—individuals.

[3] I construct a measure of S&L experience in the same way but using bank assets and number of BHCs.

After devising the Intensity measure for such CEO exposure, I proceed to investigate whether the banking crisis experiences of CEOs affect their future management of BHCs. I examine whether those BHCs that were led by a CEO who faced more intense banking crisis situations in the past fared better during the 1999–2009 period, and I find that BHCs helmed by CEOs with such experience were less likely to be delisted or placed under receivership by the FDIC during that period. More specifically, an increase in *Intensity* of one standard deviation is associated with 0.635% lower probability of failure. I then study the effects of crisis experiences on systemic risk taking; here a one–standard deviation increase in *Intensity* is associated with a 12.7 to 38.1–basis point increase in daily returns during a tail event for the market or the banking system.

Next, I investigate the *channels* through which banking crisis experiences become manifest vis-à-vis BHCs. First, BHCs led by experienced CEOs are associated with business models that are less vulnerable to interest rate risk from 1999 to 2009. Second, I show that a higher level of Intensity explains a lower level of credit risk: a one–standard deviation increase in *Intensity* is associated with 0.053% decline in net charge-offs, which accounts for a fifth of the latter's mean level (0.29%). In addition, I find that experienced CEOs exhibit an unusual amount of precautionary hoarding behavior. Thus there is a positive relationship between *Intensity* and the liquid asset holdings ratio, such that a 1% increase in that ratio is associated with one–standard deviation increase in *Intensity*.

Overall, the risk management style of experienced BHC CEOs can be described as conservative. It is important to bear in mind that my results are not explained by differences in BHC characteristics; the reason is that I include BHC fixed effects to control for time-*invariant* bank characteristics and variables (e.g., size, market-to-book ratio) to control for time-*varying* bank characteristics. My findings are robust to time and (US) state fixed effects as well.

One question that naturally arises is whether this conservative risk management style might, in itself, be sufficient to enhance BHC value. I address this question by verifying that both operating performance and stock market returns are indistinguishable among BHCs run by CEOs with high versus low exposure to the S&L crisis.

I also discuss alternative incentives that could account for the management styles of experienced CEOs. I find no differences (in comparison with other CEOs) in their executive compensation levels or in the mix of cash and stocks or options, which rules out that type of payment incentive. I rule out CEOs' empire-building incentives and "too big to fail" incentives by showing that BHC size and growth rate are unaffected by the intensity of CEO crisis experiences.

In short, I establish that CEOs learn from past banking crisis experiences. The definition of learning in my context is consistent with the "hot stove" effect, whereby individuals hesitate to repeat actions that previously led to painful outcomes. Furthermore, this learning stems from CEOs' exposure to bank failure cases through both their professional practice and social interactions. A common limitation in the literature on CEO characteristics involves interpreting the results. My paper is no exception: causality is difficult to establish because I seek to explain corporate outcomes in terms of CEOs' personal traits and experiences. My findings are consistent with two explanations. It could be that, as I argue, CEOs impose their preferences and risk attitudes on the business model and risk management. However, it is also possible that the board of directors selects CEOs of a certain style to implement their own preferred strategy; in this case, CEOs are hired primarily to be executors. An account based on such "assertive matching" between firms and CEOs yields the same expected results as a causal explanation.

To address this endogeneity concern, I explicitly control for the time-varying characteristics of both BHCs and CEOs. This paper's results are robust to controlling for CEO talent (as proxied by their education achievement), for their being Depression babies (Malmendier and Nagel 2011) or military CEOs (Benmelech and Frydman 2015), for labor market conditions at the start of their careers (Schoar and Zuo 2011), and for the extent of their "generalist" skills (Custódio et al. 2013).[4] Following Bertrand et al. 2003, I include firm fixed effects to capture unobservable time-invariant factors that affect a BHC's choice of CEO.[5]

Tackling the endogeneity issue that arises from BHC–CEO assortative matching would require me to assign CEOs to BHCs randomly. Yet if the CEO labor market were frictionless and if one could always determine the optimal matching outcome, then the counterfactual would never be observed. If one supposes the matching to be conditional on time-varying variables but the criteria have not changed over time, then it would be possible to exploit CEO turnover as the exogenous variation in matching (although the choice of a new CEO would still be endogenous). In fact, several papers have used exogenous CEO turnover—resulting from the predecessor's health issues, retirement age, or death shocks—as the identification strategy (Bennedsen et al. 2006, Frydman and Jenter 2010, Eisfeldt and Kuhnen 2013, Jenter and Kanaan 2015).

Because my sample is limited to the banking sector, idiosyncratic death or health shocks to CEOs are too scarce for sample testing to have sufficient power. Hence I rely on CEO retirement age to define exogenous CEO turnover. I must admit, however, that dynamic matching of CEOs to firms remains a

[4] I am grateful to Professor Cláudia Custódio for sharing the General Ability Index data located on her personal website (https://sites.google.com/site/claudiapcustodio/research). In my sample, 82 CEOs are evaluated by the General Ability Index.

[5] The regressions do not include CEO fixed effects. This exclusion is because my key explanatory variable is CEO experiences that do not change during 1999–2009 and so would be collinear with CEO fixed effects.

potential concern. For instance, a firm's preferred management style can change considerably over time; this means that CEO turnover could reflect CEO style as captured by *Intensity*, my core explanatory variable. But even in that event, my result still speaks to the appearance of something special about these CEOs' abilities that are targeted by a BHC board. As a result, my findings do legitimately imply that the pool of managerial talent is significantly shaped by its members early-career encounters with the 1980s banking crisis.

Another obstacle to establishing causality is that, in the 1980s, there may have been CEO–state matching—in other words, it is possible that CEOs with certain characteristics self-selected into certain states in the 1980s. To mitigate this concern, I appeal to the bank failure rates of CEOs' hometown states during the S&L crisis. Of course, CEOs cannot select their respective birthplaces; hence they have no control over their hometown's exposure to the banking crisis. I expect CEOs to be affected by hometown crises, especially since the "home bias" literature argues that agents remain connected to their hometowns through information advantages and social networks. In my subsample of CEOs whose states of birth can be identified, I find that BHCs managed by CEOs with higher-Intensity exposure in their hometowns also have lower credit risks and hold a higher fraction of liquid assets. This test is analogous to—and its results are consistent with—using bank failure rates in the states where CEOs were employed in the 1980s. Readers might also be concerned that memories are short-lived and should therefore have little effect on CEO behavior and/or corporate policy. However, medical studies document that adverse experiences early in life have long-term effects on behavior. With regard to possible doubts that state-level exposure to the banking crisis actually implies that the CEOs themselves dealt with that crisis or experienced real losses, I verify that the reported results are robust to using alternative windows when measuring CEOs' exposure to the S&L crisis.

This paper contributes to several streams of literature. First, it offers new micro-level evidence for theories of experiential learning. Buss et al. 2015, Collin-Dufresne et al. 2016, and Ehling et al. 2016 all model the asset pricing implications of investors' learning from experiences. My evidence is consistent with those implications—namely, that investors place greater weight on scenarios resembling those they experienced when forming their beliefs. My findings also complement existing empirical studies on how economic agents' financial decisions relate to past experiences. An emerging literature examines how the past experience of investors shapes expectations about inflation (Malmendier and Nagel 2016), managers' portfolio choices (Greenwood and Nagel 2009), and asset allocation and investment decisions (Chiang et al. 2011).[6] Kaustia and Knüpfer 2012 study how peers' experiences affect the financial decisions of

[6] For a review, see Greenwood and Shleifer 2014.

investors. However, bank CEOs are a type of agent that has been overlooked in this line of empirical studies. Given the systematic importance of banks and the key role played by bank CEOs, there is a critical gap in the literature that this paper fills by exploring the impact of these particular economic agents' past experiences.

Second, I contribute to the literature on banking behavior during financial crises. Existing research has incorporated many bank-level explanatory variables; these include liquidity (Brunnermeier 2009, Cornett et al. 2011, Bouwman and Malmendier 2015, Bushman et al. 2015), securitization (Loutskina 2011, Erel et al. 2013, Lo 2015), and credit lines outstanding (Beltratti and Stulz 2012, Irani and Meisenzahl 2015). In this regard, the research closest to my paper are the works by Fahlenbrach et al. 2012 and Bouwman and Malmendier 2015. According to the former paper, banks that underperformed during the Long-Term Capital Management (LTCM) hedge fund collapse in 1998 also performed poorly during the more recent 2007 financial crisis; the latter paper shows, to the contrary, that banks which underwent the threat of failure in the past take less risk. Through different lenses, my paper shows that outcomes are affected not only by bank-level experiences but also by CEOs' own personal experiences. Thus it advances our understanding of the driving forces behind cross-sectional differences in bank polices and their outcomes during the Great Recession.

Third, this paper provides new insight into how BHCs take on systemic risk.[7] My findings suggest the path-dependent nature of systemic risk taking at the BHC level. This paper also answers the calls by financial regulators[8] to plumb banking governance—and risk management in particular—more deeply. Other scholars, too, have responded to this call. Ellul and Yerramilli 2013 highlight the role of risk management functions and Chief Risk Officers in bank performance. Fahlenbrach and Stulz 2011 show that aligning CEO and shareholder incentives need not result in better-performing banks. Cheng et al. 2015 examine the relation between CEO compensation and the risk taking of financial firms. My paper proposes a new channel through which the heterogeneity of banks' risk management practices can be explained. In particular, CEOs' past experiences with banking crises can inform and shape a culture of prudence with regard to bank liquidity and credit risk management.

Finally, the analysis reported here contributes to the literature that examines how managerial styles relate to such CEO life experiences as marital status (Roussanov and Savor 2014), holding a pilot's license (Cain and McKeon 2016), political affiliation (Hutton et al. 2014), military experience (Lin et al. 2011, Malmendier et al. 2011), and past career experiences (Schoar and Zuo 2011).[9] All of

[7]Many measures have been proposed to assess systemic risk (see e.g. Acharya et al. 2010, Brownlees and Engle 2010). However, discussing the relative merits of such metrics is beyond the scope of this paper.

[8]See, for instance, https://www.sec.gov/News/Speech/Detail/Speech/1365171515784

[9]See the review paper by Bertrand 2009.

these works exclude financial service and utility industries from their analysis, so they are silent on how bank CEOs are affected by their personal experiences and on the implications of such experiences for the banks they manage. In this paper I show that bank CEOs' attitudes toward risks, as well as their risk management styles, are affected by the salient systemic failure shocks in their professions. I also find that the *categories* of policy decisions related to CEO experiences are different for banks than for corporations in other sectors. So unlike the case of other corporate sectors, banks' degrees of leverage (for example) cannot be explained by the crisis experiences of their respective CEOs.

The rest of this paper is organized as follows. Section 2 details the timeline of the S&L crisis. Section 3 describes the data and provides summary statistics, after which Section 4 presents my main empirical results. These results are interpreted in Section 5, which also includes robustness checks. Section 6 concludes.

2 Timeline of the S&L Crisis

As Figure 1 demonstrates, there are three pronounced peaks of bank failures in the recent history of the United States: the 1930s Great Depression, the 1980s S&L crisis, and the Great Recession of 2008. In this paper, I treat the S&L crisis as the formative period of banking crisis experiences for BHC CEOs. Because my empirical testing period runs from 1999 through 2009, it includes the 2008 financial crisis.

*****Figure 1*****

The decade of the 1980s witnessed the extraordinary surge in the number of bank failures. More than 1,600 banks insured by the Federal Deposit Insurance Corporation (FDIC) were closed or received FDIC financial assistance. The unprecedented magnitude of the banking crisis affected both economic and financial market conditions as well as the regulatory environment. This event has received extensive media coverage, and a large body of academic studies have analyzed its causes and consequences.[10]

To present a clear picture of what CEOs witnessed during the 1980s, I devote this section to the background and geographic pattern of the S&L crisis. I also briefly discuss its association with the banking sector.

[10] For the FDIC's comprehensive chronology and bibliography on the S&L crisis, see https://www.fdic.gov/bank/historical/sandl/

2.1 Background

Several factors injected instability into the banking sector in the 1970s. Before the crisis loomed, some major currencies were allowed to float, and their exchange rates became volatile. In response to the oil embargo and other shocks, oil prices increased drastically. Interest rates varied widely in response to inflation, expectations about inflation, and the anti-inflationary monetary policies adopted by the Federal Reserve.

In particular, thrifts[11] faced the challenge of expanding under the "stagflation" characterized by slow growth, high interest rates, and inflation. Expansion was made even more difficult by the controls on savings interest rates, which were in effect from 1955 to 1979.

When the Federal Reserve doubled the allowed interest rates to reduce inflation in 1979, the thrift industry's financial health was further challenged. Congress reacted by deregulating the thrift industry and passed two laws: the Depository Institutions Deregulation and Monetary Control Act of 1980, and the Garn–St. Germain Depository Institutions Act of 1982. This deregulation of deposit interest rates exerted upward pressure on banks' funding costs because banks and thrifts both relied on short-term funding; hence they had to compete for sources of funds by offering higher rates to attract depositors. However, the amounts earned on long-term, fixed-rate mortgages were flat, squeezing the profits of thrifts and commercial banks alike. Losses began to mount.

Adding fuel to the fire, financial innovation was ascendant and reduced profit margins of the traditional banking business. Banks faced increased competition from new financial instrument, which included money market mutual funds, the commercial paper market, and securitization. As a result, many banks shifted funds to commercial real estate lending, a field featuring higher returns but also greater risks. Some banks participated in leveraged buyouts and off–balance sheet activities. Financial futures, junk bonds, swaps, and other new financial instruments widened the scope for risk taking and facilitated banks' taking on extra risk. At the same time, the existence of deposit insurance increased moral hazard for thrifts and banks because insured depositors had little incentive to discourage banks from excessive risk taking.

As a result of these forces, thrifts and commercial banks took on substantial risks and began to suffer extensive losses. During the 1980s, the performance ratios of banks of all sizes weakened, their assumed risks increased, and loan charge-offs rose dramatically. Systemic distress naturally followed. A large number of S&L customers went bankrupt and defaulted on their loans. The S&Ls that had overextended

[11] A savings and loan or "thrift" is a financial institution that accepts savings deposits and makes personal loans (e.g., mortgages and auto loans) to individual members.

themselves were forced into insolvency proceedings, and a wave of S&L bankruptcies ensued. The Federal Savings and Loan Insurance Corporation (FSLIC) was required to repay all the depositors whose money was lost. From 1986 to 1995, 1,043 of the 3,234 S&Ls—and more than 1,600 banks insured by the FDIC—were closed or received financial assistance. The overall cost to taxpayers was estimated to be no less than $124 billion. In 1991, Congress passed the Federal Deposit Insurance Corporation Improvement Act (FDICIA), which recapitalized the FDIC's Bank Insurance Fund and reformed the deposit insurance and regulatory system.

