Essays on Risks in Banking

by

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A thesis submitted to the University of Birmingham for the degree of

DOCTOR OF PHILOSOPHY

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May 2019

ABSTRACT

Although the banking literature offers a very rich assessment of financial risks, this thesis attempts to extend the empirical literature by narrowing the important gaps in various aspects. Guided by the fundamental-based view (Calomiris, 2007) and supported by the theory of financial intermediation introduced by Allen and Santomero (1997), this thesis presents three distinctive empirical models to analyse the determinants of financial risks among banks in the United States over the past few decades. In *first essay* (chapter 2), I examine the factors and the extent to which they affect the probability of bank failure across different size categories. Results suggest that factors affecting bank failure vary across respective size categories, and the Average Marginal Effects (AMEs) of mutually significant covariates also exhibit significant variability across different size classes. In *second essay* (chapter 3), I explore the systematic trend in bank risk and its sources. I find that the risk level for each new cohort of banks are higher than its predecessors. In addition, I find that the risk differences (cohort risk phenomenon) are broadly persistent because each new cohort of banks adopts riskier business strategies than its predecessor. In *third essay* (chapter 4), I investigate the impact of tail risk on financial distress among publicly traded bank holding companies (BHCs). My results show that tail risk is significantly and positively linked to the financial distress, implying that BHCs with a higher tail risk have higher financial distress.

DEDICATION

This thesis is dedicated to my beloved uncle, Mansoor Alzugaiby, who unfortunately passed away few years ago

ACKNOWLEDGEMENTS

First and foremost, I would like to express my sincere gratitude to Dr. Jairaj Gupta who is not only my supervisor but also mentor and real friend. I am also thankful to my lead supervisor Professor Andy Mullineux. I am extremely grateful to them for giving me the opportunity to start a PhD and their continuous cooperation and inspiration throughout this valuable journey.

I would also like to give my thanks to my parents - my mother Fatimah Alzugaiby and my father Abdullah Alzugaiby, as well as my brothers and sisters for their motivation and support.

Finally, I am grateful to my lovely wife Khowlah Alsultan for her assistance and faith in me. Without her encouragement, it would have been impossible for me to complete my PhD study.

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CHAPTERS UNDER REVIEW

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CHAPTER 3

Alzugaiby, B., Gupta, J. and Mullineux, A. (2019) Cohort Risk Analysis of Banks. Under Review: *Journal of Financial and Quantitative Analysis* (SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3321229) (ABS 4*)

CHAPTER 4

Alzugaiby, B., Gupta, J. and Mullineux, A. (2019) The longer the tail, the shorter the sail. Under Review: *Journal of Banking and Finance* (SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3364841) (ABS 3*)

CONFERENCE PRESENTATION

1. *Birmingham Business School Annual Doctoral Conference*; Birmingham, UK; Bank Size and Bank Failure (**Chapter 2**) – March 2018.

2. *17th European Economics and Finance Society Annual Conference*; London, UK; Bank Size and Bank Failure (**Chapter 2**) – June 2018.

3. *The 50th Money, Macro and Finance Research Group Annual Conference*; Edinburgh, UK; Bank Size and Bank Failure (**Chapter 2**) – September 2018.

4. *Birmingham Business School Annual Doctoral Conference*; Birmingham, UK; The longer the tail, the shorter the sail (**Chapter 4**) – April 2019.

5. *9th International Conference of the Financial Engineering and Banking Society*; Prague, Czech Republic; Why Are Successive Cohorts of Banks Persistently Riskier? (**Chapter 3**) – May 2019.

6. *94th Annual Conference of the Western Economic Association International*; San Francisco, USA; Why Are Successive Cohorts of Banks Persistently Riskier? (**Chapter 3**) – June 2019.

1. THESIS OVERVIEW

1.1 Introduction

The recent global financial crisis indicates that the knowledge gained about bank financial risks is still not sufficient to avoid such crisis in the future. In addition, the banking literature has a lack of coverage in several aspects related to financial risks. The purpose of this thesis is to enhance our understanding by deeply investigating the determinants of financial risks in the U.S. banking industry, and to address the important gaps in the banking literature by focusing on certain areas remain unresolved. The thesis presents three empirical models to study a number of financial risks among banks in the United States over the past few decades.

In *first essay* (chapter 2), I extend the banking literature (e.g., Berger et al., 2016; Berger and Bouwman, 2013; Cole and Gunther, 1995; Cole and White, 2012; DeYoung and Torna, 2013; Kolari et al., 2002; Spahr, 1989) by providing a comprehensive analysis of failures across various bank size categories over the longest period of time (from 1985 until 2016) in the literature that covers data-points before, during, and after financial crises. I employ separate early-warning models for small, medium, and large banks, and report any differences in comparison to all bank failure prediction models, irrespective of bank size. Empirical results show that the accounting-based factors affecting bank failure and the magnitudes of mutually significant factors (AMEs) vary across bank size classes. The results clearly underline the importance of the heterogeneity in bank size when examining the financial risks and constructing appropriate policies and regulations.

My *second essay* (chapter 3) contributes to the existing literature of bank risk (e.g., Boyd and Prescott, 1986; Bryant, 1980; Calem and Rob, 1999; Delis and Staikouras, 2011; Demirgüç-Kunt and Huizinga, 2010; Demsetz and Strahan, 1997; Diamond and Dybvig, 1983;

Liu and Ngo, 2014; Qi, 1994) by extending the body of research focuses on a systematic increase in idiosyncratic risk among publicly listed firms. (e.g., Ang et al., 2006; Brown and Kapadia, 2007; Campbell et al., 2001; Fama and French, 2004; Irvine and Pontiff, 2009; Pástor and Pietro, 2003). Specifically, I study the systematic trend of financial risks (measured by liquidity risk and credit risk) among unlisted banks in the U.S. market and examine the potential explanations for this trend. In general, I find a clear evidence of an increase in bank financial risks over the sample period, 1980-2017. This positive trend explained by the increase of the risk levels for each successive cohort of new banks (cohort risk phenomenon). In addition, I find that the risk differences for these cohorts are broadly persistent due to the adoption of riskier business strategies based on higher brokered deposits, commercial real estate loans, off-balance sheet items, and non-interest income.

The *third essay* (chapter 4) expands the scope of the existing literature, which shows a strong connection between the information content of market indicators and individual bank risk (e.g., Coffinet et al., 2010; Curry et al., 2007; Evanoff and Wall, 2002; Flannery, 1998; Gropp et al., 2006), by incorporating tail risk measures namely, value-at-risk (VaR) and expected shortfall (ES), to substantially enhance the understanding of bank financial distress. Guided by the Extreme Value Theory (EVT), I empirically investigate the impact of extreme negative daily equity returns (tail risk) on financial distress among publicly traded bank holding companies (BHCs) in the United States. My results show that VaR and ES are significantly and positively related to the banks financial distress. Implying that BHCs with more frequent extreme negative daily equity returns induce higher tail risks, thereby increasing their likelihood of experiencing financial distress. The results also show that tail risk measures enhance the explanatory power of traditional models explaining banks distress risk based on accounting information. These results indicate that market discipline is generally beneficial in managing and regulating banks.

Overall, the main implications of this thesis are to provide deeper insights into the understanding of bank financial risks and strongly support recent regulatory requirements (e.g., the Basel III framework and the Dodd–Frank Act) to enhance the stability of banking industry, thereby avoiding the adverse effects on whole economy. In addition, this thesis should interest all parties including bank managers, supervisors, policy makers, and researchers who attempt to examine the financial risks.

1.2 Theoretical Background

1.2.1 Theoretical Perspective on The Role of Banks

The theoretical literature on the role of banks typically related to the traditional existential theories and the financial intermediation theories. The first strand focuses on the existence and main operations of banks and the second strand discusses the conditions and reasons behind the existence of banks (Swank, 1996). The core traditional theories in the literature are transaction costs (Benston et al., 1976), asymmetric information and signalling (Leland and Pyle, 1977), and delegated monitoring (Diamond, 1984). They assume banks as financial intermediaries exist due to the market imperfections that prevent the direct relationship between savers and investors and justify the transaction costs to monitor investors on behalf of savers and the engagement in asset transformation activities. In contrast, Allen and Santomero (1997) view financial intermediaries, especially banks, as facilitators of risk transfer and deal with complex financial instruments and markets. In other words, they consider the risk management as the key role of financial institutions (e.g. banks). They argue that traditional financial intermediation theories are increasingly less relevant to current financial systems due to the rapid changes such as technologies and financial innovations that have reduced the transactions costs and have increased the availability of information. Moreover, the neutral of banks is dealing in financial assets, which considers a financial risk business, and this means they expose, involve, and manage all types of risks including financial risks (e.g. credit risk, market risk, and liquidity risk) and non-financial risks (e.g. operational risks). These risks have increased in parallel with the rapid growth in banks during the past 30 years. In addition, the fixed premium deposit insurance that offered by the FDIC has increased the banks' risk-taking behaviour without limit (deposit insurance theory) (Chan, Greenbaum and Thakor, 1992).

1.2.2 Theoretical Framework

This thesis is supported by two theoretical views. First, the panic-based view that introduced by Bryant (1980), which advocates banks are inherently vulnerable and subject to contagion (Calomiris, 2007). According to this view, banks run attributed to the beliefs of depositors to withdraw their funds because others will run, and depositors withdraw the money due to ambiguous or inaccurate information (Diamond and Dybvig, 1983). In such circumstance, many banks may fail due to high withdrawal pressure and spread to the rest including the solvent and healthy banks. Second, the fundamental-based view that considers banks are inherently stable and not subject to panic. According to this view, depositors withdraw their funds due to adverse fundamental changes in the economic conditions of banks (e.g. large losses) that lead to the failure of only weak and fragile banks (Calomiris, 2007).

This thesis tends most likely to the fundamental-based view because I believe the financial status of bank generally governs current depositors' decision of withdrawal, investors, and expected depositors. Consequently, I investigate the main factors that determine the financial condition of banks to assist interested parties to make the correct decisions.

1.3 Thesis Organisation

The rest of the thesis is organised into four chapters.

Chapter 2 provides a comprehensive analysis of the differences in US bank failures engendered by size heterogeneity. In Section 2.2, I provide a review of literature on the determinants of bank failures and develop testable hypotheses. Section 2.3 presents discussion on the dataset, sample, and covariates. In Sections 2.4 and 2.5, I outline empirical methods and discuss my results. Sections 2.6 and 2.7 present additional analysis and robustness test. Section 2.8 concludes this chapter.

Chapter 3 focuses on the systematic trend in bank financial risk and its potential explanations. Section 3.2 provides an overview of the relevant literature and develops the empirical hypotheses. Section 3.3 presents a discussion on the dataset, sample, and covariates. Section 3.4 presents the results of the hypotheses tests. Section 3.5 addresses robustness issues, and Section 3.6 offers concluding remarks.

Chapter 4 provides an analysis of the impact of tail risk measures on the bank financial distress. Section 4.2 discusses data and financial covariates; Section 4.3 presents my empirical methods and main results; Section 4.4 presents additional results on robustness checks; and Section 4.5 concludes this chapter.

Chapter 5 summarises and concludes this thesis, identifies the limitations and suggests possible directions for future research.

2. A COMPREHENSIVE ANALYSIS OF BANK FAILURE

2.1 Introduction

Does size matter in predicting banks failure? The answer to this question would be helpful to policymakers and bank regulators seeking to improve their understanding of bank failures across different size categories, and thereby promoting stability of the financial system. This issue was seriously exaggerated following the failure of large and complex banks in 2008 (the recent financial crisis) which resulted in extremely high costs to national economies forced to bail them out in order to restore confidence in the financial markets (Pais and Stork, 2013). Over the last three decades, several banks have been criticised for becoming oversized and thereby carrying the associated higher systemic risk. In response, several restrictions have been enacted by federal governments to downsize or split up these banks to reduce the public finance risk. For instance, the Dodd-Frank Act of 2010 is a US federal law intended to limit banks' involvement in some risky activities and to ban mergers that result in a financial institution with total liabilities surpassing 10% of the aggregate consolidated liabilities of all financial firms (to prevent the emergence of "too big to fail" banks (Bertay et al., 2013)). Proponents of the act also argue that the constraints, particularly size limitation, shall prevent future crises and protect consumers from abusive financial services practices. However, many argue that these actions would impair the efficiency of capital allocation for some banks and add costs to the economy (Aiyar et al., 2014). Others also argue that such restrictive regulations may lead to the failure of many small banks deemed "too important to fail", which may cause the recurrence of financial crises (De Haan and Poghosyan, 2012; Wilmarth, 2011). This debate reveals the need for further investigation into the heterogeneity of bank failures across different size classes, to recognise the similarities and differences before taking appropriate measures.

The empirical literature on individual bank failures is extensive and offers a rich assessment of several aspects. However, the factors and the extent to which they affect the probability of bank failures across size classes remain overlooked. More specifically, most previous studies (e.g., Berger et al., 2016; Cole and Gunther, 1995; Cole and White, 2012; DeYoung and Torna, 2013; Kolari et al., 2002; Spahr, 1989) do not split banks into different size categories (Berger and Bouwman, 2013), nor do they examine separately the reasons for the failures and their effects on each size. A prospective exception is Berger and Bouwman (2013) who examine the impact of capital on bank performance (survival and market share) and how this effect differs among bank size classes (small, medium, and large) and across banking crises, market crises, and normal times. However, unlike my study, they focus only on one of the six CAMELS components that may misclassify distressed banks. This shortage of studies perhaps surprising because the literature shows that bank size is as an essential economical foundation as the capital (Berger and Bouwman, 2013), and plays a crucial role in many dimensions such as performance (e.g., Bertay et al., 2013), financial stability (e.g., Bhagat et al., 2015), scope (e.g., De Jonghe et al., 2015), lending (e.g., De Haas et al., 2010), funding strategies (e.g., Loutskina, 2011), and systemic risk (e.g., Laeven et al., 2016). Notwithstanding the evidence of bank size heterogeneity effects on various aspects, particularly financial stability, the literature lacks a thorough analysis of determinants and predictability of bank failures across bank size categories. Hence, this study is to improve the literature by developing separate failure prediction models for different bank size categories (small, medium, and large), and report any differences in comparison to an all-inclusive (containing all banks irrespective of their size) failure prediction model. I also compare the consistency (statistical significance and average marginal effects) of respective covariates in explaining bank failures across size categories. To capture the effects of variables linked to bank size, I use criteria based on banks' total assets in a given year *t* to classify small, medium, and large banks. Specifically, in any given year *t*, I consider banks corresponding to the bottom 25 percentile of total assets as small banks, the top 25 percentile as large banks, and the rest medium banks.

Another contribution of this paper is that, unlike the majority of previous studies that focus only on either the saving and loans crisis of the late 1980s (e.g., Cole and Gunther, 1995; DeYoung, 2003) or the recent subprime crisis (e.g., Cole and White, 2012; Deyoung and Torna, 2013; Berger et al., 2016), I analyse virtually all commercial banks in the United States over the longest period of time (from 1985 until 2016) in the literature that covers data-points before, during, and after banking crises. Moreover, the literature of bank failures draws heavily on accounting-based variables such as capital, earnings, and liquidity ratios (e.g., Cole and Gunther, 1995; Kolari et al., 2002; Cole and White, 2012; Berger et al., 2016). However, previous studies have not provided a comprehensive analysis of the relative importance of a full set of predictors. Thus, I employ univariate regression analysis, suggested by Hosmer et al. (2013), as a variable selection technique to investigate the relative importance of almost all accounting-based variables used in previous bank failure literature. Specifically, the broad categories of CAMELS, where the letters refer to Capital adequacy (e.g., total equity to total assets ratio), Asset quality (e.g., non-performing loans to total assets ratio), Management quality (e.g., cost to income ratio), Earnings (e.g., net interest margin), Liquidity (e.g., cash and due to total assets ratio), and Sensitivity to market risk (e.g., trading income to total operating income ratio); and other categories such as funding, business model, and growth, are analysed. I investigate a total of 61 accounting variables. I focus only on accounting variables for two reasons. First, some argue that bank-specific variables are more essential than market and macroeconomic variables in predicting bank failures (e.g., Cole and Wu, 2009). Second, the vast majority of my sample is of unlisted banks. This concentration on accounting variables is also supported theoretically by the fundamental-based view that attributes bank failure to negative information about fundamentals (e.g. large losses) (Allen and Gale, 1998).

To narrow down the list of covariates for further multivariate empirical analysis, I follow Gupta and Chaudhry (2019) strategy, suggested by Hosmer et al. (2013), and eliminate variables that (i) are not significant in 1-year, 2-years, and 3-years lagged univariate regression estimates, or (ii) are significant but exhibit Average Marginal Effects (AME)[1] of less than 5% in all three time periods. I repeat the univariate regression analysis for small, medium, and large banks respectively. The final lists of variables for all, small, medium, and large banks contain 19, 19, 20, and 21 variables respectively. This is a major departure from approaches that exist in the empirical literature, which often select variables that are advocated by popular studies, or that suit their empirical design.

The univariate regression analysis shows that the AMEs for most of the accounting-based predictors used in the literature vary across size categories and for the three lagged periods. Generally, the AMEs of respective covariates (1-year lag) for small banks are higher compared to estimates obtained for medium and large banks. However, for 2- and 3-years lagged estimates, AMEs of large banks are mostly the highest. This suggests that the prediction horizon of variables for small banks are stronger on short term, while the variables for large banks have a longer horizon forecast. Moreover, the variable with the highest AME among small and medium banks is net charge off to total assets (NCOTA), while the ratio of total equity to total assets has the highest AME for large banks.

[1] Marginal Effects are useful to non-linear regression analysis for examining the effect of changes in a given covariate on changes in the outcome variable, holding other covariates constant. These can be calculated as marginal change (it is the partial derivative for continuous predictors) when a covariate changes by an infinitely small quantity, and discrete change (for factor variables) when a covariate changes by a fixed quantity. Average Marginal Effects (AME) of a given covariate is the average of its marginal effects computed for each observation at its observed values. In other words, AME is the change in the outcome (failure = 1, in my case) probabilities due to unit change in the value of a given covariate, holding others constant. For more details, see Long and Freese (2006).

Subsequently, following the multivariate model building strategy applied by Gupta et al. (2018) based on the discussion suggested by Hosmer et al. (2013), I rank competing variables based on the magnitude of their AMEs, and then introduce each variable at a time, in descending order of magnitude. I perform this to develop multivariate models for all, small, medium, and large-sized banks respectively. The rationale for this approach is that a variable with a higher value of AME induces higher change in the failure probability, and thus should be given priority in the variable selection process (Gupta et al., 2018). I exclude a variable from the multivariate models if, when added: (i) it changes the sign of any previously added variable; (ii) it holds the opposite sign to that generated by univariate analysis; (iii) it holds the identical sign to univariate analysis, but is insignificant with a p-value greater than 0.10; or (iv) it makes a previously introduced variable insignificant with a p-value greater than 0.10. I end up with six, seven, six, and five variables (main variables) for building multivariate models for all, small, medium, and large banks, respectively. This divergence of main variables across the multivariate regression models reinforces that the factors affecting banks' failure vary across different size categories.

To test the discriminatory power of the main variables in identifying failed and non-failed banks for all, small, medium, and large banks, I use panel logistic regression analysis for 1-year, 2-years, and 3-years lagged estimates. This technique can address potential endogeneity issues since lagged explanatory variables (e.g., capital) and dependent variables (failure) have a low chance of being jointly determined (Berger and Bouwman, 2013). Also, it measures any temporal variation in the explanatory power of my variables. Test results illustrate that all of the main variables are strongly significant when explaining the failure risk of banks across all three-time lagged periods. This demonstrates the complementary information content of these main variables, and their statistical significance up to the 3-years lagged period establishes their intertemporal predictive ability.

Empirical results also show that credit risk plays a major role in promoting the risk of failure across the bank size classes and the three-time lagged periods, implying that poor asset quality - represented by net charge off, past due 90+ days, loan loss reserves, and other real estate owned – increases the probability of bank failure. This confirms the findings of earlier studies (Diamond and Dybvig, 1983; Meyer and Pifer, 1970), as well as recent theoretical and empirical studies by Iyer and Puri (2012) and Imbierowicz and Rauch (2014) respectively. Some critical findings of my study are that small banks are most likely to fail if they have high deposit ratios, are more cost inefficient, and have a high liquidity risk, while medium and large banks with poor capital and low net interest margin are more likely to fail. These results are consistent with the existing theoretical and empirical bank failures literature (e.g., Acharya and Naqvi, 2012; Angbazo, 1997; Betz et al., 2014; Khan et al., 2017; Kolari et al., 2002).

These results are robust to the presence of control variables including house price inflation, foreign ownership, and dummies for banking crises and regulators. To perform an additional robustness test, I follow Berger and Bouwman (2013) by splitting the sample into banking crises, market crises, and normal times, and treating them as separate groups. I rerun all multivariate regressions separately for all, small, medium, and large banks, and qualitatively similar results are obtained. In addition, the AUROC (Area under Receiver Operation Characteristics Curve) of all multivariate models developed across respective bank size classes for within-sample and out-of-sample show excellent classification performance for different forecast horizons. Furthermore, I present persuasive evidence that the magnitude of respective coefficients of different significant predictors are not equal across different size categories. This is further reaffirmed by my inclusion of interaction between bank-size and bank-charter into my regression model for all banks.

My findings emphasise the importance of considering bank size when designing appropriate policies and regulations targeted toward enhancing financial stability and resilience. Future studies should, whenever possible, separate banks by size category to clearly understand the heterogeneity in bank failures.

The remainder of this chapter is structured as follows. In Section 2.2, I provide a review of literature on the determinants of bank failures and develop testable hypotheses. Section 2.3 presents discussion on the dataset, sample, and covariates. In Sections 2.4 and 2.5, I outline empirical methods and discuss my results. Sections 2.6 and 2.7 present additional analysis and robustness test. Section 2.8 concludes this chapter.

2.2 Literature Review and Hypotheses Development

This paper is guided by theoretical models and linked to the existing empirical literature in primarily two strands of research: first, the determinants and prediction of failure at the bank level, and second, the relevance of bank size to financial stability. I review these strands in turn before proposing my empirical hypotheses.

2.2.1 Determinants of Bank Failure Prediction

In theory, two views explain the sources of bank default. First is the panic-based view introduced by Bryant (1980), which posits that banks are inherently vulnerable and subject to contagion (Calomiris, 2007). According to this view, bank runs can be attributed to the strong likelihood of depositors withdrawing their funds because others will run, or due to ambiguous or inaccurate information about the institution's health (Diamond and Dybvig, 1983). In such circumstances, many banks fail due to high withdrawal pressure and risk spreading the adverse effects within the banking system, including solvent banks. Second is the fundamental-based view which considers banks to be inherently stable and not vulnerable to panic. According to this view, depositors withdraw their funds due to adverse fundamental changes in the economic conditions of banks (e.g. large losses), leading to the failure of only weak and fragile banks (Calomiris, 2007).

The latter view supports my paper, which aims to investigate bank default reasons. I believe that the financial status of a bank generally governs current depositors' withdrawal decisions, investors, and expected depositors. Thus, it is essential to focus on the factors that determine the financial condition of banks, in order to assist interested parties in making informed decisions.

The empirical literature on the determinants of bank failures typically concentrates on the United States (US) banks and thrifts (e.g., Berger et al., 2016; Cole and White, 2012; Lane et al., 1986; Meyer and Pifer, 1970; Schaeck, 2008; Thomson, 1992; Wheelock and Wilson, 2000). Furthermore, the literature draws heavily on accounting-based indicators and aims to construct early warning models generally based on the Uniform Financial Rating System, informally known as the CAMELS ratings system, to identify distress institutions prior to their failure (e.g., Cole and Gunther, 1995; Kolari et al., 2002; Cole and White, 2012). Several studies supplement the CAMELS proxies with some information about audit quality (Jin et al., 2011), or corporate governance (ownership, management, and compensation) (Berger et al., 2016). All of these studies show that their models are significant and effective in predicting bank failures. Also, several statistical (e.g., Discriminant analysis (DA) and Logit/Probit regression models) and intelligence (e.g., Support Vector Machines (SVM) and Neural Networks) techniques have been used to analyse and predict bank failures. Demyanyk and Hasan (2010) provide a comprehensive review of these techniques and related studies; I refer interested readers to this study for more details.

The vast body of research focuses on bank failures that occurred during either the saving and loan crisis period of 1987-1992, or the 2008-2010 subprime lending crisis period. Papers studying the failed banks during the saving and loan crisis (e.g., Cole and Gunther, 1995; Wheelock and Wilson, 2000; DeYoung, 2003) show that banks with poor capitalization, extreme non-performing loans, low earnings, and less liquidity were associated with a higher probability of failure. Recently, several studies have analysed the determinants of bank failures in the United States during the recent subprime lending crisis (Berger et al., 2016; Cole and White, 2012; DeYoung and Torna, 2013; Hong et al., 2014; Imbierowicz and Rauch, 2014; Ng and Roychowdhury, 2014). Cole and White (2012) use the CAMELS indicators together with measures of “traditional” banking activities, such as commercial and residential loans, to explain the drivers of US commercial bank failures that occurred between 2004 and 2008, and to predict 2009 failures. They find that banks with less capital, bad asset quality, lower earnings, less liquidity, and with higher loan allocations to construction-and-development loans, commercial mortgages, and multi-family mortgages, are more likely to fail. DeYoung and Torna (2013) focus on “non-traditional” banking activities with mainly noninterest income such as stakeholder activities and Fee-for-Service income to analyse the US bank failures from 2007 to 2009. They find that stakeholder activities (e.g. investment banking, insurance underwriting, proprietary trading, and venture capital) increase the probability of bank failure only if the bank was already suffering from financial distress, whereas Fee-for-Service income (e.g. insurance sales, loan servicing and securities brokerage) reduce the probability of bank failure during the crisis. Hong et al. (2014) examine the links between US commercial bank failures and Basel III liquidity risk measures, liquidity coverage ratio (LCR), and net stable funding ratio (NSFR). They report that both LCR and NSFR have limited effects on explaining bank failures. Testing the impact of loan loss reserves on US bank failures, Ng and Roychowdhury (2014) employ a Cox proportional-hazard model and report that “add-backs” of loan loss reserves is positively related to bank failures. Additionally, Imbierowicz and Rauch (2014) investigate the impact of liquidity risk and credit risk on probabilities of default in US commercial banks. They document that these two risk sources separately increase the likelihood of default, but their joint effect can either aggravate or mitigate default risk. More recently, Berger et al. (2016) analyse the roles of corporate governance (ownership, management, and compensation structures) in US commercial bank failures. They find that banks with more shareholdings of lower-level managers and non-CEO higher-level managers are more likely to fail. However, the shareholdings of CEOs do not increase the risk of failure.

