Is This Time Different? Do Bank CEOs Learn From Crises?

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Abstract

This paper studies the impact of Bank Holding Company (BHC) CEO's early-life exposure to the 1980s savings and loans(S&Ls) crisis on the survival, systemic risks and policies of her BHC that she is in charge of in the future. First, I characterize the features of banks managed by CEOs who witnessed more intensely the S&L crisis (seasoned CEOs) measured by the state-level bank failure rate. I find that BHCs with seasoned CEOs are less likely to fail, and they decouple from the rest of the banking industry by taking lower systemic risks. One unit of the crisis intensity measure is associated with 0.5% lower failure rate and 0.39% lower systemic risk, measured by marginal expected shortfall. Second, I attempt to pin down the potential policy channels exploited by CEOs to account for these results. Seasoned CEOs shape their bank business models to be less reliant on interest rates. As such, these CEOs exhibit more effective control over credit risk and have higher holdings of liquid assets on their balance sheet. However, their asset growth and diversification strategies are not significantly different from those of less experienced CEOs. Finally, using exogenous turnovers, I show that the findings are not driven by bank-CEO matching.

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

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

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1 Introduction

Do economic agents learn from past experiences? Does experiencing a crises in the past affect how bank holding company (BHC) CEOs manage their banks and hence bank survivals? The existing evidence is inconclusive.

On one hand, there is evidence to suggest that past crises do not matter. For example, asset bubbles and financial crises have reoccurred over the course of the human history despite prior warning signs. As Reinhart and Rogoff point out in their 2009 book, a "this time is different" syndrome can elicit harmful actions that sow the seeds for future crises. In other words, although economic agents always believe that the current situation is different from the past and they themselves are different, they behave in the same way as before and this time ends up the same.

On the other hand, there is anecdotal evidence to suggest that past crises do affect individuals' future behavior. For example, in a Federal Reserve System publication, Lemieux (2014) 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"[1]. Are these practitioners' claims true and applicable to the financial sector at large? [2]

The question is particularly relevant for the financial service sector in the current era marked by economic, political and technological uncertainties. Identifying the impact of past experiences helps us understand the dynamics of banker and banking behavior over normal times and times of crises, and thus the financial crisis mechanism. For normal times, long term effect of past experience can provide a new angle to explain the varying banking models and policies.

Regarding the crisis period, it sheds light on the driving forces underpinning the substantial heterogeneity of bank fate that we have observed during the 2007-2008 global finance crisis, which is intriguing to both academia and practitioners.

Existing literature has posited many explanations for the substantial heterogeneity of bank performance during the crisis. The "too big to fail" (TBTF) suggests that big banks are privileged to

[1] example cited by Bouwman and Malmendier (2015)

[2] Medical studies show that traumatic events such as crises have direct impacts on individual's psyche, neurobiology, and decision-making. Trauma-exposed individuals have different brain utilization patterns and epigenetic mechanisms. (Lyoo et al. (2011), Labonte et al. (2012) and Mehta et al. (2013))

benefit from public funds and thus less likely to go under. Ellul and Yerramilli (2013), for example, argues that stronger risk management control at the bank level can curb tail risk. Kashyap et al. (2008) and Fahlenbrach and Stulz (2011) highlight the role of high-powered compensation in encouraging excessive risk-taking by bank executives and traders at the expense of shareholders. Fahlenbrach et al. (2012) show that banks' stock return performance during the 1998 crisis strongly predicted its stock return performance during the 2008 crisis.

Surprisingly, the literature has neglected managerial aspects of bank performance, despite the mounting academic work devoted to identifying CEOs' role in corporate policies and performance. Why were some CEOs able to successfully steer their bank through the market meltdown while others were not? Could having experienced previous financial crises have helped to set them apart from peers in shaping a unique business models that are less prone to fail?

To empirically investigate whether crises experiences matter for the banking sector, we specifically look at the early life banking crisis experiences of bank CEOs in this paper. Based on existing literature, we expect an inverse relationship between crises experience intensity and future BHC systematic and systemic risks. Compared to average bank managers who were assessing risks historically and neglected low-probability events(Gennaioli et al. (2012)), bank CEO who have witnessed banking crisis, liquidity evaporation, and massive shuttering of financial institutions should be more aware of these non-salient risks and build their business models to be more resilient to systematic risks and market fluctuations. Hence, these BHCs are expected to withstand liquidity shocks during the financial crisis and more likely to survive. This hypothesis is in line with the increasing evidence in the finance literature that past experiences of executives and investors affect their subsequent behaviour and performance (Custódio et al. (2013),Malmendier and Nagel (2009),Malmendier and Nagel (2015),Schoar and Zuo (2011),Bertrand et al. (2003)). In particular, Bernile et al. (2015) shows that there is a non-monotonic relation between the intensity of CEO' early-life exposure to natural disasters and subsequent corporate risk-taking. The effect of the exposure to early-life trauma on decision making has already been widely documented in the psychology and medical literature.

To test our conjecture, we focus on the CEOs of BHCs from 1999 to 2009. For each of the 241 bank CEOs from 1999 to 2009, we identify their employment history from 1985 to 1990 and hence their employment location during the S&Ls crisis. We also assemble a dataset of US state-level bank failure events from FDIC from 1985 to 1990. We combine the two datasets to infer the possible exposure of

CEO to the banking crisis and financial institution failures during the 1980s.

We employ different measures to quantify CEO's experiences. We report our main findings all with one particular measure described as the following. For each state-year pair, we scale the total amount of deposits associated with failed financial institutions by the sum of deposits in the entire state. We then take the maximum of this ratio for each CEO over the years we have information on his employment location from 1985 to 1990[3].

The first question we investigate is whether banking crisis experiences of CEOs matter for BHCs. We examine whether BHCs led by CEO who faced more intense banking crisis situations in the past fared better from 1999-2009. Indeed, we identify that BHCs with a seasoned CEO at the helm are less likely to be listed or received by FDIC during 1999-2009. One standard deviation of banking crisis experience intensity during the 1980s is associated with 0.635%(1.27*0.005) lower probability of failure. We then study the implication of crisis experiences on systematic risk-taking. One standard deviation of Intensity is associated with 12.7 to 38.1 basis point increase in daily returns during a tail event for the market or the banking system.

We then investigate the channels through which the banking crisis experience manifests itself on BHCs. First, BHCs led by seasoned CEOs are associated with business models less vulnerable to interest rate risk built up from 1999-2009. Second, we show that higher crisis experience intensity explains a lower level of credit risk. One standard deviation of Intensity is associated with 0.053% decrease in net charge-offs, which accounts for one-fifth of the latter's mean level of 0.29%. Also, we also find that CEO who have witnessed a textbook example of the banking crisis in the 1980s exhibit more unusual precautionary hoarding behavior. There exists a positive relation between crisis intensity and liquid asset holdings ratio, such that, 1% increase in liquid asset holdings associated with one standard deviation of Intensity.

Overall we summarize the risk management style of disaster-proof CEO as conservative. We must emphasize that our results cannot be explained by characteristics differences across BHCs because we include BHC fixed effects to control for time-invariant bank characteristics and variables such as size, market to book and so on to control for time-varying bank characteristics. Our findings are also robust to time and state fixed effects.

[3]We construct S&Ls experience measure in the same fashion using bank asset and number of BHCs

A common limitation in the literature on CEO characteristics is an interpretation of the results. The difficulty is to establish the causality as we seek to attribute corporate outcomes to CEO personal traits and experiences. Our paper is no exception. Our findings are consistent with two explanations. It could be that CEO impose their preference and risk attitude on the business model and risk management. It is also possible that the board selects CEO of a certain style to implement the strategy they want. In this case, CEO are only hired as executors. Assertive Matching between firm and CEO yields the same expected results as the causal explanation.

To address the endogeneity concern, we first explicitly control for time-varying characteristics on firm and CEO side respectively. We note that our results are robust to controlling for CEO overconfidence(Malmendier et al. (2011)), fast track CEO, CEO talents proxied by their education achievement, Military CEO(Benmelech and Frydman (2015)), first labor market conditions(Schoar and Zuo (2011)), Depression babiesMalmendier and Nagel (2009), and generalist skills(Custódio et al. (2013)). Following Bertrand et al. (2003), we include firm fixed effects to absorb unobservable time-invariant factors that affect BHC's choice of CEO. [4]

For a clean set-up to tackle the issue arising from firm-CEO assortive matching, we need random assignment of CEO to firms which break endogenous selection. However, if CEO labor market is subject to no friction and we always observe the optimal matching outcome, we can never see the counterfactual. If we believe the matching is conditional on time-varying variables but the criteria have been same, then we could exploit CEO turnover which provides exogenous variation in the timing of matching, even though the choice of new CEO is still endogenous. Several corporate papers have employed exogenous CEO turnover events due to predecessor's health issue, retirement age, and death shocks to pin down identification.(Jenter and Kanaan (2015),**?**,Eisfeldt and Kuhnen (2013),Frydman and Jenter (2010)).

Since we zoom in the banking sector and the idiosyncratic death or health shocks to CEO are too scarce to be constructed as a reliable regression sample, we rather rely on CEO retirement age to pin down exogenous CEO turnovers. We acknowledge that dynamic matching of CEO to firms remains a potential concern, to the extent that firm style changes significantly over time and any resulting CEO turnover depends on the CEO's style as captured by our core explanatory variable of crisis experiences. Even if this is the case, our result still speaks to the fact that there appears to be something special about these CEO' abilities that are targeted by the board. In sum, Our findings imply that the pool

[4]We cannot add CEO fixed effects because our key explanatory variable is CEO experiences that do not change with time during 1999-2009 and thus collinear with CEO fixed effect.

of managerial talent is significantly shaped by their early-life encounters with the banking crisis in the 1980s.

There are concerns that early-life memories are short-lived and should not affect CEO behavior and corporate policies. However, medical studies show that early-life adverse experiences have long-term effects on behavior. On the concern that state-level exposure to banking crisis does not mean CEO themselves have handled the banking crisis or had real losses, we verify that our results are robust to using alternative windows to measure CEO's exposure to the S&L crisis.

A natural question arises as for whether the styles identified above is value enhancing for the BHCs. Before the start of the financial crisis, the operating performance, and stock market return are indistinguishable among bank holding companies run by CEO with high and low exposures to the S&L crisis.