2.2 Geographic Patterns

The extent of bank failures differed markedly across states. Of the 1,617 failures during the entire 1980–1994 period, nearly 60% occurred in five states: California, Kansas, Louisiana, Oklahoma, and Texas. Table A1 (in the Appendix) details bank failure statistics by state. The incidence of bank failure peaked in different years across states. A domino effect caused serious strains on the FDIC's deposit insurance fund. In the 1980s, geographically confined crises transformed into a national problem. Figure 2 plots the time series of a measure of bank failures in four states. The measure is constructed as the fraction of deposits belonging to the failed institutions *divided by* the total amount of deposits for the entire state at the end of the year.

*****Figure 2*****

Regional and sectoral recessions were confounded and ended up interacting with the banking crisis. The incidence of failure was especially high in states characterized by:

- several economic downturns related to the collapse in energy prices (Alaska, Louisiana, Oklahoma, Texas, and Wyoming);
- real estate–related downturns (California, the Northeast, and the Southwest);
- the agricultural recession of the early 1980s (Iowa, Kansas, Nebraska, Oklahoma, and Texas);
- an influx of banks chartered in the 1980s (California and Texas) and the parallel phenomenon of mutual-to-stock conversions (Massachusetts);
- bans on branching, limited access to geographical diversification of loan portfolios, and funding of growth via core deposits (Colorado, Illinois, Kansas, Texas, and Wyoming);

- the failure of a single large bank (Illinois) or a small number of relatively large banks (New York and Pennsylvania).

2.3 Why S&Ls?

There are four reasons that I use the S&L crisis to measure the exposure of future BHC CEOs to the banking crisis. First and foremost, that crisis and the Great Recession had similar causes and consequences. Both events were preceded by a real estate bubble and a credit boom, and both led to historically high bank failure rates and unprecedentedly large-scale public rescues. Much academic work has explored the latter financial crisis in detail (see e.g. Brunnermeier 2009, Gorton and Metrick 2010), so I forgo further discussion here. The S&L crisis parallels the more recent crisis in terms of causes, precipitating events, damages, and regulatory responses. In particular, fire sales and the withdrawal of liquidity from financial markets led to extreme turbulence and huge bailouts. My second reason for exploiting the S&L crisis is that it spanned more than ten years and affected nearly all US states. These time- and state-varying aspects enable me to capture cross-sectional differences in the intensity of banking crisis shocks to which CEOs were exposed. Third, considerable time elapsed between the S&L crisis and the 2008 financial crisis, and a significant fraction of CEOs switched firms during that time; this fact alleviates concerns about the first crisis having a persistent effect on firms rather than on CEOs. Fourth, the state-level measure of banking crisis intensity is more exogenous to future policies adopted by the CEO than is the historical, firm-level bankruptcy event faced by that CEO. There is a lesser concern that unobserved factors were responsible for *both* the intensity of the 1980s macro-level banking crisis and the micro-level bank policies of the 2000s.

3 Data Description

This section details the data sources and my construction of the sample. It also defines the key variables used in the statistical analysis and presents the empirical tests I employ.

3.1 Construction of the Bank Holding Company Sample

The unit of analysis is the BHC–year pair. Data are retrieved from several sources. I obtain quarterly stock market performance data from the Center for Research in Security Prices (CRSP), and I obtain quarterly BHC consolidated financial data from FR Q-9C statements and from Standard & Poor's Compustat. Quarterly data are collapsed to a yearly frequency. The CEO-related data are from BoardEx and

Marquis Who's Who. I start by obtaining the name list and Committee on Uniform Security Identification Procedures (CUSIP) numbers of all BHCs that filed FR Y-9C statements with the Federal Reserve System during the 1999–2009 period.

I then require that those BHCs also existed during the same period—with the same 6-digit CUSIP (or NCUSIP in CRSP)—and were included in Standard & Poor's Compustat databases.[12] I perform manual "fuzzy" name matching whenever CUSIPs are missing. I then map the public BHCs to BoardEx using ticker and legal names. After merging across the four databases, I am left with 685 public BHCs that have existed from 1999 to 2009.[13] For the 685 BHCs identified in BoardEx, I identified the names of their CEOs during 1999–2009; I then match biography data from Marquis Who's Who using CEO names. The sample is further reduced by my requiring that information be available on CEO employment history and location from 1985 to 1990.[14] My final sample consists of 241 BHCs and 301 bank CEOs.

3.2 Characteristics of Bank Holding Companies

For each of these BHCs, I construct a set of dependent and control variables. I am interested in identifying the distinctive characteristics of BHCs that are associated with higher banking crisis intensities experienced by CEOs. I Winsorize all variables at the 5th and 95th percentiles to reduce the influence of outliers. All variables are defined in Appendix Table A2, and I report summary statistics of these variables in Table 1. The analysis is based on four sets of dependent variables.

I first look at bank failures. I use an indicator variable set equal to 1 if a firm is delisted or closed by the FDIC between 1999 and 2009. Failed banks are those appearing on the list of failed banks maintained by the FDIC. I also conduct news searches to determine whether a delisting was voluntary or forced. Targets of discounted mergers and acquisitions during this period are also coded as 1.

Second, I check the measures of systemic risk taking by BHCs. The first measure is BHC stock comovement with respect to an equal- or value-weighted banking sector portfolio. In the spirit of Barberis et al. 2005, I construct a *Co-movement* variable by regressing daily BHC stock returns against returns from a constant and daily (equal- or value-weighted) banking sector portfolio within each calendar year from 1999 to 2000. The second systemic risk measure is marginal expected shortfall, which is based on the expected shortfall (ES) measure that is widely used within financial firms to capture expected loss in the event of returns being less than some α quintile (Acharya et al. 2010, Brownlees and Engle 2010, Acharya

[12] A CUSIP number can change over time, because CUSIPs are the latest numbers used by issuers; in contrast, NCUSIPs are historical records and so do not change.

[13] I do not exclude investment banks, provided they are chartered as BHCs and are entitled to deposit insurance funds from the FDIC. There were a total of 4,660 BHCs at the end of 2011.

[14] One third of the sample is eliminated owing to lack of information on CEOs' employers during the 1980s.

et al. 2013). So for a given year, the *MES_mkt* (resp., *MES_bnk*) variable is defined as the *negative* of the average return on the BHC's stock over the worst 5% of days for returns in the entire market index (resp., banking sector stocks):

$$MES_{it-1}(C) = E_{t-1}(r_{it} \mid r_{mt} < C). \tag{1}$$

The third measure is beta, as featured in the capital asset pricing model (CAPM). The coefficient for *Beta* is estimated from a one-factor market model, which in turn is estimated by regressing daily returns on the BHC's stock against a constant and daily return on the S&P500 value-weighted portfolio.

Third, I construct interest rate betas to capture the resilience of BHC stock returns to fluctuations in the interest rate. The methodology is based on Flannery 1981, Flannery and James 1984, English et al. 2012, and Landier et al. 2013. The interest rate proxies used are the primary rate, the 6-month LIBOR rate, and the term spread—defined as the spread between the 10-year Treasury note and the 3-month Treasury bill (these two rates are available at the monthly frequency from the Federal Reserve's website). I have two ways of extracting interest rate shocks: taking the *first difference* for each proxy or the *residuals* of each proxy after fitting via an second-order autoregressive, or AR(2), model to remove autocorrelations. I then regress the BHC's daily stock returns against a constant, against the value-weighted daily returns on the market portfolio, and against the proxy for interest rate shock; the absolute values of the regression coefficients are the corresponding interest rate betas. Thus each interest rate beta corresponds to a different proxy for the interest rate shock. For instance, *Prime_d1* is the interest rate beta corresponding to the first difference of the prime lending rate whereas *Prime_res* is associated with residuals of that rate after fitting with an AR(2) model.

Finally, I examine credit and liquidity risk management. For credit risk management I focus on *BadLoan*, defined as the sum of loans at least 90 days past due, *divided by* the book value of BHC assets. The second measure for credit risk is *Net charge-offs*, or the ratio of net charge-off assets to total assets. The third measure is *Provision* (i.e., current liabilities), where *Provision/Asset* is the ratio of provisions to assets. These definitions are consistent with Fahlenbrach et al. 2012, Ellul and Yerramilli 2013, and Bouwman and Malmendier 2015. Liquid assets are defined as the sum of pledged securities, held-to-maturity securities, available-for-sale securities, cash, and federal funds sold; I use *Liquid asset1/Asset* to denote the ratio of this sum to the book value of BHC assets. As a robustness check, I exclude federal funds sold when defining *Liquid asset2/Asset*. I define *US Treasury/Asset* as the ratio of US Treasury bill holdings to the total book value of BHC assets. This latter liquid asset classification is consistent with the treatment in several other papers (see Kashyap et al. 2002, Gatev and Strahan 2006, Cornett et al. 2011, Loutskina 2011, Acharya and Mora 2015, Irani and Meisenzahl 2015.

3.3 Characteristics of BHC Chief Executive Officers

One of the main appeals of using BHCs and their CEOs as a setting is that I can observe the employment, education, and demographic information of CEOs in addition to the identity of their previous employers, dates of employment, tenure, job titles, degrees, alma-mater, gender, hometown, and birth date. I obtain the biographical data on CEOs from BoardEx and Marquis Who's Who.

The core explanatory variable is *Intensity*, which is meant to capture CEOs' exposure to the S&Lcrisis. Following the banking crisis definition of Laeven and Valencia 2008, 2013, I take 1988 to be the peak of the S&L crisis and choose the 1985–1990 window as my S&L crisis period. In the robustness checks, I instead use the range 1980–1993 when constructing the *Intensity* measure.

I first search CEO employment history during 1985–1990 from BoardEx and proxy each CEO's location at the county level based on their then-current employer's headquarters. I also verify the employment history with Marquis Who's Who biographies, from which CEO birthplace is retrieved. When data are not available from these data sets, I conduct a manual search to obtain the missing information. In this way I am able to retrieve the date, county, and state for each bank CEO in the sample for each year from 1985 to 1990. Thus each CEO has a series of state–year records during the savings and loan crisis.

The bank failure data during the S&L crisis comes from the FDIC.[15] Recall from Section 2 that I collect year- and state-level data on the number of depository institutions failed and divide it by the total number of depository institutions in that state in that year. For each state–year pair, I also calculate two ratios: that of failed banks' deposits to the total amount of deposits, and that of failed banks' assets to the entire banking industry's assets. Scaling is used to account for local economic conditions and banking development, and I log-transform the failure ratios because they are so highly skewed. For a given bank CEO, I take both the maximum and the mean of each log-transformed ratio over all her identified state–year records between 1985 and 1990. For all the empirical tests, my independent variable of interest is the failed deposit– based *Intensity*:

$$Intensity_c = \ln\left(1 + \max_t \left(\frac{\text{Failed deposits in employment state}_{it}}{\text{Total deposits in employment state}_{it}}\right)\right). \tag{2}$$

[15] https://www5.fdic.gov/hsob/SelectRpt.asp?EntryTyp=30

3.4 Summary Statistics

Table 1 reports summary statistics for the key variables in the panel data set . The data consist of one observation for each BHC–year combination during the 1999–2009 period. I have 1,499 bank–year observations comprising 241 unique BHCs and 301 CEOs. The names of 100 of these 241 publicly listed BHCs are given in Table A3 in the Appendix.

*****Table 1*****

The median value of *Intensity (max)* indicates that the average CEO in my data has witnessed a maximum statewide deposit-based bank failure ratio of 9.41% ($e^{0.09} - 1$). The median value of *Intensity (mean)* indicates that, on average, the state where a CEO worked from 1985 to 1990 has 4.08% ($e^{0.04} - 1$) of its total deposits associated with failed financial institutions per year. The average CEO in my sample is 57 years old, 3% of them are female, and 41% of them hold a master's, MBA, or PhD degree.

The book value of the median BHC's total assets is $1.77 billion, of which deposits account for three fourths. The asset size of my sample BHCs is smaller than the sample in Fahlenbrach et al. 2012. I also note that the size distribution with respect to book value of total assets is highly skewed, ranging from $0.73 billion at the 25th percentile to $5.46 billion at the 75th percentile. I use the logarithm of the book assets, which is denoted *Size* in all my empirical specifications.

On the BHC financial information side, I observe that the median BHC holds 33% of its assets in liquid assets. Revenue from business segments unrelated to interest rates account for 24% of the median BHC's total revenue. Bank holding companies' exposure to interest rate fluctuations is remarkably varied, ranging from 0 to more than 0.5 on the scale of 0 to 1. Tier-1 ratio is less variable than usually depicted in the media, and its mean value is 8%.

The stock return and risk measures indicate that heterogeneity prevails among BHCs. Average annual returns on a BHC stock during the sample period is 14%, but there is wide variation: a BHC at the 25th percentile has an annual return of −4.0% whereas a BHC at the 75th percentile has an annual return of +29%. The bank failure rate during 2001–2008 in my BHC sample is 3%. The mean value of *Marginal expected shortfall (market)* is −0.02; thus, for an average BHC, the average daily stock market return is −2% during the worst 5% of days—in terms of returns—for the market portfolio.

In Table 2, I try to better understand the differences in characteristics between BHCs managed by CEOs with high and low banking crisis *Intensity*. I classify as *Intensity High* the BHCs whose CEOs' *Intensity* is greater than the average of *Intensity* across all BHCs. *Intensity Low* refers to the rest of BHCs. As can be seen, the two groups are similar in terms of $Size$, ROA, and $Tier1$ magnitude. $Intensity\ High$ group has higher $Deposit/Asset$ and $Book\ to\ market$. The BHCs in the $Intensity\ Low$ group have higher level of $Noninterest\ Income/Revenue$. Levels of proxies for liquidity asset holdings are higher for the $Intensity\ High$ group. The $Intensity\ High$ group also has lower failure rate, systemic risk, and credit risk. I caution that the univariant differences between these two groups do not control for time trends, and any other characteristics and hence only suggestive summary statistics. I conduct formal multivariate analysis in Section 4 to examine these differences.

*****Table 2*****

4 Empirical Analysis

4.1 Do Banking Crisis Experiences Matter?

4.1.1 ***Are the BHCs Led by Experienced CEOs Less Likely to Fail?***

The first question addressed by my empirical analysis is whether CEOs' banking crisis experiences have a mitigating effect on the likelihood of BHCs failing in normal times and/or in subsequent crises. I classify 52 BHCs as having failed and 3.3% of BHC–year observations as failures from 1999 to 2009. Of the failed banks, nearly a fifth (10 out of 52) were acquired by the FDIC, and all 52 BHCs were delisted from at least one major US stock exchange. I also adopt a wider definition of failure that includes banks receiving government assistance under the Trouble Asset Relief Program (TARP). In my sample, 95 BHCs accepted funds from that program—although in extremely varied amounts. Bank of America Corp obtained nearly \$45 billion whereas Fidelity Bancorp received only \$7 million. Some banks (e.g., Bank of America Corp) requested help multiple times under TARP, which makes them more likely to have failed in the absence of government interventions. Empirically, I estimate a cross-sectional probit model for the Great Recession period as follows:

$$Failure_i = \alpha + \beta_2 Intensity_c + lambda_2 X_i + \eta_i. \tag{3}$$

In this expression, the subscript i denotes the BHC and c denotes its CEO. I test the hypothesis that CEO crisis experiences matter for bank survival against the null hypothesis that CEOs have no effect. In these regressions, I first control for BHC financial characteristics that the literature has found to be determinative of bank failures. I control for ex-ante BHC failure probability using return on assets (ROA), or the ratio of income (before extraordinary items) to assets, and I control for stock market performance via lagged annual return. The composition of BHC liabilities is controlled by way of the tier-1 capital ratio. The regressions include market-to-book book ratio in order to control for overvaluation of BHCs by equity investors. The CAPM's beta captures BHC exposure to the market, where the latter is proxied by the CRSP market index.