According to Berger and Bouwman (2013), the existing literature generally suffers from two respective limitations. First, most studies cover a short period of time (the span of one banking crisis) and do not pay attention to the periods prior to and following the crisis (normal times), or other banking crises. Second, the analysis of bank failures across size classes is largely ignored. This suggests that the findings of studies reviewing the saving and loans crisis consider small banks results, given the domination of failures among small banks (Berger and Bouwman, 2013). In this paper, however, I examine virtually all US commercial bank failures over a long period of time covering multiple-crises and normal times, clearly distinguishing between small, medium, and large banks to identify factors leading to bank failures across different size categories.

To the best of my knowledge, only one paper provided deep insight into the matter. Berger and Bouwman (2013) examine the impact of capital on bank performance (survival and market share) across bank size classes (small, medium, and large), and how this effect differs across banking crises, market crises, and normal times between 1984 and 2010, in the United States. They find that capital improves the performance of medium and large banks only during banking crises and helps to improve the performance of small banks during banking crises, market crises, and normal times. However, Berger and Bouwman's paper differs from ours in many respects. First, their study is based on only one of the six CAMELS components (capital), and ignores the others that may misclassify distressed banks (Cole and White, 2012). Second, they use a development sample up to 2010, while I extend my sample to cover the most recent observation (i.e. up to 2016). Third, they split the bank size classes into small banks (gross total assets, or GTA, up to $1 billion), medium banks (GTA exceeding $1 billion and up to $3 billion), and large banks (GTA exceeding $3 billion), while I use different and arguably more accurate criteria to determine bank size. Specifically, in any given year *t*, banks corresponding to the bottom 25 percentile of total assets are considered to be small banks, the top 25 percentile are large banks, and the rest are medium banks. Fourth, they exclude banks that are below $25 million of total assets instead of including all banks, as I do.

2.2.2 Relevance of Bank Size to Financial Stability

Theoretically, several studies focus on the relationship between bank size and bank stability. One set of theoretical models disputes that the growth of bank size generally reduces risk. This includes models that predict economies of scale and scope in intermediation (e.g. Diamond, 1984; Boyd and Prescott, 1986). A main implication of these studies is that larger banks are more stable and efficient due to the comparative advantage of enhanced economies of scale in information production, monitoring, and transaction costs, that helps to diversify loan-portfolio risks (De Nicolo, 2000). Another set of theoretical models argues that growth of bank size increases risk. These models are based on deposit insurance (e.g. Chan, Greenbaum and Thakor, 1992) and the "Too-big-to-fail" moral hazard (e.g. Mishkin, 1999). A key conclusion of these models is that larger banks are implicitly or explicitly protected by government in the form of guarantees or subsidies, and other banks are not. This protection intensifies the risk-taking behaviour of these banks that could lead to financial fragility (Beck et al., 2006).

Empirically, few studies (Bhagat et al., 2015; De Haan and Poghosyan, 2012; De Nicolo, 2000; Demsetz and Strahan, 1997) address the role of bank size on bank stability. Demsetz and Strahan (1997) focus on US bank holding companies (BHCs) to analyse the relationship between bank size and volatility in stock prices as a measure of risk. They conclude that large BHCs are better diversified, but they are not less risky than small BHCs. Analysing an international sample of banks, including 419 BHCs in the US, De Nicolo (2000) finds a positive relationship between bank size and volatility in small to medium-sized BHCs and a negative relationship in large ones. Hakenes and Schnabel (2011) analyse the relationship between bank size and risk-taking under the Basel II Capital Accord. They conclude that large banks have an advantage over small banks to choose between the Standardized and Internal Ratings Based Approach which pushes small banks to take more risk. Moreover, De Haan and Poghosyan (2012) report a non-linear relationship between size and earnings volatility. They find that bank size is negatively related to earnings volatility, but the relationship becomes positive when a bank's total assets exceed $5 billion. Recently, Bhagat et al. (2015) studied the size effect on the risk-taking of US based financial institutions, including commercial banks, investment banks and life insurance companies. They document a positive relationship between bank size and risk in the pre-crisis period (2002–2006) and the crisis period (2007–2009), but not in the post-crisis period (2010–2012). Overall, the existing literature indicates that bank size plays a pivotal role in maintaining financial stability. In line with the literature, I expect that bank size should have an impact on actual bank failure. Hence, I propose and test the following three hypotheses:

H1: Failure rate of banks varies across small, medium, and large size categories.

H2: Factors affecting the probability of bank failure vary across small, medium, and large size categories.

H3: The magnitudes of mutually significant factors explaining bank failures vary across small, medium, and large size categories.

2.3 Dataset, Sample and Covariates

The data used in my empirical analysis come from the Federal Deposit Insurance Corporation (FDIC) database. The FDIC collects financial information such as balance sheets and income statements from the Consolidated Reports of Condition and Income (Call Reports) submitted by US financial institutions on a quarterly basis. In line with several existing studies I focus only on commercial banks to obtain a homogenous sample. I exclude savings banks due to the discrepancy in directions between these banks and the commercial banks (Cole and White, 2012). To construct financial variables, I use the year end (fourth quarter) data from 1985 to 2016 for each bank in my sample.

2.3.1 Defining Bank Failure

To identify commercial bank failure, I use the Failed Bank list reported by the FDIC, which is widely used in the existing literature (e.g., Berger et al., 2016; Liu and Ngo, 2014). The list contains characteristics of failed banks, including bank names, locations, acquiring institutions, and closing dates. The FDIC generally records a bank as failed if it enters either "assistance transactions", which require restructuring and the charter survives, or "outright failure", in which a bank closes its operations and the charter is terminated. The failure list in my sample contains 1,871 banks with 1,694 outright failures and 123 assistance transactions.

2.3.2 Defining Small, Medium, and Large Banks

The literature documents the importance of bank size and the advantages generated by size heterogeneity (e.g., Berger and Bouwman, 2009, 2013). However, there is no formal definition that identifies bank size classes. Thus, I use criteria based on a bank's total assets in a given year to classify it as small, medium, or large. Specifically, I consider banks corresponding to the bottom 25 percentile of total assets as small banks, the top 25 percentile as large banks, and the rest as medium banks. I perform this exercise on a yearly basis, as my size classification is based on the relative assets size of respective banks, which changes from one year to another due to various reasons. This gives me a sample of 74,533 bank-year observations for small banks, 149,072 bank-year observations for medium banks, and 74,520 bank-year observations for large banks. This subsequently leads to 8,260 small banks, 12,977 medium banks, and 7,210 large banks in my sample[2].

2.3.3 Sample Description

Table 1 presents the annual failure rates of banks from 1985 to 2016. To observe any differences between size categories, I also report the annual failure rates of small, medium, and large banks. The average failure rate of my entire sample is around 0.54%. The average failure rate is highest for small banks (0.67%), followed by large banks (0.53%), and lowest for medium banks (0.47%). Further, I see in Table 1 that the relationship between failure rate and bank size is most likely negative, up until the onset of the subprime lending crisis in 2008. This relationship turns out to be positive, specifically between 2008 and 2012. However, after the crisis period, it becomes negative.

The failure rates of small banks experienced a significant rise around the savings and loan crisis of the 1980s and 1990s, followed by large banks, and were lowest for medium banks. Yet the failure rates of large banks escalated dramatically during the subprime lending crisis, followed by medium banks, and were lowest for small banks (see Figure 1). This transformation in the failure rates may be attributed to augmentation in bank size associated with high risk-taking by these banks, due to the moral hazard that the government will bail them out in troubled times to stabilise the financial system and avoid unfortunate consequences to the economy (Pais and Stork, 2013). Overall, this fluctuation of failure rates across different size categories supports my first hypothesis that failure rates of banks vary across small, medium, and large size categories, and time.

[2] The total of the count of banks across respective size categories is higher than the total number of banks in my sample due to the dynamic nature of banks' total assets. A bank may start small, but eventually move to the medium or large size categories as its total assets increases, or vice versa. For instance, a bank which is classified as small in 1990 may be classified as medium or large in 1995 due to increased asset size and vice-versa. Thus, some banks may appear in more than one size categories, but in different time periods.

Table1: Failures Rate of US Banks

	All Banks			Small Banks			Medium Banks			Large Banks		
Year	Failures	Total	%Failures	Failures	Total	% Failures	Failures	Total	% Failures	Failures	Total	% Failures
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1985	118	14,656	0.8051	54	3,664	1.4738	56	7,328	0.7642	8	3,664	0.2183
1986	142	14,468	0.9815	61	3,616	1.6869	63	7,235	0.8708	18	3,617	0.4977
1987	199	14,171	1.4043	107	3,542	3.0209	73	7,086	1.0302	19	3,543	0.5363
1988	276	13,626	2.0255	86	3,406	2.5250	113	6,813	1.6586	77	3,407	2.2601
1989	204	13,074	1.5603	80	3,268	2.4480	82	6,538	1.2542	42	3,268	1.2852
1990	158	12,643	1.2497	70	3,161	2.2145	67	6,321	1.0600	21	3,161	0.6643
1991	103	12,258	0.8403	34	3,063	1.1100	46	6,132	0.7502	23	3,063	0.7509
1992	75	11,796	0.6358	26	2,948	0.8820	35	5,898	0.5934	14	2,950	0.4746
1993	38	11,303	0.3362	13	2,826	0.4600	17	5,651	0.3008	8	2,826	0.2831
1994	11	10,820	0.1017	3	2,705	0.1109	3	5,410	0.0555	5	2,705	0.1848
1995	5	10,271	0.0487	1	2,567	0.0390	1	5,137	0.0195	3	2,567	0.1169
1996	4	9,897	0.0404	1	2,474	0.0404	3	4,949	0.0606	0	2,474	0.0000
1997	1	9,562	0.0105	1	2,391	0.0418	0	4,781	0.0000	0	2,390	0.0000
1998	3	9,131	0.0329	1	2,283	0.0438	1	4,566	0.0219	1	2,282	0.0438
1999	6	8,838	0.0679	3	2,210	0.1357	2	4,419	0.0453	1	2,209	0.0453
2000	6	8,597	0.0698	2	2,150	0.0930	4	4,298	0.0931	0	2,149	0.0000
2001	3	8,284	0.0362	3	2,071	0.1449	0	4,142	0.0000	0	2,071	0.0000
2002	10	8,035	0.1245	4	2,009	0.1991	3	4,018	0.0747	3	2,008	0.1494
2003	1	7,896	0.0127	1	1,975	0.0506	0	3,948	0.0000	0	1,973	0.0000
2004	3	7,760	0.0387	1	1,941	0.0515	2	3,879	0.0516	0	1,940	0.0000
2005	0	7,671	0.0000	0	1,918	0.0000	0	3,836	0.0000	0	1,917	0.0000
2006	0	7,568	0.0000	0	1,892	0.0000	0	3,784	0.0000	0	1,892	0.0000
2007	1	7,444	0.0134	0	1,861	0.0000	1	3,722	0.0269	0	1,861	0.0000
2008	22	7,238	0.3040	4	1,810	0.2210	5	3,619	0.1382	13	1,809	0.7186

2009	124	7,018	1.7669	11	1,755	0.6268	57	3,509	1.6244	56	1,754	3.1927
2010	130	6,765	1.9217	19	1,692	1.1229	55	3,383	1.6258	56	1,690	3.3136
2011	84	6,443	1.3037	9	1,611	0.5587	51	3,222	1.5829	24	1,610	1.4907
2012	40	6,235	0.6415	8	1,559	0.5131	26	3,118	0.8339	6	1,558	0.3851
2013	23	5,999	0.3834	11	1,500	0.7333	9	3,000	0.3000	3	1,499	0.2001
2014	14	6,532	0.2143	7	1,633	0.4287	5	3,266	0.1531	2	1,633	0.1225
2015	8	6,199	0.1291	5	1,550	0.3226	2	3,100	0.0645	1	1,549	0.0646
2016	5	5,927	0.0844	4	1,482	0.2699	1	2,964	0.0337	0	1,481	0.0000
Average			0.5370			0.6740			0.4715			0.5312

Notes: The table reports annual details of failed and censored US commercial banks. Column 1 lists years followed by the number of failed banks in that year (column 2), total number of banks in the database in that year (column 3), and percentage of failed banks (failed/Total banks × 100) in that year (column 4) for myentire sample of banks. The following columns show identical information for small, medium, and large sized banks. In the last row, 'Average' is the mean of annual failure rates reported in columns 4, 7, 10 and 13 respectively.

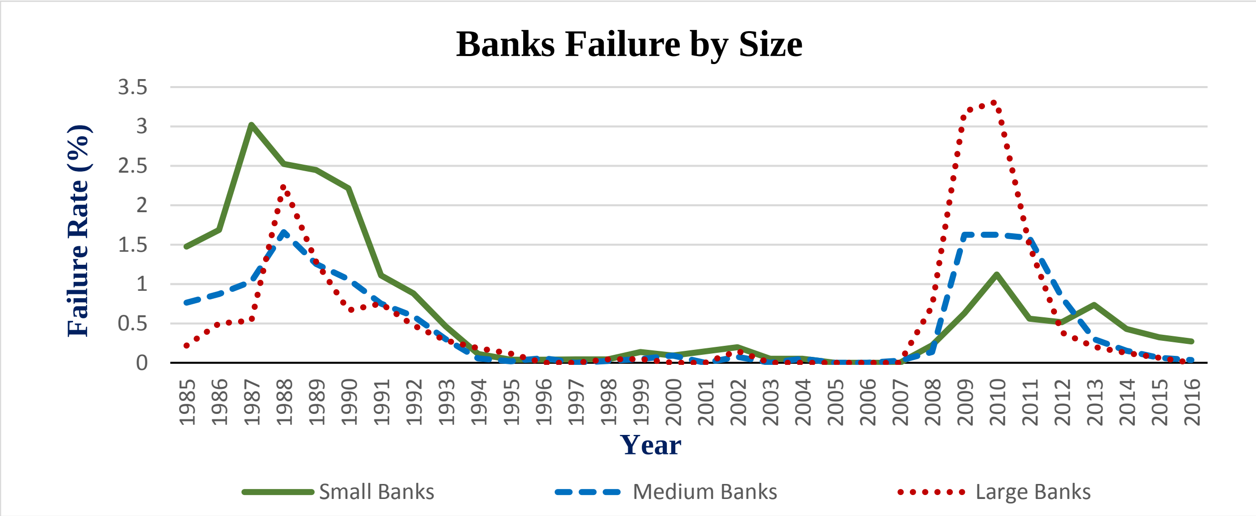


Figure 1: This figure shows the failure rate (in %) across bank size categories that occurred during my sample period from 1985 until 2016.

2.3.4 Covariates

In this section, I discuss the rationale behind my choice of dependent variable, followed by relevant discussion on the explanatory and control variables employed in this study.

2.3.4.1 Dependent Variable

One important focus of this study is the determination of factors that affect bank failure across different size classes. Therefore, the dependent variable is binary (fail/non-fail). As discussed in Section 2.3.1 and following Liu and Ngo (2014), I consider all banks in the FDIC failed list as failed banks if presented as either "assistance transactions" or "outright failures".

2.3.4.2 Explanatory Variables

To develop my multivariate regression models, i consider a comprehensive list of 61 financial (accounting-based) variables as candidate failure predictors, and briefly explain them in Table 2. These predictive variables are drawn from popular studies on bank failure, including Cole and Gunther (1995), Wheelock and Wilson (2000), Kolari et al. (2002), Arena (2008), Cole and White (2012), DeYoung and Torna (2013), Betz et al. (2014), and many others. I do not consider market-based covariates for two reasons. First, the vast majority of my sample comprises unlisted banks. Second, my prediction horizon is 1 to 3 years prior to failure, while the signals of these variables tend to have a shorter-run time horizon (Betz et al., 2014). Moreover, Cole and Wu (2009) suggest that bank-specific variables are more essential than market and macroeconomic variables when predicting bank failures.

My choice of variables reflects all dimensions in the CAMELS, as well as funding, business model, leverage, off-balance sheet, growth, non-traditional activities, and others[3].

[3] While calculating the financial ratios, I use similar approach to Campbell et al. (2008) and replace zero values for all bank-year observations with $1 to further limit the influence of outliers. For robustness check, I repeat the analysis without replacing and the results remain unchanged.

C*apital adequacy*: Capital is the most important indicator that is considered in all regulator and supervisor frameworks (e.g., Basel) to ensure the safety and soundness of banks and financial systems. It is also included as a key variable in virtually all previous studies. The level of capital reflects the capacity of banks to meet their financial obligations. Hence, a decline in capital is a clear sign of potential financial troubles. To measure the capital adequacy I use the total equity to total assets (TETA) ratio, which is largely used in the literature and a highly valuable proxy of capital, and the nonperforming assets coverage ratio (NPACR), which is shown by Chernykh and Cole (2015) to outperform regulatory capital ratios in predicting US bank failures. Higher values of these indicators are expected to reduce the probability of a bank failure. Following Poghosyan and Čihak (2011), I do not incorporate the ratio of regulatory capital to total risk-weighted assets to avoid any risk assessment, and because the calculation of these ratios is based on relatively arbitrary weights.

A*sset quality:* poor quality of assets generally increases the probability of bank failure. The most preponderant and risky assets of commercial banks are loans. Thus, I focus heavily on this asset group and employ a wide variety of potential indicators, specifically loan loss reserves, loan loss provisions, net charge off, and all types of non-performing loans. In general, these variables are expected to have a positive relationship with bank failure probability.

Management: Management competence plays a central role in the performance and success of a bank. Although the management quality is difficult to measure with financial data, DeYoung (1998) documents that cost efficiency reflects management quality. He concludes that higher management quality leads to higher efficiency of resource uses, thus I use the cost efficiency represented by cost-to-income ratio to gauge the quality of management. Following DeYoung and Torna (2013) I also use cost inefficiency, measured by total noninterest expenses to total assets. These indicators are expected to be positively associated with bank failures.

Earnings: This category reflects the profitability and performance of banks. The most frequently applied measures are return on assets (ROA), return on equity (ROE), and net interest margin (NIM). Higher earnings enhance the profitability (ROA, ROE, NIM) and capital level (equity/assets) that lead to improved bank performance. Hence, the relationship between profitability and the probability of bank failure is expected to be negative.

Liquidity: An adequate liquidity is essential for banks to meet their current obligations and to cope with unexpected withdrawals of depositors without liquidating assets. To gauge this category, I employ most of the variables that have been used in the literature, including federal funds to total assets, securities to total assets, total loans to total deposits, and others (see Table 2). In general, I expect a higher value of these ratios to have a negative relationship with bank failure probability.

Sensitivity to market risk: This category is represented by the share of trading income (TIOI). Higher trading income could be associated with a riskier business model and higher probability of failing. Liquid, however, rather than loans, is more likely to decrease fire sale losses. Thus, it is difficult to predict the direction of the influence in advance.

In addition to the CAMELS covariates, I also include many other potential explanatory variables, specifically to measure funding, business model, leverage, off balance sheet, growth, non-traditional activities, and others (see Table 2).

2.3.4.3 Control Variables

To establish the robustness of my explanatory variables, I also report my multivariate results, supplementing the following control variables (see Table 2):

Table 2: Description of Variables

No.	Category	Variable	Description	CALL Item Codes
(1)	(2)	(3)	(4)	(5)
	Bank Size	LTA	Natural Logarithm of Total Assets	rcfd2170
Explanatory Variables				
1	Capital (C)	TETA	Total Equity divided by Total Assets	rcfd3210/ rcfd2170
2		T1CR	Tier1 Capital Ratio	rcfd7206
3		NPACR	Nonperforming assets coverage ratio = [(Equity + LLR) - Weighted NPA] divided by Total Assets	[(rcfd3210+ rcfd3123) - (0.20*rcfd1406+0.50*rcfd1407+ 1*(rcfd1403+rcfd2150)]/rcfd2170
4	Asset Quality (A)	LLRTA	Loan Loss Reserves divided by Total Assets	rcfd3123/rcfd2170
5		PD90TA	Loans Past Due 90+ Days divided by Total Assets	rcfd1407/rcfd2170
6		NAATA	Nonaccrual Loans divided by Total Assets	rcfd1403/rcfd2170
7		OREOTA	Other Real Estate Owned divided by Total Assets	rcfd2150/rcfd2170
8		NPATA	Non-Performing Assets (PD38-89 + PD90 + Nonaccrual Loans + Other Real Estate Owned) divided by Total Assets	(rcfd1406+rcfd1407+ rcfd1403+rcfd2150)/rcfd2170
9		LLRNPL	Loan Loss Reserves divided by Non-Performing Loans	rcfd3123/rcfd2170
10		LLPTL	Loan Loss Provisions divided by Total Loans	riad4230/rcfd2122
11		LLPTA	Loan Loss Provisions divided by Total Assets	riad4230/rcfd2170
12		NPLTL	Non-Performing loans divided by Total Loans	(rcfd1407 + rcfd1403)/rcfd2122
13		NPLTA	Non-Performing loans divided by Total Assets	(rcfd1407 + rcfd1403)/rcfd2170
14		NCOTA	Net-Charge Offs divided by Total Assets	(riad4635-riad4605)/rcfd2170
15		RELTA	Real Estate Loans divided by Total Assets	rcfd1410/rcfd2170
16		CILTA	Commercial & Industrial Loans divided by Total Asset	rcfd1766/rcfd2170
17		CLTA	Consumer Loans divided by Total Asset	rcfd1975/rcfd2170
18		CDLTA	Construction & Development Loans divided by Total Assets	rcon1415/rcfd2170
19		RERLTA	Real Estate Residential (1–4) Family Loans divided by Total Assets	rcon1430/rcfd2170
20		REMLTA	Real Estate Residential Multifamily Loans divided by Total Assets	rcon1460/rcfd2170
21		RENFNRL TA	Real Estate Nonfarm Non-residential loans divided by total Assets	rcon1480/rcfd2170
22	Management (M)	ROA	Return on Assets; Net Income divided by Total Assets	riad4340/rcfd2170

23		NIETA	Cost Inefficiency; Noninterest expenses divided by Total Assets	riad4093/rcfd2170
24		CIR	Cost to Income Ratio; Operating Expenses divided by Operating Income	riad4130/riad4000
25		ROE	Return on Equity; Net Income divided by Total Equity	riad4340/rcfd3210
26	Earnings (E)	NIM	Net Interest Margin; Net Interest Income divided by Average Earning Assets	riad4074/rcfd3402
27	Liquidity (L)	CDTA	Cash & Due divided by Total Asset	rcfd0010/rcfd2170
28		TSTA	Total Securities divided by Total Assets	rcfd8641/rcfd2170
29		TLTA	Total Loans divided by Total Assets	rcfd2122/rcfd2170
30		LATLB	Liquid Assets divided by Total Liabilities	[rcfd0010 + (rcfd0390 & rcfd1773 + rcfd1754)]/rcfd2948
31		LATA	Liquid Assets (Cash & Due from Banks + securities held for investment + securities held for sale) divided by Total Assets	[rcfd0010 + (rcfd0390 & rcfd1773 + rcfd1754)]//rcfd2170
32		FTA	(Fed fund purchase - fed fund sold) divided by Total Assets	(rcfd2800-rcfd1350)/rcfd2170
33		TRADTA	Trading asset divided by Total Assets	rcfd3545/rcfd2170
34		TIETLB	Total Interest Expenses divided by Total Liabilities	riad4073/rcfd2948
35	Sensitivity to market (S)	TIOI	Trading Income divided by Operating Income	riada220/riad4000
36	Funding	TDTA	Total Deposits divided by Total Assets	rcfd2200/rcfd2170
37		STDTD	Short-Term Deposits (transaction deposits + demand deposits) divided by Total Deposits	(rcon2215 + rcon2210)/rcfd2200
38		BDTA	Brokered Deposits divided by Total Assets	rcon2365/rcfd2170
39		LCDTA	Large Certificates of Deposits ($100,000 & more) divided by Total Assets	rcon2604/rcfd2170
40		LCDTLB	Large Certificates of Deposits divided by Total Liabilities	rcon2604/rcfd2948
41		MBSTA	Mortgage-Backed Securities divided by Total Assets	rcfd8639/rcfd2170
42	Business Model	NDFTLB	Non-deposit funding divided by Total liabilities	rcfd2527/rcfd2948
43		NIIOI	Non-interest income divided by Operating income	riad4079/riad4000
44	Leverage	TATE	Total Assets divided by Total Equity	rcfd2170/rcfd3210
45		TLBTE	Total Liabilities divided by Total Equity	rcfd2950/rcfd3210
46		TLBTA	Total Liabilities divided by Total Assets	rcfd2948/rcfd2170
47		TLTD	Total Loans divided by Total Deposits	rcfd2122/rcfd2200
48	Growth	GTA	Growth of Total Assets	

49		GTL	Growth of Total Loans	
50	Other	GWTA	Goodwill divided by Total Assets	rcfd3163/rcfd2170
51		LIR	Loans Interest Rate; Total Interest Income divided by Total Loans	riad4107/rcfd2122
52	Market Discipline	DIR	Deposits Interest Rate; Total Interest Expense divided by Total Deposits	riad4073/rcfd2200
53		SPREAD	LIR – DIR	
54	Non-Traditional	ICFTA	Insurance Commissions and Fees divided by Total Assets	riadb494/rcfd2170
55		IRUITA	Insurance & Reinsurance Underwriting Income divided by Total Assets	riadc386/rcfd2170
56		VCRTA	Venture Capital Revenue divided by Total Assets	riadb491/rcfd2170
57		FCSBTA	Fees & Commissions from Securities Brokerage divided by Total Assets	riadc886/rcfd2170
58		NSITA	Net Securitization Income divided by Total Assets	riadb493/rcfd2170
59		IBFCTA	Investment Banking Fees & Commissions divided by Total Assets	riadb490/rcfd2170
60		NSFTA	Net Servicing Fees divided by Total Assets	riadb492/rcfd2170
61	Off Balance Sheet	TUCTA	Total Unused Commitment divided by Total Assets.	rcfd3423/rcfd2170
<u>Control Variables</u>				
62	Primary regulators	FDIC	Dummy variable indicating whether the bank is a state-chartered and non-member of the Federal Reserve System.	
63		FED	Dummy variable indicating whether the bank is a state-chartered and member of the Federal Reserve System.	
64	Foreign ownership	FOPCT	Dummy variable indicating whether the bank is foreign-owned (25% or more).	
65	Growth of House Prices Index	GHPI	State-level House Price Indices (HPIs) of the seasonally adjusted Federal Housing Finance Agency's (FHFA).	
66	Banking Crises	SL	Dummy variable indicating whether the year is on saving and loans crisis that occurred between 1987 and 1990.	
67		GFC	Dummy variable indicating whether the year is on subprime lending crisis (Global Financial Crisis) that occurred between 2008 and 2010.	