We further discuss the alternative incentives for seasoned BHCs to exhibit features. We do not find differences in their executive compensation levels and thus rule out the payment incentive channel. We exclude CEOs' incentives of empire building and "too big to fail" incentives by showing the equal BHC size and growth rate differences explained by crisis experience intensity. We also conduct a falsification test using 1998 Asia crisis to showcase, not any crisis would matter for our findings.

The paper contributes to several streams of literature. First, it contributes to the literature on banking behavior during financial crisis (Fahlenbrach et al. (2012), Ellul and Yerramilli (2013), Bouwman and Malmendier (2015), Fahlenbrach and Stulz (2011), Bouwman and Malmendier (2015), Bushman et al. (2015) ,Lo (2015) ,Fahlenbrach and Stulz (2011) ,CHENG et al. (2015) , Beltratti and Stulz (2012)). It advances our understanding of the driving force behind cross-sectional difference of bank fates during 2007 global financial crisis.

The paper also speaks to the recent calls by financial regulators[5] to tap deeper into corporate culture and risk management, particularly . Some recent academic works have responded to this call(Bushman et al. (2015), Ellul and Yerramilli (2013),Lo (2015)). Our analysis contributes to the literature that examines how managerial styles relate to CEO' life experiences such as marital status (Roussanov and Savor, 2013), holding a pilot license (Cain and McKeon, 2014), political affiliation (Hutton, Jiang, and Kumar, 2014), military experience (Malmendier, Tate, and Yan, 2011), and past career

[5]https://www.sec.gov/News/Speech/Detail/Speech/1365171515784

experiences (Schoar and Zuo, 2013)[6].

Beyond the literature on managerial style, our results may be relevant for research on investor behavior. An emerging literature examines how extreme experiences of investors shape their risk attitude, asset allocation and investment decisions(Malmendier and Nagel (2016), (Greenwood and Nagel 2009), Katia and Knupfer 2008; Chiang et al. 2011, Fuster, Laibson, and Mendel (2010), Fuster, Hebert, and Laibson (2011)).

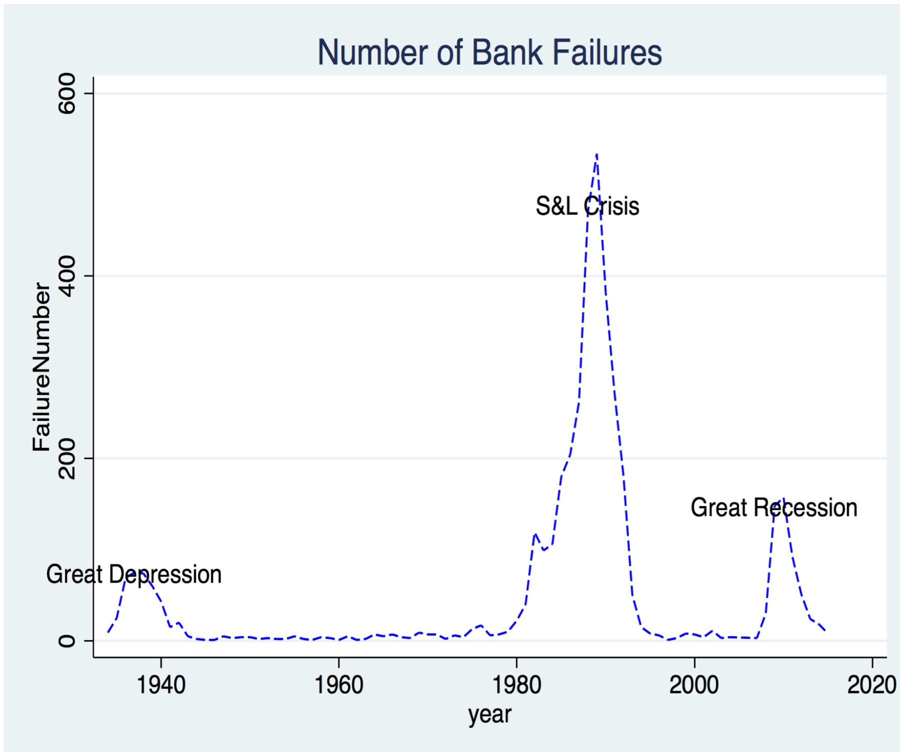
The rest of the paper is organized as follows. Section 2 details the timeline of savings and loan crisis. Section 3 describes the data and summary statistics. Section 4 presents our main empirical results. Section 5 discusses the interpretation of our results along with robustness checks and Section 6 concludes.

2 Timeline of Savings and Loans Crisis

As figure 1 demonstrates, there are three pronounced peaks of bank failures in the recent history of US, namely the 1930s great depression, 1980s S&L crisis, and the 2008 great recession. In this paper, we zoom into S&L crisis as the banking crisis formation period for BHC CEOs. Our Empirical testing period runs from 1999 to 2009, covering the recent 2008 financial crisis.

[6] see a concrete literature review by Bertrand (2009)

Figure 1: **Number of Bank Failures from 1930 to 2016.** This figure reports the total number of commercial& savings, commercial banks, savings institutions, savings banks, and savings associations that were closed, received or assisted by Federal Savings and Loan Insurance Corporation (FSLIC), and Federal Deposit Insurance Corporation (FDIC).



Source: FDIC and author calculation

The decade of the 1980s witnessed the extraordinary upsurge 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 affects the economic and financial market conditions as wells as regulatory environment. Many media coverage and academic work have analyzed causes and consequences of saving and loan crisis [7]. Here we focus on its background, geographic pattern and its association with the banking sector.

[7]FDIC provides a comprehensive chronology and bibliography on S&Ls crisis: https://www.fdic.gov/bank/historical/sandl/

2.1 Background

Several factors injected instability to banking sectors in the 1970s. Before the crisis loomed, some major currencies were allowed to float, and their exchange rates became volatile. In response to oil embargoes and other shocks, oil price levels underwent major increases. Interest rates varied widely following inflation, inflation expectations and anti-inflationary monetary policies adopted by Federal Reserve.

Particularly, thrifts [8] are facing challenges to expand in the stagflation characterized by slow growth, high interest rates, and inflations. The enactment of rate controls over savings from 1955 to 1979 made it even harder.

When the Federal Reserve doubled interest rates to reduce inflation in 1979, the financial health of the thrift industry was 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. The deregulation of deposit interest rates exerted upward pressures on banks funding costs, as thrifts institutions and banks relied on short term funding and had to compete for sources of funds by offering higher rates to attract depositors. However, the amount they earned on long-term fixed-rate mortgages were flat, squeezing profitabilities of thrifts and commercial banks. Losses began to mount.

Financial innovation, adding fuel to the fire, took off and decreased profit margins of the traditional banking business. Banks faced increased competition from new financial institutions including money market mutual funds commercial paper market and securitization. Consequently, many banks shifted funds to commercial real estate lending, an area involving higher return and risks. Some banks participated in leveraged buyouts, off-balance-sheet activities. Financial futures, junk bonds, swaps, and other new financial instruments also widened the scope for risk taking and facilitated banks to take 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 keep the banks from excessive risk taking.

As a result of these forces, thrifts and commercial banks did take on substantial risks and began to suffer extensive losses. During the 1980s, performance ratios of banks of all sizes weakened and exhibited increased risk while loan charge-offs rose dramatically. Distress in the system unfolds. A large number of S&L customers' defaulted and went bankrupted. The S&Ls that had overextended themselves

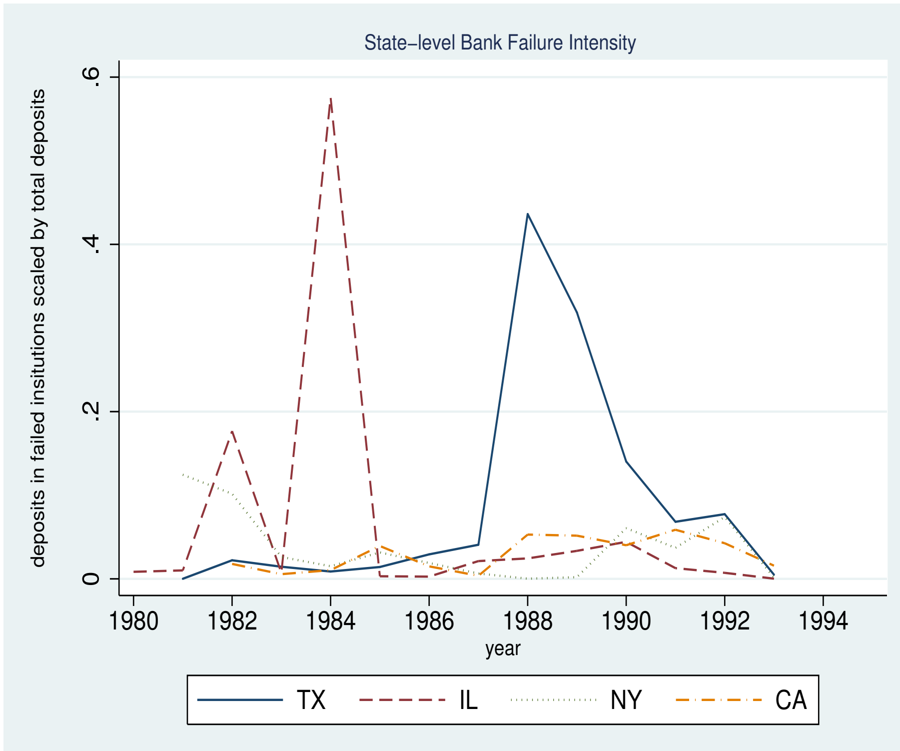
[8] A savings and loan or "thrift" is a financial institution that accepts savings deposits and makes personal loans such as mortgage and car to individual members

were forced into insolvency proceedings and large scale of bankruptcy ensued. The Federal Savings and Loan Insurance Corporation (FSLIC), then had to repay all the depositors whose money was lost. 1,043 out of the 3,234 savings and loan associations in the United States from 1986 to 1995, and more than 1,600 banks insured by the FDIC were closed or received FDIC financial assistance. The eventual cost to taxpayers was estimated to be as high as $124 billion. In 1991, Congress passed the Federal Deposit Insurance Corporation Improvement Act(FDICIA), which recapitalizes the Bank Insurance Fund of FDIC and reformed the deposit insurance and regulatory system.