To distinguish the effect of crisis experiences, I control for other CEO traits. First, my regressions include a dummy variable indicating whether the CEO earned a post-graduate degree (master's, MBA, or PhD). In unreported robustness checks, I also control for whether a CEO's alma mater belongs to the Ivy League. Educational attainment has been shown to influence CEOs management outcomes (e.g., King et al. 2016), and to reflect innate talents, such as IQ. Second, I control for CEO age because an older CEO might have been exposed to different personal, firm, industry, or market environments other than banking crisis experiences. This CEOs age control also rules out the alternative explanation that risk aversion increases with age or that management ability accrues over the life cycle.[16] Note that Bertrand et al. 2003 show CEO age to have a significant effect on corporate policies. Third, I add a control for CEO gender because prior studies have shown that men tend to have different risk attitudes than do women.[17]

It is noteworthy that, among the sample BHCs, 15 were observed to have changed CEOs during the Great Recession. In Table 3 I give the results from running the probit model for two different subsamples: columns [1]–[4] include all BHCs; in column [5]–[8], I include only those BHCs that did not experience CEO turnover during the study period. I use two dependent indicator variables to capture bank failures. The variable *FC Fail1* takes the value 1 if the BHC failed during 2007–2009 (and takes the value 0 otherwise); here "FC" denotes the financial crisis. Conditional on *FC Fail1*, the variable *FC Fail2* is set to 1 only if the BHC (a) received TARP funds during 2007–2009 and (b) did not fail. The independent variable of interest is *Intensity* and the coefficient of interest is β_2 .

*****Table 3*****

Table 3 reports marginal effects of all specifications. The empirical results indicate a negative relationship between the intensity of banking crisis experiences and the likelihood of subsequent BHC failure. This negative correlation is consistently significant across different specifications and failure measures,

[16] I also control for Depression baby CEOs, as in Malmendier and Nagel 2011 and Malmendier et al. 2011; Depression babies are those born during the period 1920—1929. Because *CEOAge* and the Depression baby dummy variable are strongly correlated, the specifications control only for the former.

[17] The research documenting gender differences in financial risk taking includes Barber and Odean 2001 and Eckel and Grossman 2008.

and the economic magnitudes are nontrivial. For the most comprehensive specification (in column [4]), at the mean level of Intensity, a marginal increase in crisis experience Intensity during the 1980s is associated with a 5.12% (1.249×0.041) *lower* probability of failure during the Great Recession. Given that the average probability of failure in my sample is 8.5%,[18] this value corresponds to an economically significant decline of 60.24% in BHC failure rates. In columns [5]–[8], the same tests are performed on the subsample of BHCs without CEO turnover during the 1980s financial crisis; I find that the estimates remain qualitatively and quantitatively similar to the outcomes reported in the corresponding columns [1]–[4].

The number of observations is lower in the even-numbered columns. The reason is that these columns require the availability of BHC 1998 stock returns as a control variable. However, my sample includes only 133 such BHCs, of which some also have missing information on CEO characteristics. In line with Fahlenbrach et al. 2012, I find that BHC performance in 1998 is negatively associated with the likelihood of future failure. I remark that my setting differs from theirs: the 1998 LTCM crisis that they study resulted in severe damage to banks but did not trigger systemic bank closures. The nature of shocks are different in the LTCM and S&L cases, and so are their effects on CEOs and banks. Whereas Fahlenbrach et al. highlight the institutional memory and persistent risk culture of banks, I stress the CEO's learning experiences and their risk management effects on BHCs.

Overall, Table 3 shows that BHCs led by CEOs with higher banking crisis Intensity are *less* likely to have failed during the Great Recession—conditional on a BHC's past financial variables and some CEO characteristics.

For an empirical test of the influence of *Intensity* on BHC survival for all the years from 1999 to 2009, I estimate the following probit model for the panel:

$$Failure_{ict} = \alpha + \beta_2 Intensity_c + f_t + \lambda_2 C_{ct} + \lambda_2 X_{it-1} + \eta_{ict}. \tag{4}$$

As before, the subscripts i and c denote (respectively) the BHC and the CEO; subscript t denotes the year. The empirical results are a test of the hypothesis that CEO crisis experiences matter for BHC survival both in normal times and in crisis years. Unlike the cross-sectional regressions reported in Table 3, in Table 4 I include year fixed effects to remove time trends and any aggregate effects on the dependent variables.[19] In 2000 and 2002 there were no BHC failures, so the observations for those two years are

[18] Fahlenbrach et al. 2012 report a 7.49% failure rate during 2007–2009 in their sample of 321 banks.

[19] In unreported probit model results, I include state fixed effects rather than year fixed effects in order to control for intrastate regulatory differences and local economic shocks that might have accounted for bank survival.

dropped; this explains why the number of observations in Table 4 is lower than in panel regressions whose results are reported later in the paper. A possible concern involves the "incidental parameters" problem, which might cast doubt on statistical properties of the estimator in a nonlinear fixed-effects model—especially for panels with a large number of groups. To alleviate concerns about too many groups in the fixed-effects dimension, I exclude bank fixed effects from the probit model. This approach accords with Greene's 2002 claim that the finite-sample behavior of a fixed-effects estimator is far more varied than suggested in the literature.

*****Table 4*****

Table 4 shows the results of a probit regression of BHC failures on the same explanatory variables used before. All specifications report marginal effects. For columns [1]–[4], the dependent variable *Failure1* accords *FC Fail1* (capturing only the delisted or closed BHCs); for columns [5]–[8], the dependent variable is the alternative failure definition (which includes BHCs that received government assistance under TARP but did not fail). As in Table 3, the key variable of interest here is *Intensity*. The empirical results reported in Table 4 show a negative relationship between the intensity of banking crisis experiences and the likelihood of subsequent BHC failure. Again, the negative correlation is consistently significant across different specifications and failure measures, and the economic magnitudes are nontrivial. For the most comprehensive specification (in column [4]), a one–standard deviation increase in crisis experience intensity during the 1980s is associated with a 0.635% (1.27×0.005) lower probability of failure during the 2001–2008 period. When one considers that the average probability of failure for my sample is 3.3%, this corresponds to an economically significant increase of 19.24%. In other words, for a manager overseeing a BHC with average characteristics, this effect is associated with a 19.24% reduction in failure instances. In columns [5]–[8], I modify the failure definition and find that the estimates remain qualitatively and quantitatively similar.

With regard to the control variables, it appears that BHCs with fewer investment opportunities (captured by a higher book-to-market ratio) are more likely to fail. Somewhat surprisingly, neither size nor the tier-1 ratio has explanatory power in these probit regressions. This lack of statistical significance may reflect the opposite roles that size plays in failure during normal versus crisis periods. Under normal circumstances, smaller banks with less leverage are more likely (than their larger peers) to be acquired and hence to be delisted. During the Great Recession, however, large and highly leveraged banks were more fragile and vulnerable to systemic negative shocks. I find some evidence that CEOs with a higher level of education are associated with a greater probability of BHC failure. Neither CEO age nor CEO gender is a significant predictor.

In comparison with Table 3, the magnitude of the coefficient for *Intensity* is greater in Table 4. This difference reflects the different scales of bank failure rates in the cross-sectional and panel regressions. The failure rate in Table 4 is given in annual terms (and averages 3.3%), whereas the dependent variable in Table 3 captures the failure rate (of 8.5%) over the entire Great Recession period. In light of the results from these tables, I conclude that a higher *Intensity* of CEO crisis experiences is associated with a reduced rate of BHCs failures during normal times (Table 4) and also during the Great Recession (Table 3).

4.1.2 *Do BHCs Managed by Experienced CEOs Differ from Their Peers?*

In this section, I investigate the risk-taking characteristics of BHCs led by higher-Intensity CEOs. Witnessing the fallout from systemic failures of financial institutions is likely to make CEOs more aware of and cautious about such shocks. I examine the relations between the intensity of CEO crisis experiences and BHC stock market performance while controlling for their particular business activities. For this purpose I use panel regressions of the form

$$Y_{ict} = \alpha + \beta_1 \mathit{Intensity}_c + f_i + f_t + \lambda_1 C_{ct} + \lambda_2 X_{it-1} + \eta_{ict}. \tag{5}$$

The panel data include one observation for each BHC–year pair, include all sample BHCs (100 of which are listed in the Appendix), and cover the 1999–2009 period. In equation (5), subscripts i, c, and t denote (as before) the BHC, the CEO, and the year, respectively; j denotes the state where the BHC is headquartered. The dependent variables are a series of proxies for systemic risk, and the main independent variable is once again *Intensity.* I include time and bank fixed effects in all of these specifications. Time fixed effects control for the time trend and demand shocks that can affect BHC systemic risk levels, and bank fixed effects control for unobservable time-invariant heterogeneity across BHCs. I further address the issue of omitted variable bias via inclusion of time-varying BHC activity controls that are intended to capture the systemic risks faced by BHCs. In some specifications, I control also for CEO personal traits that the literature has posited may affect their risk preferences. The standard errors are robust to heteroskedasticity and are clustered at the CEO level.

Table 5 reports results from my regression of systemic risk proxies on the same explanatory variables used previously. I use three sets of variables to represent systemic risks. The first set is constructed with reference to stock market co-movement (in the spirit of Barberis et al. 2005). For each BHC, I regress its daily return against the constant return of a market portfolio (where again the market is proxied by the CRSP index) and also against the average or value-weighted returns on banking stocks for each year; for this, I use a 12-month estimation window. The resultant loading on the average (resp. value-weighted) return on banking stocks defines the variable *CMV_bk* (resp. *CMV_bkw*), which captures BHC co-movement with the overall banking sector.

*****Table 5*****

My second set of risk variables is based on the marginal expected shortfall (MES) introduced by Acharya et al. (2010). Thus *MES_bk* (resp. *MES_mkt*) captures the BHC stock's average daily returns on the 5% worst-performing days for banking sector (resp. CRSP-indexed stocks). The third proxy is the BHC's equity beta (*Beta*). Equity beta is estimated from a model of daily returns in *excess* of 3-month Treasury bills each year from December 1999 to December 2009, where the market is proxied by the (value-weighted) CRSP index.

Columns [1] and [2] of Table 5 report the results from regressing on *CMV_bk* the same key variables as before. Recall that *CMV_bk* captures the extent of BHC stock co-movement with equal-weighted returns from a banking sector portfolio. Consistently with my intuition, a higher intensity of CEO banking crisis experiences correlates with lower *CMV_bk*. When the banking industry stocks perform poorly, on average, BHCs that are managed by experienced CEOs suffer relatively less. Conversely, these BHCs do not perform as well as their industry peers when the banking sector as a whole is in an "up" market. That being said, I make no claims regarding whether this risk reduction increases or reduces shareholder value.[20]

As regards co-movement, the point estimate suggests that a one–percentage point increase in *Intensity* is associated with a 3.2–percentage point decline in the co-movement measure. The point estimate suggests also that one standard deviation of the *Intensity* measure is associated with 0.14 (i.e., $(0.032 \times 1.27)/0.2823$) standard deviations of decline in the co-movement measure. For a CEO overseeing a BHC with mean characteristics, this effect translates into a reduction of 9.2% in its co-movement with the banking sector.

Regarding the coefficients for my estimates of the controls' effects, the significantly positive sign of the coefficient for *Size* means that larger BHCs have undertaken more systemic risks, in accordance with the popular belief that they are "too big to fail". It is likely that these large banks are willing to take on higher systemic risk because they anticipate being bailed out in the event of a systemic crisis.

[20] In tables omitted for space considerations, I find that stock performance has no statistically significant association with *Intensity*.

I also find that BHCs with higher operating profits tend to exhibit more co-movement with the industry. As for CEO personal traits, a higher level of education is evidently correlated with a higher level of systemic risk. One explanation is that the greater financial literacy imbued by higher education may lead CEOs to be more confident about their ability to manage systemic risk. Observe that the point estimate of the coefficient for *Intensity* increases when I control for CEO personal characteristics. Columns [3] and [4] of the table modify the dependent variable by using the *value*-weighted return on banking sector stocks rather than the *equal*-weighted return. Nonetheless, the estimates remain both qualitatively and quantitatively similar.

In columns [5]–[8] of Table 5, the dependent variables are *MES_mkt* and *MES_bnk*, which measure an individual bank's contribution to the losses incurred—during an extreme event—by (respectively) the overall market and the banking system.[21] I follow Acharya et al. 2010 in estimating these measures as "the average return of each firm during the 5% worst days for the market." Those authors provide an empirical demonstration that this measure could have predicted emerging risks prior to the financial crisis of 2007–2009. It is intuitive that stronger stock market performance during a tail event implies a lesser contribution to systemic losses. For this reason, the measure is signed such that a higher MES value corresponds to a lower systemic risk. A one–standard deviation increase in *Intensity* is associated with a 12.7 to 38.1–basis point increase in daily returns during a tail event for the market or the banking system.

Columns [9] and [10] of the table complete our picture of the role played by a CEO's experience of banking crises in the systemic risk–taking behavior of BHCs. The CAPM-implied market *Beta* is a general measure of systemic risk that is applicable to all industries. As anticipated, a higher intensity is associated with a lower market *Beta*.

Thus I have shown that, overall, my measure of crisis intensity captures a significant effect on systemic risk taking and the likelihood of bank failure—that is, beyond bank-, state-, and market- level determinants—when I control for a range of CEO traits that could affect his preferences. In short, CEOs' banking crisis experiences do carry forward to the future and have a measurable influence on particular banking outcomes.

[21] Value-at-Risk (VaR) is another widely used risk measure employed by financial institutions. One distinction between ES and VaR is that the former captures all losses—that is, including those beyond the VaR threshold.

4.2 *How* Do Banking Crisis Experiences Matter?

4.2.1 *Exposure to Interest Rate Fluctuations*

Having described the effects of banking crisis experiences on banking outcomes regarding survival rates and systemic risk taking, I now attempt to identify channels through which those experiences manifest themselves in terms of influencing outcomes. I am mainly interested in the resilience of BHC business models to interest rate variation in the market. Interest rates are central to the business model of BHCs, which are traditionally viewed as "maturity transformers". However, it remains a mystery whether rising interest rates benefit or destroy a BHC's equity value. As described by English et al. 2012, the literature has reported contradictory empirical findings about the sign of the correlation between interest rate shocks and equity value. On the one hand, conventional wisdom holds that the maturity transformers should benefit from interest rate reductions—or (equivalently) a steeper yield curve—because BHCs are in the business of borrowing "short" and lending "long". Thus the sign and magnitude of the effect should depend on the resulting maturity gap. On the other hand, the asset value of a BHC should decline as long-term interest rates rise because the latter trend offsets the associated net interest income. Moreover, BHCs can also use derivatives to hedge against interest rate volatility. In sum, the net effect of interest rate fluctuations on BHC equity value can be positive, negative, or zero. I address the overall (unsigned) effects on BHCs of interest rate shocks but not the direction of those effects.