Notes: This table reports the set of explanatory and control variables that I use in my empirical analysis. The first column is the number of explanatory and control variables, while the second column lists the category of explanatory and control variables. The third column lists names of variables. The fourth column provides their respective definitions. Financial information is obtained from the Call Report (FDIC) database, covering an analysis period from 1985 to 2016. The last column states the specific codes of Call Report data items that I use to calculate explanatory variables.

Primary regulator: US commercial banks are regulated by one of three federal regulators. National banks are regulated by the Comptroller of the Currency (OCC), state-chartered banks that are members of the Federal Reserve System (FRS) are regulated by the Federal Reserve, and state-chartered banks that are not members of the FRS are regulated by the Federal Deposit Insurance Corporation (FDIC). To investigate the influence of the regulator on bank failures, I include three dummies: OCC, FED, and FDIC. Due to collinearity, I use only two of them (FED and FDIC), and treat OCC as the reference category.

Foreign ownership: Foreign ownership is captured by a dummy variable that takes the value of 1 if 25% or more of a bank is foreign-owned, and 0 otherwise. Arena (2008) concludes that foreign banks in emerging countries can mitigate their probability of failure due to better risk-based management practices, capitalization, and access to parent funding, however in the United States, Berger et al. (2000) find that domestic banks are generally more efficient than foreign banks. I therefore expect a positive relationship between foreign ownership and the probability of failure.

Growth of House Prices Index: This economic variable is a broad measure to capture real estate prices at state-level. The movements of the real estate prices can impair the stability of banks because defaulted mortgage loans are generally covered by real estate as collaterals, and banks will not be able to recover all of the value of collaterals in a situation of deteriorating real estate prices. To capture the effect of this variable, I obtain the seasonally adjusted House Price Indices (HPIs) from the Federal Housing Finance Agency. Following Berger and Bouwman (2013) I use all transactions index (based on purchases and appraisals) data until 1990 and purchase only index (based on purchases) data from 1991onward.

Banking Crises: To measure the effects of previous banking crises, I create two dummy variables. First, the saving and loans crisis that takes the value of 1 for the years from 1987 to

1990, and 0 otherwise. Second, the subprime lending crisis takes the value of 1 for the years from 2008 to 2010, and 0 otherwise.

2.4 Econometrics Technique, Selection of Variables, and Descriptive Analysis

In this section, I discuss the statistical model and the methodology of selecting the explanatory variables for multivariate analysis as well as summary statistics and correlations.

2.4.1 Panel Logistic Regression

Numerous statistical methodologies have been used to analyse and predict bank failures. These methods range from simple Discriminant Analysis (e.g., Haslem et al., 1992) and Logit/Probit regressions (e.g., Berger et al., 2016) to advanced machine learning techniques, such as Extreme Gradient Boosting (e.g., Climent et al., 2018). To investigate the factors that affect bank failure and establish my empirical validation, I use panel logistic regression with random effects. Although hazard models are emerging as a popular choice (e.g., Cole and Wu, 2009; Ng and Roychowdhury, 2014), Gupta et al. (2018) argue that the discrete-time hazard model with logit link is essentially a panel logistic model that controls for firms' age. Accordingly, I assume that the marginal probability of bank failure over the next time period follows a logistic distribution that is estimated as follows:

$$P(Y_{it} = 1) = \frac{1}{1 + \exp(-\alpha - \beta X_{i,t-1})} \qquad (1)$$

where Y_{it} is an indicator variable that equals 1 if the bank is failed in time t, and $X_{i,t-1}$ is a vector of explanatory variables known at the end of the previous (or any appropriate lagged) period.

2.4.2 Variable Selection Method

Although previous studies have introduced numerous variables to enhance the prediction accuracy of failure models, the answer to the question of which variables should be selected to predict failures is inconclusive. The choice of variables is often driven by the popularity and/or significance of certain indicators across the literature. However, this is associated with the high risk of omitting unsuccessful variables in the past, which could be influential when confronted with new data. Thus, the selection of variables is useful to identify relevant variables and to enhance predictability (Tian et al., 2015). Stepwise selection is a commonly used traditional variable selection approach that allows changes in either direction, dropping or adding one variable at a time according to some test statistics (Tian et al., 2015). However, it has a potential drawback. It ignores stochastic errors in the variable selection process (Fan and Li, 2001).[4]

Consequently, I rely on univariate regression analysis, suggested by Hosmer et al. (2013), for the selection of variables from a comprehensive list of variables considered in the literature (see Table 2). Following Gupta et al., (2018) and Gupta and Chaudhry (2019), I perform univariate regression analysis of each of the 61 variables in turn, using the failure definition and econometric specification discussed earlier. To gauge the intertemporal discriminatory power of respective covariates, I report regression estimates for 1-year ($T – 1$), 2-years ($T – 2$), and 3-years ($T – 3$) lagged time periods. To narrow down this list for further multivariate analysis, I exclude variables that (i) are not significant in all three time periods (to ensure that the selected covariates are consistent predictors of banks' financial soundness over a sufficiently long-time interval to allow for developing a reasonable early warning system), or (ii) are significant but exhibit Average Marginal Effects (AME) of less than 5% in all three time periods. The rationale is that a unit change in the value of significant variables must induce sufficient change in the magnitude of the outcome probability to clearly distinguish between failed and censored banks (Gupta et al., 2018).

[4] Fan and Li (2001) propose methods based on penalty functions to select variables and estimate coefficients simultaneously.

Most considered variables are statistically significant at the 1%, 5%, or 10% significance levels across all lagged time periods (see Table 3). However, only 19 out of 61 variables have AME values of 5% or more in at least one of the three time periods. This suggests that, although these variables are significant predictors, a unit change in their value does not transmit significant change in the probability of outcome variable. Table 4 reports the final list of explanatory variables that I use for further multivariate regression analysis among all banks. An interesting observation in Table 4 is that the variable with the highest AME, net charge off to total assets (NCOTA), is largely ignored in the literature. Furthermore, the aggregated non-performing loans to total assets (NPLTA) ratio, which is considered to be one of the most common default predictors in the literature, has lower AME than one of its components (PD90TA) for the 1-year and 2-years lagged periods, but higher AME for the 3-years lagged period. This indicates that the aggregated non-performing loans to total assets (NPLTA) is a superior predictor for bank failure in the longer time horizon (3 years and above).

I rerun the univariate regression analysis of each variable (total 61 variables) to verify its power to explain the failure of small, medium, and large banks respectively. Specifically, I verify whether the statistical significance of the variables vary across size categories or not. Most of the considered variables are statistically significant at the 1%, 5%, or 10% significance levels in explaining the failure of small, medium, and large sized banks (see Table 5). Subsequently, I repeat the elimination process performed above using different bank size classifications (small, medium, and large). I find relatively similar results of univariate regression analysis compared with all banks, but different AME and ranking as well as additional variables across size categories. The final lists contain 19, 20, and 21 variables for small, medium, and large banks respectively. All of the 19 variables that I report as significant and that have AME of 5% or more in one of the three time periods for all banks (see Table 4) are the same across size categories, except the ratio of total deposits to total assets (TDTA), which is rejected among large banks. Furthermore, I find additional variables such as net interest margin (NIM) that meet the criteria for medium and large banks. Table 6 reports the final list of variables that I use for further multivariate regression analysis for small, medium, and large banks.

A noteworthy observation in Table 6 is that the AMEs of small banks' variables are mostly the highest for the 1-year lagged estimate. However, the ranking is changed for the second and third year lagged periods. The variables of large banks have the highest AMEs. This implies that the variables of small banks tend to have a strong prediction on a shorter horizon, while the variables of large banks tend to have a longer horizon prediction. Overall, these findings strongly support my third hypothesis (H3) that the magnitudes (AMEs) of mutually significant factors explaining bank failures vary across small, medium, and large size categories.

Table 3: Univariate Regression Analysis for All Banks

Variable	**Lag Years**		
	L1	L2	L3
T1CR			
β	-0.041[a]	-0.013[b]	-0.049[a]
SE	0.006	0.006	0.007
AME%	-0.02[a]	-0.01[b]	-0.02[a]
LCDTA			
β	8.54[a]	11.03[a]	12.81[a]
SE	0.261	0.304	0.383
AME%	2.26[a]	2.05[a]	1.19[a]
LCDTLB			
β	6.09[a]	8.79[a]	10.53[a]
SE	0.247	0.268	0.330
AME%	1.26[a]	1.44[a]	0.91[a]
CIR			
β	4.08[a]	3.23[a]	2.09[a]
SE	0.076	0.072	0.096
AME%	1.36[a]	0.54[a]	0.07[a]
NIM			
β	-87.80[a]	-48.96[a]	-16.73[a]
SE	5.240	4.934	4.874
AME%	-3.94[a]	-2.55[a]	-0.72[a]

LATA			
β	-7.55[a]	-8.51[a]	-9.54[a]
SE	0.259	0.311	0.361
AME%	-1.48[a]	-0.90[a]	-0.83[a]
LATLB			
β	-8.42[a]	-8.68[a]	-9.22[a]
SE	0.260	0.306	0.336
AME%	-1.79[a]	-1.02[a]	-0.81[a]
TIOI			
β	155.9[a]	96.91[b]	41.19
SE	39.55	48.52	58.95
AME%	63.44[a]	42.78[b]	19.82
TSTA			
β	-10.07[a]	-10.67[a]	-11.69[a]
SE	0.297	0.339	0.442
AME%	-2.76[a]	-1.74[a]	-1.10[a]
NDFTLB			
β	0.53	0.31	0.32
SE	1.073	1.041	1.088
AME%	0.76	0.51	0.48
ROE			
β	-5.01[a]	-5.68[a]	-4.67[a]
SE	0.058	0.124	0.141
AME%	-2.67[a]	-1.66[a]	-0.17[a]
TLTA			
β	3.36[a]	5.02[a]	6.52[a]
SE	0.216	0.253	0.297
AME%	0.36[a]	0.51[a]	0.40[a]
CDTA			
β	4.49[a]	3.37[a]	2.23[a]
SE	0.437	0.465	0.539
AME%	0.35[a]	0.31[a]	0.13[a]
FTA			
β	-4.44[a]	-3.36[a]	-2.29[a]
SE	0.417	0.501	0.535
AME%	-0.13[a]	-0.02[a]	-0.05[a]
NIIOI			
β	1.49[a]	0.07	-1.41[a]
SE	0.395	0.426	0.508
AME%	0.08[a]	0.01	-0.08[a]
TATE			
β	0.24[a]	0.32[a]	0.21[a]
SE	0.003	0.007	0.006
AME%	0.13[a]	0.05[a]	0.01[a]
TLBTE			
β	0.24[a]	0.32[a]	0.21[a]
SE	0.003	0.007	0.007
AME%	0.13[a]	0.05[a]	0.01[a]

TLTD			
β	-0.25	2.01[a]	3.67[a]
SE	0.167	0.167	0.191
AME%	-0.01	0.18[a]	0.19[a]
GTA			
β	-12.85[a]	-13.42[a]	-3.11[a]
SE	0.265	0.339	0.226
AME%	-0.07[a]	-0.02[a]	-0.01[a]
GTL			
β	-9.07[a]	-9.72[a]	-2.84[a]
SE	0.254	0.253	0.186
AME%	-1.64[a]	-1.03[a]	-0.11[a]
GWTA			
β	-37.34[a]	-7.98	12.06[a]
SE	7.582	5.586	5.018
AME%	-2.42[a]	-0.70	0.70[a]
CILTA			
β	6.46[a]	7.79[a]	8.82[a]
SE	0.311	0.346	0.422
AME%	1.23[a]	0.94[a]	0.40[a]
RELTA			
β	0.99[a]	1.96[a]	3.40[a]
SE	0.190	0.200	0.223
AME%	0.11[a]	0.15[a]	0.14[a]
CDLTA			
β	7.13[a]	12.19[a]	15.76[a]
SE	0.466	0.515	0.510
AME%	0.73[a]	0.57[a]	1.30[a]
CLTA			
β	0.37	1.05[b]	0.25
SE	0.482	0.453	0.508
AME%	0.02	0.09[b]	0.01
MBSTA			
β	-0.64	-2.94[a]	-3.85[a]
SE	0.893	0.853	0.836
AME%	-0.09	-0.75[a]	-1.33[a]
LIR			
β	-0.435	-2.48[a]	-4.81[a]
SE	0.464	0.525	0.637
AME%	-0.02	-0.21[a]	-0.27[a]
SPREAD			
β	-6.10[a]	-11.31[a]	-15.68[a]
SE	0.688	0.892	1.096
AME%	-0.64[a]	-0.99[a]	-0.96[a]
TRADTA			
β	-51.14	82.17[b]	28.18
SE	44.63	36.07	43.32
AME%	-2.95	7.23[b]	1.59
NSFTA			
β	108.32	29.74	9.92

SE	76.60	86.25	89.93
AME%	48.83	14.39	5.30
NIITA			
β	-77.79[a]	-39.90[a]	-13.48[a]
SE	3.265	3.340	3.741
AME%	-4.03[a]	-3.42[a]	-0.76[a]
RERLTA			
β	-2.95[a]	-3.55[a]	-3.92[a]
SE	0.366	0.380	0.423
AME%	-0.25[a]	-0.34[a]	-0.26[a]
REMLTA			
β	15.79[a]	14.80[a]	15.88[a]
SE	1.727	1.703	1.848
AME%	0.85[a]	1.28[a]	0.97[a]
RENFNRLTA			
β	8.61[a]	11.36[a]	11.96[a]
SE	0.743	1.055	1.272
AME%	1.61[a]	0.18[a]	0.03[a]
BDTA			
β	11.62[a]	13.53[a]	15.55[a]
SE	0.598	0.564	0.611
AME%	0.93[a]	1.23[a]	0.85[a]
TUCTA			
β	-9.60[a]	-4.52[a]	0.05
SE	0.581	0.490	0.450
AME%	-0.82[a]	-0.40[a]	0.00
STDTD			
β	-3.84[a]	-4.08[a]	-4.18[a]
SE	0.222	0.225	0.247
AME%	-0.19[a]	-0.30[a]	-0.15[a]
VCRTA			
β	-0.22[a]	-0.28[a]	-0.28[a]
SE	0.030	0.028	0.036
AME%	-0.10[a]	-0.13[a]	-0.13[a]
FCSBTA			
β	-0.07[a]	-0.10[a]	-0.12[a]
SE	0.015	0.023	0.030
AME%	-0.03[a]	-0.01[a]	-0.01[a]
LLRNPL			
β	-0.67[a]	-0.60[a]	-0.27[a]
SE	0.021	0.023	0.017
AME%	-0.07[a]	-0.02[a]	-0.01[a]

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). The table reports univariate panel logistic regression results of all independent variables that are not significant in all three time periods or are significant but exhibit Average Marginal Effects (AME) of less than 5% in all three time periods. β is the regression coefficient, SE is standard error and AME is Average Marginal Effects in percentage.

Table 4: Univariate Regression Analysis for All Banks with ranking

Variable	1 Year Lag	2 Years Lag	3 Years Lag	Rank
(1)	(2)	(3)	(4)	(5)
TETA				5
β	-118.0046[a]	-78.3307[a]	-26.8250[a]	
SE	1.958	1.991	1.437	
AME%	-52.21[a]	-12.44[a]	-1.40[a]	
NPACR				13
β	-61.8227[a]	-59.8196[a]	-32.0309[a]	
SE	1.4194	1.5158	0.9211	
AME%	-23.19[a]	-10.53[a]	-1.92[a]	
LLRTA				4
β	226.1444[a]	202.4610[a]	132.0195[a]	
SE	4.5209	4.2604	4.7299	
AME%	58.06[a]	21.11[a]	2.60[a]	
PD90TA				2
β	132.8156[a]	128.1063[a]	107.1189[a]	
SE	2.5497	3.4981	4.8608	
AME%	68.22[a]	19.31[a]	2.35[a]	
NAATA				9
β	93.0304[a]	95.5749[a]	64.8830[a]	
SE	1.7678	2.0556	1.8676	
AME%	35.26[a]	9.25[a]	4.31[a]	
OREOTA				12
β	133.7940[a]	130.1982[a]	77.7526[a]	
SE	3.0969	2.7788	2.4406	
AME%	28.78[a]	8.81[a]	5.08[a]	
NPATA				15
β	61.4833[a]	68.4851[a]	43.4345[a]	
SE	1.3492	1.6684	1.0674	
AME%	21.43[a]	9.11[a]	2.92[a]	
LLPTL				14
β	58.7813[a]	54.5288[a]	36.4989[a]	
SE	0.9237	1.2300	1.3511	
AME%	22.87[a]	7.97[a]	2.96[a]	
LLPTA				3
β	120.3485[a]	115.2256[a]	93.5506[a]	
SE	1.5309	2.2250	2.9432	
AME%	62.07[a]	29.44[a]	2.67[a]	
NPLTL				17
β	44.6085[a]	41.7751[a]	26.9399[a]	
SE	0.8300	0.9684	0.8418	
AME%	14.73[a]	4.82[a]	1.95[a]	
NPLTA				8
β	77.9467[a]	79.7153[a]	59.6845[a]	
SE	1.2544	1.7377	1.6073	
AME%	35.36[a]	14.33[a]	5.01[a]	
NCOTA				1
β	142.3555[a]	130.1408[a]	91.1873[a]	

SE	1.9951	2.8493	3.0657	
AME%	68.69[a]	20.40[a]	7.06[a]	
NCOTL				10
β	78.7936[a]	69.5501[a]	45.6649[a]	
SE	1.2693	1.7141	1.7668	
AME%	34.64[a]	8.03[a]	3.22[a]	
ROA				7
β	-95.7321[a]	-76.4859[a]	-58.5776[a]	
SE	1.1160	1.5979	1.8411	
AME%	-48.40[a]	-32.34[a]	-3.70[a]	
TIETLB				16
β	50.5999[a]	45.5311[a]	33.0639[a]	
SE	1.6673	1.8924	2.2087	
AME%	15.80[a]	5.70[a]	0.70[a]	
TDTA				11
β	52.3850[a]	15.0219[a]	3.7117[a]	
SE	1.0468	0.7647	0.5178	
AME%	30.77[a]	1.51[a]	0.20[a]	
TLBTA				6
β	117.2084[a]	77.9171[a]	26.8385[a]	
SE	1.9600	2.0430	1.4386	
AME%	51.65[a]	12.67[a]	1.42[a]	
DIR				18
β	47.7084[a]	44.6106[a]	34.7815[a]	
SE	1.5661	1.8040	2.1400	
AME%	14.31[a]	5.42[a]	0.76[a]	
NIETA				19
β	78.0376[a]	53.8628[a]	32.1676[a]	
SE	2.0561	2.0986	2.1687	
AME%	13.32[a]	3.70[a]	2.51[a]	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). The table reports univariate panel logistic regression results of final set of variables that I use for multivariate logit regression analysis. This excludes variables that are not significant in all three time periods or are significant but exhibit Average Marginal Effects (AME) of less than 5% in all three time periods. *β* is the regression coefficient, SE is standard error and AME is Average Marginal Effects in percentage. Ranking is based on the absolute values of AME for the 1-year lagged time estimate, where the highest value gets 1, second highest get 2 and so on.

Table 5: Univariate Regression Analysis by Size Categories

	1 Year Lag			2 Years Lag			3 Years Lag		
Variable	Small Banks	Medium Banks	Large Banks	Small Banks	Medium Banks	Large Banks	Small Banks	Medium Banks	Large Banks
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
T1CR									
β	-0.0522[a]	-0.0395[a]	-0.0303[a]	-0.0098	-0.0074	-0.0130	-0.0197	-0.0389[a]	-0.0942[a]
SE	0.0145	0.0096	0.0119	0.0125	0.0083	0.0115	0.0134	0.0098	0.0169
AME%	-0.01[a]	-0.01[a]	-0.02[a]	-0.01	-0.01	-0.01	-0.01	-0.02[a]	-0.07[a]
LCDTA									
β	6.9635[a]	9.1758[a]	9.6523[a]	10.1704[a]	11.9750[a]	10.6419[a]	12.2691[a]	13.5446[a]	11.6008[a]
SE	0.5640	0.3966	0.4758	0.6220	0.4709	0.5300	0.7265	0.5890	0.6528
AME%	1.06[a]	1.87[a]	4.73[a]	1.15[a]	1.67[a]	4.28[a]	1.06[a]	0.64[a]	3.05[a]
LCDTLB									
β	3.6191[a]	6.7362[a]	7.6911[a]	7.2912[a]	9.5619[a]	9.0527[a]	9.6107[a]	11.0393[a]	10.0263[a]
SE	0.5087	0.3722	0.4228	0.5487	0.4090	0.4734	0.6221	0.5044	0.5851
AME%	0.46[a]	1.02[a]	3.74[a]	0.76[a]	1.18[a]	3.50[a]	0.78[a]	0.50[a]	2.45[a]
CIR									
β	3.3758[a]	4.4042[a]	5.8322[a]	3.7419[a]	3.0850[a]	4.2537[a]	2.8670[a]	1.8569[a]	2.3266[a]
SE	0.1180	0.1305	0.2379	0.1631	0.1066	0.2026	0.1670	0.1386	0.2019
AME%	1.19[a]	1.07[a]	1.40[a]	0.18[a]	0.34[a]	0.88[a]	0.22[a]	0.04[a]	0.34[a]
LATA									
β	-7.572[a]	-8.1826[a]	-7.1650[a]	-8.0728[a]	-9.5089[a]	-7.3258[a]	-8.7778[a]	-11.7216[a]	-8.4475[a]
SE	0.4811	0.3892	0.4780	0.5386	0.4685	0.5286	0.6361	0.6032	0.6753
AME%	-1.18[a]	-1.54[a]	-4.17[a]	-0.75[a]	-0.91[a]	-4.03[a]	-0.56[a]	-0.30[a]	-1.51[a]
LATLB									
β	-8.8840[a]	-8.9201[a]	-7.7038[a]	-8.4974[a]	-9.6625[a]	-7.2781[a]	-8.5310[a]	-11.4797[a]	-8.0802[a]
SE	0.5042	0.3889	0.4615	0.5127	0.4573	0.5054	0.5660	0.5765	0.6322
AME%	-1.52[a]	-1.85[a]	-4.47[a]	-0.75[a]	-1.00[a]	-4.02[a]	-0.40[a]	-0.29[a]	1.56[a]
TDTA									
β			8.8027[a]			1.6607[b]			-1.3802[b]
SE			0.9847			0.6797			0.6726
AME%			2.16[a]			0.31[b]			-0.10[b]
TSTA									

β	-8.6739[a]	-10.9957[a]		-9.5133[a]	-11.8198[a]		-10.2561[a]	-13.0528[a]	
SE	0.5403	0.4570		0.6572	0.5284		0.6931	0.6422	
AME%	-1.39[a]	-2.95[a]		-0.99[a]	-1.80[a]		-0.66[a]	-0.77[a]	
NDFTLB									
β	-0.2394	3.5957	3.4052[a]	4.4099	1.5689	2.2322[c]	-3.0404	1.3124	2.4690[c]
SE	3.4931	2.2543	1.4002	3.6198	2.4678	1.3577	5.4197	2.5421	1.3498
AME%	-0.58	4.20	3.64[a]	2.73	2.08	3.00[c]	-1.03	1.62	3.50[c]
ROE									
β	-4.4351[a]	-5.2891[a]	-5.2738[a]	-6.2301[a]	-6.0581[a]	-5.5514[a]	-5.6339[a]	-4.9294[a]	-3.7541[a]
SE	0.1019	0.0889	0.1202	0.2511	0.1956	0.2614	0.2821	0.2231	0.2920
AME%	-3.38[a]	-2.36[a]	-2.53[a]	-1.77[a]	-1.20[a]	-1.37[a]	-0.13[a]	-0.11[a]	-0.38[a]
TLTA									
β	5.4205[a]	4.1157[a]	1.2829[a]	6.5851[a]	6.4929[a]	2.5276[a]	6.7373[a]	9.2323[a]	4.5209[a]
SE	0.4281	0.3462	0.3821	0.4805	0.4211	0.4212	0.5544	0.5581	0.5412
AME%	0.67[a]	0.27[a]	0.36[a]	0.46[a]	0.23[a]	0.61[a]	0.35[a]	0.07[a]	0.42[a]
CDTA									
β	1.5602[b]	5.8812[a]	5.6162[a]	1.5414[c]	4.0491[a]	3.7458[a]	1.8841[b]	1.1356	3.1841[a]
SE	0.7292	0.7093	0.7897	0.8381	0.8255	0.9237	0.9180	1.0489	1.1021
AME%	0.14[b]	0.20[a]	1.46[a]	0.04[c]	0.07[a]	0.77[a]	0.06[b]	0.01	0.31[a]
FTA									
β	0.3693	-4.1357[a]	-8.2792[a]	1.6148[c]	-3.2472[a]	-8.4080[a]	-0.3068	-1.0412	-5.2451[a]
SE	0.7270	0.7176	0.6031	0.9278	0.8225	0.8067	0.9864	1.0373	1.1876
AME%	0.05	-0.06[a]	-2.28[a]	0.03[c]	-0.02[a]	-0.53[a]	-0.01	0.01	-0.02[a]
NIIOI									
β	4.4919[a]	0.8369	-3.4542[a]	3.8830[a]	-1.0210	-3.2621[a]	3.6829[a]	-3.9671[a]	-5.1988[a]
SE	0.5737	0.6764	0.7444	0.6920	0.8242	0.7800	0.7889	1.0657	0.9751
AME%	0.44[a]	0.02	-0.96[a]	0.10[a]	-0.01	-0.67[a]	0.07[a]	-0.02[a]	-0.45[a]
TATE									
β	0.2077[a]	0.2560[a]	0.2589[a]	0.3241[a]	0.3822[a]	0.2473[a]	0.2214[a]	0.2857[a]	0.1781[a]
SE	0.0052	0.0047	0.0073	0.0123	0.0122	0.0109	0.0128	0.0139	0.0130
AME%	0.16[a]	0.12[a]	0.13[a]	0.06[a]	0.03[a]	0.12[a]	0.01[a]	0.01[a]	0.04[a]
TLTD									
β	0.5701[b]	-0.1199	-0.3885	2.5502[a]	2.6556[a]	1.2739[a]	3.3416[a]	4.9792[a]	3.4556[a]
SE	0.2877	0.2710	0.2761	0.3217	0.2857	0.2860	0.3698	0.3540	0.3869