2.2 Geographic Patterns

The difference of bank failure intensity is evident across states. Of the total 1,617 failures during the entire 1980-1994 period, nearly 60 percent were in only 5 states: California, Kansas, Louisiana, Oklahoma, and Texas. Table 1 details on the bank failure statistics by state. Bank failure incidence peaks in different years across states. Domino effect cause serious strains on the deposit insurance fund of FDIC. In the 1980s, geographically confined crises were translated into a national problem. Figure 1 plots the time-series of bank failure measure for four states. The measure is constructed as the fraction of deposits belonging to the failed institutions over the total amount of deposits for the entire state at the end of the year.

Figure 2: **Example of Bank Failure Time Series During Savings and Loan Crisis.** This figure plots the fraction of banks that failed at state-wide for Texas(TX), Illinois(IL), New York(NY), and California(CA) respectively. The time period spans from 1980 to 1993.



Regional and sectoral recessions were confounded and interacted with banking crises. We illustrate some of the factors associated with bank failures. The incidence of failure is 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,theNortheast,andtheSouthwest);
- 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);
- banning on branching and limited access to geographical diversification of loan portfolios, and funding the growth through core deposits (Colorado, Illinois, Kansas, Texas, and Wyoming);

Table 1: **Bank Failure Statistics by State during 1980-1993**

State	Number of Bank Failures	Asset of Failed Banks($Thousands)	Deposit of Failed Banks($Thousands)
AK	13	3351116	3199220
AL	24	4927131	3896180
AR	33	6606628	6008020
AZ	27	19628310	15731625
CA	195	141330275	101082589
CO	83	10699910	8368310
CT	39	18768826	17177989
DC	8	3607518	2793989
DE	1	582350	164867
FL	116	68396459	55972005
GA	27	5130530	4014673
HI	4	59703	47344
IA	68	5933625	5430787
ID	4	649308	587447
IL	131	72003699	54991462
IN	28	2423691	2436005
KS	99	17210923	11353926
KY	18	1651017	1650794
LA	156	19070690	18362751
MA	50	33583865	26872832
MD	21	8572425	6866249
ME	5	2594925	2429094
MI	16	4649773	3707026
MN	52	7061523	5538933
MO	67	13810158	13152226
MS	30	3082667	2679555
MT	13	441052	369284
NC	15	3683148	2990830
ND	14	1547480	1113646
NE	42	2582345	2314019
NH	18	5763487	4937516
NJ	61	35854095	28823090
NM	28	5076446	4727403
NV	4	334619	325632
NY	67	79480864	66014713
OH	47	16702903	14123718
OK	162	16110436	14263062
OR	29	9571028	6961379
PA	29	31926305	23589644
RI	6	2662845	2482011
SC	9	1680643	1506584
SD	18	1335339	946523
TN	59	4754473	4206000
TX	847	196813168	170220125
UT	20	4901312	3721557
VA	39	14098201	11583007
VT	2	329478	317946
WA	18	4583398	3663328
WI	7	711086	658898
WV	13	1212675	1047146
WY	27	1321866	1278202

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

2.3 Why S&Ls?

We exploit the savings and loan crisis to measure the exposure to the banking crisis of bank CEO for four reasons. First and foremost, the two events share similarities regarding the causes and consequences. Both events were preceded by the frenetic real estate bubble and credit boom and concluded with historically high bank failure rates and unprecedentedly large scale of public rescue. Much academic work review the recent Global Financial Crisis (e.g., Brunnermeier (2009),Gorton and Metrick (2010)) in detail and we do not report here. The savings and loan crisis parallel the recent crisis in the events, causes, damages and regulatory actions. In particular, fire sales and withdrawal of liquidity from financial markets cause huge turbulence and bail-outs on a large scale, a strikingly similar pattern featuring the two crises. Secondly, savings and loan crisis spanned over ten years and across almost all the states. The time-varying and state-varying feature enable us to capture better the cross-sectional difference in the intensity of banking crisis shocks CEO have been exposed to. Thirdly, the time gap between the two crisis is relatively long and a significant fraction of CEO switch firms in between, which alleviate the concern that the first crisis has a persistent consequence on the firm level rather than CEO level. Last but not the least, the state-level and county-level measure of banking crisis intensity is more exogenous to the future policies made by the CEO than historical firm level bankruptcy event CEO has faced. There is less concern that unobserved factors drive both the macro-level banking crisis intensity during the 1980s and bank-level bank policies in the 2000s.

3 Data Description

This section details on the data source, construction of our sample, defines the key variables used in the statistical analysis and lays out our empirical tests.

3.1 BHC Sample Construction

Our analysis unit is Bank Holing Company, and the data come from several sources. We obtain quarterly stock market performance data from Center for Research in Security Prices (CRSP), quarterly BHC consolidated financial data from FR Q9C statements and Standard & Poor's Compustat, CEO-related information from BoardEx and Marquis Who's Who. We start by obtaining the name list and CUSIP of all BHCs that file FR Y9C statements with the Federal Reserve System during 1999 to 2015.

We then require those BHCs also existed during the same period with the same 6digit CUSIP in CRSP and Standard & Poor's Compustat databases. We do manual fuzzy name matching where CUSIPs are missing. We then map the overlapped public BHCs to BoardEx using ticker and legal names. We include all firms for which the identifiers are the same, but the name is changed. After merging across the four databases, we are left with 685 public BHCs that have existed from 1999 to 2009[9]. For the 685 BHCs identified in BoardEx, we identified the names of their CEO in position during 1999-2009. We finally match biography data from Marquis Who's Who using CEO names. We further reduce our sample by requiring the information availability of CEO employment history and location during 1985 to 1990. Our final sample consists of 241 BHCs and 301 Bank CEOs.

3.2 BHC Characteristics

For each of these BHCs, we construct a set of dependent and control variables. We are interested in the distinctive characteristics of BHC associated with higher banking crisis intensity experienced by CEOs. We winsorize all variables at the 5th and 95th percentiles to lessen the influence of outliers. All variables are defined in Appendix B, and we report summary statistics of these variables in Table 2. We use four sets of dependent variables in our analysis. We introduce them as following.

We first look at the bank failure probability. We use an indicator variable equal to one if a firm is delisted or closed by FDIC between 1999 and 2009. Failed banks are those appearing on the list of failed banks maintained by the Federal Deposit Insurance Corporation (FDIC). We further do news searches to determine whether a delisting was voluntary or forced. Targets of Merger and Acquisition at a discount during this period are also coded as 1.

[9] We do not exclude investment banks if they are chartered as BHC and entitled to deposit insurance funds from FDIC.

Secondly, we check the systematic risk-taking measures of BHCs. The first measure is BHC stock *Commovement* vis-a-vis equally or valued weighted banking sector portfolio. Following the spirits of Barberis et al. (2005), we construct *Commovement* (equally or valued weighted) by regressing daily BHC stock return against a constant and daily banking sector portfolio (equally or valued weighted) within each calendar year from 1999 to 2009. The second systematic risk measure is Marginal Expected Shortfall. It is based on the 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 et al. (2013)). Specifically, in a given year, the *MES_mkt*(*MES_bank*) is defined as the negative of the average return on the BHC's stock over the 5% worst return days for the entire market index(banking sector stocks).

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

The third measure is Capital Asset Pricing Model Beta. The Beta coefficient is estimated from a one-factor market model, where the market model is estimated by regressing daily returns on the BHC's stock versus a constant and daily return on the S&P500 value-weighted portfolio.

Thirdly, we construct interest betas to capture BHC stock return resilience to interest rate fluctuations. The methodology is based on Flannery (1981); Flannery and James (1984); Landier et al. (2013); English et al. (2012). Interest rate proxies we choose are primary rate, 6-month LIBOR rate, and the term-spread defined as the spread between the 10-year Treasury note and the 3-month Treasury bill. They are available monthly from the Federal Reserve's website. We have two ways to extract interest rate shocks. We take the first differential of each proxy time series or the residuals of each proxy after fitting in an AR(2) model to remove autocorrelations. We then regress daily BHC stock return against a constant, value-weighted daily market portfolio return and interest rate shock proxy. The absolute value of the regression coefficients are the corresponding interest rate betas. Hence, each interest rate beta corresponds to a different interest rate shock proxy. For instance, $Prime\_d1$ is the interest rate beta corresponding to the first differential of primary rate, whereas $Prime\_res$ is associated with residuals of the primary rate after fitting in the AR(2) model.

Lastly, we examine credit and liquidity risk management. For credit risk management, we focus on *Badloan* defined as the ratio of the sum of loans past due 90 days or more, ratio of net charge off asset to asset, and provision/asset. This definition is consistent with Ellul and Yerramilli (2013); Fahlenbrach et al. (2012); 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. $Liquid\ Asset1$ is the ratio between this sum and total book assets. As a robustness check, we exclude federal funds sold to have $Liquid\ Asset\ 2$. $USTreasury$ is defined as the ratio between US-Treasury bill holdings and the total book value of assets. Our liquid asset classification is consistent with several papers such as Loutskina (2011); Irani and Meisenzahl (2015); Acharya and Mora (2015); Kashyap et al. (2002); Gatev and Strahan (2006); Cornett et al. (2011).

3.3 Bank CEO Characteristics

A key appealing feature to use BHC and their CEOs as a laboratory is that we can observe the private employment, education and demographic information concerning the identity of previous employers, dates of employment, tenure, job titles, degrees, alma-mater, gender, hometown, and birth date. We obtain the biographic data on CEO from BoardEx and Marquis Who's Who. Our core explanatory variable is CEO exposure to Savings and Loan Crisis. Following the banking crisis definition of Laeven and Valencia (2008, 2013), we take the year 1988 as the climax of S&L and choose the window 1985-1990 as our S&Ls crisis period. In the robustness checks, we use alternative definitions for crisis period. We first search CEO employment history during 1985-1990 from BoardEx and proxy their location at state-county level with the headquarter of their employer at the time. We also verify the employment history with Marquis Who's Who biographies from which the CEO birth place is gathered. When data are not available from these datasets, we manually search to fill out missing information. We are thus able to retrieve the date, county, and state for bank CEO from 1985 to 1990. Each CEO has a series of state-year records during the savings and loan crisis. The bank failure data during the savings and loan crisis come from FDIC[10]. As introduced in Section 2, we collect year-state level data on the number of banks failed and divided by the total number of banks in that state in that year. For each state-year, we also calculate the ratio of deposits of the failed banks to the total amount of deposits, and the proportion of failed banks assets to the asset of the entire banking industry. The scaling is used to account for local economic conditions and banking development. We apply the log transformation to failure ratios given their highly skewed nature. For a given Bank CEO, we take the max(mean) of each log-transformed ratios respectively over all her identified state-year records between 1985 and 1990. Throughout our empirical tests, our independent

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

variable of interest is the failed deposit based $Intensity$:

$$Intensity_c = ln\left(1 + \max_t \left(\frac{\text{Failed Deposits in Employment State}_{it}}{\text{Total Deposits in Employment State}_{it}}\right)\right) \tag{2}$$

3.4 Summary Statistics

We present summary statistics for the key variables in our panel data set in Table 2. The data comprise one observation for each BHC-year combination, span the 1999 to 2009 period. We have 1499 bank-year observations, representing 241 unique BHCs and 301 bank CEOs. The names of 241 publicly listed BHCs are quoted in Appendix A.