Interest rate shocks can impose destructive risks on BHCs. Regardless of the direction of the effect, ex ante unpredictable interest rate movements generate uncertainty in banks' equity valuation and stock market performance. This uncertainty contributed to escalation of the S&L crisis in the 1980s. I hypothesize that CEOs who witnessed more severe S&L losses where they worked are more averse to such uncertainty and will therefore engineer their business models to be less sensitive to changes in the interest rate.

Yet a BHC's business model is an intangible, overarching concept related to income sources, hedging policies, business segments, and so forth. Hence I am unable to specify a metric for such models. I therefore opt to use the bank's market valuation as a proxy for its business model.

There are many proxies for interest rates. Among these, I choose bank prime lending rates (*Prime*), the 3-month London Interbank Offered Rate (*Libor*), and the spread between 10-year Treasury "constant maturity" rate and the 3-Month Treasury rate (*Termspread*).[22] I adopt two approaches to extracting interest rates shocks. The first is to take the *first difference* (subscript "d1") of monthly interest rate

[22] I obtain qualitatively similar results (not reported here) when using other interest rate proxies, including the T-bill–Eurodollar (TED) spread, Treasury bill yields, credit spreads, etc.

time series, which eliminates the time trend and seasonality and therefore stabilizes the mean of that time series. The second approach is to take the *residuals* (subscript "res") of the monthly time series of each proxy after fitting with AR(2) models to preclude the possibility of autocorrelation. To measure each BHC's exposure to interest rate shocks, I regress the monthly returns on its stock against monthly interest rate shocks (extracted as just described). So with two methods to extract shocks via three proxies, I obtain six interest rate betas: *Prime_d1*, *Prime_res*, *Libor_d1*, *Libor_res*, *Termspread_d1*, and *Termspread_res*.

Finally, I conduct panel regressions by regressing the obtained betas on *Intensity*. In this way I verify whether (or not) the intensity of crisis experiences is associated with BHC resilience to interest rate movements. The results are reported in Table 6, where (as in Table 5) I include both year and BHC fixed effects.

*****Table 6*****

Table 6 gives results of the panel regression using the most complete set of control variables. The first observation is that greater experience intensity correlates with lower interest rate betas regardless of which proxy is used for interest rates. A one–standard deviation increase in intensity is associated with a decline of 0.58% to 2.29% in interest rate betas. Other control variables seem not to have a significant effect on the dependent variables. Overall, the findings support my intuition that BHCs managed by CEOs with more crisis experience adopt business models that are less affected by interest rate shocks. A natural question is whether these results continue to hold during times of financial crisis, when liquidity evaporates and short-term interest rates spike. Additional regressions (not reported here) yield results that are qualitatively similar in subsamples of crisis and non-crisis years; in particular, the effect is not stronger in times of crisis.

4.2.2 *Credit Risk Management*

In this section, I check for whether experienced CEOs, who already have bank crisis experiences, exhibit distinctive ways of managing credit risk. As stated previously, the 1980s witnessed tighter money and intensified competition among financial institutions. Those that were locked in by rate ceilings assumed greater credit risk in order to boost their profitability, and these risk-shifting practices were a proximate cause of S&L failures. I expect CEOs who lived through this part of history to be especially careful when dealing with credit risks—and to be more aware than unseasoned CEOs of deteriorating loan quality.

Table 7 provides evidence concerning the association between credit risk proxies and my measure of experience intensity. The variables I select to represent credit risks are the ratio of net charge-offs to assets, of provisions to assets, and of nonperforming loans (*BadLoan*, at least 90 days past due) to assets; all of these variables are frequently used in the literature (Fahlenbrach et al. 2012, Ellul and Yerramilli 2013, Bouwman and Malmendier 2015). As the baseline regressions clearly show, the CEO experience Intensity measure is negatively correlated with loan quality and credit risk. With regard to economic magnitudes, column [2] of the table reveals that a one–standard deviation increase in *Intensity* is associated with an 0.053% decrease in net charge-offs, which accounts for a fifth of the latter's mean level of 0.29%. When I control for both firm and CEO time-varying characteristics, a one–standard deviation increase in *Intensity* is associated with an 0.673% (resp., a 1.168%) decrease in the ratio of provisions (resp., nonperforming loans) to assets. A general pattern evident in Table 7 is that the estimated coefficients of interest are both larger in magnitude and more robust when I control for CEOs' personal traits. This pattern can be explained by the more precise estimates of error terms when the proper controls are in place.

*****Table 7*****

As for other controls, it is hardly surprising—given the persistent nature of loan quality and credit risks—that the most significant predictor for a current level of risk taking is its lagged level. The credit quality of larger banks is lower, which suggests that major banks are more likely to engage in risky mortgage practices. The fraction of non-interest income (*Noninterest*) is negatively related to loan quality: ceteris paribus, BHCs whose income depends less on interest rate–related business have better credit quality. Overall, my findings indicate that CEOs who weathered a more severe banking crisis are associated with lower credit risks when they subsequently manage BHCs.

One caveat is that the negative relationship between *Intensity* and *Badloan* does not determine whether the observed lower *BadLoan* is due to less risk taking or to more effective risk management. It could be that experienced CEOs set up a more efficient and stronger risk control system and exert stringent monitoring of loan quality. Alternatively, managers may avoid risk so as to minimize the possibility of being fired by the board; in this scenario, risk aversion reduces BHC value. Yet because I find that the ROA is not statistically distinguishable from zero, the implication is that the reduced risk taking associated with experienced CEOs does not reduce BHC profitability. Also, if I change the denominator in *BadLoan* from book value of total asset to total amount of loans, the negative relation between *Intensity* and *BadLoan* remains, which is another piece of evidence in favor of effective risk management.

4.2.3 *Liquidity Risk Management*

In this section I examine another important aspect of a BHC's risk profile: liquidity risk. I have two motivations. First, the corporate literature claims that holding large amounts of cash may demonstrate for strong aversion to risk and a more conservative management style (Malmendier et al. 2011, Schoar and Zuo 2011, Bernile et al. 2015, Dessaint and Matray 2015, Dittmar and Duchin 2015). Since my hypothesis is based on the notion that early-career experiences with a banking crisis raise one's awareness of the risks—embedded in bank operations—that can trigger failures, a CEO's preference regarding the amount of liquidity buffer is also likely to be affected.

Second, the management of liquidity has become a core part of banks' strategic planning and balance sheet management. The Bank for International Settlements introduced the liquidity coverage ratio (LCR) and the net stable funding ratio (NSFR) in 2010 as part of Basel III. Beginning 1 January 2015, banks were required to maintain a minimum LCR ratio of 60% and to reach 100% by 1 January 2019 via annual increments of 10%. Banks were also required to comply with the NSFR disclosure requirements no later than 1 January 2018. The NSFR is a critical component of Basel III, and its goal is to reduce the risk of bank failures and the possibility of broader systemic stress in case disruptions to a bank's regular funding sources erode its liquidity position. Basel III's liquidity rules mark the first time that banks were required to meet global and quantitative minimum standards for liquidity. This regulation was initiated in response to calls for a sound liquidity environment following the unprecedented evaporation of liquidity observed during 2007–2008 (Brunnermeier 2009). Given the vital role that liquidity positions played in the 2008 episode, a close check is warranted on the ex ante factors underlying cross-sectional differences in handling liquidity buffers at the BHC level.

My sample period starts in 1999 and ends in 2009, during which time BHCs used their own discretion in managing liquidity risk—albeit in accordance with the general principles laid out by regulators. In the absence of binding rules, the discretionary holdings of liquid assets are more informative about BHCs' intrinsic attitudes toward liquidity risks and their management of those risks.

With regard to composition of the liquidity buffer, I follow the spirit of the LCR's definition of high-quality liquid assets. Data required by the NSFR ratio is seldom publicly disclosed and so requires a nontrivial extent of estimation. The LCR definition stipulates that the ratio's numerator (i.e., high-quality liquid assets) be easily and quickly convertible into cash. In line with that definition, liquid assets in this paper include cash, pledged securities, held-to-maturity securities, available-for-sale securities, and federal funds sold. Other scholars adopt similar constructions (see Kashyap et al. 2002, Gatev and

Strahan 2006, Cornett et al. 2011, Loutskina 2011, Acharya and Mora 2015, Irani and Meisenzahl 2015). As an alternative, I also check BHC holdings of US Treasury bills. Note that my liquidity measure is based on market value, just as with the accounts reported in FR Y-9C statements.

It would be ideal if I could separate the market valuation change of liquid assets from the BHC's propensity to hold liquid assets, but data constraints prevent this. Certain categories of liquid assets can appreciate or depreciate dramatically absent active BHC management; as a result, a BHC's liquid asset market value does not strictly reflect its willingness to hold a liquidity buffer and is confounded by its asset picking skills. A liquid assets measure based on turnover or flow would be more appropriate but is precluded by data limitations. Fortunately, this concern is attenuated by the relatively stable pricing of liquid assets. Observe also that I scale the value of liquid assets value by the book value of all assets.

Panel B of Table 7 presents the baseline regressions of liquid asset holdings. I point out the suggestive positive relations between liquidity positions and the Intensity of 1980s bank failure experiences encountered by BHC CEOs. Higher liquidity holdings would have served as a buffer against the "black swan" (tail) risk that exploded to instigate the global financial crisis. The numerator of *Liquid asset1* (columns [1] and [2]) consists of cash, pledged securities, held-to-maturity securities, available-for-sale securities, and federal funds sold; that of *Liquid asset2* (columns [3] and [4]) is the same but excludes federal funds sold. The statistical power and economic significance of my key variable of interest (*Intensity*) is similar in both cases. On average, federal funds sold amount to 1.7% of the total book value of assets. Since the mean of *Liquid asset1* is 35.7%, it follows that the 1% increase in liquid asset holdings associated with a one–standard deviation increase in *Intensity* is less significant economically than is the effect of an identical *Intensity* increase on credit risk. The two liquid asset variables are significant only at the 10% level, which means that they have less explanatory power than my other predictive variables.

In columns [5] andf [6] of Table 7's Panel B, the dependent variable is the BHC's amount of US Treasury bills held (scaled by its book value of assets). The signs of the coefficients in these columns can be interpreted in much the same way as before. I find that a one–standard deviation increase in *Intensity* is associated with an 0.38% increase in the holdings of US Treasury bills, where the mean level of these holdings is 3.66%.

In sum, my results are consistent with this paper's previous findings that link banking crisis experiences and stronger control over risks. A higher intensity of such experiences is associated a higher level of liquid assets held, with a lower level of credit risks, and with greater resilience to interest rate shocks. Overall, then, my empirical evidence suggests that enhancement of asset safety is the major channel through which a CEO's banking crisis experiences become manifest in their subsequent management of

BHCs. Experienced CEOs manage the asset side of the balance sheet differently than do other CEOs. However, I find no evidence of a like effect on financing policies related to the balance sheet's liability side—*contra* the claims typically made in the corporate literature. Managerial studies addressing general corporate sectors reveal that CEOs' personal traits are often reflected in their firms' strategies vis-à-vis corporate investment, financing, and diversification. My results do not yield a parallel finding for the banking sector. One reason could be that BHCs are subject to tighter regulation of their funding sources and core capital levels, leaving less room for CEOs to exert influence; in contrast, the corporate C-suite has relatively more decision power and leeway over their own leverage policies.

Taken as a whole, the results of my empirical analysis support the hypothesis that management experiences with previous banking crises affect both the systemic risk taking and the chances for survival of a BHC. Stronger liquidity positions, better-quality loans, and a greater ability to withstand interest rate shocks are all possible explanations of my findings—detailed in Sections 4.1.1 and 4.1.2—that BHCs led by experienced CEOs are less likely to fail and more likely to differ from their peers in terms of stock market performance.

4.3 Heterogeneous Effects of Experiences

4.3.1 *Large versus Small BHCs*

I split the sample based on BHC size to see whether the previously documented effects differ between the two groups. The result, not tabulated here, is that there is no statistically meaningful difference in the coefficients estimated for the samples of "big" and "small" bank holding companies.

4.3.2 *Sectors during the S&L crisis period*

One might reasonably suppose that the "imprinting" effect of crises experienced by an individual varies as a function of salience. When the S&L crisis broke out, foo foo fooWhen the S&Ls crisis breaks out, people who work in the S&Ls, thrifts, banks, and other depository institutions would be exposed to the shocks of institutions closures more than those working in other sectors. Hence, bank failures are more salient for people within the banking sector because these people have larger networks, information sources, and business connections related to the banking sector. There are 89% CEOs working in the banking sector during the 1980s. In Table 8, I report that the relationship between bank risk management and *Intensity* is stronger if BHCs CEOs from 1999 to 2009 worked in the banking sector during the S&L crisis, compared to the full sample. Hence, I show that the relation between risk management and *Intensity* is stronger when the bank failures are more salient for CEOs in the S&L crisis.

*****Table 8*****

4.3.3 *Position Held during the S&L Crisis*

An individual who has led a financial institution during the S&L crisis is likely to have faced precarious situations more often and vividly than if she were located near the bottom of the corporate ladder. Hence the imprinting effect on individuals is expected to be stronger in the former case than in the latter. I test this hypothesis by first splitting the sample in terms of whether the BHC CEO was, during the 1980s, a C-suite member when the S&L crisis occurred; I then compare the magnitude of effects between the two groups. Table 9 reports the *Intensity* coefficient for the subsample of CEOs who held C-suite positions during the S&L crisis. In our sample, 41% of BHCs CEOs held C-suite positions during 1980s. Next, I run a Student's t-test to see if the size of that coefficient is statistically distinguishable from that for the entire sample. I find that the predictive power of *Intensity* is significantly greater in the case of BHC CEOs who occupied C-suite positions during the S&L crisis. This result fits the intuition that crisis shocks are more salient for CEOs who held higher positions during that crisis—most likely because such positions expose individuals to more information about conditions of the industry and in the US state where they worked. In addition, I expect that their personal outlooks are similarly more affected by industry and state shocks.

*****Table 9*****

5 Endogeneity, Alternative Accounts, and Robustness Checks

This section addresses several concerns related to endogeneity. It also explores alternative explanations for my results and tests the robustness of those results.

5.1 Endogeneity Concerns

The ideal experiment for testing the causal effect of banking crisis experiences on BHCs would involve the exogenous assignment of crisis shocks to identical CEOs randomly paired with identical BHCs. Of course, such an assignment is impossible in reality. I must therefore deal with the impairment of any causal claims that is due to possible matching between the employment circumstances of individuals during the S&L

crisis and their subsequent selection into BHCs. Hence I seek to isolate matching processes from the identification and thereby more firmly establish the effect of crisis experiences.