AME%	0.05[c]	0.01	-0.08	0.15[a]	0.06[a]	0.26[a]	0.07[a]	0.04[a]	0.21[a]
GTA									
β	-10.5866[a]		-10.5270[a]	-13.5371[a]		-10.3964[a]	-4.0062[a]		-1.8601[a]
SE	0.6727		0.5186	0.6577		0.6042	0.5322		0.3689
AME%	-2.87[a]		-0.58[a]	-1.50[a]		-0.12[a]	-0.04[a]		-0.07[a]
GTL									
β	-8.3703[a]	-10.2954[a]	-7.4900[a]	-8.1913[a]	-12.0490[a]	-8.5302[a]	-2.1919[a]	-3.3367[a]	-2.9409[a]
SE	0.5470	0.3869	0.4413	0.4769	0.4603	0.4309	0.3467	0.2989	0.3787
AME%	-0.25[a]	-1.71[a]	-3.17[a]	-0.20[a]	-0.22[a]	-2.29[a]	-0.02[a]	-0.05[a]	-0.12[a]
GWTA									
β	-14.5980[a]	-104.7285[a]	-36.7457[a]	-1.5949	-15.8040	-9.2876	27.6268[a]	-5.7619	11.4870
SE	11.9250	26.7816	10.2001	11.5297	11.7553	7.8129	9.6711	12.2323	7.5505
AME%	-1.39[a]	-3.23[a]	-9.80[a]	-0.07	-0.23	-1.77	0.38[a]	-0.03	0.79
CILTA									
β	10.1078[a]	7.7677[a]	1.7804[a]	12.6912[a]	8.9642[a]	2.3917[a]	13.5057[a]	10.3087[a]	3.8282[a]
SE	0.5988	0.4291	0.6421	0.6805	0.4732	0.6666	0.7908	0.5796	0.7231
AME%	1.57[a]	1.38[a]	0.49[a]	1.82[a]	1.07[a]	0.53[a]	1.29[a]	0.47[a]	0.49[a]
RELTA									
β	1.0490[a]	1.5218[a]	1.4017[a]	1.5928[a]	3.2402[a]	2.1762[a]	2.5273[a]	3.9208[a]	3.9239[a]
SE	0.3669	0.3016	0.3063	0.4029	0.3474	0.3511	0.4481	0.3418	0.4767
AME%	0.09[a]	0.04[a]	0.35[a]	0.07[a]	0.03[a]	0.36[a]	0.06[a]	0.11[a]	0.14[a]
CDLTA									
β	2.8389[b]	7.8635[a]		8.9305[a]	12.5435[a]		13.6913[a]	18.1662[a]	
SE	1.3248	0.6875		1.2282	0.7305		1.2440	0.8666	
AME%	0.30[b]	0.55[a]		0.74[a]	0.53[a]		0.62[a]	0.35[a]	
TLBTE									
β	0.2077[a]	0.2560[a]	0.2591[a]	0.3241[a]	0.3822[a]	0.2474[a]	0.2214[a]	0.2857[a]	0.1781[a]
SE	0.0052	0.0047	0.0073	0.0123	0.0122	0.0109	0.0128	0.0139	0.0130
AME%	0.16[a]	0.12[a]	0.13[a]	0.06[a]	0.03[a]	0.12[a]	0.01[a]	0.01[a]	0.04[a]
CLTA									
β	7.5144[a]	0.5503	-7.5830[a]	7.6814[a]	0.2516	-7.1797[a]	7.4591[a]	-0.5557	-7.4446[a]
SE	0.6804	0.7456	1.0513	0.7513	0.8354	1.1063	0.8608	0.9639	1.2589
AME%	0.97[a]	0.02	-1.55[a]	0.58[a]	0.01	-1.03[a]	0.47[a]	-0.01	-0.40[a]
MBSTA									
β	0.6494	-1.6820	-1.5964	-4.8826[c]	-4.7150[a]	-2.7702[b]	-3.8813	-5.1033[a]	-4.5602[a]
SE	1.8506	1.5711	1.4216	2.6380	1.5336	1.2073	2.3946	1.3790	1.2737
AME%	0.07	-0.20	-0.36	-0.90[c]	-1.01[a]	-1.12[b]	-0.76	-1.61[a]	-2.36[a]

LIR									
β	-0.6797	-1.2629	1.4972[c]	-3.2734[a]	-4.5719[a]	-0.3171	-5.0943[a]	-7.3982	-1.5774
SE	0.7039	0.7940	0.8054	0.8943	0.9934	0.9851	1.1994	1.2146	1.2032
AME%	0.06	-0.03	0.37[c]	-0.08[a]	-0.06[a]	-0.06	-0.04[a]	-0.03[a]	-0.11
SPREAD									
β	-6.1172[a]	-10.0043[a]	-3.5569[a]	-10.3972[a]	-18.4982[a]	-8.3618[a]	-11.9769[a]	-24.3364[a]	-16.0074[a]
SE	1.0654	1.2983	1.3084	1.4562	1.7440	1.7401	1.6760	2.1362	2.4162
AME%	-0.65[a]	-0.36[a]	-0.88[a]	-0.41[a]	-0.34[a]	-1.55[a]	-0.40[a]	-0.13[a]	-0.97[a]
TRADTA									
β	89.7684	-13.9184	-30.5807	9.2615	119.0759	91.4177[a]	304.6563[a]	-176.7780	-39.4006[a]
SE	108.3878	94.151	48.8628	133.2548	77.9609	7.4045	95.0434	168.5809	7.3900
AME%	8.52	-0.37	-7.40	0.23	1.70	-12.03[a]	7.60[a]	-0.91	-3.10[a]
NIITA									
β	-18.6458[a]	-97.1302[a]		3.8238	-52.7417[a]		12.8367[c]	-16.7123[a]	
SE	5.2556	5.1856		6.3593	5.4710		7.6069	6.2698	
AME%	-1.69[a]	-2.80[a]		0.18	-0.84[a]		0.20[c]	-0.10[a]	
RERLTA									
β	0.4428	-3.0140[a]	-6.0275[a]	0.4778	-3.2125[a]	-6.8234[a]	0.4260	-2.8865[a]	-8.3303[a]
SE	0.6137	0.5546	0.6605	0.6684	0.6173	0.7250	0.7727	0.6942	0.8616
AME%	0.04	-0.12[a]	-2.10[a]	0.02	-0.06[a]	-1.83[a]	0.01	-0.02[a]	-1.14[a]
REMLTA									
β	18.6465[a]	15.5434[a]	13.3932[a]	19.0738[a]	17.6875[a]	14.3176[a]	16.7800[a]	20.0907[a]	15.4857[a]
SE	3.4344	2.5867	2.4106	3.9394	2.8744	2.6466	4.6133	3.1800	3.1926
AME%	1.92[a]	0.45[a]	3.23[a]	0.68[a]	0.23[a]	2.57[a]	0.46[a]	0.10[a]	1.13[a]
RENFNRLTA									
β	10.6773[a]	9.0961[a]	5.7021[a]	11.9684[a]	12.9172[a]	6.2298[a]	12.8180[a]	13.4702[a]	8.1425[a]
SE	1.7904	1.0785	1.3671	2.3789	1.5463	1.5849	2.7048	1.8666	2.0276
AME%	1.25[c]	1.30[a]	1.35[a]	0.22[c]	0.16[a]	0.62[a]	0.15	0.03[a]	0.10[a]
BDTA									
β	8.0703[a]	16.2543[a]	11.4863[a]	7.8173[a]	15.1256[a]	15.1578[a]	12.9337[a]	18.5776[a]	17.9425[a]
SE	1.4128	1.3251	0.8340	1.5872	0.9836	1.0449	1.6069	1.2114	1.1843
AME%	0.85[a]	0.94[a]	4.83[a]	0.27[a]	0.31[a]	2.40[a]	0.25[a]	0.11[a]	0.96[a]
TUCTA									
β	-11.8125[a]	-14.4943[a]	-5.5267[a]	-7.3750[a]	-6.3925[a]	-1.9082[a]	-2.1256	-0.6428	1.5723[b]
SE	1.4966	1.1147	0.7493	1.5088	0.9426	0.6534	1.4178	0.8630	0.6606
AME%	-1.32[a]	-0.32[a]	-1.12[a]	-0.21[a]	-0.06[a]	-0.33[a]	-0.01	-0.01	0.12[b]
STDTD									
β	-1.7062[a]	-5.2038[a]	-3.9550[a]	-2.3061[a]	-6.3418[a]	-4.4467[a]	-2.3812[a]	-5.9328[a]	-5.6942[a]

SE	0.3507	0.3753	0.4047	0.4015	0.4472	0.4709	0.4636	0.4909	0.5232
AME%	-0.17^{a}	-0.17^{a}	-0.56^{a}	-0.08^{a}	-0.07^{a}	-0.31^{a}	-0.06^{a}	-0.02^{a}	-0.07^{a}
IRUITA									
β	-0.1680	-0.6289^{a}	-0.1296^{a}	-1.4493^{a}	-0.9279^{a}	-0.1209^{b}	-0.9008^{a}	-1.5591^{a}	-0.0966^{c}
SE	0.1384	0.1387	0.0545	0.2782	0.1512	0.0530	0.2584	0.2000	0.0506
AME%	-0.02	-0.30^{a}	-0.09^{a}	-0.13^{c}	-0.25^{a}	-0.10^{b}	-0.06	-0.10^{a}	-0.08
VCRTA									
β	-0.9208^{a}	-1.0250^{a}	-0.2213^{a}	-1.5727^{a}	-1.6921^{a}	-0.3056^{a}	-1.8046^{a}	-2.2448^{a}	-0.3079^{a}
SE	0.2450	0.1393	0.0685	0.2693	0.1875	0.0671	0.2965	0.2447	0.0666
AME%	-0.08	-0.40^{a}	-0.14^{a}	-0.12^{c}	-0.20^{a}	-0.21^{a}	-0.07^{b}	-0.05^{a}	-0.23^{a}
FCSBTA									
β	-0.0913	-0.0826^{a}	-0.0717^{a}	-0.1698	-0.1203^{a}	-0.0950^{a}	-0.3026	-0.1978^{a}	-0.1080^{a}
SE	0.1023	0.0257	0.0173	0.1378	0.0397	0.0252	0.1872	.0712	0.0369
AME%	-0.01	-0.03^{b}	-0.05^{a}	-0.01	-0.01^{a}	-0.01^{a}	-0.01	-0.01^{a}	-0.01^{b}
NSITA									
β	-0.9189^{a}	-1.1907^{a}	-0.0982	-1.5607^{a}	-1.7555^{a}	-0.2024^{a}	-1.7683^{a}	-2.0992^{a}	-0.1854^{a}
SE	0.2436	0.1571	0.0685	0.2676	0.1904	0.0683	0.2912	0.2269	0.0677
AME%	-0.10	-0.30^{a}	-0.06	-0.13^{c}	-0.20^{a}	-0.13^{a}	-0.08^{c}	-0.05^{a}	-0.13^{a}
IBFCTA									
β	-0.3850	-0.4603	-1.0516^{c}	-0.9098	-1.4898^{a}	-0.1550^{a}	-1.3430^{b}	-0.0582^{c}	-0.0826^{a}
SE	0.3758	0.4233	0.6220	0.6338	0.5936	0.0649	0.5787	0.0347	0.0232
AME%	-0.04	-0.01	-0.03	-0.07	-0.05	-0.02^{b}	-0.18^{b}	-0.02^{c}	-0.05^{a}

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). The table reports univariate panel logistic regression results of all independent variables across different bank size categories that are not significant in all three time periods or are significant but exhibit Average Marginal Effects (AME) of less than 5% in all three time periods. The sampling period is between 1985-2016. I consider banks corresponding to the bottom 25 percentile of total assets as small banks, those in the top 25 percentile as large banks, and the rest medium banks. If a bank fails in year t, the bank's failure indicator is '1' in that year t and '0' otherwise. β is the regression coefficient, SE is standard error and AME is Average Marginal Effects in percentage.

Table 6: Univariate Regression Analysis by Size Categories with ranking

	1 Year Lag			2 Years Lag			3 Years Lag			Ranking		
Variable	Small Banks	Medium Banks	Large Banks	Small Banks	Medium Banks	Large Banks	Small Banks	Medium Banks	Large Banks	SB	MB	LB
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
TETA										6	5	1
β	-104.5323[a]	-130.1084[a]	-120.8708[a]	-79.3857[a]	-100.3526[a]	-62.2437[a]	-27.4832[a]	-35.8680[a]	-22.1070[a]			
SE	3.2361	4.2753	3.1002	3.3538	3.6284	2.9461	2.4525	2.4180	2.9787			
AME%	-62.18[a]	-44.10[a]	-54.59[a]	-10.96[a]	-4.08[a]	-34.83[a]	-0.45[a]	-1.11[a]	-3.94[a]			
NPACR										13	12	16
β	-57.2967[a]	-68.9085[a]	-53.1749[a]	-54.6331[a]	-72.6386[a]	-46.1104[a]	-30.8899[a]	-47.1803[a]	-28.4403[a]			
SE	2.2476	2.9380	2.0797	2.1369	2.1867	2.1660	1.6521	2.0623	1.7933			
AME%	-29.20[a]	-21.26[a]	-20.61[a]	-13.27[a]	-7.71[a]	-14.17[a]	-1.06[a]	-0.15[a]	-6.58[a]			
LLRTA										5	4	5
β	213.0666[a]	240.7152[a]	231.7835[a]	198.8182[a]	286.6373[a]	176.7561[a]	141.3965[a]	173.0129[a]	78.7335[a]			
SE	8.0482	7.3646	10.1898	8.0616	8.4806	10.0358	8.7002	9.7912	10.1420			
AME%	63.01[a]	48.09[a]	47.76[a]	22.69[a]	6.29[a]	15.84[a]	4.50[a]	0.50[a]	4.56[a]			
PD90TA										10	3	3
β	133.9768[a]	139.6740[a]	117.3466[a]	128.8366[a]	140.7921[a]	104.5770[a]	113.9995[a]	117.5897[a]	92.9058[a]			
SE	4.9223	4.1417	6.7189	6.2654	5.6501	8.0909	7.2826	7.7970	10.1162			
AME%	43.65[a]	50.76[a]	51.97[a]	18.07[a]	11.99[a]	29.47[a]	7.59[a]	1.21[a]	12.05[a]			
NAATA										11	10	9
β	87.7152[a]	98.6135[a]	89.9165[a]	91.2369[a]	106.0918[a]	90.1672[a]	60.6484[a]	85.2727[a]	65.1436[a]			
SE	2.8367	3.0422	3.5646	3.5265	3.0938	4.1568	3.5138	3.7726	4.1951			
AME%	43.59[a]	28.57[a]	36.72[a]	6.58[a]	4.89[a]	15.74[a]	2.88[a]	0.50[a]	4.66[a]			
OREOTA										12	13	11
β	122.6557[a]	148.6665[a]	128.2099[a]	108.5423[a]	148.4729[a]	100.4943[a]	88.4473[a]	100.6918[a]	64.8086[a]			
SE	5.8518	4.2552	6.1331	4.1746	4.2838	5.5546	4.4715	5.2020	5.7444			
AME%	28.78[a]	20.01 [a]	27.70[a]	14.76[a]	4.83[a]	15.47[a]	4.21[a]	0.69[a]	5.60[a]			
NPATA										14	15	18
β	57.5061[a]	63.4320[a]	59.719[a]	67.9820[a]	73.0869[a]	58.4588[a]	45.2425[a]	58.9372[a]	40.8855[a]			
SE	2.0917	2.2385	3.1924	2.5115	2.0663	2.7041	2.0632	2.2254	2.4771			
AME%	27.42[a]	18.06[a]	17.85[a]	10.14[a]	5.97[a]	9.27[a]	3.03[a]	0.50[a]	2.58[a]			

LLPTL										15	14	15
β	50.3822[a]	62.6381[a]	71.1554[a]	52.4631[a]	59.8731[a]	58.3550[a]	36.1935[a]	43.3581[a]	32.1781[a]			
SE	1.4754	1.5675	2.5860	2.1884	1.9814	2.8988	2.2964	2.5763	3.2276			
AME%	24.71[a]	18.93[a]	21.14[a]	3.94[a]	4.69[a]	10.59[a]	1.87[a]	0.44[a]	3.16[a]			
LLPTA										2	2	4
β	111.6439[a]	125.6934[a]	130.3305[a]	112.8078[a]	123.4805[a]	117.4030[a]	92.0200[a]	93.5506[a]	93.5506[a]			
SE	2.3703	2.1606	4.2779	3.9636	3.7424	5.2697	4.5473	2.9432	2.9432			
AME%	81.30[a]	56.30[a]	48.55[a]	29.72[a]	21.26[a]	24.12[a]	7.86[a]	2.67[a]	2.67[a]			
NPLTL										17	16	19
β	37.7979[a]	48.1177[a]	52.6437[a]	33.6181[a]	47.8420[a]	43.2023[a]	24.2412[a]	36.2740[a]	27.6767[a]			
SE	1.2911	1.4320	2.3153	1.3998	1.4320	2.0705	1.4766	1.7402	1.9735			
AME%	14.77[a]	11.87[a]	14.32[a]	5.50[a]	2.50[a]	7.06[a]	1.19[a]	0.22[a]	2.17[a]			
NPLTA										9	9	10
β	72.1163[a]	81.9581[a]	80.1566[a]	76.6422[a]	88.3124[a]	77.8734[a]	59.0820[a]	78.4115[a]	57.4972[a]			
SE	2.0370	2.1214	3.1803	3.2444	2.7119	3.5575	2.8788	3.1037	3.5359			
AME%	46.56[a]	30.02[a]	31.61[a]	15.90[a]	8.81[a]	15.62[a]	4.63[a]	0.75[a]	5.26[a]			
NCOTA										1	1	6
β	134.5371[a]	145.7577[a]	156.7221[a]	128.4773[a]	143.0513[a]	126.1068[a]	97.0111[a]	108.7911[a]	75.2839[a]			
SE	2.8553	3.2351	5.8626	4.9892	4.5495	6.4348	5.3360	5.7823	7.4377			
AME%	96.88[a]	63.92[a]	47.15[a]	21.35[a]	11.32[a]	20.64[a]	5.72[a]	0.93[a]	6.36[a]			
NCOTL										8	11	12
β	71.0714[a]	84.7499[a]	91.1711[a]	68.6089[a]	77.1802[a]	69.2162[a]	47.4138[a]	53.2410[a]	39.9651[a]			
SE	1.5848	2.3689	3.4579	2.8728	2.6383	3.6113	2.9994	3.3405	4.3282			
AME%	53.11[a]	24.72[a]	26.30[a]	5.60[a]	3.43[a]	12.30[a]	2.38[a]	0.35[a]	3.70[a]			
ROA										4	7	7
β	-86.9303[a]	-102.0375[a]	-103.9933[a]	-82.1382[a]	-78.7770[a]	-91.1763[a]	-76.9376[a]	-56.2362[a]	-53.4303[a]			
SE	1.9747	1.7691	2.3017	3.2715	2.5243	4.1054	3.7828	2.8210	4.2183			
AME%	-63.23[a]	-43.17[a]	-43.95[a]	-26.60[a]	-23.25[a]	-22.14[a]	-2.62[a]	-2.10[a]	-7.34[a]			
TIETLB										18	19	14
β	61.4023[a]	47.7399[a]	40.9523[a]	57.8087[a]	44.3314[a]	39.8235[a]	36.4754[a]	36.8810[a]	41.0876[a]			
SE	3.1827	2.5850	3.1309	3.6377	2.9744	3.3368	4.0068	3.4618	3.7925			
AME%	14.07[a]	6.76[a]	22.92[a]	6.90[a]	1.98[a]	14.84[a]	1.70[a]	0.37[a]	7.04[a]			
TDTA										3	8	
β	93.2730[a]	73.8422[a]		46.6249[a]	24.8628[a]		14.1678[a]	6.6342[a]				
SE	2.6247	1.8049		2.4809	1.5792		1.7131	1.0472				

AME%	65.22[a]	35.73[a]		3.34[a]	0.69[a]		0.66[a]	0.03[a]				
TLBTA										7	6	2
β	104.0208[a]	129.7856[a]	118.6901[a]	79.5195[a]	91.3966[a]	61.8247[a]	26.9838[a]	35.8971[a]	22.1775[a]			
SE	3.2385	4.3062	3.0341	3.2817	2.9565	2.9201	2.4658	2.4175	2.9764			
AME%	61.66[a]	43.66[a]	53.71[a]	9.85[a]	8.57[a]	34.59[a]	0.66[a]	1.10[a]	3.99[a]			
DIR										19	18	17
β	57.6155[a]	46.8472[a]	36.4952[a]	55.6349[a]	44.4691[a]	37.9377[a]	33.6129[a]	38.6343[a]	43.0988[a]			
SE	2.9947	2.4835	2.7541	3.4871	2.8618	3.0714	3.8476	3.3762	3.6524			
AME%	12.90[a]	7.09[a]	20.42[a]	6.59[a]	2.26[a]	13.28[a]	1.43[a]	0.41[a]	6.87[a]			
NIETA										16	17	
β	93.6376[a]	92.4090[a]		75.5076[a]	52.9018[a]		63.1194[a]	26.8552[a]				
SE	4.1514	3.3347		3.5111	3.3639		3.8580	4.1414				
AME%	15.86[a]	7.23[a]		8.31[a]	1.79[a]		3.84[a]	0.24[a]				
NIM											20	8
β		-109.2913[a]	-108.9558[a]		-64.2987[a]	-72.3164[a]		-24.8567[a]	-34.0273[a]			
SE		8.0180	10.1674		7.3971	9.6534		7.4900	8.9746			
AME%		-6.11[a]	-38.72[a]		-2.79[a]	-24.13[a]		-0.75[a]	-9.27[a]			
CDLTA												20
β			10.2700[a]			12.6876[a]			14.1905[a]			
SE			0.5645			0.5577			0.5723			
AME%			5.96[a]			7.27[a]			8.00[a]			
TSTA												21
β			-10.3733[a]			-9.9772[a]			-10.3493[a]			
SE			0.5779			0.6435			0.7304			
AME%			-6.01[a]			-4.79[a]			-2.86[a]			
NIITA												13
β			-128.8201[a]			-90.1715[a]			-39.4006[a]			
SE			7.2345			7.4045			7.3900			
AME%			-24.09[a]			-12.03[a]			-3.10[a]			

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). The table reports univariate panel logistic regression results of the final set of variables for 1-year (columns 2 to 4), 2-years (columns 5 to 7), and 3-years (columns 8 to 10) lagged time periods across different size categories that I use for multivariate logit regression analysis. This excludes variables that are not significant in all three time periods or are significant but exhibit Average Marginal Effects (AME) of less than 5% in all three time periods. The sampling period is between 1985-2016. I consider banks corresponding to the bottom 25 percentile of total assets as small banks, those in the top 25 percentile as large banks, and the rest medium banks. If a bank fails in year t, the bank's failure indicator is '1' in that year t and '0' otherwise. β is the regression coefficient, SE is standard error and AME is Average Marginal Effects in percentage. Ranking (columns 11 to 13) is based on the absolute values of AME for the 1-year lagged time estimate for small banks (SB), medium banks (MB), and large banks (LB), where the highest value gets 1, second highest gets 2 and so on.

2.4.3 Summary Statistics and Correlations

Table 7 provides descriptive statistics for the set of explanatory variables[5] selected in the preceding section for further multivariate analysis. Column 1 presents the list of covariates along with five measures of descriptive statistics: mean, median, standard deviation, minimum and maximum. Columns 2 and 3 report descriptive measures for all banks in my sample for failed and censored (when no fail has been observed) groups of banks, respectively. Subsequent columns present similar information for small, medium, and large banks respectively.

Conventionally, the average total assets of failure banks exhibit lower amount compared to the censored group across bank size categories. In addition, the mean of covariates bearing a positive relationship with bank failure is higher for the failed group of observations than for its censored counterpart, and vice-versa. For example, PD90TA is expected to have a positive relationship with bank failure, and its mean across all size categories show that its values is higher for the failed group of observations than for its censored counterpart. Contrarily, TETA, for instance, is expected to have a negative relationship with bank failure, and its mean across all size categories show that its value is lower for the failed group of observations than for its censored counterpart. My expectations are well supported by all covariates across respective size categories except TDTA. The mean of TDTA for failed groups of banks is higher than for its censored counterpart, implying that failed banks have higher total deposits. This is contrary to the intuition, where I expect failed banks to have funding and liquidity problems, and hence lower total deposits. In subsequent regression analysis, this might lead to a positive relationship between TDTA and bank failure. Generally, median values of respective covariates reported in Table 5 are also sufficiently close to their respective mean values, thus problems that could arise due to significant skewness are not expected.

[5]To mitigate the effect of outliers on my statistical estimates, all explanatory variables are winsorised at the 1st and 99th percentile.