The median value of Intensity(Max) means that the average CEO in our data has witnessed 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 an average CEO has worked for 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 is 57 years old, and 3% of CEOs are females. 41% of CEOs in our data holds a master, MBA or Ph.D. degree.

The median BHC has book value of total assets as large as \$1.77BN, with the deposits accounting for 75%. The asset size of our sample BHCs is smaller than the sample in Fahlenbrach et al. (2012). We also note that the size distribution regarding the book value of total assets is highly skewed varying from the 0.73 billion at lower 25 percentile to the 5.46 billion at higher 75 percentile. We use the logarithm of the book assets denoted as Size in all our empirical specification.

On the BHC financial information side, we observe that the median BHC holds 33% of their assets in liquid assets. The non-interest bearing asset account for 24% of assets for an average BHC. BHCs exposure to interest rate fluctuations is remarkably varying, from 0 to more than 0.5. On average non-interest bearing deposit accounts for 24% of book assets in our sample BHCs. The tier-1 ratio is not as variable as what media press depicts, with the mean of 8%.

From the stock return and risk measures, we notice the prevalent heterogeneity among BHCs. The average annual return on a BHC stock during our sample period is 14%. However, annual stock returns are highly variable: the BHC at the 25th percentile cutoff has an annual return of -4.0%, whereas the BHC at the 75th percentile cutoff has an annual return of 29%. The actual bank failure rate of our sample BHC from 1999 to 2009 is 3%. The $Marginal\ Expected\ Shortfall(Market)$ takes the mean of

-0.02, meaning that for an average BHC, the average daily stock market return stands at -2% during the 5% worst performing days of the market portfolio.

Table 2: **Summary Statistics**

This table reports summary statistics of Firm and CEO-related Variables. All variables are defined in Appendix A.

Variable	Number	Mean	Std.Dev	Min	p25	Median	p75	Max
CEO-Specific Variables								
$Intensity(Max)$	1424	0.09	0.11	0.00	0.03	0.05	0.07	0.71
$Intensity(Mean)$	1424	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
$Female$	1499	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
$Tier1\ Capital/Risk\ Weighted\ Asset$	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
$Nonint.Asset/Assets$	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
$BookLeverage$	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								
$Annual\ Return$	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
$Commovement(equally\ weighted)$	1499	0.40	0.29	-0.16	0.10	0.46	0.66	0.90
$Commovement(value\ weighted)$	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

4 Empirical Analysis

4.1 Do Banking Crisis Experiences Matter?

4.1.1 Less Likely to Fail?

The first question we want to address in the formal empirical analysis is whether CEO banking crisis experiences can mitigate the failure chances of banks in both normal times and the subsequent crisis. We classify 52 BHCs as having failed and 3% of BHC-year observations as failures from 1999 to 2009. 10 out of the 52 failed banks were acquired by FDIC, and all the 52 BHCs were delisted from some major U.S. stock exchange. We also adopt a wider definition of failure that includes banks that have received government assistance under Trouble Asset Rescue Package(TARP). 95 BHCs in our sample has accepted funds from the program, with vastly varying amounts. Bank of America Corp obtained as much as \$45 BN while Fidelity Bancorp only got \$7 MN. Some banks such as Bank of America Corp have requested help multiple times under TARP, which is more likely to have failed absent from government interventions. Empirically, we estimate a probit model as the following.

$$Failure_{ijct} = \alpha + \beta_2 Intensity_c + f_j + f_t + \lambda_2 C_{ct} + \lambda_2 X_{it-1} + \eta_{ijct} \tag{3}$$

In the above equations, subscript ıdenotes the BHC, ǫdenotes the CEO, ȷdenotes the state where the BHC is headquartered, and d̂enotes the year. We test the hypothesis that CEO crisis experiences matter for bank survival against the null hypothesis CEOs have no effect. In these regressions, we first control for BHC financial characteristics that are found to be determinants of bank failures in the literature. We control for BHC prior probability using the ratio of income before the extraordinary items to assets (ROA), and for stock market performance using the lagged annual return. The composition of BHC liability is controlled by using book leverage ratio and tier-1 capital ratio. Market to book ratio is put in place to control for over-valuation of BHC in the perspective of equity investors. Beta captures the BHC exposure to the market where the market is proxied by CRSP market Index.

To distinguish the effect of crisis experiences, we control for other CEO traits. Firstly, we include in our regression the dummy indicating whether CEO has achieved the Master Degree, MBA or Ph.D. In unreported robustness checks, we also control for whether their alma mater belongs to Ivy League. Educational achievements are established evidence of innate talents such as intelligence quotient.

Secondly, we control for CEO age because an older CEO might have been exposed to different personal, firm, industry, or market environments on top of banking crisis experiences. CEO age control also rules out the alternative explanation that risk aversion increases with age or management ability accrues over the life cycle. Bertrand et al. (2003) also shows that CEO age has a significant effect on corporate policies. Thirdly, we add the CEO gender control because prior studies show that men have different risk attitudes than females[11].

We include year fixed effects to remove time trends or any aggregate effects on dependent variables. In the probit model, we also include state fixed effects to take away state-wide regulation differences and local economics shocks that may explain bank survivals. To avoid the incidental parameters problem and biased coefficient estimates, we do not include firm fixed effects in the probit model.

Table 3 shows the results of probit regressions of bank failures on the same explanatory variable we used before. All specifications report marginal effects. From column 1 to 4, the dependent variable is our first definition of failure capturing only the delisted or closed BHCs, while column 5 to 8 have the alternative failure definition as dependent variable which includes BHCs that have received government assistance under TARP. The key variable of interest is $Intensity$. The empirical results in Table 3 indicate a negative relationship between the banking crisis experience intensity and BHC failure chances. The negative correlation is consistent significant across different specifications and failure measures. The economic magnitudes are nontrivial. In the most comprehensive specification in column 4, one standard deviation of banking crisis experience intensity during the 1980s is associated with 0.635%(1.27*0.005) lower probability of failure during the period spanning from 1999 to 2009. Considering the average probability of failure for our sample of 3.3%, this corresponds to an economically significant increase of 19.24%. Namely, for a manager overseeing a BHC with mean characteristics, this effect is associated with a reduction of 19.24% in failure instances. From column 5 to 8, we modify the failure definition and find the estimates remain qualitatively and quantitatively similar.

Regarding the control variables, it appears that banks with fewer investment opportunities represented by Book to Market Ratio are more likely to fail. Somewhat surprisingly, neither size nor tier1 ratios has explanatory power in the probit regressions. The missing of significance could be reconciled by the opposing role of size in failure during normal and crisis times. In normal circumstances, smaller banks with lower leverage are more likely to be acquired and thus get de-listed than their larger counterparts.

[11] Papers show financial risk-taking differs by gender: Barber and Odean (2001), Weber, Blais, and Betz (2002), Byrnes, Miller and Schafer (1999) and Eckel and Grossman(2008)

However, during the recent global financial crisis episode, highly levered large banks are more fragile and vulnerable to systematic negative shocks. We also find modest evidence that CEOs with a higher level of education are associated with higher failure likelihoods. Age and gender are not significant predictors.

Consistent with Fahlenbrach et al. (2012), BHC performance in 1998 is negatively associated with failure rates. Fahlenbrach et al. (2012) argues that the effect of bank performance in 1998 be driven neither by CEO learning from 1998 Asian crisis nor by the time-invariant personality and risk attitudes. They interact a dummy indicating the bank was falling into the worst quintile of 1998 performance and a same-CEO in 1999 and 2006 indicator, and find that the interaction term is statistically indistinguishable from zero. Their empirical results are also consistent with banks always choosing CEOs who share same characteristics as their predecessors.

We want to point out that our setting is different from theirs. Fahlenbrach et al. (2012) implicitly requires banks survived from 1998 and made it all the way to 2006. It is possible that these survivors from 1998 crisis have preserved their business models and risk preferences which have worked compatible from the survival perspective at the very least. The high institutional inertia is instilled into all CEOs stepping into positions. Said differently, institutional inertia and memory is transferred from banks to individuals working inside firms. Moreover, hence, even if the types of CEOs are different at the point of recruitment, CEOs working for the same CEO will converge in their risk attitudes under the influence of banks during their tenures. Also, hence the firms effect cannot be separated from CEO effects.

Apart from inertia, perfect CEO-Bank type matching can also explain the consistent preference for CEO characteristics of survival banks. These survivor BHCs could have found the kind of CEO in position during 1999 fit for a bank's survival and hence keep hiring candidates with same features. In this case, the CEO-Bank optimal matching cannot be severed and therefore the Bank and CEO effects are indistinguishable.

However, our paper does not require banks to have survived throughout our sample period, and our sample banks are less likely to have strong institutional inertia. The effect we are interested in is the impact arising from CEO's memory of what happened outside their current employees along with their career trajectories. Thus, the direction of transferring is from CEOs to BHCs. Our results show that on top of BHCs' experiences during 1998, CEO's personal experiences outside the bank in the 1980s also hold explaining power in failure probit regressions. However, we do acknowledge that the economic magnitudes of the 1998 crisis performance are larger than our experience intensity measure, standing at

0.45% (0.18*0.025). We also show that the CEO effect is stronger for BHCs that have not encountered the 1998 crisis or have failed earlier during our sample period. In this subsample, the inertia of banks is less likely to be prevailing over the CEO personal learning from the past.