5.1.1 *CEO–Firm Matching after the S&L Crisis*

The common limitation of CEO-related research is that the matching between CEO and firm is not random. Thus the findings reported here might result not from my hypothesized mechanisms but rather from unobservable factors that drive both the matching and my predicted variables. Since my focus is the banking sector and since idiosyncratic death or health shocks to CEOs are too scarce to allow construction of a reliable regression sample, I rely on CEO retirement age to identify exogenous CEO turnovers and then exploit CEO turnover to tackle the endogeneity concern.

There are two reasons why this use of the retirement age is appropriate in the banking sector. First, the media often pressures older CEOs to retire because the banking sector is fast paced and thus presumed to require vigorous leadership.[23] Hence CEO succession often occurs in response to a lack of strategy innovation or other fundamental improvements. To ensure that older CEOs are not forced to exit because of BHC policy changes, I check for the existence of significant trends in the year *before* the new CEO is appointed (cf. Schoar and Zuo 2011). Second, a CEO's ideal retirement age is typically subject to debate, and the timing of CEO retirement is seldom exactly known in advance. It follows that CEO replacement can be delayed. This variation in CEO selection—that is, due to random timing—allows me to evaluate the role of CEO experience in bank management.

Recall from Table 1 the summary statistics that the median CEO retirement age in my BHC sample is 61. I adopt a fairly conservative approach in taking age 65 to be the threshold. So for any succession, if the retired CEO is older than 65 then I classify the CEO turnover event as exogenous. Under this classification, I find that 30% of the sample BHCs experienced exogenous CEO turnovers (and are therefore included in my subsample used to control for endogeneity) and also that there is substantial variance across BHCs. (In a subsequent robustness check, I use retirement ages other than 65.) I acknowledge that this approach does not entirely resolve the problem of assortative matching. However, my findings at least suggest that banking crisis experiences cultivate certain qualities in CEOs that enable them to be chosen as the successor by corporate boards. These CEOs are hired to implement a certain type of corporate strategies. In Table 10, I replicate Section 4's main findings when testing the subsample of exogenous CEO turnovers.

[23] http://www.americanbanker.com/bank think/time-to-rethink-mandatory-retirement-for-bank-directors-1066015-1.html

*****Table 10*****

In column [1] I present the marginal effects from the probit model of bank failures. The definition of *Failure1* considers BHCs receiving assistance from TARP to be survivors. The size of the coefficient for *Intensity* when estimated using the exogenous turnover subsample is 30% larger than when estimated from the complete sample, although the coefficients estimated in the CEO turnover sample have less statistical power—which is not surprising in light of the smaller sample size and the associated noisier error terms. In columns [2]–[4] of the table, the dependent variables are proxies for systemic risk taking (viz., co-movement with the equal-weighted banking sector portfolio, marginal expected shortfall, and market beta). Throughout the sample period, an increase of one standard deviation in *Intensity* translates into an *MES* increase of 0.254 percentage points, which is a bit less than one seventh of the 1.8–percentage point unconditional mean of MES. Recall that a greater MES corresponds to a lower level of systemic risk. Column [5] reports the results from regressing *Net charge-offs* on *Intensity*, and column [6] summarizes the liquid asset holdings regression. Both the economic and statistical significance of *Intensity* in explaining the management of credit risk and liquidity risk are higher for the turnover subsample than for the full sample. Finally, column [7] shows the results from regressing BHC stock returns on term spread shocks. Here the coefficient in the turnover sample case differs little from that in the regression using the full sample.

5.1.2 *CEO–State Matching before the S&L Crisis*

The second main endogeneity concern stems from endogenous mobility during the savings and loan crisis. For instance, it could be that a risk-averse CEO in Texas anticipates the banking crisis in that state and therefore decides to move to a "safer" state in which banks take less risk. These risk-averse CEOs will tend to adopt conservative business models and loan policies after stepping into the CEO position. In that event, my intensity measure captures only the innate risk aversion of CEOs and so my findings should be attributed mainly to CEOs' risk attitudes, not to their early-career banking crisis experiences. However, this account would entail a *positive* correlation between *Intensity* and risk taking, which is the opposite of what my empirical results show.

It might also be that CEOs in the most heavily hit states are shunned by the labor market following the S&L crisis. Thus the CEOs from those states would then be employed only by lower-quality BHCs, which are less likely to survive in any case. This account would entail a positive correlation between *Intensity* and *Failure*, which likewise contradicts the sign of my coefficients in Table 4. I further alleviate this concern by repeating my analysis on a subsample of BHC CEOs who remain in a single state throughout the 1985–1990 period. The sign of my predictors are similar, both statistically and economically, to regressions including the entire CEO sample.

In seeking further support for a causal link, I change location of employment during the S&L crisis from the state where the CEO worked to the state where he was born. Since one's birthplace is (from the CEO's perspective) a random assignment, it follows that the S&L crisis severity in a CEO's home state more closely approximates—than does its severity in the state where he then worked—a random assignment of crisis intensity to CEOs across BHCs. Hence the S&L intensity in a CEO's home state is a valid exogenous variation to the dependent variables examined previously. I collect the birthplace of BHC CEOs from Marquis Who's Who and then redefine *Intensity* by incorporating the highest bank failure rate in each CEO's home state over the 1985–1990 period. Because the home bias literature suggests that individuals are connected to their hometowns through social networks and emotional bonding, I assume that CEOs are also exposed to crisis *Intensity* not only in their states of employment but also in their hometown states.

I then replicate key regressions while using *Intensity_Birth*, my hometown-based measure of *Intensity*. As shown in Table 11, BHCs led by CEOs whose home states are characterized by a higher Intensity of the the S&L crisis differ from their peers in terms of stock returns, employ business models that are more resilient to interest rate shocks, and exhibit better management of credit and liquidity risk. This test confirms that my paper's main results are not driven by matching between CEOs and states during the S&L crisis.

*****Table 11*****

5.2 State- versus Bank-Level Experiences

Another possible objection is that my intensity measure could be highly correlated with micro-level bank failures within a state and so my Intensity measure might reflect losses of the firm for which a CEO worked during the 1980s. In that case, *Intensity* would be confounded by CEO–firm matching in that period. For example, less competent CEOs may have been hired by institutions that performed poorly during the 1980s and then, following the bankruptcy of those institutions, may have ended up working for similarly underperforming BHCs. Thus variable levels of latent talent could be driving both CEO–firm matching in the 1980s and BHC performance during 1999–2009.

I address this objection by, first of all, using CEOs' education achievement to proxy for their talent; doing so allows me to rule out the possibility of my results being a function of CEO talent. I then control for the financial conditions of CEOs' past employers during the S&L crisis to compare the predictive power of state- versus firm-level losses. If the significance of my state-level *Intensity* measure survives the inclusion of firm-level financial conditions, then I can be confident that CEO–firm matching in the 1980s is not the main driver of my results.

Next I consider the incidence of firm bankruptcy during the 1980s. Toward that end, I create a dummy variable set equal to 1 when the institution employing (a subsequent BHC) CEO during the S&L crisis goes under (and set equal to 0 otherwise). In the full sample, roughly 4% of CEOs have experienced firm-level bankruptcy. The variation in this firm bankruptcy indicator is insufficient for identification purposes, and the estimated coefficients are too noisy for drawing any reliable inference.

I therefore turn to the ratio of nonperforming loans to all loans (*BadLoan/Loan*) for measuring employer bank–level crisis shocks to CEOs during the 1980s. Table 12 reveals that, in the subsample consisting of CEOs' prior employer banks for which this ratio can be identified, the employer shocks have similar effects on BHCs subsequently run by these individuals. In addition, the economic and statistical power of the *BadLoan/Loan* coefficients are greater than that of those pertaining to state-level crisis experiences. This result is consistent with the view that micro-level experiences matter more for individuals than do macro-level ones—that is, because the micro-level context involves more individual action and interactions.

*****Table 12*****

5.3 Other Crises

A natural question to ask is whether some types of crisis are more relevant for CEOs than other types. Do all economic recessions or asset bubbles leave an imprint on future BHC CEOs and/or influence their management styles? Is there something unique about the S&L crisis? I address this question by changing the "experience formation" period from the 1980s S&L crisis to the 1997 Asian crisis. So in Table 13, *Intensity* now captures the state-level bank failure rates where future BHC CEOs were employed in 1998. I find that exposure to this non–banking-related crisis does *not* affect CEOs in the same way as exposure to the S&L crisis. In fact, the coefficient estimates reported in this table are statistically insignificant for all but one (*Net charge-offs*) of the dependent variables.

*****Table 13*****

5.4 Alternative Incentives

5.4.1 *Destructive Risk Aversion*

So far, my findings suggest that experienced CEOs have more conservative styles with respect to risk taking. The relevant welfare question is whether such risk avoidance creates or rather destroys shareholder value. If CEOs refrain, for personal reasons, from assuming a level of risk exposure that is optimal for the BHCs they manage, then the risk-averse patterns documented here are destructive of value. A similar dynamic plays out in the case of a CEO who is so concerned about her career that she takes no risks that could increase the likelihood of being fired; it is almost certain that this strategy will not maximize shareholder value. However, I find that neither operating performance nor stock returns differ significantly between BHCs managed by experienced versus unseasoned CEOs, which suggests that the risk-aversion tendencies I observe do not compromise shareholder value. The ideal test case would require constructing a counterfactual optimal risk level to be taken by BHCs—a project of doubtful feasibility.

5.4.2 *Executive Compensation*

It is also possible that compensation packages provide CEO incentives that result in a range of preferences for systemic risk, credit risk, and liquidity risk. Therefore, it seems advisable to see whether the effect of banking crisis experiences varies as a function of executive compensation. I have compensation data for only 20% of the CEOs in my sample, but I can include compensation level as a control variable in my main specifications. I find that the sign of the *Intensity* coefficient is unaffected by CEO compensation. Owing to the drastic decline in observations for the regression, statistical power is greatly diminished when compensation controls are included.

5.4.3 *Too Big to Fail*

A notable aspect of S&L crisis is that its resolution ended up costing taxpayers more than $124 billion. The Resolution Trust Corporation was established to dispose of failed institutions taken over by regulators and to restore insured customers' deposits. It is widely acknowledged that such government bailouts create a moral hazard and may well encourage lenders to assume more risk than they would in the absence of this "backstop". It follows that CEOs may be incentivized to engage in empire building so that their BHCs become too big to fail. However, I find no evidence of a positive assocation between *Intensity* and either the size or growth rates of BHCs.

5.5 Robustness Checks

In this section, I briefly discuss a battery of robustness checks undertaken to ensure that my findings are not artefacts of how the key variables are defined. I first alter the definition of *Intensity* by expanding the S&L crisis period from the years 1985–1990 to the years 1980–1993. I also use the mean, rather than the maximum, of the state-level bank failure rate. In addition, I change the specification used to estimate interest rate betas by controlling for Fama–French three factors. With the endogeneity tests, I use different cutoffs for the retirement age. None of my results are materially changed by any of these alternative specifications.

Another concern is the issue of oversampling. This could occur because my BHC-specific dependent variables vary from one year to the next whereas the key independent variable (*Intensity*) varies only across CEOs and, moreover, remains the same for all years of a given CEO's tenure. Hence observations related to CEOs with longer tenure periods will have a greater effect on the empirical relation between *Intensity* and my dependent variables. To mitigate this concern, I carry out cross-sectional tests in which all time-varying dependent variables and controls are collapsed to their mean value over the focal CEO's BHC tenure. The paper's main results remain much the same in terms of significance and the sign of coefficients.[24]

Finally, one might question why I focus on the years 1999–2009 but do not address the years *following* the Great Recession. The reason is that the financial regulatory landscape underwent considerable change after that crisis, especially in terms of the allowed business scope and required core capital for banks. In light of the different environment faced by BHCs before and after the financial crisis, I believe that a cleaner and more informative analysis results from limiting my examination to the crisis and pre-crisis periods only. I also use 1999 not years before as my pre-crisis cutoff to avoid interactions with the 1980s S&L crisis experience, which would confound my empirical analysis of the research questions posed in this paper. I conclude my response to this question by using the 2010–2015 period as an out-of-sample test of results related to the management of credit and liquidity risk; this test confirms my main intuition: that *Intensity* increases CEO awareness of risk management.

6 Conclusion

This paper seeks to explain the substantial heterogeneity among BHC performance from 1999 to 2009, a period that includes the global financial crisis, from the perspective of CEOs' early-career crisis experi-

[24]Tables reporting results for all these robustness checks are available from the author upon request.

ences. It also sheds light on how sophisticated agents learn from extreme events. I document empirically that the banking crisis experiences of CEOs do affect their subsequent risk management style, and I offer suggestive evidence regarding the channels through which these effects work and the policies most likely to be affected by such experiences. In particular, I find an inverse relation between a BHC's likelihood of survival and the intensity of its CEO's preceding experience with banking crises. Systemic risk levels are also inversely related to CEO crisis experiences. Those experiences explain the strategies that CEOs subsequently adopt to be more resilient against the interest rate shocks encountered by BHCs. I show that "experienced" CEOs control risk more effectively, as indicated by lower provision levels and proportions of nonperforming loans. To establish causality, I focus on exogenous CEO turnover to establish that my findings are not driven by BHC–CEO matching. I conclude that early-career banking crisis experiences reduce systemic risks—and the likelihood of subsequent bank failure—in both normal and turbulent times. Thus such experiences matter for BHC operations during crisis and non-crisis periods alike, and the operational aspect most likely to be affected is the management of credit risk and liquidity risk. Although some endogeneity concerns remain unresolved, I aim to provide more causal evidence in future work.

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Figure 1: Number of US Bank Failures, 1930–2016. This figure reports the total number of commercial banks, commercial and savings banks, savings institutions, savings banks, and savings associations that were assisted, put under receivership, or closed by the Federal Savings and Loan Insurance Corporation (FSLIC) or the Federal Deposit Insurance Corporation (FDIC). (*Source:* FDIC and author calculations.)