Additionally, there is no unexpected variability in the values of standard deviation, minimum, and maximum descriptive statistics for all variables across different bank size categories.

The correlation matrix in Table 8 shows that some of the variables exhibit moderate to strong correlation with other variables. Issues associated with multicollinearity therefore need to be addressed carefully when developing multivariate models. Section 2.5.1 discusses how I address this issue in my study.

2.5 Multivariate Regression Analysis

In this section, I discuss the development and performance evaluation of multivariate regression models. I then provide a comparative discussion on the results for all, small, medium, and large banks.

2.5.1 Model-Building Strategy

Although several studies attempted to develop a model that is numerically stable and applicable, they lack consensus on the criteria for including a variable in the multivariate model. According to Hosmer et al. (2013), the standard error of a multivariate regression model increases with the number of variables and makes the model more dependent on the observed data. Thus, I use the approach suggested by Gupta et al. (2018) to minimise the number of explanatory variables entering the multivariate models. This approach requires the ranking of variables in univariate regression (reported in Table 3 and 4) based on the magnitude of their AME (the variable with the highest value of AME for 1-year lagged (T-1) is ranked 1, and so on), and then each variable is introduced in turn into the multivariate model in declining order of their respective AME. Gupta et al. (2018) justify that the higher the value of AME, the higher the change in the predicted probability due to unit changes in the variable's value. In addition, a variable with a higher value of AME (e.g. NCOTA in Table 3) is more efficient than a variable with a lower value of AME (e.g. NIETA in Table 3) in discriminating between failed and

Table 7: Descriptive Statistics

	All Banks		Small Banks		Medium Banks		Large Banks	
Variable	Failed	Censored	Failed	Censored	Failed	Censored	Failed	Censored
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LTA								
Mean	10.9246	11.3457	9.5470	9.9575	10.9893	11.2158	12.9477	12.9897
Median	10.6463	11.2007	9.5273	9.9256	10.8479	11.1810	12.8090	12.7849
SD	1.4872	1.3444	0.5951	0.6346	0.7409	0.6589	1.1271	1.1391
Minimum	8.7324	8.7324	8.7324	8.7324	9.8074	9.8032	11.2188	11.2180
Maximum	15.8916	15.8916	11.4079	11.4803	12.7020	13.0739	15.8916	15.8916
NCOTA								
Mean	0.0202	0.0031	0.0216	0.0030	0.0200	0.0030	0.0185	0.0035
Median	0.0190	0.0010	0.0225	0.0006	0.0184	0.0010	0.0155	0.0014
SD	0.0152	0.0062	0.0155	0.0066	0.0153	0.0059	0.0143	0.0063
Minimum	-0.0023	-0.0023	-0.0023	-0.0023	-0.0023	-0.0023	-0.0023	-0.0023
Maximum	0.0395	0.0395	0.0395	0.0395	0.0395	0.0395	0.0395	0.0395
PD90TA								
Mean	0.0108	0.0025	0.0124	0.0028	0.0113	0.0025	0.0073	0.0022
Median	0.0063	0.0006	0.0091	0.0003	0.0073	0.0006	0.0029	0.0008
SD	0.0108	0.0046	0.0110	0.0053	0.0110	0.0045	0.0091	0.0039
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.0273	0.0273	0.0273	0.0273	0.0273	0.0273	0.0273	0.0273
LLRTA								
Mean	0.0239	0.0091	0.0233	0.0090	0.0236	0.0089	0.0251	0.0097
Median	0.0259	0.0081	0.0250	0.0078	0.0256	0.0080	0.0282	0.0085
SD	0.0117	0.0054	0.0117	0.0058	0.0120	0.0050	0.0114	0.0057
Minimum	0.0007	0.0007	0.0007	0.0007	0.0007	0.0007	0.0007	0.0007
Maximum	0.0359	0.0359	0.0359	0.0359	0.0359	0.0359	0.0359	0.0359
TETA								
Mean	0.0318	0.1009	0.0312	0.1174	0.0303	0.0982	0.0355	0.0897
Median	0.0224	0.0915	0.0224	0.1005	0.0224	0.0918	0.0224	0.0838
SD	0.0197	0.0431	0.0192	0.0607	0.0169	0.0337	0.0246	0.0327
Minimum	0.0224	0.0224	0.0224	0.0224	0.0224	0.0224	0.0224	0.0224
Maximum	0.2292	0.3445	0.1496	0.3445	0.1308	0.3445	0.2292	0.3445
OREOTA								
Mean	0.0324	0.0041	0.0312	0.0040	0.0347	0.0043	0.0296	0.0038
Median	0.0335	0.0006	0.0324	0.0000	0.0393	0.0008	0.0266	0.0009

SD	0.0213	0.0087	0.0211	0.0091	0.0211	0.0088	0.0215	0.0079
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.0566	0.0566	0.0566	0.0566	0.0566	0.0566	0.0566	0.0566
NIETA								
Mean	0.0353	0.0319	0.0423	0.0353	0.0329	0.0309	0.0292	0.0306
Median	0.0296	0.0297	0.0385	0.0321	0.0275	0.0291	0.0233	0.0287
SD	0.0232	0.0129	0.0252	0.0149	0.0213	0.0115	0.0211	0.0128
Minimum	0.0080	0.0080	0.0080	0.0080	0.0080	0.0080	0.0080	0.0080
Maximum	0.0950	0.0950	0.0950	0.0950	0.0950	0.0950	0.0950	0.0950
NIM								
Mean	0.0207	0.0393	0.0241	0.0400	0.0194	0.0396	0.0183	0.0380
Median	0.0172	0.0390	0.0216	0.0399	0.0157	0.0392	0.0133	0.0377
SD	0.0129	0.0097	0.0137	0.0110	0.0120	0.0090	0.0124	0.0096
Minimum	0.0089	0.0089	0.0089	0.0089	0.0089	0.0089	0.0089	0.0089
Maximum	0.0693	0.0693	0.0693	0.0693	0.0693	0.0693	0.0693	0.0693
TDTA								
Mean	0.9305	0.8539	0.9455	0.8540	0.9385	0.8652	0.8923	0.8310
Median	0.9587	0.8761	0.9587	0.8802	0.9587	0.8805	0.9251	0.8581
SD	0.0585	0.0817	0.0357	0.0941	0.0388	0.0618	0.0920	0.0970
Minimum	0.3926	0.3926	0.3926	0.3926	0.6253	0.3926	0.3926	0.3926
Maximum	0.9587	0.9587	0.9587	0.9587	0.9587	0.9587	0.9587	0.9587
TIETLB								
Mean	0.0315	0.0333	0.0343	0.0322	0.0302	0.0340	0.0297	0.0329
Median	0.0284	0.0333	0.0307	0.0323	0.0268	0.0340	0.0275	0.0328
SD	0.0202	0.0186	0.0210	0.0191	0.0196	0.0185	0.0198	0.0182
Minimum	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0029	0.0015
Maximum	0.0725	0.0725	0.0725	0.0725	0.0725	0.0725	0.0725	0.0725
LLPTL								
Mean	0.0388	0.0073	0.0427	0.0082	0.0374	0.0068	0.0358	0.0074
Median	0.0301	0.0030	0.0356	0.0025	0.0277	0.0030	0.0289	0.0035
SD	0.0352	0.0139	0.0375	0.0171	0.0349	0.0126	0.0312	0.0130
Minimum	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054	-0.0054
Maximum	0.0963	0.0963	0.0963	0.0963	0.0963	0.0963	0.0963	0.0963
ROA								
Mean	-0.0283	0.0075	-0.0306	0.0049	-0.0284	0.0081	-0.0244	0.0089
Median	-0.0292	0.0095	-0.0345	0.0081	-0.0293	0.0097	-0.0209	0.0101
SD	0.0212	0.0110	0.0210	0.0139	0.0208	0.0100	0.0218	0.0093
Minimum	-0.0520	-0.0520	-0.0520	-0.0520	-0.0520	-0.0520	-0.0520	-0.0520
Maximum	0.0286	0.0286	0.0286	0.0286	0.0173	0.0286	0.0286	0.0286

TLBTA								
Mean	0.9686	0.8991	0.9692	0.8826	0.9701	0.9018	0.9646	0.9103
Median	0.9780	0.9085	0.9780	0.8995	0.9780	0.9082	0.9780	0.9161
SD	0.0199	0.0431	0.0192	0.0607	0.0170	0.0337	0.0249	0.0328
Minimum	0.7615	0.6557	0.8504	0.6557	0.8692	0.6557	0.7615	0.6557
Maximum	0.9780	0.9780	0.9780	0.9780	0.9780	0.9780	0.9780	0.9780
NPLTA								
Mean	0.0625	0.0097	0.0597	0.0093	0.0643	0.0096	0.0632	0.0102
Median	0.0774	0.0051	0.0664	0.0041	0.0819	0.0051	0.0856	0.0058
SD	0.0277	0.0135	0.0271	0.0141	0.0271	0.0133	0.0293	0.0134
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.0856	0.0856	0.0856	0.0856	0.0856	0.0856	0.0856	0.0856
NCOTL								
Mean	0.0335	0.0056	0.0364	0.0057	0.0330	0.0054	0.0300	0.0058
Median	0.0296	0.0018	0.0370	0.0012	0.0285	0.0018	0.0251	0.0023
SD	0.0258	0.0109	0.0267	0.0123	0.0261	0.0105	0.0231	0.0102
Minimum	-0.0051	-0.0051	-0.0051	-0.0051	-0.0051	-0.0051	-0.0051	-0.0051
Maximum	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692	0.0692
NPACR								
Mean	-0.0301	0.0968	-0.0321	0.1138	-0.0343	0.0938	-0.0193	0.0861
Median	-0.0521	0.0905	-0.0521	0.1002	-0.0521	0.0907	-0.0521	0.0835
SD	0.0408	0.0492	0.0352	0.0667	0.0361	0.0408	0.0530	0.0388
Minimum	-0.0521	-0.0521	-0.0521	-0.0521	-0.0521	-0.0521	-0.0521	-0.0521
Maximum	0.3073	0.3482	0.1205	0.3482	0.1222	0.3482	0.3073	0.3482
NPATA								
Mean	0.1058	0.0169	0.1024	0.0168	0.1098	0.0171	0.1033	0.0166
Median	0.1299	0.0096	0.1146	0.0090	0.1388	0.0099	0.1388	0.0096
SD	0.0423	0.0221	0.0399	0.0227	0.0411	0.0221	0.0471	0.0215
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.1388	0.1388	0.1388	0.1388	0.1388	0.1388	0.1388	0.1388
DIR								
Mean	0.0330	0.0351	0.0353	0.0334	0.0314	0.0353	0.0326	0.0364
Median	0.0293	0.0351	0.0313	0.0333	0.0281	0.0355	0.0293	0.0361
SD	0.0213	0.0195	0.0219	0.0196	0.0205	0.0190	0.0218	0.0201
Minimum	0.0017	0.0017	0.0017	0.0017	0.0017	0.0017	0.0034	0.0017
Maximum	0.0803	0.0803	0.0803	0.0803	0.0803	0.0803	0.0803	0.0803
LLPTA								
Mean	0.0218	0.0039	0.0230	0.0037	0.0214	0.0038	0.0209	0.0044
Median	0.0187	0.0018	0.0201	0.0012	0.0182	0.0018	0.0170	0.0021

SD	0.0183	0.0070	0.0190	0.0073	0.0183	0.0066	0.0174	0.0073
Minimum	-0.0025	-0.0025	-0.0025	-0.0025	-0.0025	-0.0025	-0.0025	-0.0025
Maximum	0.0463	0.0463	0.0463	0.0463	0.0463	0.0463	0.0463	0.0463
NPLTL								
Mean	0.1125	0.0178	0.1066	0.0195	0.1151	0.0172	0.1165	0.0173
Median	0.1214	0.0091	0.1103	0.0083	0.1257	0.0091	0.1352	0.0096
SD	0.0536	0.0259	0.0522	0.0307	0.0536	0.0241	0.0552	0.0240
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.1690	0.1690	0.1690	0.1690	0.1690	0.1690	0.1690	0.1690
CDLTA								
Mean	0.0539	0.0319	0.0233	0.0171	0.0582	0.0325	0.0926	0.0453
Median	0.0206	0.0127	0.0034	0.0026	0.0280	0.0133	0.0649	0.0255
SD	0.0715	0.0480	0.0420	0.0352	0.0711	0.0478	0.0861	0.0545
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577	0.2577
TSTA								
Mean	0.1246	0.2615	0.1406	0.2733	0.1183	0.2678	0.1122	0.2373
Median	0.1026	0.2440	0.1158	0.2588	0.0970	0.2517	0.0956	0.2195
SD	0.1029	0.1547	0.1144	0.1683	0.0971	0.1537	0.0917	0.1389
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Maximum	0.6886	0.6886	0.6886	0.6886	0.5197	0.6886	0.5694	0.6886
Number of observations	1,817	296,308	630	73,903	783	148,289	404	74,116

NOTE: The table provides descriptive statistics of the annual data of bank-specific variables over the period 1985 to 2016, followed by measures across respective size categories. Banks corresponding to the bottom 25 percentile of total assets are considered as small banks, those in the top 25 percentile as large banks, and the rest medium banks. Banks are separated between failed and censored (for which the failure rate has not yet occurred) groups, and descriptive measures are reported for both groups separately. If a bank fails in year t, the bank's failure indicator is '1' in that year t and '0' in other years. Column 1 lists the main variables that are described in Table 2 along with the names of descriptive measures that I report in subsequent columns. Columns 2 and 3 report descriptive measures for failed and censored groups respectively, while subsequent columns present similar information for respective size categories.

Table 8: Correlation Matrix of Final Set of Variables

Variable	PD90TA	NCOTA	LLPTA	LLRTA	TETA	TLBTA	ROA	NAATA	NCOTL	TDTA	OREOTA	NPACR	LLPTL
PD90TA	1												
NCOTA	0.2984	1											
LLPTA	0.303	0.9003	1										
LLRTA	0.1135	0.4864	0.5516	1									
TETA	-0.1406	-0.2214	-0.2	-0.132	1								
TLBTA	0.1404	0.221	0.1998	0.1315	-0.9997	1							
ROA	-0.144	-0.5808	-0.6448	-0.4097	0.0637	-0.064	1						
NAATA	0.1725	0.5786	0.5667	0.5947	-0.1998	0.1998	-0.5047	1					
NCOTL	0.2957	0.9632	0.8557	0.4018	-0.2076	0.2073	-0.54	0.5155	1				
TDTA	0.1487	0.1446	0.1209	0.042	-0.6036	0.6051	-0.0428	0.1148	0.1608	1			
OREOTA	0.1683	0.4289	0.3656	0.3906	-0.1848	0.1849	-0.3949	0.5312	0.3925	0.1481	1		
NPACR	-0.2381	-0.3936	-0.3544	-0.2577	0.9245	-0.9243	0.2376	-0.5	-0.3645	-0.5708	-0.4629	1	
LLPTL	0.2666	0.7997	0.8722	0.3902	-0.0617	0.0617	-0.5574	0.448	0.8191	0.0191	0.2937	-0.2032	1
NPATA	0.3773	0.5653	0.5387	0.5815	-0.1998	0.1997	-0.488	0.8578	0.4979	0.1306	0.7402	-0.5278	0.4131
TIETLB	0.3796	0.2989	0.3196	-0.0807	-0.2794	0.2797	-0.078	0.0669	0.3465	0.2353	0.053	-0.2832	0.3192
NPLTL	0.4545	0.5534	0.5326	0.4339	-0.1023	0.1025	-0.4477	0.8203	0.5394	0.06	0.4725	-0.3894	0.6172
DIR	0.3705	0.2974	0.3198	-0.0734	-0.2643	0.2644	-0.0732	0.0655	0.3402	0.1339	0.0451	-0.2673	0.3273
NIETA	0.1244	0.2226	0.2148	0.1848	0.0881	-0.0887	-0.3443	0.1599	0.1981	-0.0479	0.1961	0.0035	0.238
NIM	0.1816	0.0856	0.0799	0.054	-0.0841	0.0838	0.2784	-0.0727	0.0739	0.1822	-0.0167	-0.0506	0.0156
CDLTA	-0.0992	0.0213	0.0881	0.2149	-0.0238	0.0236	-0.1188	0.1631	-0.0378	-0.0935	0.134	-0.0692	-0.0107
TSTA	-0.0306	-0.1125	-0.1498	-0.3316	0.0549	-0.0544	0.1803	-0.1972	-0.0105	0.0497	-0.1642	0.1036	-0.0168

	NPATA	TIETLB	NPLTL	DIR	NIETA	NIM	CDLTA	TSTA
NPATA	1							
TIETLB	0.0501	1						
NPLTL	0.7755	0.1894	1					
DIR	0.0482	0.9857	0.1934	1				

NIETA	0.2052	0.0568	0.2051	0.0612	1			
NIM	-0.0109	0.2728	-0.0795	0.2547	0.3607	1		
CDLTA	0.1686	-0.1135	0.0245	-0.0994	0.037	0.0108	1	
TSTA	-0.2313	0.1119	-0.0401	0.098	-0.2296	-0.161	-0.3677	1

Notes: This table presents the correlation among the final set of variables estimated over the sample period 1985-2016.

censored banks. I also exclude a variable from the multivariate models if, when added it (i) changes the sign of any previously added variable, (ii) holds the opposite sign to that generated by univariate analysis, (iii) holds the identical sign to univariate analysis, but is insignificant with a p-value greater than 0.10, and (iv) makes a previously introduced variable insignificant with a p-value greater than 0.10. This screening mechanism ensures that the method is useful to appropriately address the issue of multicollinearity and develops a multivariate model with a 'best' set of variables that explains the variance of the dependent variable. Using panel logistic regression, this process is applied to all, small, medium, and large banks respectively for all three ($T-1$, $T-2$, and $T-3$) respective lagged time periods. I do this to observe any variances that may arise due to different estimation models across different bank size classes.

I eventually end up with six variables to be used in the multivariate model for all banks. The variables are net charge off (NCOTA), past due 90+ days (PD90TA), loan loss reserves (LLRTA), total equity (TETA), other real estate owned (OREOTA), and total of non-interest expense (NIETA), and they are expressed as a ratio with respect to the bank's total assets. For small banks, the multivariate regression model is explained by seven variables. Five out of the seven variables (NCOTA, PD90TA, LLRTA, OREOTA, and NIETA) are common to explanatory variables for all banks. The other two variables are total deposits to total assets ratio (TDTA) and total interest expenses to total liabilities (TIETLB). Among large banks, five variables (PD90TA, LLRTA, TETA, Net Interest Margin (NIM), and Loan Loss Provisions to Total Loans (LLPTL)) are included in the multivariate regression model. Only three variables (PD90TA, LLRTA, and TETA) are similar to the variables of all banks. For medium banks, the multivariate regression model contains six variables as a combination of the explanatory variables for small and large banks (NCOTA, PD90TA, LLRTA, TETA, OREOTA, and NIM). These results generally underpin my second hypothesis (H2) that the factors affecting the probability of banks' failure vary across small, medium, and large size categories.

To further evaluate the consistency and strength of respective sets of main variables in jointly predicting the probability of banks' failure (robustness check), I estimate another set of multivariate models supplementing control variables (discussed in Section 2.3.4.3). This also helps me to control for potential differences in bank stability, banking crises, and state-level economic conditions. To gauge their intertemporal predictive ability, I estimate regression models for 2-years and 3-years lagged periods. The models and their results are presented in Tables 9, 10, and 11.

2.5.2 Evaluation of Classification Performance

The Receiver Operating Characteristics (ROC) curve and the area under the ROC (AUROC) curve are viable measures to evaluate the classification performance of early-warning models developed to identify distressed banks (Betz et al., 2014). The ROC curve describes the trade-off between true-positive (sensitivity: a bank actually fails, and the model classifies it as expected failure) and false-negative (1 – specificity: a bank actually fails but the model classifies it as expected survival) for an entire range of classification thresholds (Gupta et al., 2018). However, ROC offers a range of performance assessments. This means that the accuracy of the predicted class probabilities is mostly overlooked. I therefore use the AUROC, which is by far the most common non-parametric method for evaluating a fitted prediction model's ability to assign a randomly chosen positive instance higher than a randomly chosen negative one (Betz et al., 2014; Cole and White, 2012). In other words, the AUROC gauges the ability of the prediction model to discriminate between those banks which experience the event of interest, and those which do not. Its value varies between 0.5 and 1.0, which summarises the classification performance of the model developed. The value of 1 represents a perfect model, whereas the value of 0.5 represents no discrimination ability of the model. Generally, there is no guide for classifying the predictive accuracy of a model based on AUROC, however any value above 0.7 is acceptable and above 0.8 is considered to be excellent (Hosmer et al., 2013). Thus, the higher the AUROC, the better the model's prediction.

Table 9: Multivariate Regression Model for All Banks

Panel A: Regression Results						
	Without Control Variables			With Control Variables		
Variable	1 Year Lag	2 Years Lag	3 Years Lag	1 Year Lag	2 Years Lag	3 Years Lags
(1)	(2)	(3)	(4)	(5)	(6)	(7)
NCOTA						
β	39.8244[a]	35.8465[a]	29.6089[a]	19.3895[a]	22.7565[a]	22.8679[a]
SE	2.6997	3.6711	4.1561	3.4203	4.1896	5.4609
AME%	15.0422[a]	6.1886[a]	2.5228[a]	5.3925[a]	5.1108[a]	2.2872[a]
PD90TA						
β	30.8333[a]	68.6989[a]	67.0855[a]	35.7708[a]	63.9088[a]	87.8005[a]
SE	3.6360	4.6782	4.7960	4.7021	5.5617	6.3381
AME%	11.6461[a]	11.8604[a]	5.7161[a]	9.9483[a]	14.3532[a]	8.7816[a]
LLRTA						
β	38.7496[a]	90.7056[a]	41.4054[a]	45.3049[a]	66.7501[a]	35.3956[a]
SE	3.8866	5.8187	5.9059	4.8571	6.4110	7.4069
AME%	14.6362[a]	15.6597[a]	3.5280[a]	12.5999[a]	14.9913[a]	3.5401[a]
TETA						
β	-75.4119[a]	-40.1401[a]	-12.6109[a]	-81.5346[a]	-48.3109[a]	-25.2473[a]
SE	2.2137	1.8575	1.2173	2.7717	2.4545	1.8338
AME%	-28.4841[a]	-6.9299[a]	-1.0745[a]	-22.6759[a]	-10.8501[a]	-2.5251[a]
OREOTA						
β	25.6350[a]	56.5833[a]	47.0656[a]	11.9870[a]	32.9740[a]	33.8065[a]
SE	1.9345	3.0603	2.8371	2.2337	3.3489	3.5696
AME%	9.6827[a]	9.7687[a]	4.0103[a]	3.3337[a]	7.4056[a]	3.3812[a]
NIETA						
β	3.4345[c]	3.5456	6.5127[b]	17.1175[a]	12.1606[a]	21.1530[a]
SE	1.8988	2.8338	2.8252	2.3013	2.8837	3.4003
AME%	1. 2972[c]	0.6121	0.5549[b]	4.7606[a]	2.7311[a]	2.1156[a]
GHPI						
β				-11.8082[a]	-12.2518[a]	-16.3320[a]
SE				0.7100	0.7338	0.8243
AME%				-3.2840[a]	-2.7516[a]	-1.6334[a]
SL						
β				2.3327[a]	2.7928[a]	2.2307[a]
SE				0.1377	0.1448	0.1479
AME%				0.6487[a]	0.6272[a]	0.2231[a]
GFC						
β				1.7208[a]	2.4787[a]	3.5303[a]
SE				0.1319	0.1392	0.1290
AME%				0.4786[a]	0.5566[a]	0.3531[a]
FOPCT						
β				2.7074[a]	3.1634[a]	3.2666[a]
SE				0.1368	0.14717	0.1289
AME%				0.7529[a]	0.7104[a]	0.3267[a]
FDIC						
β				2.8677[a]	2.4352[a]	1.4718[a]
SE				0.1399	0.1502	0.1426
AME%				0.7975[a]	0.5469[a]	0.1472[a]
FED						
β				2.8925[a]	2.4565[a]	1.4033[a]
SE				0.1853	0.1925	0.1974
AME%				0.8044[a]	0.5517[a]	0.1403[a]
Panel B: Goodness of Fit Measures						
Wald Chi2	2615[a]	1805[a]	1495[a]	1923[a]	1308[a]	1560[a]

Log Likelihood	-4722	-6698	-7189	-3230	-4606	-4683
R2	0.7569	0.3018	0.0810	0.7722	0.5131	0. 2998
No. of "0"	276,981	258,270	240,317	257,801	239,877	223,809
No. of "1"	1,694	1,554	1,342	1,546	1,337	1,040

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). Panel A presents multivariate panel logistic regression results for 1-year, 2-years, and 3-years lagged periods, estimated over a sampling period of 1985-2016. Columns 2, 3 and 4 do not include control variables and the rest include control variables in the multivariate estimates. If a bank fails in year t, the bank's binary indicator is '1' in that year t and '0' otherwise. A positive coefficient (β) suggests a positive relationship with failure likelihood and vice-versa. SE is standard error of respective coefficients and AME is Average Marginal Effects in percentage. Panel B reports the chi-square, the likelihood ratio and the coefficient of determination (McKelvey and Zavoina's R2) to measure the model's goodness of fit. No. of "1" counts the number of failures in my sample, while No. of "0" counts the number of "non-failure" observations.