Table 3: **Bank Failure during 1999-2009 and Crisis Experiences**

This table reports marginal effects from probit regressions predicting bank failure during the period from December 1999 through December 2009. Variable definitions are provided in Appendix B. Concurrent controls include the CEO age, gender, and education. Lagged control variables include the lagged annual stock return, size(the natural log of the book value of assets), book to market ratio, tier 1 ratio, and market beta. The dependent variable in columns 1 to 4 is an indicator ($Failure1$) equal to one if the BHC is delisted or acquired by FDIC, while the dependent variable in columns 5 to 8 is a dummy variable ($Failure2$) equal to 1 if the BHC is delisted or closed by FDIC or has received government assistance under Troubled Asset Relief Package (TARP). Standard errors are clustered at CEO level. T-statistics are presented in parentheses below the coefficient estimates, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Failure1$	$Failure1$	$Failure1$	$Failure1$	$Failure2$	$Failure2$	$Failure2$	$Failure2$
$Intensity_t$	-0.004**	-0.004**	-0.004**	-0.005*	-0.005**	-0.004*	-0.005**	-0.005**
	(-2.30)	(-2.10)	(-2.08)	(-1.89)	(-2.20)	(-1.89)	(-2.23)	(-2.42)
$CEOAge_t$			-0.010*	-0.007			-0.006	0.000
			(-1.81)	(-0.96)			(-0.79)	(0.03)
$Female_t$			0.012	0.010			0.008	0.007
			(1.21)	(0.57)			(0.56)	(0.25)
$Highdegree_t$			0.001**	0.001*			0.002***	0.003***
			(1.99)	(1.75)			(3.80)	(3.53)
$Return_{1998}$				-0.025				-0.056**
				(-1.26)				(-1.99)
$Return_{t-1}$		-0.011	-0.007	0.022*		-0.019	-0.012	0.015
		(-0.66)	(-0.44)	(1.94)		(-0.80)	(-0.56)	(0.83)
BM_{t-1}		0.029**	0.029**	0.032**		0.037**	0.037**	0.052**
		(2.32)	(2.82)	(2.16)		(2.21)	(2.75)	(2.31)
$Size_{t-1}$		0.002	0.003	0.002		-0.000	0.000	-0.002
		(0.75)	(1.13)	(0.75)		(-0.05)	(0.02)	(-0.41)
$Tier1_{t-1}$		0.062	0.059	0.052		-0.073	-0.080	-0.146
		(0.31)	(0.36)	(0.25)		(-0.29)	(-0.35)	(-0.44)
$Beta_{t-1}$		0.011*	0.009	0.031***		0.011	0.009	0.038***
		(1.75)	(1.63)	(3.84)		(1.30)	(1.17)	(3.31)
FE_Time	Y	Y	Y	Y	Y	Y	Y	Y
FE_State	Y	Y	Y	Y	Y	Y	Y	Y
Clustering	CEO	CEO	CEO	CEO	CEO	CEO	CEO	CEO
N	2 207	1 531	1 531	1 306	2 207	1 531	1 531	1 306

4.1.2 Uncouple from Peers?

In this section, we investigate the risk-taking characteristics of BHCs led by Crisis CEOs. Witnessing more intense systematic financial institution fallouts is likely to make CEOs more aware of and cautious about such shocks. We examine the relations between CEO crisis experience intensity and BHC stock market performance, controlling for the underlying business activities. We use panel regressions of the form

$$Y_{ict} = \alpha + \beta_1 Intensity_c + f_i + f_t + \lambda_1 C_{ct} + \lambda_2 X_{it-1} + \eta_{ict} \tag{4}$$

The panel data has one observation for each BHC-year pair, includes BHC listed in the appendix, and covers 1999 to 2009 period. In the above equations, subscript ıdenotes the BHC, ̧denotes the CEO, ȷdenotes the state where the BHC is headquartered, and ̂denotes the year. The dependent variables are a series of systematic risk proxy variables, and the main independent variable is the *Intensity*. We include time and bank fixed effects in all our specifications. Time fixed effects remove the time trend and demand shocks that can affect BHC systematic risk levels. Bank fixed effects control the time-invariant unobservable heterogeneity across BHCs. To further address the omitted variable bias, we add time-varying BHC activity controls that are expected to determine systemic risks loaded on BHCs. In some specification, we further control for CEO personal traits proposed by the literature to affect risk preferences of CEOs. The standard errors are robust to heteroskedasticity and clustered at the CEO level.

Table 4 reports the regression of systematic risk proxies on the same explanatory variables we used before. We have three sets of variables to represent systematic risks. The first set of systematic risks is constructed based on stock market co-movement in the spirits of Barberis et al. (2005). For each BHC, we regress its daily return against a constant, market portfolio return where the market is defined as CRSP index, and the average or value weighted return of banking stocks for each year. We use the 12-month estimation window. The resulting loading on the average(value-weighted) return of banking stocks defines CMV_bk (CMV_bkw) which refer to the BHC comovement with the banking sector. The second set relates to the Marginal Expected Shortfall explained in the seminal paper Acharya et al. (2010). Specifically, our MES_mkt (MES_bk) captures the average daily returns of BHC's stock on the 5% worst performing days for the banking sector(CRSP index) stocks. The last set is the BHC's equity beta (*Beta*). Equity beta is estimated from a model of daily returns in excess of three-month T-bills each year from December 1999 to December 2009, where the market is represented by the value-weighted

CRSP index.

In table 4, columns (1) and (2) tabulate the results from regressing CMV_bk on the same key independent variable we are interested in as before. Recall that CMV_bk is meant to capture the extent of the BHC's stock market comovement with the equally-weighted returns on the banking sector portfolio. Consistent with our intuition, higher intensity of CEO banking crisis experiences correlate with lower CMV_bk. When the average banking industry does poorly in the stock market, BHCs managed by "seasoned" CEOs do less wrong. On the contrary, these BHCs will not perform as well the industry peers when the banking sector as a whole enjoys an upmarket. However, we do not take a stand on whether this risk reduction is value enhancing or destroying from the perspective of shareholders. [12] We come back to this point in later sections. The point estimate suggests that one- percentage-point increase in the *Intensity* measure is associated with 3.2- percentage-point decline in the comovement measure. The point estimate suggests that one standard deviation of the *Intensity* measure is associated with 0.14(0.032*1.27/0.2823) standard deviation of decline in the comovement measure. For a CEO overseeing a BHC with mean characteristics, this effect is translated into a reduction of 9.2% in their comovement with the banking sector. Regarding the coefficients estimates on controls, the significantly positive sign of the coefficient before *Size* means that larger BHCs have loaded more on systematic risks, consistent with the popular belief of "too big to fail". These large banks take on higher systematic risk possibly anticipating to be bailed out in the event of a systematic crisis. Also, BHCs with better operating profitabilities seem to comove more with the industry. Regarding CEO personal traits, a higher level of education appears to be correlated with a higher level of systematic risks. One explanation is that the greater financial literacy accompanied by higher education may lead CEOs to be more confident about or capable of managing systematic risks. Noticeably, the point estimate of the *Intensity* coefficient gets larger if we control for CEO personal characteristics. Column (3) and (4) modify the dependent variable by using the value-weighted return on banking sector stocks in place of equally-weighted ones. The estimates remain qualitatively and quantitatively similar.

In column (5) through (8) of table 4, the dependent variables are MES_mkt (MES_bk), which measure individual bank's contribution to the losses incurred by the overall market (banking system) in an extreme event [13]. We estimate the measure as laid out in Acharya et al. (2010) as *"the average return of each firm during the 5% worst days for the market"*. They also demonstrate empirically the ability of

[12] In unreported tables (in the interest of space), we find that the performance not statistically significantly associated with *Intensity*.

[13] Value-at-Risk is another popular widely risk measure adopted by financial institutions in practice. One distinction between Expected Shortfall and VaR is that the former captures all the losses equal and beyond the VaR threshold.

this measure to predict emerging risks during the financial crisis of 2007-2009. Intuitively, the stronger stock market performance in the tail event of the market implies a lower contribution to systematic losses. Hence, the measure is signed such that a higher value of MES implies a lower systematic risks. one standard deviation of *Intensity* is associated with 12.7 to 38.1 basis point increase in daily returns during a tail event for the market or the banking system.

The last two columns in table 4 completes a picture about the role played by the CEO banking crisis experience in the systematic-risk-taking behavior of BHCs. The market *Beta* implied by Capital Asset Pricing Model (CAPM) is a general form of systematic risk measure applicable to all industries. Consistent with our previous intuition, a higher intensity is associated with lower market *Beta*.

Taken together, we show that our measure of crisis intensity captures a significant effect on bank failure probability and systematic risk-taking beyond key bank-, state-, and market- level determinants, controlling for a range of CEO traits that may affect her preferences. CEOs' experiences in banking crisis do carry forward to the future and matter for key aspects of banking outcomes.

Table 4: **Systematic Risk Taking**

This table reports the results of panel regressions that investigate the relationship between systematic risks and CEO crisis experience intensity. We estimate the regression.

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

The panel data has one observation for each BHC-year pair, includes BHC listed in the appendix, and covers 1999 to 2009. The dependent variables are a series of systematic risk proxy variables including , and the main independent variable is the *Intensity*. All variables definitions can be found in the Appendix. We include time and bank fixed effects in all our specifications. BHC characteristics are controlled for in all specifications. Columns indexed by even numbers also include CEO characteristics controls. The standard errors are robust to heteroskedasticity and clustered at the CEO level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CMV_bk	*CMV_bk*	*CMV_bkw*	*CMV_bkw*	*MES_mkt*	*MES_mkt*	*MES_bk*	*MES_bk*	*Beta*	*Beta*
Intensity	-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)
Dep_{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)
$Noninc_{t-1}$	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)
Ret_{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)
FE_Time	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE_Bank	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1499	1197	1499	1197	1498	1196	1498	1196	1489	1189
R^2	0.881	0.880	0.900	0.902	0.748	0.770	0.749	0.757	0.814	0.810

4.2 How Do Banking Crisis Experiences Matter?

4.2.1 Exposure to Interest Rate Fluctuations

Now that we have seen the impacts of banking crisis experience on the banking outcomes regarding survival rates and systematic risk-taking, we attempt to assess the possible channels through which the experiences manifest themselves in the outcome differences. We are, first of all, interested in the resilience of BHC business model to the variations of interest rates in the market. The interest rates are central to the business model of BHCs which are traditionally viewed as maturity transformers. But it remains a mystery as to whether interest rates increase will benefit or destroy the equity value of BHCs. As reported in the English et al. (2012), the literature yielded different empirical findings regarding the sign of the correlation between interest rates shocks and equity value. Conventional wisdom holds that the maturity transformers should benefit from interest rates reductions or the steepening of the yield curve because the BHCs are engaged in borrow "short"short and lend "long". The sign and magnitude of the effect should depend on the maturity gap. On the other hand, the asset value of BHCs should decrease as long-term interest rates rise, which offsets the associated net interest income. Moreover, BHCs can also be involved in hedging against using derivatives. As can be seen, the gross effect of interest rates fluctuations on BHC equity value can be positive, negative or zero. In our paper, we are only interested in the overall unsigned exposure of BHCs to interest rates shocks, rather than the direction of this exposure.