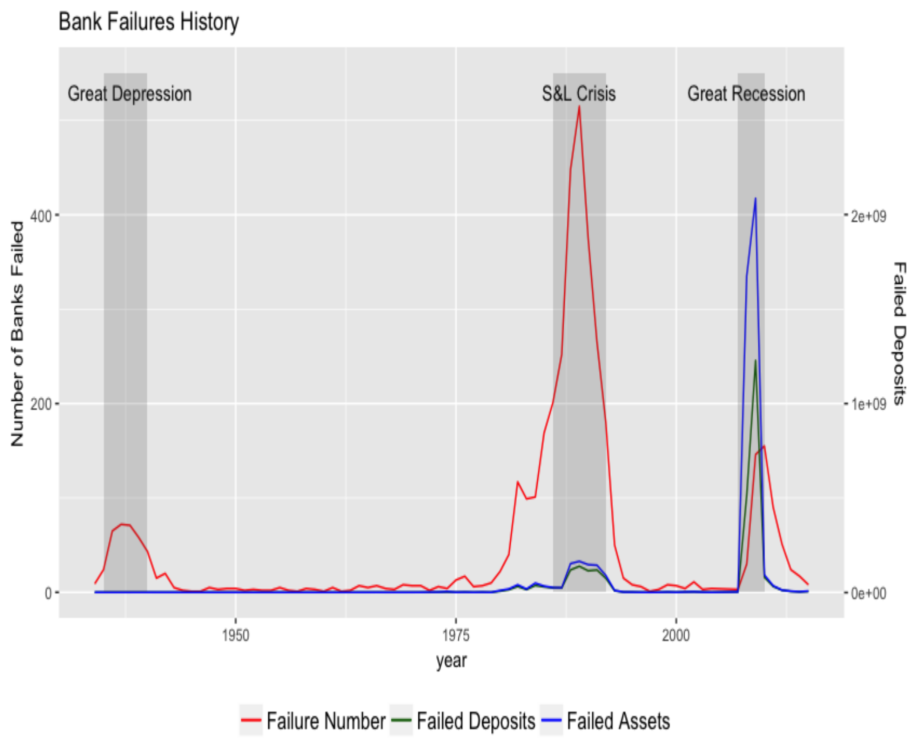

Figure 2: Example of Bank Failure Time Series during the S&L Crisis. This figure plots the fraction of banks that failed, during the period 1980–1993, in the states of California (CA), North Carolina (NC), New York (NY), Texas (TX), and Virginia (VA).

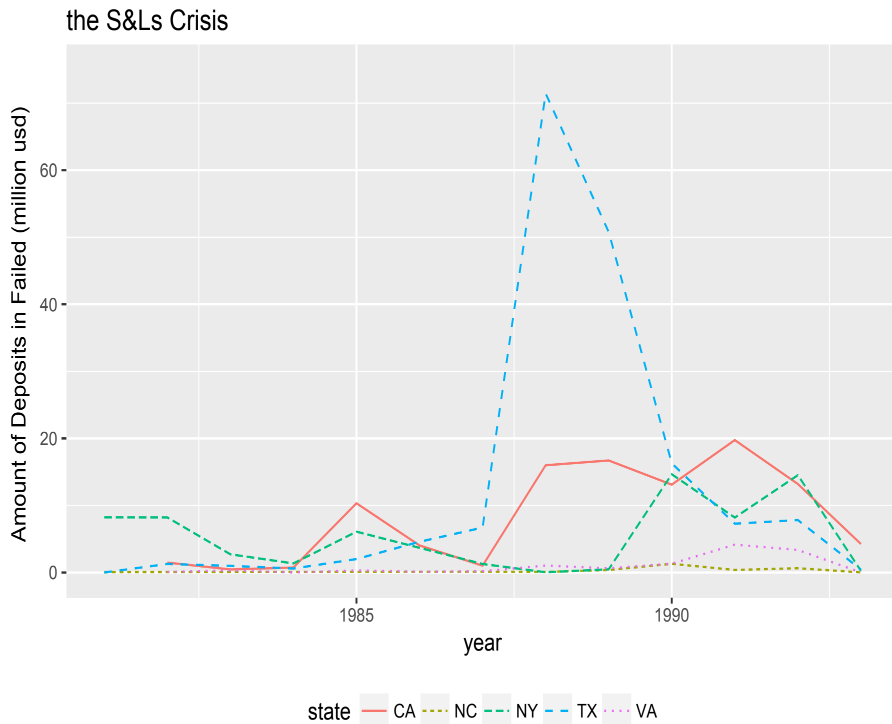

Table 1: Summary Statistics

This table reports summary statistics of BHC- and CEO-related variables, all of which are defined in Appendix Table A2.

Variable	Number	Mean	S.D.	Min	p25	Median	p75	Max
CEO-Specific Variables								
Failure rate in Intensity (max)	1499	0.09	0.11	0.00	0.03	0.05	0.07	0.71
Failure rate in Intensity (mean)	1499	0.04	0.05	0.00	0.01	0.02	0.04	0.71
Age	1494	56.88	57.15	37.00	52.00	57.00	61.00	86.00
HighDegree	1199	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Female	1199	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Financial Characteristics								
Book asset	1499	24.82	139.99	0.16	0.73	1.77	5.46	2175.05
Size	1499	14.59	1.66	11.97	13.39	14.23	15.43	21.27
ROA	1499	0.01	0.00	−0.02	0.01	0.01	0.01	0.05
Deposit/Asset	1499	0.75	0.09	0.39	0.69	0.76	0.82	0.92
Tier-1 capital/Risk-weighted asset	1499	0.09	0.02	0.03	0.07	0.08	0.10	0.28
Loan/Asset	1499	0.67	0.13	0.05	0.61	0.69	0.75	0.95
BadLoan/Assets (%)	1499	0.00	0.00	0.00	0.00	0.00	0.01	0.09
Noninterest Income/Revenue	1499	0.24	0.23	0.01	0.12	0.18	0.27	2.53
Book to market	1495	0.64	0.87	0.14	0.44	0.55	0.72	25.35
Book leverage	1499	0.91	0.02	0.68	0.90	0.91	0.92	0.97
Net charge-offs/Asset (%)	1498	0.22	0.39	−0.34	0.04	0.12	0.26	4.90
Provision/Asset (%)	1498	0.32	0.55	−0.41	0.09	0.18	0.33	7.63
Liquid asset1/Asset	1498	0.36	0.18	0.01	0.23	0.33	0.46	1.04
Liquid asset2/Asset	1498	0.36	0.18	0.01	0.23	0.34	0.47	1.04
US Treasury/Asset	1479	0.04	0.06	0.00	0.00	0.01	0.05	0.51
Risk and Return Characteristics								
Return	1499	0.14	0.30	−0.71	-0.04	0.11	0.29	2.25
Failure	1499	0.03	0.18	0.00	0.00	0.00	0.00	1.00
Co-movement (equal weighted)	1499	0.40	0.29	−0.16	0.10	0.46	0.66	0.90
Co-movement (value weighted)	1499	0.36	0.29	−0.19	0.08	0.38	0.63	0.93
Marginal expected shortfall (market)	1498	−0.02	0.02	−0.14	−0.02	−0.01	−0.00	0.03
Marginal expected shortfall (bank)	1498	−0.02	0.02	−0.15	−0.03	−0.01	−0.00	0.04
Beta	1452	0.62	0.58	−1.06	0.12	0.56	0.98	2.49
Prime_d1	1409	0.03	0.03	0.00	0.01	0.02	0.03	0.33
Prime_res	1409	0.04	0.04	0.00	0.01	0.02	0.05	0.33
Libor_d1	1409	0.06	0.07	0.00	0.02	0.04	0.09	0.52
Libor_res	1409	0.07	0.08	0.00	0.02	0.05	0.10	0.67
Termspread_d1	1409	0.02	0.02	0.00	0.01	0.01	0.03	0.12
Termspread_res	1409	0.02	0.02	0.00	0.01	0.02	0.03	0.13

Table 2: Summary Statistics by Intensity

This table reports summary statistics of BHC- and CEO-related variables for the group of CEOs experiencing less than average banking crisis intensity (Low Intensity) and greater than average banking crisis intensity (High Intensity). All variables are defined in Appendix Table A2.

	Low Intensity	High Intensity
CEO-Specific Variables		
Failure rate in Intensity (max)	0.025	0.119
Failure rate in Intensity (mean)	0.012	0.050
Age	55.646	57.024
HighDegree	0.297	0.477
Financial Characteristics		
Size	14.456	14.742
ROA	0.008	0.008
Deposit/Asset	0.745	0.752
Tier-1 capital/Risk-weighted asset	0.089	0.086
Loan/Asset	0.698	0.661
BadLoan/Assets	0.009	0.008
Noninterest Income/Revenue	0.260	0.222
Return	0.048	0.064
Book to market	0.843	0.865
Book leverage	0.911	0.908
Net charge-offs/Asset (%)	0.333	0.280
Provision/Asset (%)	0.487	0.386
Liquid asset1/Asset	0.313	0.381
Liquid asset2/Asset	0.317	0.385
US Treasury/Asset	0.036	0.044
Risk and Return Characteristics		
Failure	0.037	0.031
Co-movement (equal weighted)	0.317	0.393
Co-movement (value weighted)	0.291	0.360
Marginal expected shortfall (market)	−0.016	−0.019
Marginal expected shortfall (bank)	−0.019	−0.021
Beta	0.603	0.705
Prime_d1	0.025	0.024
Prime_res	0.033	0.032
Libor_d1	0.076	0.074
Libor_res	0.087	0.084
Termspread_d1	0.022	0.021
Termspread_res	0.026	0.025

Table 3: Cross-sectional Probit Regressions of Bank Failure during the Great Recession

This table reports marginal effects from cross-sectional probit regressions explaining the correlation between BHC failure during the Great Recession and CEOs' banking crisis Intensity in the S&L crisis. The model specification is as follows:

$$Failure_{ic} = \alpha + \beta_2 Intensity_c + \lambda_2 X_i + \eta_i.$$

See Appendix A2 for the definition of variables. My CEO controls include age, gender, and education (*High-Degree*). The BHC control variables are measured as of the end of 2016; they include the annual stock return *ROA*), size (i.e., the natural log of the book value of assets), book-to-market (BM) ratio, tier-1 ratio, and market beta. The dependent variable in columns [1], [2], [5], and [6] is the *FC Fail1* indicator (see text for details); the dependent variable in columns [3], [4], [7], and [8] is the *FC Fail2* indicator. Standard errors are clustered at the CEO level.

	All BHCs				BHCs without CEO Turnover during FC			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Failure1	*Failure1*	*Failure2*	*Failure2*	*Failure1*	*Failure1*	*Failure2*	*Failure2*
Intensity	−0.041**	−0.019	−0.063**	−0.038*	−0.052**	−0.024	−0.066**	−0.050*
	(−2.41)	(−1.45)	(−2.85)	(−1.74)	(−2.55)	(−1.44)	(−2.59)	(−1.74)
CEOAge		−0.002		0.001		−0.002		0.003
		(−0.95)		(0.27)		(−0.78)		(0.57)
HighDegree		0.016		0.050		0.021		0.057
		(0.59)		(0.96)		(0.63)		(0.90)
Female		0.064		0.221**		0.075		0.260**
		(1.44)		(2.30)		(1.30)		(2.15)
ROA_{1998}		−0.077		−0.149		−0.082		−0.142
		(−0.90)		(−1.05)		(−0.69)		(−0.76)
BM_{2006}	0.022	0.014	0.091*	0.072	0.020	0.020	0.100	0.104
	(0.57)	(0.69)	(1.79)	(1.47)	(0.41)	(0.65)	(1.59)	(1.45)
$Size_{2006}$	−0.004	0.017	0.006	0.017	−0.003	0.020	0.007	0.021
	(−0.18)	(0.96)	(0.23)	(0.65)	(−0.12)	(0.88)	(0.21)	(0.61)
$Tier1_{2006}$	1.959	1.120	1.936	−0.401	2.138	1.138	1.044	−1.769
	(1.37)	(1.63)	(1.02)	(−0.20)	(1.24)	(1.18)	(0.47)	(−0.68)
$Beta_{2006}$	−0.007	−0.026	−0.057	−0.070	0.002	−0.025	−0.026	−0.061
	(−0.16)	(−0.73)	(−0.96)	(−1.08)	(0.03)	(−0.54)	(−0.38)	(−0.75)
Observations	198	121	198	121	168	98	168	98

Marginal effects; t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$

Table 4: Probit Regressions of Bank Failure during 1999–2009

This table reports marginal effects from probit regressions predicting bank failure during the period from 1999 through 2009. The model specification is as follows:

$$Failure_{ict} = \alpha + \beta_2 Intensity_c + f_t + \lambda_2 C_{ct} + \lambda_2 X_{it-1} + \eta_{ict}.$$

Here the *lagged* control variables include the BHC's annual stock return, size, book-to-market ratio, tier-1 ratio, and market beta. See Table 3 caption—and the last paragraph in Section 4.1.1—for additional details.

	[1] *Failure1*	[2] *Failure1*	[3] *Failure1*	[4] *Failure1*	[5] *Failure2*	[6] *Failure2*	[7] *Failure2*	[8] *Failure2*
$Intensity_t$	-0.004^{**}	-0.004^{**}	-0.004^{**}	-0.005^{*}	-0.006^{**}	-0.006^{**}	-0.007^{**}	-0.010^{**}
	(−2.30)	(−2.10)	(−2.08)	(−1.89)	(−2.55)	(−2.27)	(−2.56)	(−2.80)
$CEOAge_t$			0.001^{**}	0.001^{*}			0.002^{***}	0.003^{***}
			(1.99)	(1.75)			(4.00)	(3.56)
$HighDegree_t$			-0.010^{*}	−0.007			−0.004	0.002
			(−1.81)	(−0.96)			(−0.55)	(0.21)
$Female_t$			0.012	0.010			0.011	0.009
			(1.21)	(0.57)			(0.73)	(0.32)
ROA_{1998}				-0.025				-0.061^{**}
				(−1.26)				(−2.23)
ROA_{t-1}		−0.011	−0.007	0.022^{*}		-0.041^{*}	−0.032	0.006
		(−0.66)	(−0.44)	(1.94)		(−1.74)	(−1.58)	(0.36)
BM_{t-1}		0.029^{**}	0.029^{**}	0.032^{**}		0.041^{**}	0.041^{**}	0.049^{**}
		(2.32)	(2.81)	(2.16)		(2.28)	(2.86)	(2.29)
$Size_{t-1}$		0.002	0.003	0.002		−0.000	−0.000	−0.002
		(0.75)	(1.13)	(0.75)		(−0.11)	(−0.06)	(−0.34)
$Tier1_{t-1}$		0.062	0.059	0.052		−0.151	−0.151	−0.169
		(0.31)	(0.36)	(0.25)		(−0.55)	(−0.60)	(−0.52)
$Beta_{t-1}$		0.011^{*}	0.009	0.031^{***}		0.010	0.008	0.035^{**}
		(1.75)	(1.63)	(3.84)		(1.17)	(1.02)	(3.22)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,170	1,108	1,021	1,021	1,170	1,108	1,021	1,021

Marginal effects; t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$

Table 5: Systemic Risk Taking

This table reports the results of panel regressions that investigate the relationship between systemic risks and the intensity of CEO crisis experiences. I estimate the regression specification

$$Y_{ict} = \alpha + \beta_1 Intensity_c + f_i + f_t + \lambda_1 C_{ct} + \lambda_2 X_{it-1} + \eta_{ict}.$$

The panel data include one observation for each BHC–year pair and covers the 1999–2009 period. The dependent variables are a series of proxies for systemic risk, and the main independent variable is *Intensity*. All specifications include time and bank fixed effects and control for BHC characteristics; even-numbered columns also control for CEO characteristics. Standard errors are robust to heteroskedasticity and are clustered at the CEO level.