Table 10: Multivariate Regression Models without Control Variables by Size Categories

Panel A: Regression Results

	1 Year Lag				2 Years Lag				3 Years Lag			
Variable	All Banks	Small Banks	Medium Banks	Large Banks	All Banks	Small Banks	Medium Banks	Large Banks	All Banks	Small Banks	Medium Banks	Large Banks
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NCOTA												
β	39.8244[a]	47.7780[a]	26.7794[a]		35.8465[a]	35.2795[a]	24.3572[b]		29.6089[a]	34.9807[a]	18.6729[c]	
SE	2.6997	4.3729	6.9356		3.6711	5.8198	9.7469		4.1561	7.7074	9.7194	
AME%	15.0422[a]	25.9338[a]	8.2233[a]		6.1886[a]	9.2955[a]	2.4260[b]		2.5228[a]	2.3449[a]	0. 4449[c]	
PD90TA												
β	30.8333[a]	40.0387[a]	49.2210[a]	30.7840[b]	68.6989[a]	60.4810[a]	103.1499[a]	49.6830[a]	67.0855[a]	74.9498[a]	59.3297[a]	49.4819[a]
SE	3.6360	5.5941	9.7116	13.4527	4.6782	7.5487	12.4985	14.7570	4.7960	9.4391	12.5299	13.6310
AME%	11.6461[a]	21.7330[a]	15.1145[a]	14.3720[b]	11.8604[a]	15.9356[a]	10.2738[a]	17.2549[a]	5.7161[a]	5.0242[a]	1.4135[a]	21.8576[a]
LLRTA												
β	38.7496[a]	37.2199[a]	76.9432[a]	90.8796[a]	90.7056[a]	80.8907[a]	151.7489[a]	111.7549[a]	41.4054[a]	48.9785[a]	89.8852[a]	51.0923[a]
SE	3.8866	6.2611	11.4386	13.0387	5.8187	9.6021	14.3551	16.0917	5.9059	12.0932	14.1703	15.1547
AME%	14.6362[a]	20.2029[a]	23.6273[a]	42.4285[a]	15.6597[a]	21.3132[a]	15.1143[a]	38.8126[a]	3.5280[a]	3.2832[a]	2.1416[a]	22.5689[a]
TETA												
β	-75.4119[a]		-76.8456[a]	-58.5020[a]	-40.1401[a]		-46.1721[a]	-28.6889[a]	-12.6109[a]		-19.4217[a]	-16.7651[a]
SE	2.2137		7.2994	5.3171	1.8575		4.4201	3.5789	1.2173		2.9238	2.9133
AME%	-28.4841[a]		-23.5974[a]	-27.3126[a]	-6.9299[a]		-4.5988[a]	-9.9637[a]	-1.0745[a]		-0. 4627[a]	-7.4056[a]
OREOTA												
β	25.6350[a]	30.3981[a]	29.5583[a]		56.5833[a]	50.6729[a]	58.6815[a]		47.0656[a]	56.9582[a]	50.5365[a]	
SE	1.9345	2.9128	5.6556		3.0603	5.2876	7.1723		2.8371	6.1759	7.4430	
AME%	9.6827[a]	16.5000[a]	9.0766[a]		9.7687[a]	13.3513[a]	5.8447[a]		4.0103[a]	3.8181[a]	1.2040[a]	
NIETA												
β	3.4345[c]	24.7046[a]			3.5456	50.8636[a]			6.5127[b]	56.7940[a]		
SE	1.8988	3.2496			2.8338	5.1278			2.8252	5.8014		
AME%	1. 2972[c]	13.4096[a]			0.6121	13.4016[a]			0.5549[b]	3.8071[a]		
TDTA												
β		40.3383[a]				15.4303[a]				6.7069[a]		
SE		2.6588				2.0183				1.4217		
AME%		21.8956[a]				4.0656[a]				0.4496[a]		
TIETLB												
β		6.4420[c]				25.9831[a]				10.8052[b]		
SE		3.3363				4.4912				5.2393		
AME%		3.4967[c]				6.8460[a]				0.7243[c]		
NIM												
β			-69.8740[a]	-61.2067[a]			-90.6152[a]	-77.2748[a]			-42.6528[a]	-37.2785[a]

SE			9.5580	9.3690			11.4190	10.8521			9.7505	8.6466
AME%			-21.4566[a]	-28.5753[a]			-9.0253[a]	-26.8376[a]			-1.0162[a]	-16.4670[a]
LLPTL												
β				14.8423[a]				18.7471[a]				6.1916
SE				4.0385				4.9228				5.4214
AME%				6.9293[a]				6.5109[a]				2.7350
Panel B: Goodness of Fit Measures												
Wald Chi2	2615[a]	1134[a]	184[a]	332[a]	1805[a]	473[a]	614[a]	199[a]	1495[a]	599[a]	336[a]	106[a]
Log Likelihood	-4722	-1561	-931	-580	-6698	-1920	-1691	-1153	-7189	-1859	-2043	-1413
R2	0.7569	0.7765	0.6956	0.6850	0.3018	0.2818	0.2508	0.2723	0.0810	0.1003	0.0796	0.1141
No. of "0"	276,981	67,482	53,792	26,753	258,270	62,347	48,553	24,137	240,317	58,013	43,297	21,532
No. of "1"	1,694	573	347	198	1,554	515	398	256	1,342	403	403	276

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). Panel A presents multivariate panel logistic regression results without control variables for 1-year (columns 2 to 5), 2-years (columns 6 to 9), and 3-years (columns 10 to 13) lagged periods across different size categories. The sampling period runs between 1985-2016. I consider banks corresponding to the bottom 25 percentile of total assets as small banks, those in the top 25 percentile as large banks, and the rest medium banks. If a bank fails in year t, the bank's failure indicator is '1' in that year t and '0' otherwise. A positive coefficient (β) suggests a positive relationship with failure likelihood and vice-versa. SE is standard error of respective coefficients and AME is Average Marginal Effects in percentage. Panel B reports the chi-square, the likelihood ratio and the coefficient of determination (McKelvey and Zavoina's R2) to measure the model's goodness of fit. No. of "1" counts the number of failures in my sample, while No. of "0" counts the number of "non-failure" observations.

Table 11: Multivariate Regression Models with Control Variables by Size Categories

Panel A: Regression Results												
	1 Year Lag				2 Years Lag				3 Years Lag			
Variable	All Banks	Small Banks	Medium Banks	Large Banks	All Banks	Small Banks	Medium Banks	Large Banks	All Banks	Small Banks	Medium Banks	Large Banks
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
NCOTA												
β	19.3895[a]	23.6037[a]	16.1267[b]		22.7565[a]	16.8937[a]	7.9462		22.8679[a]	9.4457	11.5266	
SE	3.4203	5.9249	7.8013		4.1896	6.2052	7.1901		5.4609	6.9608	8.1313	
AME%	5.3925[a]	8.3371[a]	5.0714[b]		5.1108[a]	6.3238[a]	4.8672		2.2872[a]	3.6989	8.1205	
PD90TA												
β	35.7708[a]	36.8391[a]	29.7863[a]	74.9467[b]	63.9088[a]	41.6546[a]	41.1333[a]	23.3172	87.8005[a]	49.0316[a]	50.1830[a]	25.9338
SE	4.7021	7.3648	11.5435	18.1738	5.5617	7.8294	9.5826	20.0476	6.3381	8.2395	10.4303	19.1263
AME%	9.9483[a]	13.0121[a]	9.3670[a]	30.3851[a]	14.3532[a]	15.5926[a]	25.1950[a]	9.5130	8.7816[a]	19.2007[a]	35.3538[a]	24.0660

LLRTA												
β	45.3049[a]	55.4850[a]	74.4268[a]	48.0865[a]	66.7501[a]	63.1352[a]	75.4361[a]	109.3064[a]	35.3956[a]	32.9799[a]	52.4253[a]	58.7668[a]
SE	4.8571	7.9362	11.1310	14.5004	6.4110	8.6515	9.3138	21.5749	7.4069	9.1973	10.1822	14.3517
AME%	12.5999[a]	19.5980[a]	23.4054[a]	19.4953[a]	14.9913[a]	23.6334[a]	46.2061[a]	44.5949[a]	3.5401[a]	12.9149[a]	36.9335[a]	54.5342[a]
TETA												
β	-81.5346[a]		-80.0039[a]	-78.6671[a]	-48.3109[a]		-28.9044[a]	-32.2108[a]	-25.2473[a]		-13.3598[a]	-12.8896[a]
SE	2.7717		6.4577	5.8419	2.4545		2.9681	5.6366	1.8338		2.4391	3.1857
AME%	-22.6759[a]		-25.1593[a]	-31.8934[a]	-10.8501[a]		-17.7045[a]	-13.1414[a]	-2.5251[a]		-9.4119[a]	-11.9612[a]
OREOTA												
β	11.9870[a]	21.5538[a]	23.7403[a]		32.9740[a]	22.1463[a]	25.7580[a]		33.8065[a]	13.5405[a]	24.2017[a]	
SE	2.2337	3.5277	4.8817		3.3489	3.9491	4.1493		3.5696	4.3868	4.9287	
AME%	3.3337[a]	7.6131[a]	7.4657[a]		7.4056[a]	8.2900[a]	15.7773[a]		3.3812[a]	5.3024[a]	17.0500[a]	
NIETA												
β	17.1175[a]	41.0303[a]			12.1606[a]	44.0242[a]			21.1530[a]	43.3831[a]		
SE	2.3013	3.8786			2.8837	4.6609			3.4003	4.8454		
AME%	4.7606[a]	14.4924[a]			2.7311[a]	16.4796[a]			2.1156[a]	16.9887[a]		
TDTA												
β		35.1497[a]				12.6272[a]				5.0683[a]		
SE		2.9340				1.8330				1.3056		
AME%		12.4153[a]				4.7267[a]				1.9847[a]		
TIETLB												
β		56.1849[a]				61.8262[a]				71.8786[a]		
SE		5.5543				5.5448				5.6244		
AME%		19.8453[a]				23.1434[a]				28.1475[a]		
NIM												
β			-31.9666[a]	-8.4281			-56.3848[a]	-77.9860[a]			-35.9209[a]	-26.9491[a]
SE			9.7895	11.9581			7.9308	14.1350			7.9246	9.1266
AME%			-10.0527[a]	-3.4169			-34.5369[a]	-31.8168[a]			-25.3062[a]	-25.0081[a]
LLPTL												
β				18.0002[a]				20.5102[a]				20.4884[a]
SE				11.9581				6.1476				5.0810
AME%				7.2977[a]				8.3678[a]				19.0128[a]
GHPI												
β	-11.8082[a]	-8.0294[a]	-13.0414[a]	-10.1367[a]	-12.2518[a]	-14.9996[a]	-10.3922[b]	-9.2679[a]	-16.3320[a]	-16.8950[a]	-16.8401[a]	-12.8330[a]
SE	0.7100	1.6400	1.4633	1.3588	0.7338	1.4891	0.9543	1.4679	0.8243	1.4993	1.0103	1.2233
AME%	-3.2840[a]	-2.8361[a]	-4.1012[a]	-4.1096[a]	-2.7516[a]	-5.6148[a]	-6.3654[a]	-3.7811[a]	-1.6334[a]	-6.6160[a]	-11.8638[a]	-11.9087[a]
SL												

β	2.3327[a]	2.2009[a]	2.1595[a]	-0.9551[b]	2.7928[a]	2.4410[a]	4.5441[a]	3.9445[a]	2.2307[a]	2.3423[a]	4.2429[a]	3.5135[a]
SE	0.1377	0.2429	0.3850	0.4718	0.1448	0.2372	0.3478	0.4437	0.1479	0.2350	0.3504	0.3618
AME%	0.6487[a]	0.7773[a]	0.6791[a]	-0.3872[b]	0.6272[a]	0.9137[a]	2.7833[a]	1.6093[a]	0.2231[a]	0.9172[a]	2.9891[a]	3.2605[a]
GFC												
β	1.7208[a]	1.6672[a]	1.7609[a]	1.7093[a]	2.4787[a]	1.6290[a]	2.0769[a]	3.0810[a]	3.5303[a]	2.9303[a]	3.3281[a]	4.8514[a]
SE	0.1319	0.2904	0.2593	0.3044	0.1392	0.2998	0.2174	0.3424	0.1290	0.2600	0.2226	0.2969
AME%	0.4786[a]	0. 5888[a]	0.5537[a]	0.6930[a]	0.5566[a]	0.6098[a]	1.2722[a]	1.2570[a]	0.3531[a]	1.1475[a]	2.3447[a]	4.5020[a]
FOPCT												
β	2.7074[a]	3.8462[a]	2.1136[a]	2.0205[a]	3.1634[a]	4.4577[a]	1.8411[a]	2.6174[a]	3.2666[a]	4.6263[a]	2.0534[a]	3.3944[a]
SE	0.1368	0.2568	0.3237	0.4021	0.14717	0.2738	0.2120	0.3828	0.1289	0.2598	0.2167	0.2461
AME%	0.7529[a]	1.3585[a]	0.6647[a]	0.8191[a]	0.7104[a]	1.6686[a]	1.1277[a]	1.0678[a]	0.3267[a]	1.8116[a]	1.4466[a]	3.1499 [a]
FDIC												
β	2.8677[a]	3.9195[a]	1.9182[a]	0.1997	2.4352[a]	3.0064[a]	2.9880[a]	1.3465[a]	1.4718[a]	1.8555[a]	2.0219[a]	0.3370
SE	0.1399	0.2334	0.3215	0.2826	0.1502	0.2303	0.3095	0.3201	0.1426	0.2292	0.2945	0.2151
AME%	0.7975[a]	1.3844[a]	0.6032[a]	0.0809	0.5469[a]	1.1254[a]	1.8302[a]	0.5493[a]	0.1472[a]	0.7266[a]	1.4244[a]	0.3127
FED												
β	2.8925[a]	3.8668[a]	1.9393[a]	0.4448	2.4565[a]	3.2687[a]	2.7800[a]	1.1506[a]	1.4033[a]	2.1849[a]	1.7908[a]	0.3549
SE	0.1853	0.3366	0.4273	0.3625	0.1925	0.3124	0.3721	0.7462	0.1974	0.3092	0.3535	0.2743
AME%	0.8044[a]	1.3658[a]	0.6098[a]	0.1803	0.5517[a]	1.2236[a]	1.7028[a]	0.4694[a]	0.1403[a]	0.8556[a]	1.2616[a]	0.3294
Panel B: Goodness of Fit Measures												
Wald Chi2	1923[a]	140[a]	364[a]	551[a]	1308[a]	655[a]	1025[a]	177[a]	1560[a]	617[a]	671[a]	421[a]
Log Likelihood	-3230	-952	-596	-392	-4606	-1064	-1167	-843	-4683	-1101	-1273	-803
R2	0.7722	0.7901	0.7872	0.7678	0.5131	0.6240	0.6088	0.4522	0. 2998	0.5564	0.5107	0.5532
No. of "0"	257,801	62,329	45,696	22,627	239,877	57,999	40,643	20,122	223,809	54,301	36,202	18,030
No. of "1"	1,546	512	284	175	1,337	403	321	230	1,040	308	285	194
Panel C: Model Performance												
			All Banks			Small Banks			Medium Banks		Large Banks	
AUROC-W				0.9805			0.9767		0.9864			0.9709
AUROC-H				0.9785			0.9077		0.9212			0.9869

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). Panel A presents multivariate panel logistic regression results with control variables for 1-year (columns 2 to 5), 2-years (columns 6 to 9), and 3-years (columns 10 to 13) lagged periods across different size categories. The sampling period runs between 1985-2016. I consider banks corresponding to the bottom 25 percentile of total assets as small banks, those in the top 25 percentile as large banks, and the rest medium banks. If a bank fails in year t, the bank's failure indicator is '1' in that year t and '0' otherwise. A positive coefficient (β) suggests a positive relationship with failure likelihood and vice-versa. SE is standard error of respective coefficients and AME is Average Marginal Effects in percentage. Panel B reports the chi-square, the likelihood ratio and the coefficient of determination (McKelvey and Zavoina's R2) to measure the model's goodness of fit. No. of "1" counts the number of failures in my sample, while No. of "0" counts the number of "non-failure" observations. Panel C shows the accuracy of models' performance measured by area under the ROC curve. AUROC-W represents within sample and AUROC-H represents hold-out sample area under ROC curves.

performance. Although few studies (e.g., Betz et al., 2014; Poghosyan and Čihak, 2011) in the literature of bank failure have reported the AUROC, from a policy perspective and for the empirical tests in this paper this metric is fundamental for comparing performance and providing a validation of the models.

Following the approach of Gupta et al., (2018), I report area under ROC (AUROC) curves for respective models to evaluate the within-sample and out-of-sample classification performance of the models developed. For within-sample validation, I estimate the models using the entire sample data. To validate models' out-of-sample predictive performance, I first estimate the models using all available information up to the year 2011, and then predict the probability of bank failure for the year 2012. Subsequently, I incorporate 2012 in the estimation sample and predict the probability of bank failure for 2013 and so on, up to the year 2016. Finally, I use these predicted probabilities from the year 2012 until the year 2016 to estimate out-of-sample AUROC for respective multivariate regression models.

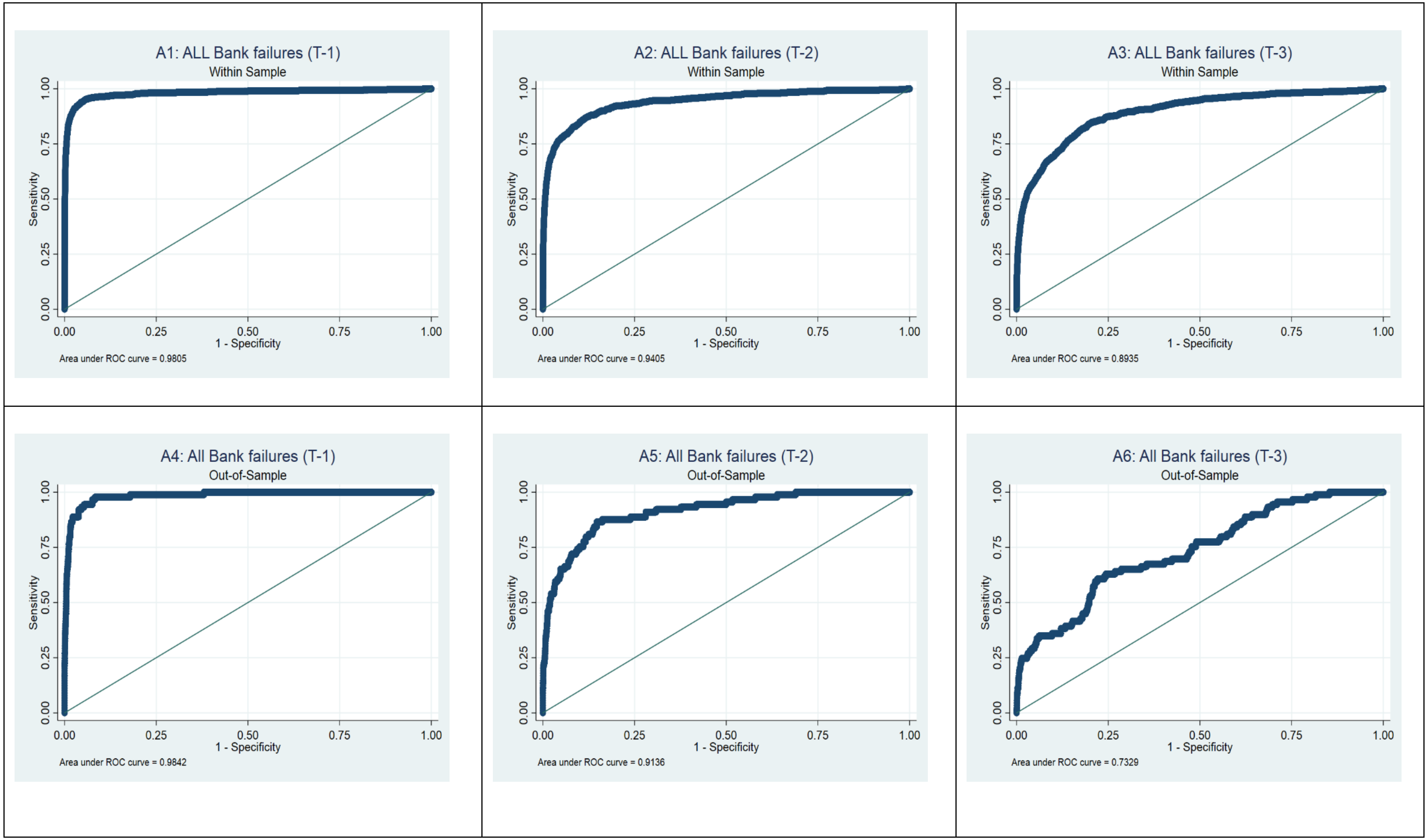
2.5.3 Multivariate Regression Results and Discussion

2.5.3.1 All Banks

The results in columns 1, 5 and 9 of Table 9 indicate that the coefficients on NCOTA, PD90TA, LLRTA, and OREOTA have a positive influence on the probability of failure, implying that a weaker asset quality is associated with a higher bank failure. This is consistent with Imbierowicz and Rauch (2014), who find that credit risk has a prominent role in the overall stability of a bank. The coefficient on NIETA is positively related to bank failure. This suggests that a high level of bank operating expenses increases the likelihood of failure. This is in line with the findings of DeYoung (1998) who shows that poor management reduces the efficiency of using resources, thereby increasing the probability of default. In contrast, the coefficient on TETA is negative, suggesting that a higher capital is associated with a lower probability of failure. This is intuitive as the capital serves as a main line of defence against bank failure (Berger and Bouwman, 2013). All of these results are supported by several studies within the theoretical literature (e.g., Bryant, 1980; Repullo, 2004).

Turning to the control variables, house price inflation shows significantly negative values for all three-time lagged periods. This implies that declining real estate prices increase the probability of bank failure. This result is similar to the findings of Berger et al. (2016) who report that house price inflation has a negative effect, mostly on the 2 years preceding the failure. In contrast, foreign ownership is positively related to bank failure, suggesting that banks are more likely to fail if they have a greater percentage of foreign ownership. This result is in line with the findings of Berger et al. (2000) who show that foreign banks are generally less efficient than domestic banks in the US. The banking crises (SL and GFC) and primary regulator (FED and FDIC) dummies have significant and positive values for all lagged periods. Overall, the baseline model is parsimonious and offers a good model that fits the data. This is illustrated by, for example, the McKelvey and Zavoina pseudo R-squared, which is 77%. This value outperforms similar models in the early warning system literature (e.g., Cole and White, 2012; Poghosyan and Čihak, 2011). Additionally, the results of area under ROC (AUROC) curves of multivariate model for all banks, as shown in Figure 2, exhibit that my models are excellent (around or above 90%) in classifying within-sample bank failures across all lagged time periods. However, AUROC values of the hold-out sample vary across different forecast horizons. The lowest estimate is 73% for the 3 years prior to the forecasting horizon, which is considered to be acceptable, while the 1- and 2-year forecast horizons are above 91%, suggesting excellent classification performance of my multivariate models.

Figure 2: Table of Area under ROC curves for All Banks



Notes: This table reports area under ROC curves for respective multivariate regression models developed for all banks.

2.5.3.2 Small Banks

Table 10 (columns 2, 6 and 10) reports the results of the main variables of multivariate regression models for small banks. NCOTA, PD90TA, LLRTA, OREOTA, and NIETA are identical to the multivariate regression models for all banks, are statistically significant, and have signs consistent with the discussion in Section 2.2.4.2. The other two variables are total deposits to total assets ratio (TDTA) as a measure of funding, and total interest expenses to total liabilities (TIETLB) as a proxy of liquidity. The coefficient on TDTA is significantly positive, suggesting that higher deposits are associated with a higher probability of failure. This is consistent with Acharya and Naqvi (2012) who theoretically show that banks with excessive deposits are more likely to take risks by mitigating the lending standards to increase loans, because managers compensate based on the volume of loans. It is also consistent with a recent empirical paper by Khan et al. (2017) who find that banks holding higher deposits generally take more risks. This risk-taking can be attributed to the moral hazard of deposit insurance (Keeley, 1990). Moreover, I find the coefficient of TIETLB is significant and positively related to bank failure, implying that a higher share of interest expenses to total liabilities is associated with a higher probability of failure. This is in line with the findings of Betz et al. (2014) who show that the share of interest expenses to total liabilities has a positive effect on bank failure. These results are important to the literature in two ways. First, the low funding risk, as proxied by higher deposit ratios, has a more adverse effect on small banks and participates heavily in their failures. Second, the ratio of total interest expenses to total liabilities (TIETLB) contributes to explaining the relationship between liquidity risk and bank failure, specifically in small banks.

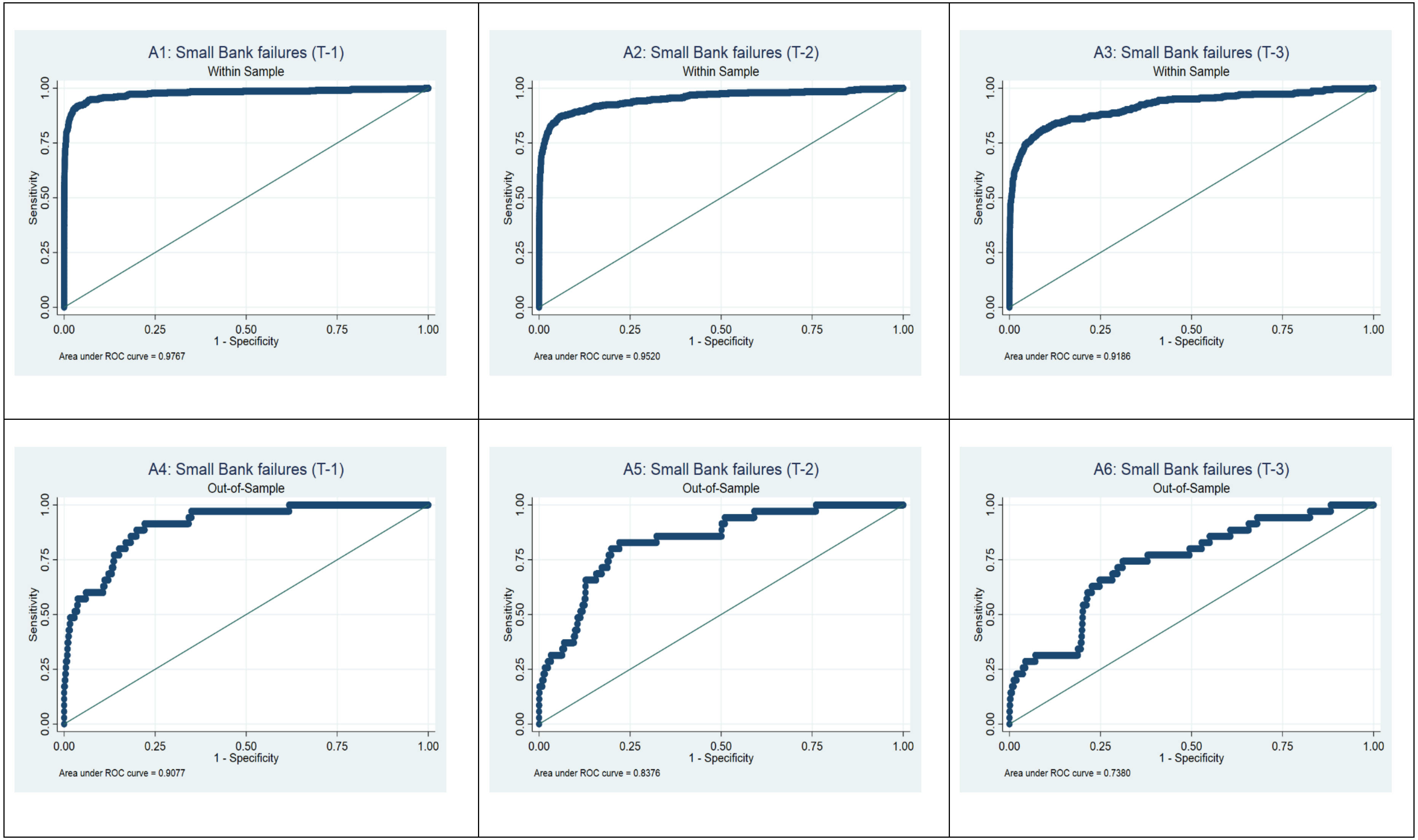
Next, I complement the models estimated in Table 8 with control variables (see columns 2, 6 and 10 in Table 11). I find that all variables are statistically significant, and the sign of respective coefficients remains the same as the multivariate models estimated without control variables. An exception is NCOTA, which is insignificant for the 3-years lagged estimate. Furthermore, all control variables are statistically significant, and have a sign consistent with the control variables of the multivariate regression model for all banks.