Interest rates fluctuations can impose destructive risks on BHCs. Regardless of the direction of the effect, the ex-ante unpredictable interest rates movement poses an uncertainty on banks' equity valuation and stock market performance. This uncertainty partially contributed to the escalation of S&Ls crisis in the 1980s. Our premise is that CEOs witnessing more severe S&Ls in their working states are more averse to this uncertainty and will engineer their business models to be less sensitive to interest rates change.

However, since the business model is an intangible overarching concept touching numerous aspects including income sources, hedging policies, business segments and so on so forth, we cannot specify the measurement for business model. Hence, we opt to check the valuation of the company in the stock market as the reflection for business model.

There are many proxies for interest rates, amongst which we choose Bank Primary Loan Rates (prime), 3-month London Interbank Offered Rate in USD 3-month (libor), Term-spread defined as 10-

Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity (term-spread)[14]. We adopt two approaches to extract interest rates shocks. The first way is to take the first difference of monthly interest rates time-series, which eliminate time trend and seasonality and thus help stabilize the mean of the time-series in question. The second approach is to take the residuals of monthly time-series of each proxy after fitting in AR(2) models and remove the potential autocorrelation.

To measure each BHC's exposure to interest rates shocks, we regress monthly stock returns on the BHC against the extracted monthly interest rates shocks. Based on two methods to extract shocks in three proxies, we obtain six interest rates betas denoted as $Prime\_d1$, $Prime\_res$, $Libor\_d1$, $Libor\_res$, $Termspread\_d1$, $Termspread\_res$. They correspond to betas constructed using first difference and AR(2) residuals of bank primary rates, libor rates, and term-spread respectively.

Finally, we conduct panel regressions by regressing the obtained betas on $Intensity$, to verify whether crisis experience intensity is associated with BHC resilience against interest rates movements. The same as before, we include Bank and Time fixed effects throughout Table 5. Notice that the interest rates change can also be interpreted as funding liquidity shocks. We sign each interest rates proxy such that a large value indicates an adverse funding liquidity shock. Accordingly, a small value of interest rates beta implies a stronger ability to withstand adverse funding liquidity conditions.

Table 5 reports the panel regression with the most complete set of control variables. The first observation is that higher value of experience intensity correlates with lower interest rates betas regardless of which proxy is used for interest rates. One standard deviation of intensity is associated with 0.58% to 2.29% decline in interest rates betas. Other control variables do not seem to exert significant influence on the dependent variables. Overall, the results are in supportive of our intuition that BHCs with more "seasoned" CEOs in place have business models less affected by interest rates shocks over time. It is natural to ask whether the results hold differently during crisis time when the liquidity evaporates and short-term interest rates spike. In unreported regressions, we find the results remain qualitatively similar in the subsample of noncrisis years and crisis period, but the effect is not additionally strong in times of crisis.

[14]In unreported tables, we obtain qualitatively similar results from other interest rates proxies such as TED, Treasury Bill Yields, Credit Spread etc.

Table 5: **Resilience to Interest Rates Fluctuations**

This table reports estimations from panel regressions predicting interest rates betas during the period from December 1999 through December 2009. Variable definitions are provided in Appendix B. Concurrent controls include the CEO age, gender, and education. Lagged control variables include the lagged annual stock return, size(the natural log of the book value of assets), book to market ratio, tier 1 ratio, and market beta. All specifications include band and time fixed effects. The dependent variables in column (1) and (2), column (3) and (4), and column (5) and (6) are BHC's stock returns sensitivity to bank prime loans rates, libor rates, and term-spread. Standard errors are clustered at CEO level. T-statistics are presented in parentheses below the coefficient estimates, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Prime\_d1$	$Prime\_res$	$Libor\_d1$	$Libor\_res$	$Termspread\_d1$	$Termspread\_res$
$Intensity$	-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)
Dep_{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)
$Noninc_{t-1}$	-0.008	-0.013	0.033	0.030	0.004	0.010
	(-0.56)	(-0.66)	(0.93)	(0.74)	(0.42)	(0.96)
Ret_{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)
N	1116	1116	1116	1116	1116	1116
R^2	0.344	0.340	0.383	0.359	0.237	0.237
FE_Year	Y	Y	Y	Y	Y	Y
FE_Bank	Y	Y	Y	Y	Y	Y

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

4.2.2 Credit Risk Management

In this section, we check if "seasoned" CEOs exhibit specific features in managing credit risks. As stated earlier, the decade of the 1980s has seen the tightening of money and intensifying of competitions among financial institutions. Financial institutions which are locked in by rates ceilings at the time assume greater credit risks to boost profitability. These risk shifting practices lead up to the failures. We expect CEOs living through this part of the history to be particularly careful dealing with credit risks and more aware of loan quality deterioration.

Table 6 provides evidence about for the association between credit risk proxies and the experience intensity measure. The variables we select to represent credit risks are the ratio of net charge-offs to assets, provision to the asset, and nonperforming loans past due by 90 days or above to asset, all of which are commonly used in the literature (Bouwman and Malmendier (2015); Fahlenbrach et al. (2012); Ellul and Yerramilli (2013)). As can be readily seen from baseline regressions, CEO experience intensity measure is negatively correlated with loan quality and credit risk. Regarding economic magnitudes, we can see from column (2) that one standard deviation of *Intensity* is associated with 0.053% decrease in net charge-offs, which accounts for one-fifth of the latter's mean level of 0.29%. Controlling for both firm and CEO time-varying characteristics, one standard deviation of *Intensity* is associated with 0.673% and 1.168% decrease in the provision and non-performing loans ratio respectively. A general pattern in Table 6 is that the coefficient estimates of interest are larger in magnitude and more robust with CEO personal traits control variables. The pattern can be explained by the most precise estimates of error terms with more proper controls in place. As for other controls, it is no surprise that the most significant predictors for a current level of risk-takings are their lagged levels, given the persistent nature of loan qualities and credit risks. The credit quality of larger banks are poorer, suggesting that more major banks are more involved in risky mortgage practices. The fraction of non-interest income is negatively related to loan quality. BHCs whose income comes less from interest rates related business have better credit qualities, all else equal.

Overall, our findings reveal that CEOs weathering through more severe banking crisis are associated with lower credit risks when they are running BHCs as CEOs. The results are consistent with the claim made by Mr. Hickman that the reckless lending practices in the past have made him a better and more conservative banker.

A caveat is that we do not differentiate whether the lower level of risk matrices is due to less risk-taking or effective risk management. It could be that CEOs put in place a more efficient and stronger risk control system and exert stringent monitoring on the loan quality. If the mechanism is through effective risk management, then we should observe higher operating profitability associated with the lower ratios of bad loans. Alternatively, it could be about less risk-taking, and then the question is whether the less risk is still optimal for shareholders. It is possible that managers are involved in too little risk-taking to minimize the chance of being fired by the board. In this scenario, the risk-aversion is value-destroying for the BHC. We find that the ROA is not statistically distinguishable from zero, suggesting that the less risk taking explained by CEO experience does no harm to the BHC concerning profitability.

4.2.3 Liquidity Risk Management

In this section, we examine another important aspect of BHC's risk profile, the liquidity risk. We have two motivations. Firstly, in the corporate literature, a high level of cash-holding often serves as a demonstration for high risk-aversion and a more conservative style (Dessaint and Matray (2015); Bernile et al. (2015); Schoar and Zuo (2011); Dittmar and Duchin (2015); Malmendier et al. (2011)). Since our hypothesis lies on the foundation that early-life experiences in banking crisis raise one's awareness of risks embedded in the bank operations which can trigger failures, CEO's preference for the amount of liquidity buffer is also likely to be affected.

Secondly, the management of liquidity is increasingly a core part of banks' strategic planning and balance sheet management. Bank for International Settlements first introduces Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) in 2010, as part of Basel III. Starting on 1 January 2015, banks have to maintain the LCR ratio at a minimum of 60% and reach 100% on 1 January 2019 with an annual growth step of 10%. Banks are also required to comply with the disclosure requirements of NSFR as of 1 January 2018. NSFR is a critical component of Basel III, aimed to attenuate the risk of bank failures and possible broader systemic stress in the case that disruptions to a bank's regular sources of funding will erode its liquidity position. Liquidity rules in Basel III mark the first time that global quantitative minimum standards for liquidity are explicitly set for banks to meet. The regulation responds to the calling for a sound liquidity environment in the aftermath of the phenomenal liquidity dry-up observed in 2007-2008 (Brunnermeier (2009)). Considering the vital role played by liquidity positions in the 2008 episode, it warrants a close check on ex-ante factors influencing the cross-sectional

Table 6: **Credit and Liquidity Risk Management**

Panel A of this table reports estimations from panel regressions predicting credit risks during the period from December 1999 through December 2009. Variable definitions are provided in Appendix B. Concurrent controls include the CEO age, gender, and education. Lagged control variables include the lagged annual stock return, size(the natural log of the book value of assets), book to market ratio, tier 1 ratio, and market beta. All specifications include band and time fixed effects. For panel A, The dependent variables in column (1) and (2), column (3) and (4), and column (5) and (6) are BHC's ratio of net charge-offs to assets, provision, and non-performing loans past due by at least 90 days. Panel B presents the regressions of liquid asset holdings. The numerator of $LiquidAsset1$ comprises of cash, pledged securities, held-to-maturity securities, available-for-sale securities and federal funds sold, while that of $LiquidAsset2$ excludes federal funds sold from $LiquidAsset1$. The denominator in both $LiquidAsset1$ and $LiquidAsset2$ is book value of assets. The dependent variable in column (5) and (6) is the amount of US Treasury Bills scaled by book value of assets. The ratios are all scaled by concurrent book value of assets. Standard errors are clustered at CEO level. T-statistics are presented in parentheses below the coefficient estimates, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	Panel A: Panel Regression of Credit Risks					
	(1)	(2)	(3)	(4)	(5)	(6)
	$netchargeoffs$	$netchargeoffs$	$provision$	$provision$	$badloan$	$badloan$
$Intensity$	-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)
Dep_{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)
$Noninc_{t-1}$	-0.378***	-0.376**	-0.464**	-0.444**	-0.396	-0.540*
	(-3.65)	(-3.17)	(-3.26)	(-2.67)	(-1.24)	(-1.87)
Ret_{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)	(2)	(3)	(4)	(5)	(6)
	$LiquidAsset1$	$LiquidAsset1$	$LiquidAsset2$	$LiquidAsset2$	$USTreasury$	$USTreasury$
$Intensity$	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	N	Y	N	Y	N	Y
Bank Controls	Y	Y	Y	Y	Y	Y
FE_Year	Y	Y	Y	Y	Y	Y
FE_Bank	Y	Y	Y	Y	Y	Y
N	1498	1196	1498	1197	1483	1188

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

difference in the handling of liquidity buffer at BHC level.