	[1] *CMV_bk*	[2] *CMV_bk*	[3] *CMV_bkw*	[4] *CMV_bkw*	[5] *MES_mkt*	[6] *MES_mkt*	[7] *MES_bk*	[8] *MES_bk*	[9] *Beta*	[10] *Beta*
$Intensity_t$	−0.024**	−0.032**	−0.020*	−0.025**	0.002**	0.003**	0.001	0.002**	−0.080**	−0.098**
	(−2.36)	(−3.04)	(−1.83)	(−2.30)	(2.29)	(2.75)	(1.09)	(2.01)	(−2.76)	(−2.86)
$CEOAge_t$		−0.000		0.001		−0.000		0.000		0.004
		(−0.17)		(0.41)		(−0.07)		(0.73)		(0.94)
$Female_t$		0.058		0.048		−0.006*		−0.010***		0.220*
		(1.02)		(0.79)		(−1.84)		(−4.04)		(1.68)
$HighDegree_t$		0.049*		0.051*		−0.005**		−0.006***		0.146*
		(1.96)		(1.94)		(−2.80)		(−3.78)		(1.93)
$Size_{t-1}$	0.163***	0.159***	0.178***	0.182***	−0.008***	−0.008***	−0.007***	−0.006**	0.308***	0.269***
	(5.85)	(5.00)	(7.29)	(6.72)	(−4.71)	(−3.88)	(−3.73)	(−2.81)	(4.92)	(3.77)
ROA_{t-1}	4.388**	4.086**	4.195**	3.987**	−0.004	0.099	−0.134	−0.044	1.502	−0.519
	(2.39)	(2.23)	(2.47)	(2.35)	(−0.03)	(0.70)	(−0.96)	(−0.31)	(0.35)	(−0.12)
$Deposit_{t-1}$	−0.071	−0.040	−0.062	−0.034	0.008	0.008	0.003	0.001	−0.068	−0.006
	(−0.53)	(−0.29)	(−0.50)	(−0.28)	(0.78)	(0.75)	(0.28)	(0.09)	(−0.20)	(−0.02)
$Tier1_{t-1}$	1.037**	0.998	1.017**	1.041*	−0.051	−0.077*	−0.017	−0.035	1.097	1.137
	(2.00)	(1.65)	(2.05)	(1.79)	(−1.44)	(−1.94)	(−0.48)	(−0.83)	(0.85)	(0.76)
$Loan_{t-1}$	0.177	0.152	0.185*	0.175	−0.013	−0.015*	−0.009	−0.006	0.017	0.035
	(1.58)	(1.25)	(1.91)	(1.63)	(−1.59)	(−1.71)	(−1.02)	(−0.65)	(0.06)	(0.11)
$BadLoan_{t-1}$	−1.124	−1.137	−1.376	−1.453	0.038	0.035	0.002	0.006	−0.457	−1.080
	(−1.16)	(−1.01)	(−1.44)	(−1.30)	(0.34)	(0.26)	(0.02)	(0.04)	(−0.19)	(−0.38)
$Noninterst_{t-1}$	0.084	0.104	0.130**	0.154**	−0.002	−0.009	−0.000	−0.005	0.156	0.210
	(1.37)	(1.55)	(2.19)	(2.36)	(−0.34)	(−1.29)	(−0.08)	(−0.71)	(0.86)	(1.04)
$Return_{t-1}$	0.015	0.013	0.020	0.014	−0.002	−0.001	−0.001	−0.002	0.012	0.004
	(0.98)	(0.71)	(1.31)	(0.83)	(−1.49)	(−1.02)	(−1.12)	(−1.01)	(0.31)	(0.09)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,499	1,197	1,499	1,197	1,498	1,196	1,498	1,196	1,489	1,189
Adjusted R^2	0.856	0.853	0.878	0.880	0.694	0.718	0.695	0.703	0.774	0.768

${}^{*}p < 0.10$, ${}^{**}p < 0.05$, ${}^{***}p < 0.001$

Table 6: Resilience to Interest Rate Fluctuations

This table reports estimations from panel regressions predicting interest rate betas during the period from December 1999 through December 2009. All variables are defined in the Appendix Table A2. Concurrent controls include CEO age, gender, and education. Lagged control variables include the annual stock return, size (the natural log of the book value of assets), ROA, Deposit/Asset, Tier1, Loan/Asset, BadLoan/Asset, and Noninterest Income/Revenue. The dependent variables in columns [1] and [2], in columns [3] and [4], and in columns [5] and [6] are the BHC's stock returns sensitivity to (respectively) the prime lending rate, LIBOR rates, and the term spread. Standard errors are clustered at the CEO level.

	[1]	[2]	[3]	[4]	[5]	[6]
	Prime_d1	*Prime_res*	*Libor_d1*	*Libor_res*	*Termspread_d1*	*Termspread_res*
$Intensity_t$	−0.005**	−0.006**	−0.018**	−0.016**	−0.004**	−0.004**
	(−2.50)	(−2.14)	(−3.16)	(−2.39)	(−2.16)	(−2.09)
$CEOAge_t$	0.000	0.000	0.001	0.001**	−0.000	−0.000
	(1.27)	(0.76)	(1.15)	(2.13)	(−1.04)	(−1.40)
$Female_t$	−0.006	0.030***	−0.051*	−0.060**	0.003	0.017
	(−0.58)	(3.95)	(−1.88)	(−2.17)	(0.27)	(0.98)
$HighDegree_t$	0.009**	0.007*	0.018**	0.016*	0.005	0.006
	(2.60)	(1.72)	(1.97)	(1.74)	(1.36)	(1.24)
$Size_{t-1}$	−0.004	−0.003	−0.012	−0.008	0.001	0.002
	(−0.81)	(−0.67)	(−1.39)	(−0.78)	(0.34)	(0.60)
ROA_{t-1}	−0.399	−0.733	−0.796	−0.722	−0.339	−0.233
	(−1.23)	(−1.55)	(−0.89)	(−0.70)	(−1.44)	(−0.82)
$Deposit_{t-1}$	0.021	0.014	−0.032	−0.012	0.027	0.028
	(1.01)	(0.48)	(−0.54)	(−0.21)	(1.52)	(1.48)
$Tier1_{t-1}$	0.006	0.133	0.119	−0.009	−0.016	−0.028
	(0.09)	(1.30)	(0.55)	(−0.04)	(−0.26)	(−0.37)
$Loan_{t-1}$	−0.005	−0.021	−0.031	−0.034	0.006	0.017
	(−0.30)	(−0.86)	(−0.57)	(−0.53)	(0.42)	(1.02)
$BadLoan_{t-1}$	−0.179	0.035	0.383	0.362	0.032	0.153
	(−0.87)	(0.10)	(0.53)	(0.40)	(0.17)	(0.71)
$Noninterest_{t-1}$	−0.008	−0.013	0.033	0.030	0.004	0.010
	(−0.56)	(−0.66)	(0.93)	(0.74)	(0.42)	(0.96)
$Return_{t-1}$	0.001	0.001	−0.004	0.001	0.007**	0.008**
	(0.36)	(0.25)	(−0.37)	(0.05)	(2.48)	(2.40)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,116	1,116	1,116	1,116	1,116	1,116
Adjusted R^2	0.190	0.184	0.238	0.210	0.058	0.058

t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$

Table 7: Management of Credit Risk and Liquidity Risk

Panel A of this table reports estimations from panel regressions predicting credit risks during the period from December 1999 through December 2009. See Table 6 caption for additional details. The dependent variables in columns [1] and [2], in columns [3] and [4], and in columns [5] and [6] are the BHC's ratio of net charge-offs to (respectively) assets, provisions to assets, and nonperforming loans to assets. Panel B presents the regressions related to liquid asset holdings. The numerator of *Liquid asset1* includes cash, pledged securities, held-to-maturity securities, available-for-sale securities, and federal funds sold; *Liquid asset2*'s numerator is the same except that it excludes federal funds sold. The denominator in both of these liquid asset terms is book value of assets. The dependent variable in columns [5] and [6] is the amount of US Treasury bills held scaled by the book value of assets. All other ratios are likewise scaled by concurrent book value of assets. Standard errors are clustered at the CEO level.

Panel A: Panel Regression of Credit Risk						
	[1] *Net charge-offs*	[2] *Net charge-offs*	[3] *Provision*	[4] *Provision*	[5] *BadLoan*	[6] *BadLoan*
Intensity	-0.039^{**}	-0.042^{**}	-0.050^{**}	-0.053^{**}	-0.071	-0.092^{**}
	(-2.61)	(-3.06)	(-2.56)	(-2.70)	(-1.51)	(-1.98)
$CEOAge_t$		-0.002		-0.003		-0.003
		(-0.81)		(-0.96)		(-0.32)
$Female_t$		0.004		0.143		0.473
		(0.09)		(1.22)		(1.06)
$HighDegree_t$		0.013		-0.013		0.138
		(0.36)		(-0.23)		(1.17)
$Size_{t-1}$	0.129^{***}	0.130^{**}	0.143^{**}	0.118^{*}	0.628^{***}	0.460^{***}
	(3.53)	(3.31)	(2.66)	(1.95)	(4.51)	(3.39)
ROA_{t-1}	-7.281^{**}	-7.396^{**}	-3.220	-2.502	12.951^{*}	10.085
	(-2.45)	(-2.39)	(-0.95)	(-0.66)	(1.76)	(1.35)
$Deposit_{t-1}$	-0.036	0.008	-0.218	-0.327	0.844	0.487
	(-0.20)	(0.04)	(-0.87)	(-1.19)	(1.42)	(0.81)
$Tier1_{t-1}$	0.418	1.076^{*}	0.563	1.730^{*}	-0.268	0.943
	(0.73)	(1.72)	(0.65)	(1.88)	(-0.13)	(0.47)
$Loan_{t-1}$	0.091	0.153	0.422^{*}	0.588^{**}	1.795^{***}	2.124^{***}
	(0.58)	(0.86)	(1.93)	(2.44)	(3.69)	(4.11)
$BadLoan_{t-1}$	20.162^{***}	21.154^{***}	15.916^{***}	16.549^{**}	43.858^{***}	49.589^{***}
	(6.77)	(6.13)	(3.74)	(3.13)	(6.26)	(6.06)
$Noninterest_{t-1}$	-0.378^{***}	-0.376^{**}	-0.464^{**}	-0.444^{**}	-0.396	-0.540^{*}
	(-3.65)	(-3.17)	(-3.26)	(-2.67)	(-1.24)	(-1.87)
$Return_{t-1}$	-0.026	0.005	-0.048	-0.025	-0.233^{**}	-0.133^{*}
	(-0.96)	(0.17)	(-1.37)	(-0.66)	(-2.76)	(-1.65)
Panel B: Panel Regression of Liquid Asset Holdings						
	[1] *Liquid asset1*	[2] *Liquid asset1*	[3] *Liquid asset2*	[4] *Liquid asset2*	[5] *US Treasury*	[6] *US Treasury*
Intensity	0.008^{*}	0.008^{*}	0.008^{*}	0.008^{*}	0.003^{*}	0.003^{*}
	(1.83)	(1.83)	(1.69)	(1.68)	(1.91)	(1.85)
CEO controls	No	Yes	No	Yes	No	Yes
BHC controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,498	1,196	1,498	1,197	1,483	1,188

t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$

Table 8: CEOs Who Worked for the Banking Sector during the S&L Crisis Period

This table replicates the previous findings regarding the relation between the banking crisis experience intensity and risk management on the subsample of CEOs who have worked in the banking sector during the S&L crisis.

	Net charge-offs	*BadLoan*	*Provision*	*Liquid asset1*	*Liquid asset2*	*UST*
$Intensity_t$	-0.053^{*}	-0.107^{**}	-0.058^{**}	0.015^{**}	0.010^{*}	0.008^{**}
	(-1.90)	(-2.46)	(-2.59)	(2.27)	(1.95)	(2.73)
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
BHC controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1048	1049	1042	1048	1048	1027
Adjusted R^2	0.653	0.599	0.688	0.904	0.900	0.734

UST = book value of US Treasury bills held; t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$

Table 9: Bank Holding Company CEOs Who Held C-level Positions during the S&L Crisis

This table replicates the previous findings regarding the relation between the banking crisis experience intensity and risk management on the subsample of CEOs who held C-level Positions during the S&L crisis.

	Net charge-offs	*BadLoan*	*Provision*	*Liquid asset1*	*Liquid asset2*	*UST*
$Intensity_t$	-0.058^{*}	-0.111^{**}	-0.052^{***}	0.014	0.020^{*}	0.009^{*}
	(-1.83)	(-2.04)	(-3.57)	(1.36)	(1.70)	(1.72)
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
BHC controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	477	478	476	478	478	470
Adjusted R^2	0.681	0.661	0.694	0.928	0.906	0.715

UST = book value of US Treasury bills held; t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$

Table 10: Endogeneity Test 1: Exogenous CEO Turnovers

This table reports estimations from panel regressions predicting interest rate betas during the period from December 1999 through December 2009. Concurrent controls include CEO age, gender, and education. Lagged control variables include the annual stock return, size, ROA, Deposit to asset ratio, tier-1 ratio, Loan to asset ratio, Nonperforming Loan to asset ratio, and Noninterest income to revenue ratio. Standard errors are clustered at the CEO level.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Failure1	*CMV_bk*	*MES*	*Beta*	*Net charge-offs*	*Liquid asset1*	*Termspread_d1*
$Intensity_t$	−0.006*	−0.052**	0.002*	−0.101	−0.056**	−0.014**	−0.008**
	(−1.74)	(−2.35)	(1.67)	(−1.63)	(−3.08)	(−2.33)	(−2.16)
$CEOAge_t$	0.002*	0.000	−0.000	0.005	−0.014***	−0.001	−0.001***
	(1.83)	(0.06)	(−0.76)	(0.76)	(−4.38)	(−1.19)	(−3.57)
$Female_t$	0.048**	0.150**	−0.008*	0.545**	−0.094	−0.035**	0.010
	(2.02)	(2.42)	(−1.84)	(3.25)	(−1.36)	(−2.74)	(1.08)
$HighDegree_t$	0.003	0.021	−0.003	−0.037	−0.059	0.007	−0.008
	(0.26)	(0.55)	(−1.38)	(−0.36)	(−1.19)	(0.80)	(−1.64)
$Size_{t-1}$	0.011**	0.116*	−0.006	0.252	0.089*	−0.058**	0.011
	(2.27)	(1.84)	(−1.41)	(1.56)	(1.71)	(−2.66)	(1.62)
ROA_{t-1}	−1.499	4.482	−0.162	−0.188	−10.802**	0.828	−0.658
	(−1.19)	(1.18)	(−0.55)	(−0.02)	(−2.17)	(0.93)	(−1.52)
$Deposit_{t-1}$	0.080	−0.299	0.021	−0.341	−0.061	−0.046	−0.011
	(1.10)	(−1.45)	(1.41)	(−0.63)	(−0.22)	(−0.57)	(−0.33)
$Tier1_{t-1}$	0.322	−0.542	0.048	−2.140	−0.469	0.303	−0.079
	(1.02)	(−0.48)	(0.65)	(−0.75)	(−0.41)	(0.99)	(−0.66)
$Loan_{t-1}$	−0.069	0.217	−0.027*	−0.175	0.350	−0.474***	0.021
	(−1.12)	(0.96)	(−1.75)	(−0.30)	(1.20)	(−8.85)	(0.81)
$BadLoan_{t-1}$	−1.238	−1.158	0.044	0.978		0.054	−0.315
	(−0.88)	(−0.72)	(0.26)	(0.20)		(0.06)	(−0.99)
$Noninterest_{t-1}$	−0.053	0.127	−0.010	−0.170	0.038	−0.050	0.017
	(−1.19)	(0.85)	(−0.91)	(−0.41)	(0.14)	(−1.20)	(0.69)
$Return_{t-1}$	−0.037**	0.025	−0.003	0.065	−0.039	0.003	0.007
	(−2.13)	(0.73)	(−1.19)	(0.83)	(−0.84)	(0.34)	(1.34)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	432	423	423	423	488	423	396
Adjusted R^2		0.855	0.752	0.760	0.631	0.814	0.094

t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$

Table 11: Endogeneity Test 2: Home State Bank Failures during the S&L Crisis

	CMV_bk	*UST*	*Termspread_d1*	*Net charge-offs*
$Intensity\_Birth_t$	-0.013^{**}	0.007^{**}	-0.001^{*}	-0.020^{**}
	(-2.52)	(2.58)	(-1.96)	(-2.53)
CEO controls	Yes	Yes	Yes	Yes
BHC controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes
Observations	118	118	112	118
Adjusted R^2	0.607	0.790	0.043	0.279