The within-sample area under ROC (AUROC) curves of multivariate models developed across small banks are above 91%, suggesting excellent classification performance of my multivariate models for small banks across all time periods. The AUROC for out-of-sample for the 1- and 2-year horizons are excellent (above 83%), while that for the 3-year horizon is acceptable with 73% (see Figure 3). These values and the shapes of ROC curves are relatively similar to the values and shapes of the ROC curves of all banks. This might indicate that small banks dominate the sample. Therefore, the effects of medium and large banks could be disregarded, thereby leading to a heterogeneous sampling and biased estimates. This clearly supports the necessity of distinction between different size classes when analysing bank failures.

2.5.3.3 Medium Banks

Table 10 (columns 3, 7 and 11) illustrates that five out of six main variables (NCOTA, PD90TA, LLRTA, OREOTA, and TETA) of the multivariate regression model for medium banks remain the same as the multivariate models estimated for all and small banks. They are statistically significant and have the expected sign of respective coefficients across all lagged periods. The sixth main variable is net interest margin (NIM), which is also statistically significant and has a negative sign across the three lagged periods, suggesting that a larger amount of returns generated by investments reduces the probability of failure for medium banks. This is consistent with the hypothesis that banks dealing heavily with risky loans tend to have higher net interest margins (Angbazo, 1997).

Figure 3: Table of Area under ROC curves for Small Banks



Notes: This table reports area under ROC curves for respective multivariate regression models developed for small banks.

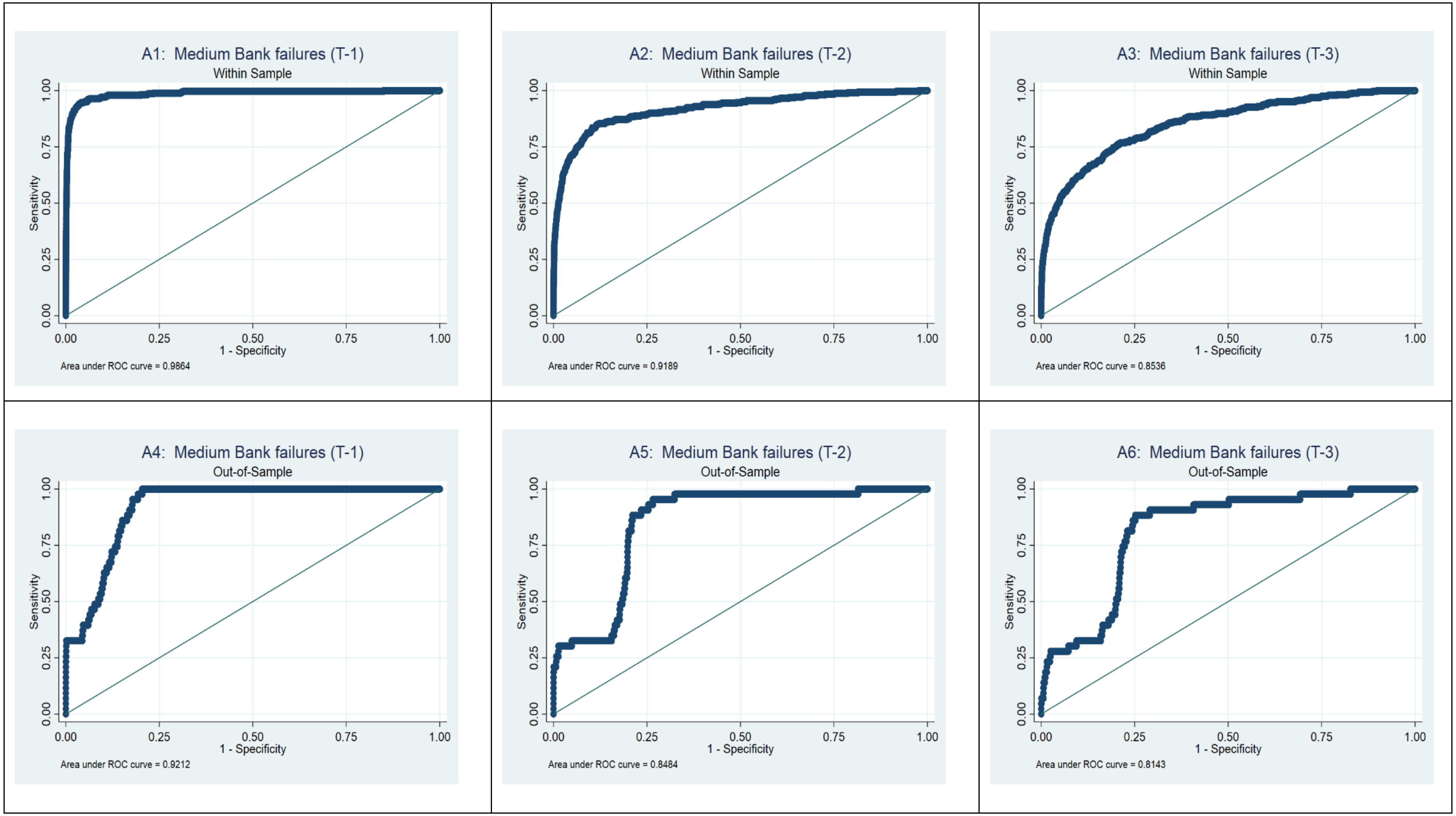
Table 11 reports the results after introducing control variables. All variables (main and control) are statistically significant and all coefficients hold the same sign previously reported except NCOTA, which is insignificant for 2-years and 3-years lagged estimates. Both within-sample and out-of-sample classification of all multivariate models across all time periods are above 81%, which is considered to be excellent (see Figure 4).

2.5.3.4 Large Banks

As reported in Table 10 (columns 4, 8 and 12), multivariate regression models for large banks contain the ratio of loan loss provisions to total loans (LLPTL) as one of the main variables that has not been reported for all, small, and medium banks. The coefficient on LLPTL is positive and statistically significant for 1-year and 2-years lagged estimates but becomes insignificant for the 3-years lagged estimate. This indicates that risky loan portfolios increase the probability of failure of large banks more than other banks. Similarly, Poghosyan and Čihak (2011) find that the deterioration of the loan portfolio enhances the probability of bank default. The rest of the main variables (PD90TA, LLRTA, TETA, and NIM) are statistically significant and have a sign consistent with the discussion in Section 2.4.2 across all three-time lagged periods.

In the presence of control variables, I find that three out of the five main variables are statistically significant and have the same sign as those of large banks' multivariate models estimated without control variables across the three-time lagged periods (see Table 11). However, of the other two variables, NIM is insignificant for the 1-year lagged period, and PD90TA is insignificant for 2-years and 3-years lagged estimates. The control variables are statistically significant, and their coefficients have expected signs, except primary regulators (FED and FDIC) are insignificant for the 1-year and 3-years lagged estimates.

Figure 4: Table of Area under ROC curves for Medium Banks



Notes: This table reports area under ROC curves for respective multivariate regression models developed for medium banks.

The within-sample and out-of-sample AUROC estimated for multivariate models for large banks are close to, or higher than, 0.80, implying superior classification performance across all time periods (see Figure 5). Yet the shapes of ROC curves of hold-out sample estimates are steps rather than concave, due to the scarcity of failures in out-of-sample validation[6].

2.6 Interaction between Bank Size and Bank Charter

To test the hypothesis that the impact of bank size on the probability of bank failure varies with bank charter, I add interaction between bank size and bank charter to the multivariate regression models reported in Table 9. Table 12 reports the results of multivariate regression models with interaction terms for bank size and bank charter. These results are presented with and without control variables, and for the three lagged periods. The size category "Small Banks" and bank charter "National Chartered Banks" are taken as the reference group, and thus main and interaction effects are reported for medium banks, large banks and state-chartered banks.

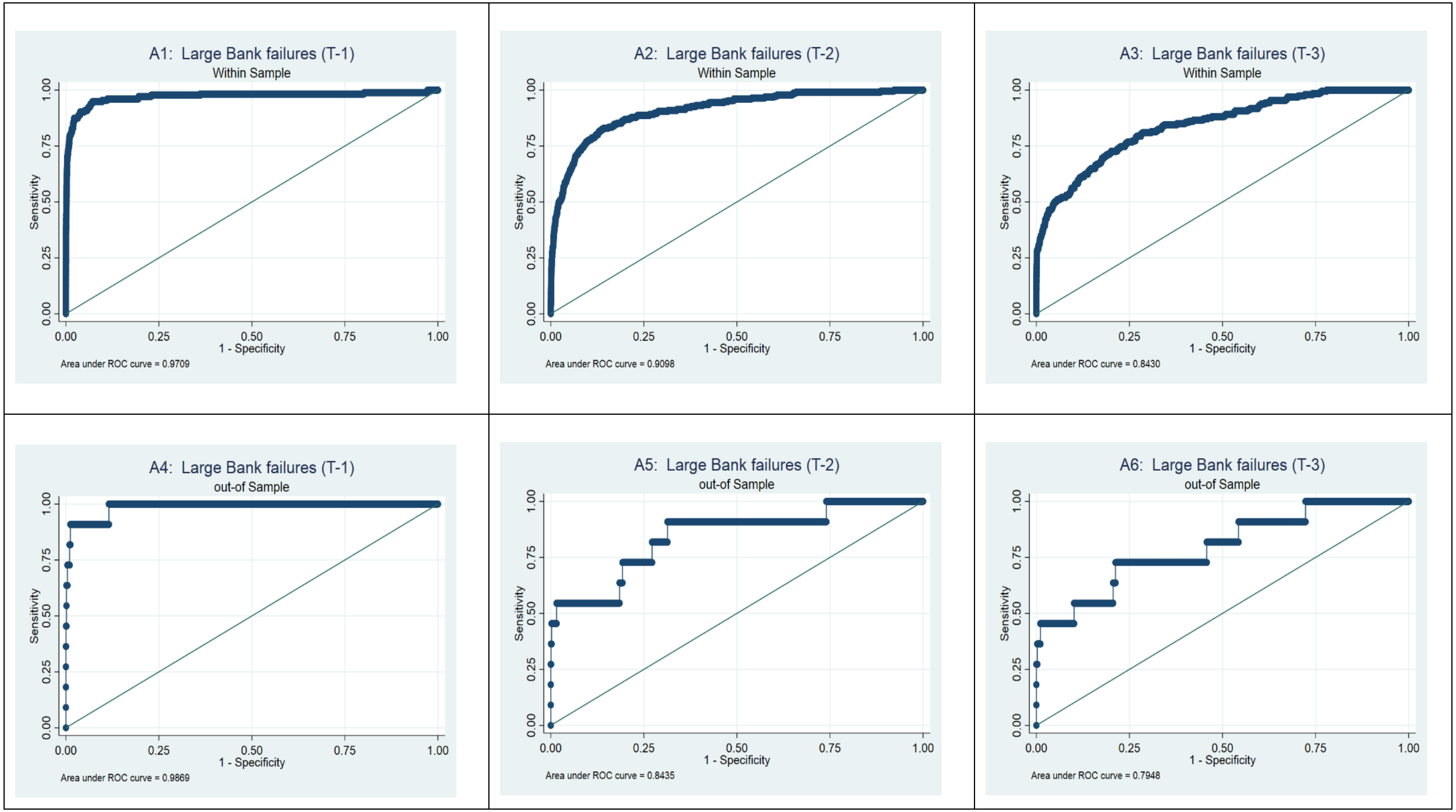
The notable result of interactions between bank size and bank charter is that all explanatory variables, as well as control variables, are statistically significant and have signs consistent with the discussion in section 2.5.2.1.[7] This shows the robustness and consistency of my explanatory variables.

The impact of medium sized banks (MB) is significantly negative across all estimates, but the main effect of large banks (LB) is only significantly negative for 2-years and 3-years lagged estimates. These results are robust to the inclusion of control variables. The sign and statistically significant differences between medium and large banks for the 1-year lagged

[6] One should be aware of this when analysing the performance of forecasting models for hold-out samples because it may mislead the estimates of AUROC (Gupta et al., 2018).

[7] Except NIETA, which is insignificantly negative for 2-years lagged estimate and positive for 3-years lagged time without control variables.

Figure 5: Table of Area under ROC curves for Large Banks



Notes: This table reports area under ROC curves for respective multivariate regression models developed for large banks.

period, which is the main concern of this paper, confirms my earlier results and clearly reinforces my hypothesis that the probability of bank failure varies with size categories. The effects of state-chartered banks are significantly negative for all estimates with and without control variables[8]. This is mostly consistent with Danisewicz et al. (2017), who show that the depositor preference law leads to less risk taking, and a lower probability of failure among state-chartered banks.[9]

Turning to the effects of bank size and bank charter, I observe a negative but insignificant relationship between medium sized banks and bank charter "MB×State Charter" for the 1-year lagged estimate. However, this relationship becomes positive and statistically significant for 2- and 3-years lagged estimates. For interaction terms between large sized banks and bank charter "LB×State Charter", I find relatively similar findings of "MB×State Charter". These results are robust to the presence of control variables.

Overall, the impact of bank size on probability of bank failure varies with bank charter, and it might be appropriate to consider this when predicting the failure of US banks.

2.7 Additional Robustness Check

According to Berger and Bouwman (2013), the effects of financial crises are likely to differ by crisis type. To test the reliability of my multivariate results, I examine bank failure during banking crises (the credit crunch and subprime lending crisis), market crises (the 1987 stock market crash, the 1998 Russian debt crisis and long-term capital management bailout, the dot.com bubble, and the September 11 terrorist attack (2000–2002)), and normal times (all non-crisis years) as three separate groups. I rerun all multivariate regressions separately for

[8] An exception is the coefficient of the 1-year lagged time without control variables, which is significantly positive.
[9] State chartered banks were subject to depositor preference law (DPL), which changes the priority structure of debt claims, from 1909, whereas nationally chartered banks were subject to DPL from 1993 onwards.

Table 12: Multivariate Regression Models with interaction between Bank Size and Bank Charted

Panel A: Regression Results																		
	Without Control Variables									With Control Variables								
	1 Year Lag			2 Years Lag			3 Years Lag			1 Year Lag			2 Years Lag			3 Years Lag		
Variable	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
NCOTA	38.998[a]	2.7118	14.73[a]	35.666[a]	3.7124	5.99[a]	29.939[a]	4.1816	2.66[a]	27.606[a]	3.8695	6.50[a]	31.308[a]	4.5665	6.74[a]	33.890[a]	6.4200	2.55[a]
PD90TA	30.512[a]	3.6420	11.52[a]	67.238[a]	4.7684	11.30[a]	66.400[a]	4.8608	5.90[a]	41.919[a]	5.3508	9.87[a]	70.985[a]	5.8977	15.27[a]	100.822[a]	7.4880	7.58[a]
LLRTA	40.001[a]	3.9157	15.11[a]	91.097[a]	5.9487	15.31[a]	40.211[a]	5.9427	3.58[a]	37.022[a]	5.5305	8.71[a]	60.303[a]	6.6313	12.97[a]	30.747[a]	8.7848	2.31[a]
TETA	-75.874[a]	2.2259	-28.65[a]	-40.615[a]	1.8965	-6.83[a]	-12.508[a]	1.2240	-1.11[a]	-83.817[a]	2.9414	-19.73[a]	-46.240[a]	2.2630	-9.95[a]	-26.354[a]	2.0396	-1.98[a]
OREOTA	25.653[a]	1.9475	9.69[a]	58.195[a]	3.1593	9.78[a]	48.086[a]	2.8721	4.28[a]	16.834[a]	2.5731	3.96[a]	37.812[a]	3.3371	8.13[a]	42.443[a]	4.4424	3.19[a]
NIETA	3.459[c]	1.9709	1.31[c]	-0.480	2.9576	-0.08	2.792	2.8957	0.25	15.257[a]	2.6780	3.59[a]	7.812[a]	3.0852	1.68[a]	15.721[a]	4.0011	1.18[a]
MB	-0.276[b]	0.1330	-0.11[a]	-1.272[a]	0.1888	-0.15[a]	-1.264[a]	0.1686	-0.07[a]	-0.218	0.1692	-0.09[a]	-0.751[a]	0.1895	-0.09[a]	-1.395[a]	0.2405	-0.05[a]
LB	0.057	0.1457	-0.03	-1.108[a]	0.2077	-0.11[a]	-1.110[a]	0.1869	-0.05[a]	0.511[a]	0.1843	-0.02	-0.107	0.2002	-0.03	-1.022[a]	0.2650	-0.03[a]
SC	0.316[b]	0.1258	0.09[a]	-0.953[a]	0.1836	-0.08[a]	-1.487[a]	0.1684	-0.08[a]	-6.359[a]	0.8218	-10.75[a]	-7.894[a]	0.8515	-18.5[a]	-9.594[a]	1.1271	-16.2[a]
MB × SC	-0.040	0.1602		0.845[a]	0.2230		1.099[a]	0.2052		-0.255	0.2145		0.583[a]	0.2301		1.353[a]	0.2894	
LB × SC	-0.194	0.1789		0.947[a]	0.2512		1.259[a]	0.2315		-1.049[a]	0.2402		-0.012	0.2497		1.233[a]	0.3239	
GHPI										-11.935[a]	0.7770	-2.81[a]	-11.666[a]	0.7378	-2.51[a]	-17.606[a]	1.0134	-1.32[a]
FOPCT										2.673[a]	0.1496	0.63[a]	3.074[a]	0.1427	0.66[a]	3.449[a]	0.1621	0.26[a]
SL										2.595[a]	0.1441	0.61[a]	3.319[a]	0.1440	0.71[a]	2.991[a]	0.1619	0.22[a]
GFC										1.790[a]	0.1390	0.42[a]	2.576[a]	0.1403	0.55[a]	3.764[a]	0.1542	0.28[a]
FED										9.141[a]	0.8382	2.15[a]	9.295[a]	0.8519	2.00[a]	9.138[a]	1.1092	0.69[a]
FDIC										9.077[a]	0.8261	2.14[a]	9.222[a]	0.8411	1.98[a]	9.191[a]	1.0954	0.69[a]
Panel B: Goodness of Fit Measures																		
Wald Chi2		2616[a]			1692[a]			1540[a]			1586[a]			1387[a]			1187[a]	
Log Likelihood		-4689			-6665			-7137			-2941			-4234			-4408	
R^2		0.7599			0.299			0.0889			0.8093			0.6433			0.4554	

No. of “0”	276,973	258,269	240,317	257,800	239,877	223,809
No. of “1”	1,687	1,554	1,342	1,546	1,337	1,040

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). Panel A presents multivariate panel logistic regression results with interaction terms (between bank size and the bank charted) for 1-year, 2-years, and 3-years lagged periods. Size category “Small Banks” and bank charted “National Charted” are considered reference groups, and thus main and interaction effects are reported for medium banks (MB), large banks (LB) and State charted banks (SC). Results are reported separately for multivariate models without control variables (columns 2 to 10) and with control variables (columns 11 to 19). The sampling period runs between 1985-2016. I consider banks corresponding to the bottom 25 percentile of total assets as small banks, those in the top 25 percentile as large banks, and the rest medium banks. If a bank fails in year t, the bank’s failure indicator is ‘1’ in that year t and ‘0’ otherwise. A positive coefficient (β) suggests a positive relationship with failure likelihood and vice-versa. SE is standard error of respective coefficients and AME is Average Marginal Effects in percentage. Panel B reports the chi-square, the likelihood ratio and the coefficient of determination (McKelvey and Zavoina's R2) to measure the model’s goodness of fit. No. of “1” counts the number of failures in my sample, while No. of “0” counts the number of “non-failure” observations.

all, small, medium, and large banks with the same control variables used in the main multivariate regressions (see Section 2.3.4.3) with the exception of the credit crunch and subprime lending crisis, to avoid collinearity. Table 13 reports the findings for all, small, medium, and large banks across various types of financial crises and normal times. For all banks, the results are the same at all times except that OREOTA becomes insignificant during the market crises. For small banks, all variables are significant with expected signs and have AMEs above 5% during banking crises. However, some variables (NCOTA, OREOTA, and TIETLB) during market crises and PD90TA during normal times become insignificant. For medium and large banks, the main result is that the ratio of total equity to total assets (TETA) remains significant with high AMEs at all times, primarily during banking crises. This is in line with Berger and Bouwman (2013) who find that higher capital improves the probability of surviving for medium and large banks during banking crises. Other findings among medium and large banks are relatively similar to the main results.

2.8 Conclusion

The threat of bank failure affects not only the stability of the financial system but also the economy as a whole. For example, the failure of small banks in the early 1990s and the failure of large banks during the recent financial crisis are associated with considerable costs, high unemployment, and low economic performance. Thus, a comprehensive analysis of such failures is central to policy-makers, regulators, bank managers, and academics. Although the literature has clarified the relevant drivers of bank failures, almost none of existing studies have empirically analysed the factors and the extent to which they affect the probability of bank failure across size classes. In this paper, I contribute to the extant literature by recognising the differences in US bank failures engendered by size heterogeneity. I develop separate early-warning models for small, medium, and large banks, and report any differences in comparison to all bank failure prediction models, irrespective of bank size. I also compare

Table 13: Financial Crises and Normal Times

Panel A: Regression Results																		
	All Banks									**Small Banks**								
	Banking Crises			Market Crises			Normal Times			Banking Crises			Market Crises			Normal Times		
Variable	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
NCOTA	13.07[a]	4.58	9.28[a]	24.99[b]	11.54	3.76[b]	28.22[a]	6.53	3.79[a]	20.71[b]	9.77	11.84[b]	23.68	17.48	6.51	26.43[a]	10.38	5.29[a]
PD90TA	17.34[a]	6.37	12.30[a]	28.49[b]	13.22	4.28[b]	39.96[a]	9.18	5.36[a]	33.32[a]	11.88	19.05[a]	45.38[b]	19.36	12.47[b]	10.52	14.20	2.11
LLRTA	48.11[a]	6.21	34.13[a]	69.45[a]	15.43	10.44[a]	54.85[a]	9.57	7.36[a]	55.07[a]	13.90	31.48[a]	40.08[c]	22.40	11.01[c]	89.77[a]	13.72	17.97[a]
TETA	-70.40[a]	3.11	-49.95[a]	-51.27[a]	7.66	-7.71[a]	-98.57[a]	5.19	-13.22[a]									
OREOTA	12.16[a]	2.89	8.63[a]	2.39	8.46	0.36	19.17[a]	4.06	2.57[a]	24.02[a]	5.91	13.73[a]	-0.80	13.16	-0.22	25.25[a]	5.68	5.06[a]
NIETA	7.84[a]	3.18	5.56[a]	36.45[a]	6.43	5.48[a]	15.91[a]	4.04	2.13[a]	33.84[a]	6.53	19.34[a]	45.72[a]	9.82	12.56[a]	41.70[a]	6.53	8.35[a]
TIETLB										47.45[a]	13.74	27.12[a]	17.64	21.22	4.85	28.48[a]	7.12	5.70[a]
TDTA										29.37[a]	4.87	16.79[a]	37.03[a]	9.31	10.18[a]	39.68[a]	4.75	7.94[a]
Panel B: Goodness of Fit Measures																		
Wald Chi2			2054[a]			518[a]			700[a]			442[a]			209[a]			498[a]
Log Likelihood			-1685			-327			-907			-344			-140			-332
R^2			0.7776			0.8473			0.797			0.8458			0.8775			0.7709
No. of "0"			57,668			45,976			154,156			13,926			10,808			37,595
No. of "1"			908			218			420			269			115			128

Table 13: Financial Crises and Normal Times (*continued*)

Panel C: Regression Results																		
	Medium Banks									**Large Banks**								
	Banking Crises			Market Crises			Normal Times			Banking Crises			Market Crises			Normal Times		
Variable	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*	*β*	*SE*	*AME%*
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
NCOTA	9.96	13.12	5.17	-47.14	34.12	-9.43	33.05[a]	13.44	5.69[a]									
PD90TA	25.50	20.61	13.22	-10.10	26.88	-2.02	14.99	26.78	2.58	79.96[a]	26.04	96.53[a]	-960.30[b]	493.9	-9.78[b]	75.38	67.98	7.47
LLRTA	104.35[a]	20.49	54.12[a]	120.19[b]	51.23	24.05 [b]	56.08[a]	19.52	9.66[a]	28.76	18.75	34.73	430.60	291.87	4.39	147.42[c]	80.04	14.61[c]
TETA	-63.56[a]	9.46	-32.96[a]	-171.12[a]	48.29	-34.23 [a]	-102.02[a]	10.92	-17.58[a]	-59.96[a]	6.56	-72.39[a]	-625.78[b]	295.70	-6.37[b]	-123.09[b]	59.14	-12.20[b]
OREOTA	18.16[b]	8.43	9.42[b]	17.27	19.54	3.45	20.10[a]	8.19	3.46[a]									
NIM	-78.38[a]	17.85	-40.65[a]	-17.44	25.22	-3.49	-41.51[b]	20.30	-7.15[b]	-24.01[c]	14.92	-28.98[c]	543.82[c]	294.48	5.54[c]	-69.24	47.17	-6.86
LLPTL										28.52[a]	6.32	34.43[a]	41.54	81.17	0.42	-12.10	20.44	-1.20
Panel D: Goodness of Fit Measures																		
Wald Chi2			92[a]			17[b]			207[a]			294[a]			5			20[b]
Log Likelihood			-241			-47			-174			-261			-13			-54
R^2			0.6818			0.9341			0.8411			0.6932			0.9213			0.8730
No. of "0"			10,191			6,847			28,656			5,054			3,467			14,103
No. of "1"			98			21			95			121			5			35

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level (two-sided test). Panels A and C present the results of checks to establish the robustness of my results. The crises include banking crises (the credit crunch and the subprime lending crisis), market crises (the stock market crash; the Russian debt crisis; the dot.com bubble and September 11), and normal times. The sampling period runs between 1985-2016. I consider banks corresponding to the bottom 25 percentile of total assets as small banks, those in the top 25 percentile as large banks, and the rest medium banks. If a bank fails in year t, the bank's failure indicator is '1' in that year t and '0' otherwise. A positive coefficient (β) suggests a positive relationship with failure likelihood and vice-versa. SE is standard error of respective coefficients and AME is Average Marginal Effects in percentage. Panels B and D report the chi-square, the likelihood ratio and the coefficient of determination (McKelvey and Zavoina's R2) to measure the model's goodness of fit. No. of "1" counts the number of failures in my sample, while No. of "0" counts the number of "non-failure" observations.

the consistency (statistical significance and average marginal effects) of covariates when analysing bank failures across size categories. Furthermore, I contribute to the existing body of literature by using univariate regression analysis as a variable selection technique to examine the relative importance of an exhaustive list of 61 accounting-based variables that have been employed as candidate predictors within the previous bank failure literature. I also propose an atheoretical econometric method suggested by Gupta et al. (2018) on multivariate model building strategy based on variables' AMEs and their inter-temporal discrimination ability.