Our sample period starts in 1999 and ends in 2009, during which time BHCs use discretions to manage their liquidity risk in accordance with the principals laid out by regulators. Without the binding rules, the discretionary holdings of liquid assets can be more informative about BHCs' intrinsic attitudes towards liquidity risks and the propensity to manage them.

Regarding the particular composition of liquidity buffer, we follow the spirits of high-quality liquid assets defined in LCR. Data required by NSFR ratio is not readily disclosed and requires the nontrivial extent of estimation. The LCR definition stipulates that its numerator, high-quality liquid assets, should have a high potential to be converted easily and quickly into cash. In line with the definitions, our liquid assets include cash, pledged securities, held-to-maturity securities, available-for-sale securities and federal funds sold. Other academic works adopt similar constructions, such as Loutskina (2011); Irani and Meisenzahl (2015); Acharya and Mora (2015); Kashyap et al. (2002); Gatev and Strahan (2006); Cornett et al. (2011). Alternatively, we also check the holdings of US treasury bills. Notice that our liquidity measure is market value based, the same as all the accounts reported in FR Y9C statements. Ideally, we would like to isolate the market valuation change of liquid assets from BHC's propensity to hold liquid assets, if not for data constraints. Certain categories of liquid assets can appreciate or depreciate dramatically in the absence of active management of BHCs, and hence the level of liquid asset market value does not adequately reflect BHCs' willingness to hold liquidity buffer but rather confounds with BHCs' skills in picking assets. A turnover or flow based liquid assets would fit. However, the relatively stable pricing of liquid assets attenuates this concern. Also, we also scale the liquid assets value by the book value of assets.

In panel B of table 6, we presents the baseline regressions of liquid assets holdings, and first point out the suggestive positive relations between liquidity positions and the $Intensity$ of state-wise bank failure rate experienced by BHC CEOs in the 1980s. Higher liquidity holdings could have acted as a buffer against the swan-black risk during the global financial crisis. The numerator of $LiquidAsset1$ in column (1) and (2) comprises of cash, pledged securities, held-to-maturity securities, available-for-sale securities and federal funds sold, while that of $LiquidAsset2$ (3) and (4) excludes federal funds sold from $LiquidAsset1$. The denominator in both $LiquidAsset1$ and $LiquidAsset2$ is book value of assets. The economic and statistical power of our key variable of interest $Intensity$ remain similar for both cases. The amount of federal funds of sold constitutes 1.7% of total book value of assets on average. Given the 35.7% mean of $LiquidAsset1$, the 1% increase in liquid asset holdings associated with one standard deviation of $Intensity$ is not as economically significant as the impact on credit risk. The statistical significance of the two variables are both at 10%, which again is not as powerful as that of our other predictions.

The dependent variable in column (5) and (6) is the amount of US Treasury Bills scaled by book value of assets. We interpret the coefficient signs in column (5) and (6) in the same veil. We find that one standard deviation of $Intensity$ is associated with 0.38% increase in the holdings of US Treasury Bills, while the mean level of the latter is 3.66%.

To sum up, the results are consistent with the earlier reports linking banking crisis experiences and stronger control over risks. Higher intensity is associated a higher level of holdings of liquid assets, a lower level of credit risks, and stronger resilience against interest rates shocks. Overall, our empirical evidence suggest that asset safety enhancement is the major channel through which the CEO banking crisis experience manifest itself on BHCs. Seasoned CEOs manage the asset side of the balance sheet differently. We do not find evidence about the influence on financing policies of the liability side, which contrasts to the usual conclusions in corporate literature. The managerial studies for general corporate sectors reveal that CEO personal traits are often reflected in the corporate investment, financing and diversification strategies. We do not find the parallel in the banking sector. One reason could be that BHCs are subject to more regulations on their funding sources and core capital level, which leave less room for CEOs to exert influence, whereas corporate C-suits has stronger leeway and decision power over their own leverage policies.

Taking all findings in the empirical analysis part, we show that evidence is more supportive of hypothesis H1b. Banking crisis matter for BHCs' survival and systematic risk-taking. In addition, stronger liquidity position, better loan qualities, and stronger ability to withstand interest rates fluctuations are potential mechanism to explain the findings in section 4.1.1 and 4.1.2 that BHCs led by seasoned CEOs are less likely to fail and uncouple from peers in assuming systematic risks.

4.3 *Heterogeneous Effects of Experiences*

4.3.1 *Before and During Crisis*

We turn our focus to the generalization of our findings. Does our finding holds for the recent Global Financial Crisis? Does our measure of *Intensity* have additional predicting power during crisis time? We show that our results go through in both pre-crisis and crisis period. However, seasoned CEOs do not demonstrate more distinctions in handling the BHCs than they would during normal times.

4.3.2 *Big or Small BHCs*

We also split the sample by the size of BHCs, and check if the effect documented so far differ for the two groups. In unreported tables, we find the difference of the coefficients estimated from the big and small BHCs sample are not statistically distinguishable.

4.3.3 *Position Held during S&Ls*

It is reasonable to suspect that the imprinting effect of past crisis solicited on individuals varies according to the salience degree. If an individual was under the helm of a financial institution during the crisis, he or she is likely to have faced more precarious situations more often and vividly than if she was at the bottom of the corporate ladder. The imprinting effect on individuals is expected to be stronger in the first case than the second. We therefore split the sample by whether the CEO was part of C-suite in the 1980s when S$Ls crisis took place, and test our main hypothesis group by group to compare the magnitude of the effects. We then run a simple student t-test to check if the magnitude difference is statistically distinguishable from zero. We find that the predictive power of *Intensity* associated with C-suits positions during S&Ls crisis is significantly stronger.

5 Alternative Explanation and Robustness Check

In this subsection, we seek to investigate alternative explanations for the findings we have shown so far.

5.1 Endogeneity Concern

The ideal experiment to test the causal effect of banking crisis experiences on BHCs will be an exogenous assignment of crisis shocks to twin CEOs randomly paired with twin BHCs. Needless to say, the matching between CEOs and their employment locations during the S&Ls crisis, and their subsequent selection into BHCs can impair any causal claim regarding the crisis effect. In this subsection, we aim to isolate the matching processes from the identification seeking to establish the effect of crisis experiences.

5.1.1 *CEO Firm Matching after Savings and Loan Crisis?*

The common limitation of CEO-style literature is that the matching between CEO and firm is not random and therefore any of our findings can be attributed to the unobservable factors driving both the matching and our predicted variables. Since we zoom in the banking sector and the idiosyncratic death or health shocks to CEO are too scarce to be constructed as a reliable regression sample, we rather exploit rely on CEO retirement age to pin down exogenous CEO turnovers, and exploit CEO turnovers as the playground to tackle the endogeneity concern.

We believe the banking sector is an appropriate setting to exploit the retirement age for two reasons. Firstly, public media often puts pressure on prior bank CEO due to the stereotype that banking sector is fast paced and requires constant vigor[15]. The CEO succession takes place often in the absence of fundamental changes or strategy innovation. To ensure that the older CEO are not forced to exit because of bank necessary or policy changes, we also check whether there exist significant pre-trends in the year before new CEO is appointed (Schoar and Zuo (2011)). Secondly, the retirement age of CEO is often debatable, and the exact timing of CEO retirement is not 100 percent anticipated. Thus, the optimal replacement might be delayed, and this variation in CEO selection due to random timing allows us to test how CEO experience plays a role in bank management.

As shown in the summary statistics section, the median retirement age in our BHCs sample is 61, and we are rather conservative to take 65 as the threshold. In the CEO succession, if the retired CEO is above 65, we classify the CEO turnover event as exogenous. Our assumption of 65 is not groundless. As argued above, the mandatory retirement age for bank CEO is younger than average.

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

Under this restriction, we find 30% of BHCs have experienced exogenous CEO turnovers and hence belong to our subsample controlling for endogeneity and there is quite a variance across BHCs. We change the threshold of 65 to other ages in the robustness section. We acknowledge that this approach can not completely address the concern of assortive matching. But at least our findings suggest banking crisis experiences cultivate certain qualities in CEOs and enable them to be chosen as the successor by corporate boards. The CEOs are hired to implement a certain type of corporate strategies. In table 7, we replicate our main findings in section 4 on the subsample of exogenous CEO turnovers. We keep selected proxies for each economic force examined in previous tables, in the interest of space. In column (1), we present the marginal effects from the probit model of bank failures. The definition of $Failur1$ regards BHCs receiving assistance from TARP as survivors. The magnitude of the coefficient before $Intensity$ estimated from the exogenous turnover subsample is 30% larger than from the complete sample. The statistical power of the coefficient estimates is lower in the exogenous CEO turnover sample, which is not surprising given the smaller sample size and the associated noisier error terms. In column (2) to (4), the dependent variables are proxies for systematic risk-taking, namely the co-movement with the equally-weighted banking sector portfolio, marginal expected shortfall, and market beta. Throughout the sample period, an increase of one standard deviation in the $Intensity$ translates into an increase in the MES of roughly 0.254 percentage points, which is a bit less than one seventh of the unconditional mean of MES of 1.8 percentage points. Recall that a higher level of MES corresponds to a lower systematic risk level. Column (5) reports the regression of net charge-offs on $Intensity$. Column (6) exhibits the liquid asset holdings regression. The economic and statistical significance of $Intensity$ in explaining the credit and liquidity risk management are both higher for the turnover subsample than the full sample. At last, column (7) shows the regression of BHC stock return sensitivity to term-spread shocks. The coefficient magnitude remains similar across the turnover and full sample.