UST = book value of US Treasury bills held; t-statistics in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$

Table 12: Effect of Employer Bank–level Experiences during the 1980s

	Net charge-offs	*BadLoan*	*Provision*	*Liquid asset1*	*Liquid asset2*	*UST*
BadLoan/Loan	-0.009^{***}	-0.100^{***}	-0.012^{***}	0.017^{***}	0.012^{**}	0.004^{**}
	(-3.86)	(-6.47)	(-3.66)	(6.42)	(2.66)	(3.10)
CEO controls	Yes	Yes	Yes	Yes	Yes	Yes
BHC controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	304	282	305	305	305	293
Adjusted R^2	0.454	0.578	0.517	0.794	0.762	0.100

UST = book value of US Treasury bills held; t-statistics in parentheses

$^{**}p < 0.05$, $^{***}p < 0.001$

Table 13: Falsification Test-Effects of Exposure to Crisis Unrelated to the Banking Sector

This table reports estimates from panel regressions predicting interest rate betas during the period from December 1999 through December 2009. Standard errors are clustered at the CEO level.

	[1] *Failure*	[2] *CMV_bk*	[3] *CMV_bkw*	[4] *MES*	[5] *Beta*	[6] *BadLoan*	[7] *Liquid asset1*	[8] *Termspread_d1*
$Intensity_t$	−0.005	−0.003	−0.002	−0.000	0.000	−0.021	−0.002	0.000
	(−0.30)	(−0.38)	(−0.30)	(−0.07)	(0.02)	(−0.58)	(−0.51)	(0.14)
$CEOAge_t$	0.004	−0.002*	−0.001	0.000**	−0.002	−0.010	0.000	−0.000
	(0.85)	(−1.79)	(−0.91)	(2.01)	(−0.47)	(−0.88)	(0.36)	(−1.00)
$Female_t$	0.008	0.008	0.007	−0.003	0.121	0.814*	−0.030*	0.002
	(0.05)	(0.13)	(0.10)	(−0.84)	(0.81)	(1.70)	(−1.89)	(0.15)
$HighDegree_t$	−0.066	0.039	0.042	−0.002	0.111	0.103	0.014	0.000
	(−0.90)	(1.36)	(1.44)	(−1.33)	(1.35)	(0.73)	(1.19)	(0.02)
$Size_{t-1}$	−0.047	0.162***	0.187***	−0.008***	0.283***	0.509***	−0.033**	−0.000
	(−1.50)	(4.39)	(6.01)	(−3.35)	(3.55)	(4.40)	(−2.09)	(−0.12)
ROA_{t-1}	−20.620**	3.729*	3.692**	0.069	0.005	2.214	0.547	−0.216
	(−2.68)	(1.87)	(2.04)	(0.45)	(0.00)	(0.27)	(0.64)	(−0.86)
$Deposit_{t-1}$	−0.597	−0.025	−0.018	0.008	0.147	0.584	−0.104	0.026
	(−1.33)	(−0.17)	(−0.13)	(0.71)	(0.37)	(0.86)	(−1.35)	(1.30)
$Tier1_{t-1}$	2.461	0.893	0.983	−0.062	0.970	−0.238	0.221	−0.034
	(1.34)	(1.39)	(1.59)	(−1.53)	(0.62)	(−0.10)	(0.87)	(−0.54)
$Loan_{t-1}$	0.776**	0.154	0.186	−0.012	0.112	2.740***	−0.727***	0.003
	(2.39)	(1.20)	(1.63)	(−1.39)	(0.33)	(3.98)	(−9.26)	(0.23)
$BadLoan_{t-1}$	4.725	−0.493	−0.839	0.038	0.212		−0.383	0.109
	(0.81)	(−0.39)	(−0.68)	(0.25)	(0.06)		(−0.41)	(0.49)
$Noninterest_{t-1}$	−0.280	0.098	0.151**	−0.006	0.220	−0.629*	−0.073*	0.003
	(−1.11)	(1.39)	(2.20)	(−0.89)	(1.06)	(−1.88)	(−1.79)	(0.37)
$Return_{t-1}$	0.145**	0.014	0.014	−0.002	0.003	−0.189**	0.003	0.006*
	(2.40)	(0.72)	(0.82)	(−1.18)	(0.06)	(−2.37)	(0.38)	(1.95)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1126	1102	1102	1101	1094	1183	1101	1047
Adjusted R^2		0.852	0.881	0.711	0.771	0.668	0.901	0.052

Appendix

Table A1: Bank Failure Statistics by State, 1980–1993

State	Number of Bank Failures	Assets of Failed Institutions ($ thousands)	Deposits of Failed Institutions ($ thousands)
AK	13	3,351,116	3,199,220
AL	24	4,927,131	3,896,180
AR	33	6,606,628	6,008,020
AZ	27	19,628,310	15,731,625
CA	195	141,330,275	101,082,589
CO	83	10,699,910	8,368,310
CT	39	18,768,826	17,177,989
DC	8	3,607,518	2,793,989
DE	1	582,350	164,867
FL	116	68,396,459	55,972,005
GA	27	5,130,530	4,014,673
HI	4	59,703	47,344
IA	68	5,933,625	5,430,787
ID	4	649,308	587,447
IL	131	72,003,699	54,991,462
IN	28	2,423,691	2,436,005
KS	99	17,210,923	11,353,926
KY	18	1,651,017	1,650,794
LA	156	19,070,690	18,362,751
MA	50	33,583,865	26,872,832
MD	21	8,572,425	6,866,249
ME	5	2,594,925	2,429,094
MI	16	4,649,773	3,707,026
MN	52	7,061,523	5,538,933
MO	67	13,810,158	13,152,226
MS	30	3,082,667	2,679,555
MT	13	441,052	369,284
NC	15	3,683,148	2,990,830
ND	14	1,547,480	1,113,646
NE	42	2,582,345	2,314,019
NH	18	5,763,487	4,937,516
NJ	61	35,854,095	28,823,090
NM	28	5,076,446	4,727,403
NV	4	334,619	325,632
NY	67	79,480,864	66,014,713
OH	47	16,702,903	14,123,718
OK	162	16,110,436	14,263,062
OR	29	9,571,028	6,961,379
PA	29	31,926,305	23,589,644
RI	6	2,662,845	2,482,011
SC	9	1,680,643	1,506,584
SD	18	1,335,339	946,523
TN	59	4,754,473	4,206,000
TX	847	196,813,168	170,220,125
UT	20	4,901,312	3,721,557
VA	39	14,098,201	11,583,007
VT	2	329,478	317,946
WA	18	4,583,398	3,663,328
WI	7	711,086	658,898
WV	13	1,212,675	1,047,146
WY	27	1,321,866	1,278,202

Table A2: Definitions of Variables

Variable Name	Definition
CEO-Specific Variables	
Intensity (max)	Maximum state-level bank failure rate experienced by sample CEOs during 1985–1990
Intensity (mean)	Mean state-level bank failure rate experienced by sample CEOs during 1985–1990
CEOAge	Age of CEO
HighDegree	Dummy set equal to 1 only if CEO was awarded a post-graduate degree
Female	Dummy set equal to 0 (resp. 1) if CEO is female (resp. male)
Financial Characteristics	
Book asset	Book value of BHC assets
Size	Market capitalization of BHC
ROA	Return *divided by* book value of assets
Deposit/Asset	Deposits *divided by* book value of assets
Tier-1 capital/Risk-weighted asset	Core capital (as defined by Basel III) *divided by* risk-weighted assets
Loan/Asset	Total amount of loans *divided by* book value of assets
BadLoan/Assets (%)	Nonperforming loans *divided by* book value of assets
Noninterest Income/Revenue	Revenue from business segments unrelated to interest rates *divided by* total revenue
Book to market	Book value of assets *divided by* market capitalization
Book leverage	Book value of leverage
Net charge-offs/Asset (%)	Written-off loans *divided by* book value of assets
Provision/Asset (%)	Provisions *divided by* book value of assets
Liquid asset1/Asset	Liquid asset book value *divided by* book value of assets
Liquid asset2/Asset	Alternative liquid asset book value *divided by* book value of assets
US Treasury/Asset	Book value of US Treasury bill holdings *divided by* book value of assets
Risk and Return Characteristics	
Return	Annualized stock market return
Failure	Dummy set equal to 1 only if BHC failed
Co-movement (equal weighted)	BHC stock market return co-movement with return on equal-weighted banking sector portfolio
Co-movement (value weighted)	BHC stock market return co-movement with return on value-weighted banking sector portfolio
Marginal expected shortfall (market)	Marginal expected shortfall with respect to the 5% worst performance days for the entire market
Marginal expected shortfall (bank)	Marginal expected shortfall with respect to the 5% worst performance days for the banking sector
Beta	CAPM beta
Prime_d1	BHC stock market return resilience to first difference of the prime lending rate
Prime_res	BHC stock market return resilience to residuals of a post–AR(2) model fitting of the prime lending rate
Libor_d1	BHC stock market return resilience to first difference of the LIBOR
Libor_res	BHC stock market return resilience to residuals of a post–AR(2) model fitting of the LIBOR
Termspread_d1	BHC stock market resilience to first difference of the term spread
Termspread_res	BHC stock market resilience to residuals of a post–AR(2) model fitting of the term spread

Table A3: 100 Examples of Sample Bank Holding Companies

BHC Name	**BHC Name**
1ST UNITED BANCORP INC	ABIGAIL ADAMS NATIONAL BANCORP
ALABAMA NATIONAL BANCORP	ALLIANCE BANKSHARES CORP
AMCORE FINANCIAL INC	AMERIANA BANCORP
AMERIS BANCORP	AMERISERV FINANCIAL INC
ANNAPOLIS BANCORP INC	ARROW FINANCIAL CORP
ATLANTIC BANCGROUP INC	ATLANTIC SOUTHERN FINANCIAL GROUP INC
AUBURN NATIONAL BANCORPORATION INC	BANCFIRST CORP
BANCORP INC	BANCORPSOUTH INC
BANCTRUST FINANCIAL GROUP INC	BANK OF AMERICA CORP
BANK OF COMMERCE HOLDINGS	BANK OF FLORIDA CORP
BANK OF GRANITE CORP	BANK OF KENTUCKY FINANCIAL CORP
BANK OF NEW YORK MELLON CORP	BANK OF SOUTH CAROLINA CORP
BANNER CORP	BAR HARBOR BANKSHARES INC
BB&T CORP	BERKSHIRE BANCORP INC
BOE FINANCIAL SERVICES OF VIRGINIA INC	BOSTON PRIVATE FINANCIAL HLDGS INC
BRIDGE BANCORP INC	BRIDGE CAPITAL HOLDINGS
BRITTON & KOONTZ CAPITAL CORP	BWC FINANCIAL CORP
C & F FINANCIAL CORP	CAMCO FINANCIAL CORP
CAMDEN NATIONAL CORP	CAPITAL BANK CORP
CAPITAL CITY BANK GROUP INC	CAPITALSOUTH BANCORP
CAPITOL BANCORP LTD	CASCADE BANCORP
CASCADE FINANCIAL CORP	CATHAY GENERAL BANCORP
CAVALRY BANCORP INC	CCF HOLDING CO
CENTER FINANCIAL CORP	CENTERSTATE BANKS INC
CENTRAL PACIFIC FINANCIAL CORP	CENTRAL VIRGINIA BANKSHARES INC
CHEMICAL FINANCIAL CORP	CHITTENDEN CORP
CITIZENS HOLDING CO	CITY HOLDING CO
CITY NATIONAL CORP	CIVITAS BANKGROUP INC
COAST FINANCIAL HOLDINGS INC	COBIZ FINANCIAL INC
CODORUS VALLEY BANCORP INC	COLONIAL BANCGROUP INC
COLUMBIA BANKING SYSTEMS INC	COMERICA INC
COMMERCIAL BANKSHARES INC	COMMERCIAL NATIONAL FINANCIAL CORP
COMMONWEALTH BANKSHARES INC	COMMUNITY BANK SYSTEMS INC
COMMUNITY BANKS INC PA	COMMUNITY CAPITAL CORP
COMMUNITY SHORES BANK CORP	COMMUNITY TRUST BANCORP INC
COMMUNITY VALLEY BANCORP	COMMUNITY WEST BANCSHARES
CORUS BANKSHARES INC	COWLITZ BANCORP
CRESCENT BANKING CO	CULLEN FROST BANKERS INC
CVB FINANCIAL CORP	DEARBORN BANCORP INC
EAST PENN FINANCIAL CORP	ECB BANCORP INC
ENCORE BANCSHARES INC	EVANS BANCORP INC
FIDELITY BANCORP INC	FIDELITY SOUTHERN CORP
FIFTH THIRD BANCORP	FIRST BANCORP NC
FIRST BUSEY CORP	FIRST BUSINESS FINANCIAL SERVICES INC
FIRST CHARTER CORP	FIRST CITIZENS BANCSHARES INC
FIRST COMMONWEALTH FINANCIAL CORP PA	FIRST COMMUNITY BANCSHARES INC
FIRST COMMUNITY BANK CORP OF AMERICA	FIRST COMMUNITY CORP
FIRST CONSTITUTION BANCORP	FIRST FINANCIAL BANCORP
FIRST FINANCIAL BANKSHARES INC	FIRST HORIZON NATIONAL CORP
FIRST INDIANA CORP	FIRST M & F CORP