5.1.2 *CEO State Matching before Savings and Loan Crisis?*

The other concern relates to the endogenous mobility during the savings and loan crisis. For instance, it could be that a risk-averse CEO in TEXAS anticipates the future banking crisis in TEXAS and decides to switch states and join a safer state which takes less risk in the 1980s. These risk-averse CEOs will inevitably take conservative positions on their business model and loan policies when they step into the CEO position. If this is the case, our intensity measure only captures the innate risk aversion of CEOs our findings are primarily attributed to CEO risk attitude rather than the early-life banking crisis

Table 7: **Endogeneity Test**

This table reports estimations from panel regressions predicting interest rates betas during the period from December 1999 through December 2009. Variable definitions are provided in Appendix B. Concurrent controls include the CEO age, gender, and education. Lagged control variables include the lagged annual stock return, size(the natural log of the book value of assets), book to market ratio, tier 1 ratio, and market beta. All specifications include band and time fixed effects. The dependent variables through column (1) to (7) are bank failure rates, stock return comovement with equally-weighted banking sector portfolio, marginal expected shortfall, CAPM beta, net charge-offs ratio, liquid asset holdings ratio, and BHC's stock returns sensitivity to term-spread first differentials. Standard errors are clustered at CEO level. T-statistics are presented in parentheses below the coefficient estimates, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$Failure1$	CMV_bk	MES	$Beta$	$Netchargeoffs$	$LiquidAsset1$	$Termspread\_d1$
$Intensity$	-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)
Dep_{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)
$Noninc_{t-1}$	-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)
Ret_{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)
FE_Year	Y	Y	Y	Y	Y	Y	Y
FE_Bank	Y	Y	Y	Y	Y	Y	Y
N	432	423	423	423	423	414	396
R^2		0.887	0.807	0.813	0.911	0.821	0.300

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

experiences. However, this explanation suggests that risk-averse CEO self-selects into safer states and will have conservative risk management style and business model, leading to a positive correlation between *Intensity* and risk-taking which is exactly the opposite of our findings.

Alternatively, it could be the case that CEO in the most heavily hit states is discounted on the labor market after the S&L crisis is over. Hence, CEOs from more badly hit states end up with worse BHC which cannot survive over time. This story suggests a positive relation linking S&L *Intensity* and *Failure*, which again appears inconsistent with the sign of our findings in Table 3. To further alleviate the concern, we repeat our analysis on the subsample in which BHC CEOs stay in the same state throughout the period 1985-1990. The sign of our predictors remains similar statistically and economically.

To further investigate the causal link, we change employment location during the S&Ls to CEO hometown area. The birth place is randomly assigned to BHC CEOs beyond their choices and controls, and hence the S&Ls crisis severity in their hometown state most closely approximates a random assignment of crisis intensity to CEOs across BHCs. Hence, the S&L intensity of CEO hometown acts as a valid exogenous variation to the dependent variables we have examined before. We collect the birth place of BHC CEOs from Marquis WhosWho, and redefine the *Intensity* by taking he maximum of Bank Failures Rate in each CEO's hometown state over the period of 1985-1990. Furthermore, we replicate our key regressions shown before using the home-town based *Intensity*.

5.2 *State or Bank Level Experiences?*

One may worry that our intensity measure is highly correlated to the micro-level bank failures within the state and our intensity measure captures the losses of the firm CEO worked for during the 1980s. This issue leads to the possibility that our intensity measure is confounded with the CEO-firm matching during the 1980s. For example, the less competent CEOs can be hired by poorly performing institutions during the 1980s and forced to join worse BHCs when their previous employers go bankrupt in the 1980s. The latent variable talents can drive both the CEO-firm matching in the 1980s and the BHC performance in the recent 1999-2009 period.

We first proxy talents with CEO education achievement to explicitly rule out the possibility that CEO talents are driving our results. We then control for the financial conditions of CEO past employers during the S&Ls to compare the predicting power of state-level and firm-level losses. If state-level intensity measure survives the inclusion of firm-level financial conditions, we are surer that CEO-firm matching in the 1980s is not entirely driving our results.

We then identify the firm bankruptcy incidence during the 1980s. We create a dummy variable equal to 1 if the institution CEO works for during the S&Ls crisis goes under, and 0 otherwise. In the full sample, roughly 4% of CEOs have been through firm-level bankruptcy. The variation of firm bankruptcy dummy is too little for identification and the estimated coefficients are too noisy to draw any reliable inference.

5.3 ***Any Crisis?***

A natural question to ask is what kind of crisis is relevant for CEOs? Any economic recessions or asset bubbles create memories for BHC CEOs and leave traces on their management styles? Is there anything special about the event of S&Ls? In this section, we change the experience formation period to the 1998 Asian crisis. *Intensity* in Table 8 represents the state-level bank failures rates of CEO's employment area in the 1998. We show that this non-banking related crisis does not expose CEOs in the same way as the S&Ls crisis. In fact in Table 8, the coefficient estimate is statistically significant for none of the dependent variable in any column except the net charge-offs.

Table 8: **Falsification Test**

This table reports estimations from panel regressions predicting interest rates betas during the period from December 1999 through December 2009. Variable definitions are provided in Appendix B. Concurrent controls include the CEO age, gender, and education. Lagged control variables include the lagged annual stock return, size(the natural log of the book value of assets), book to market ratio, tier 1 ratio, and market beta. All specifications include band and time fixed effects. The dependent variables from column (1) to (7) are bank failure rates, stock return co-movement with the equally-weighted banking sector portfolio, marginal expected shortfall, CAPM market beta, net charge-offs, ratio of US Treasury Bills holdings to book value of assets, and sensitivity to first-differential term-spread. Standard errors are clustered at CEO level. T-statistics are presented in parentheses below the coefficient estimates, and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Failure	*CMV_bk*	*CMV_bkw*	*MES*	*Beta*	*Badloan*	*LiquidAsset1*	*Termspread_d1*
Intensity	-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)
Dep_{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)
$Noninc_{t-1}$	-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)
Ret_{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)
N	1126	1102	1102	1101	1094	1101	1101	1270
R^2		0.880	0.903	0.766	0.814	0.720	0.920	0.229
FE_Year	Y	Y	Y	Y	Y	Y	Y	Y
FE_Bank	Y	Y	Y	Y	Y	Y	Y	Y

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$

5.4 *Alternative Incentives*

5.4.1 *Destructive Risk Aversion?*

So far, our findings suggest that seasoned CEOs have more conservative styles with respect to risk taking. The relevant welfare question is whether the avoidance of risks create or destroy values for shareholders. If CEOs are refrained from taking the optimal level of risk exposure for BHCs out of personal considerations, then the risk-averse patterns we have reported actually destroy value. For instance, CEO are susceptible to career concern, and only willing to take on the risk level that minimizes their chance of being fired by the board, which can deviate from the level maximizing shareholder value. However, we find that the operating performance and stock returns are not significantly different between BHCs managed by seasoned or inexperienced CEOs, which suggest that CEOs are not excessively risk averse at the expense of shareholder value. The ideal case would be to construct a counterfactual optimal risk level taken by BHCs, which is not feasible at the moment.

5.4.2 *Executive Compensation?*

It is also possible that the compensation provides different incentives for CEOs that result in differing preferences for systematic risk, credit risk, and liquidity risk. Hence it warrants a check on the explaining of banking crisis experiences vis a vis executive compensation level. We have compensation data available for 20% of CEOs in our sample, and we include compensation level as control variables in our main specifications. We find the sign of *Intensity* remain unchanged. Due to the drastic drop of regression observations, the statistical power diminishes after the inclusion of compensation controls.

5.4.3 *Too Big to Fail?*

One particular aspect of S&Ls crisis is the eventual resolution which costs the taxpayers approximately $124–132.1 billion at the time. The Resolution Trust Corporation (RTC) was established to dispose of failed institutions taken over by regulators and repay the insured depositis to customers. Some believe that a government bailout could have created a moral hazard and encourage lenders to engage in risky loan businesses in the new era. In this vein, CEOs can be incentiviezd to do empire building so that their BHCs are "too big to fail". However, we do not find evidence suggesting a positvel assocation between *intensity* and BHCs size or growth rates.

5.5 *Robustness Checks*

In this section, we do a battery of robustness checks to ensure our findings are not driven by the way we define our key variables. We first alter our intensity measure definitions by changing the S&L crisis period to 1980-1990. We also change the definition from the max to mean of state-wise bank failure rate. We then control for county-level fixed effects instead of state-level in our regressions. We then change our specification for interest rates beta estimation by controlling for Fama-French 3 Factors. As for endogeneity tests, we change the retirement threshold to different cutoffs and results appear similar.

6 Conclusion

This paper seeks to explain the wide heterogeneity among BHCs performance from 1999-2009, including the Global Financial Crisis, from the perspective of CEO early-life experiences. It also sheds light on the learning from extreme events of sophisticated agents. We present empirical evidence to confirm that CEO banking crisis experiences matter, and provide suggestive evidence on the channels and policies most likely to be influenced by the experience. In particular, we find an inverse relation between BHC survival rate and intensity of banking crisis experiences. Systematic risk levels are also inversely related to CEO crisis experiences. Regarding the policies exploited, CEO-level banking crisis experiences explain future choice of loadings on interest rates shocks at BHC level. We show disaster-experienced CEOs take more effective risk control suggested by lower bad loan ratios and provision level. To establish causality, we focus on exogenous CEO turnovers to test if we our findings are driven by firm-CEO matching. We conclude that early-life banking crisis experiences lower the bank failure probability and systematic risks in normal and turbulent times. Experiences matter for BHC operations during normal times and the crisis period alike, and the dimensions most likely to be influenced are credit and liquidity risk management, However, we do not fully address some of the endogeneity concerns and we intend to provide more causal evidence in future work.

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