The main results show that factors affecting bank failure and the magnitudes of mutually significant factors (AMEs) vary across small, medium, and large banks. Further interesting results of this paper are as follows. First, credit risk has a significant impact on bank failure probability across size classes and for the three-time lagged periods, implying that weak assets quality, represented by net charge off, past due 90+ days, loan loss reserves, and other real estate owned, increases the risk of failure. Second, small banks are most likely to fail if they have high deposit ratios, are more cost inefficient, and have a high liquidity risk, while medium and large banks with poor capital and low net interest margins are more likely to fail.

My results are robust to up-to three years of lagged regression estimates, the inclusion of various control variables such as regulatory effects and house price inflation, interaction between bank size and bank charter, and macroeconomic crisis periods and normal times. Moreover, the AUROC of all multivariate models developed across bank size classes for out-of-sample have an excellent performance for different forecast horizons.

My study sheds light on the importance of bank size in explaining bank failure. It provides a broad implication which may assist policy-makers, regulators, and researchers in analysing all types of bank risk. They should put strong emphasis on the variances among bank size categories.

3. COHORT RISK ANALYSIS OF BANKS

3.1 Introduction

Over the last few decades, the United States (U.S.) banking industry has undergone a substantial change that has featured an increase in the number of bank mergers and acquisitions. This has led to the opening of thousands of new banks, reorganisations of multibank holding companies (MBHCs), and a large number of bank failures. This transformation has been driven by several forces, including but not limited to: deregulation of deposit accounts, implementation of capital requirements, financial innovations in off-balance sheet items, and technology.[10] All these forces have significantly contributed towards shrinking the role of banks in reducing transaction costs and asymmetric information; and boosting the function of risk management by transferring risk, and dealing with financial instruments and markets (Allen and Santomero, 1997). In fact, risk management has become the most important activity in the banking industry and has permanently changed the business over recent decades (Bülbül et al., 2019). Typically, banks are dealing in financial assets and services, implying that they are in risk business and the risk management role can exaggerate the effects on the overall risk either directly or indirectly over time. It clearly appears that banking organisations, particularly large banks, have intensified their risk exposure by substituting from cash and securities holdings into loans (specially commercial real estate loans), and increasing their reliance on financial innovations such as derivatives and securitisations (Allen and Santomero, 1997; Berger et al., 1995; Berger and Bouwman, 2009).

The academic literature has significantly analysed most aspects of bank risk. Several theory papers have explained the major risks in banks, particularly liquidity risk and credit risk

[10] See Berger et al. (1995) for a comprehensive review of the transformation in the U.S. Banking Industry.

(e.g., Boyd and Prescott, 1986; Bryant, 1980; Diamond and Dybvig, 1983; Qi, 1994). In addition, a tremendous number of empirical studies have dealt with the determinants of these risks related to bank-specific, market, and macroeconomic factors (e.g., Calem and Rob, 1999; Delis and Staikouras, 2011; Demirgüç-Kunt and Huizinga, 2010; Demsetz and Strahan, 1997), with special emphasis on bank failures or default risk (e.g., Berger et al., 2016; DeYoung and Torna, 2013; Liu and Ngo, 2014). Nevertheless, the systematic trend in bank risk and the determinants of this trend have not received much attention. I am aware of only two studies, Demirgüç-Kunt and Huizinga (2010) and Stiroh (2004), who study the trends in non-interest income and their effects on bank risk. While a considerable amount of research has documented a systematic increase in idiosyncratic risk in publicly listed firms. (e.g., Ang et al., 2006; Brown and Kapadia, 2007; Campbell et al., 2001; Fama and French, 2004; Irvine and Pontiff, 2009; Pástor and Pietro, 2003),[11] to the best of my knowledge, almost no empirical study has systematically analysed this subject broadly across the banking sector. Exceptions can be Delis et al. (2014) and Berger and Bouwman (2009). Delis et al. (2014) provide a new bank risk indicator, using the variability of the profit function, and show that the average bank's risk has increased from 1985 to 2007. Berger and Bouwman (2009) develop comprehensive measures of bank liquidity creation and report that it has increased over time. However, they do not focus on the systematic trend in bank risk, nor do they examine the reasons behind this trend as I do in this study. This is perhaps surprising because banks play crucial roles in the economy by providing financial funds to all industries and facilitating the transfer of risk. Consequently, any shocks to the banking system can have severe effects on the majority of firms and industries that can lead to adverse crisis (e.g., global financial crisis in 2008). The purpose of this study is to address the gap in the banking literature and focus more on the trend in bank risk and its determinants.

[11] The number of listed banks is extremely small compared to other listed firms. In addition, most studies exclude financial firms.

My primary contributions to the literature are threefold. First, I analyse the trend in two major sources of bank risk: liquidity risk and credit risk over time. Secondly, I provide an explanation for this trend. And finally, I examine the trends of several bank-specific characteristics and their relationships to explain trends in these risks.

In the first step for my study I assess bank risk using two main measures. First, I consider liquidity risk measure introduced by Berger and Bouwman (2009) as the ratio of liquidity creation to gross total assets or GTA (total assets plus allowance for loan and lease losses and the allocated transfer risk reserve).[12] Second, credit risk measure is calculated as a bank's risk-weighted assets and off-balance sheet activities divided by GTA.[13] To identify the systematic trend in bank risks, I calculate the annual averages of liquidity risk and credit risk using annual data for virtually all U.S. banks over the period 1980-2017. On average, liquidity risk and credit risk have been rising for all banks over this sampling period. Figures 1 and 2 graphically display the same information as is presented in Table 1 and can be interpreted as the time trend of liquidity and credit risk for all U.S. banks. They clearly show that the average of liquidity risk has increased steadily from 0.93% in 1980 to 37% in 2017; and the average of credit risk increased from 57% in 1992 to a peak of 71 % in 2008, dropped sharply between 2008 and 2012, then accelerated strongly from about 2012 onward.

I hypothesise that this increasing risk is related to an incredible number of new banks that joined the industry after 1980.[14] This growth of new banks can be attributed to the evolution of regulatory changes, and technical and financial innovations. Generally, these banks adopt risker business strategies to grow faster and compete aggressively against their established counterparts. In addition, the financial crises, specifically banking crises, have contributed to a

[12] Table 3 illustrates Berger and Bouwman's (2009) three-step procedure to develop the bank liquidity creation measure.
[13] As a robustness check, I use two alternative risk measures: first, liquidity risk measure as developed by Imbierowicz and Rauch (2014); second, Z-score as a measure of credit risk. A detailed discussion of the measures and the results of their analyses are provided in Section 6.6 of the paper.
[14] More than 6500 banks have entered the market from 1980 to 2017.

situation whereby these banks have to take more risk in order to offset the losses. My general strategy to test the hypothesis is to split the data by bank age into two subsamples: young banks subsample and old "established" banks.[15] The young subsample contains all banks that were started from 1980 onwards and are separated into three ten-year groups: cohort of banks started between 1980 and 1989, cohort of banks started between 1990 and 1999, and cohort of banks started between 2000 and 2009. The old "established" banks consist of all banks that started operations before 1980 and are considered as a benchmark group for assessing the risk of young banks. Next, I compute cross-sectional averages of risk measures, growth, and profitability on a cohort–year basis. Interestingly, I find that banks in each cohort grow faster than those in preceding cohorts but are less profitable. More importantly, I show that there is generally no significant trend in bank risk after accounting for successive cohorts of young banks.[16] In addition, risk differences across successive cohorts, which I refer to as the cohort risk phenomenon, seem to persist.

To explain the cohort risk phenomenon, I focus on banks', particularly young banks' business strategies which have contributed to their fast growth over recent decades. Specifically, I consider internal factors that have been adopted heavily by these banks. These factors include brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income. I derive these factors from an extensive prior literature (e.g., Berger and Bouwman, 2013; Cole and White, 2012; Deyoung and Roland, 2001; Stiroh, 2004). I find that successive cohorts of new or young banks are characterised by their increasing reliance on these factors. I then demonstrate that the cohort risk phenomenon decreases or is even eliminated once I control for these factors. In general, I conclude that the adoption of business strategy based on more brokered deposits, commercial real estate loans, off-balance sheet

[15] The average age of young banks is 26 years, while the average age of old banks is 83 years.
[16] For example, simply accounting for the decade in which banks started causes the trend in my measures of bank risk to change from a statistically significant to a statistically insignificant trend (see Table 4).

items, and non-interest income, along with less capital in each new cohort explains the cohort risk phenomenon.

Finally, I perform a variety of robustness checks on my main results. First, I split my sample into small, medium and large banks, and re-estimate my regressions separately for these three groups. Second, I control for time trend. Third, I exclude mergers and acquisitions and bank failures. Fourth, I control for two banking crises (savings and loan crisis and subprime mortgage crisis). Fifth, I limit my sample to “true” commercial banks. Sixth, I use two alternative measures of liquidity risk and credit risk. Seventh, I apply an alternative cohort measurement period of five years. In all cases, my main results remain qualitatively unchanged.

In summary, my results make three contributions to the banking literature. First, I systematically show that there is a positive trend in bank risk measured by liquidity risk and credit risk. Second, I propose a simple explanation for the increase in bank risk: banks that start or open later in the sample have persistently higher risk than banks that open earlier. Third, I document that the increasing riskiness of successive cohorts and the persistence in their risk differences are consistent with their continuing adoption of risky business strategies that rely predominantly on brokered deposits, commercial real estate loans, off-balance sheet items, and non-interest income.

The remainder of the paper is structured as follows. Section 3.2 provides an overview of the relevant literature and develops the empirical hypotheses. Section 3.3 presents a discussion on the dataset, sample, and covariates. Section 3.4 presents the results of the hypotheses tests. Section 3.5 addresses robustness issues, and Section 3.6 offers concluding remarks.

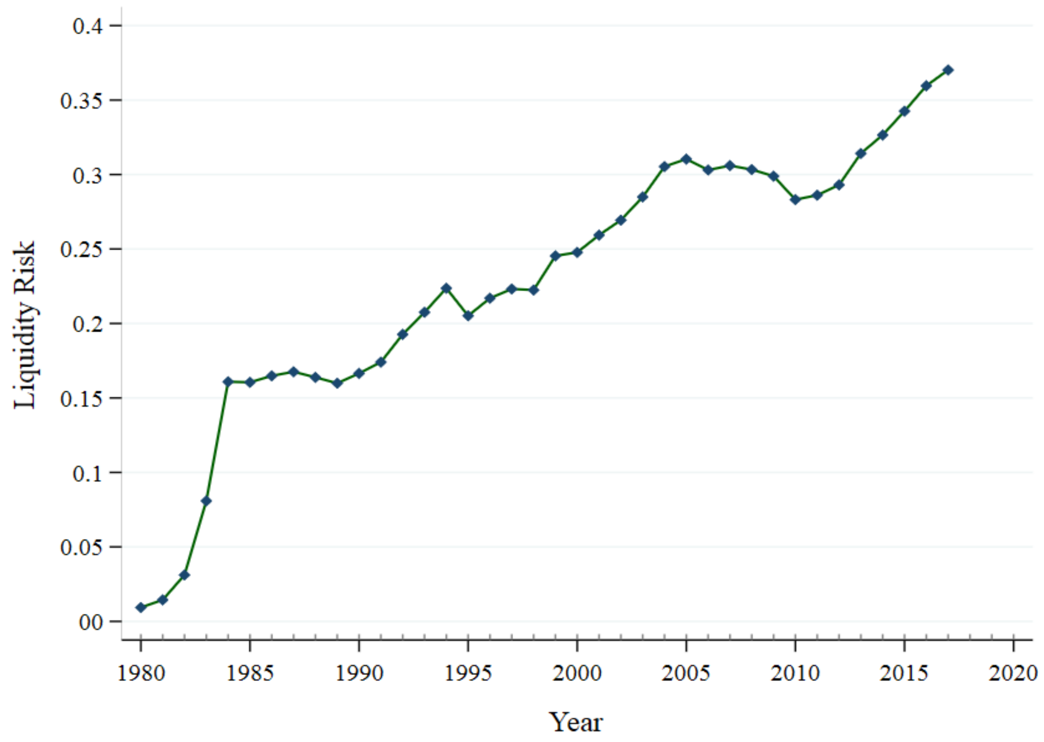


Fig. 1. Liquidity Risk

This figure illustrates the average liquidity risk for all banks on yearly basis.

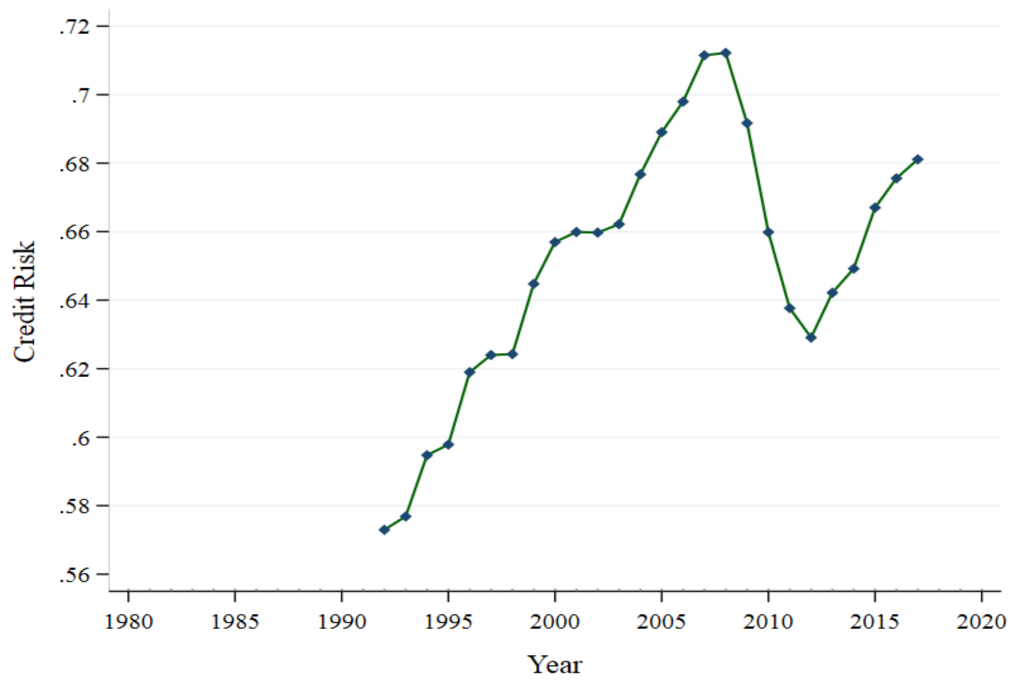


Fig. 2. Credit Risk

This figure illustrates the average credit risk for all banks on yearly basis.

3.2 Related Literature and Hypotheses Development

The literature on bank risk is extensive and diversified. I limit my review to the existing studies that help to develop my empirical hypotheses regarding the trend in bank risk, increasing risk levels for successive cohorts of new banks, and internal bank factors that explain the cohort risk phenomenon.

3.2.1 Trend in Bank Risk

Numerous studies have analysed trends in firm-specific risk across listed, financial and non-financial companies (e.g., Ang et al., 2006; Brown and Kapadia, 2007; Campbell et al., 2001; Irvine and Pontiff, 2009; Pástor and Pietro, 2003). In the most important paper, Campbell et al. (2001) provide empirical evidence that the average levels of idiosyncratic risk using stock return volatility have noticeably increased over the past 50-60 years. However, I am aware of only two studies that consider the trend of risk over time using data on unlisted banks, which represent the great majority of financial firms in the United States. First, Berger and Bouwman (2009) report that liquidity risk, measured by liquidity creation in real terms to GTA, increased between 1993 and 2003. Second, Delis et al. (2014) show that the average for risk weighted assets ratio for the U.S. banking industry increased over the period 1986 to 2007. Yet, they do not focus on the systematic trend in bank risk, nor do they examine the reasons for this trend, as I do in this paper. According to a recent empirical study by Imbierowicz and Rauch (2014) which is supported by several theoretical models (e.g., Acharya and Viswanathan, 2011; Diamond and Dybvig, 1983), liquidity risk and credit risk individually and jointly contribute to banks' probability of default. Hence, I expect the liquidity risk and credit risk are positively related, and increase over time. Based on the existing literature and my expectation, I hypothesise the following:

> **H1:** The US banks have exhibited increasing liquidity risk and credit risk over the past few decades.

3.2.2 Explanation for Increase in Bank Risk

3.2.2.1 Successive Cohorts of New Banks

The seminal work of Campbell et al. (2001) has been extended by several studies to investigate the determinants of firm-specific risk trends. These studies suggest that the increase in idiosyncratic volatility is attributable to the changes in firm characteristics, stock market conditions, and/or macroeconomic conditions (e.g., Ang et al., 2006; Brandt et al., 2010; Irvine and Pontiff, 2009). However, Fink et al. (2005) report that the rise in idiosyncratic risk is driven by firms listing earlier in their lives. Brown and Kapadia (2007) also show that increases in idiosyncratic risk are the result of new listings by young and risker firms.

In a related vein, DeYoung and Hasan (1998) examine the profit efficiency of new bank charters and report that de novo banks are less profit efficient than established banks due to costly excess branch capacity, reliance on expensive large deposits, and affiliation with a multibank holding company. They also find that the low profit efficiency across these banks associated with high and significant standard deviation, suggests that, young banks tend to be riskier than established banks. New banks initially experience low financial performance and may take years to become financially mature. This financial fragility can lead to the ultimate risk a bank faces which is the risk of failure, especially during difficult economic conditions.

Few studies have focused on the failure of new financial institutions in the United States. DeYoung (1999) estimates a series of split-population duration models and finds that compared to small established banks, new banks have low initial failure rates due to large initial capital cushions, then high failure rates as fast growth and losses erode capital, and finally normal failure rates as de novo banks reach financial maturity. DeYoung (2003) shows that new banks and established banks fail for similar operational reasons, but that new banks are more sensitive to adverse changes in local market conditions. In general, these studies conclude that new banks are riskier and more likely to fail than established banks. Thus, I expect that risk for banks that start up later, specifically post deregulation, should remain persistently higher than for banks that start up earlier. Pairing these results with my expectation leads me to the following hypothesis:

> **H2**: The increase in liquidity risk and/or credit risk becomes insignificant once successive cohorts of new banks are accounted for.

3.2.3 Reasons for the Cohort Risk Phenomenon

To examine the potential explanation for the increasing risks of successive cohorts of new banks, I concentrate on five bank-specific factors (brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income) that have been focused on and have indicated high risks in the banking literature in recent decades.

3.2.3.1 Brokered Deposits

My first bank-specific factor is the amount of brokered deposits borrowed by banks. A sizable number of banks, especially young banks, tend to have a higher proportion of their funding in the form of brokered deposits to allow them to grow fast and compete intensely with other financial institutions (Berger and Bouwman, 2013; Cole and White, 2012). Consequently, I expect successive cohorts of new banks to exhibit an excessive concentration on these deposits. Though, such funds are expensive and usually invested in high-risk activities to cover the high interest costs (Berger and Bouwman, 2013), Goldberg and Hudgins (2002) document that failing thrifts are more active in using brokered deposits than solvent thrifts.[17] Cole and White (2012) suggest that higher levels of brokered deposits have a positive effect on bank failure. More recently, Berger and Bouwman (2013) conclude that banks, especially small banks, are less likely to survive if they have more brokered deposits. Therefore, I hypothesise that the

[17] The Financial Institutions Reform, Recovery, and Enforcement Act of 1989; and the Federal Deposit Insurance Corporation (FDIC) Improvement Act restricted the acceptance of brokered deposits to well and adequately capitalised banks only.

increasing risks in successive cohorts of new banks are related to their greater reliance on brokered deposits.

H3.1a: Successive cohorts exhibit increasing brokered deposits.

H3.1b: The cohort risk effect becomes insignificant once brokered deposits factor is accounted for.

3.2.3.2 Commercial Real Estate Loans

According to Berger et al. (1995), commercial real estate lending is one of the riskiest and least diversifiable investments that banks make. They also show that the commercial real estate loans rose by more than 50 percent, from 6.3 percent in 1979 to 9.8 percent in 1994. This category of loans has demonstrated its toxic nature during the 07/08 crisis. Cole and White (2012) report that this type of commercial real estate loan has been one of the main determinants of bank failure during the recent banking crisis. Furthermore, Berger and Bouwman (2013) find that banks, specifically small banks, are more likely to fail if they have more commercial real estate loans. Thus, I conjecture that each new cohort relies more on commercial real estate loan than preceding cohorts, thereby increasing the risks for successive cohorts.

H3.2a: Successive cohorts exhibit increasing commercial real estate loans.

H3.2b: The cohort risk effect becomes insignificant once commercial real estate loan is accounted for.

3.2.3.3 Capital

Berger et al. (1995) show that the ratio of equity to gross total assets for all banking organisations in the U.S. market increased from 5.7 percent in 1979 to 7.7 percent in 1994. Hence, I expect this growth in capital to continue due to the major impact of capital on a bank's soundness. Several studies, such as Allen et al. (2011), Mehran and Thakor (2011), and Thakor (2012), suggest that a higher amount of capital reduces the overall bank risk. Moreover, most empirical studies conclude that the capital and bank risk are negatively related (e.g., Berger and Bouwman, 2013; Khan et al., 2017). In contrast, some theories argue that increasing bank capital could increase bank risk taking (e.g., Besanko and Kanatas, 1996; Koehn and Santomero, 1980). I therefore predict that bank capital plays a central role in the increasing risks for successive cohorts.

H3.3a: Successive cohorts banks exhibit increasing equity capital.

H3.3b: The cohort risk effect becomes insignificant once banks equity capital is accounted for.

3.2.3.4 Off-Balance Sheet Items

Off-balance sheet items are generally classified into lending products (e.g., loan commitments and letters of credit) and derivative products (e.g., futures, options and swaps) (Angbazo, 1997). Before 1990, banks were not required to hold capital against off-balance sheet activities. As a result, some banks shifted into off-balance sheet activities (Berger et al., 1995). (Berger et al., 1995) show that derivatives, for example, grew from 1.9 percent in 1990 to 3.9 percent in 1994, even after the implementation of Basel Accord risk-based capital standards.[18] I expect this transformation to continue and the concentration on off-balance sheet items to grow over time because banks can use these products not only to reduce monitoring costs and increase returns, but also to avoid capital adequacy requirements, 'regulatory arbitrage' and elude taxation (Diamond, 1984; Flannery, 1998; Papanikolaou and Wolff, 2014; Pennacchi, 1988). However, this growth can increase asset risk and enhance the subsidy from deposit insurance

[18] The Basel Accord risk-based capital standards were implemented in 1990 to correct the issues that related to the flat rate standards by requiring banks to hold different amounts of capital, depending on the perceived credit risk of different on- and off-balance sheet assets (Berger et al., 1995).

if the flat rate deposit insurance premium does not reflect the marginal risk associated with new investment opportunities (Angbazo, 1997), which is consistent with the moral hazard hypothesis that off-balance sheet items increase bank risk (e.g., Avery and Berger, 1991). Based on the above discussion, I test the following hypotheses:

H3.4a: Successive cohorts exhibit increasing off-balance sheet items.

H3.4b: The cohort risk effect becomes insignificant once the off-balance sheet items factor is accounted for.

3.2.3.5 Non-Interest Income

According to DeYoung and Torna (2013), the Gramm–Leach–Bliley Act of 1999, which allowed banks to deal with non-traditional activities, accelerated the changes in banks' business models and income mixes. For instance, the ratio of non-interest income to operating income for all U.S. banks peaked at 35% in 2013, up from 10% in 1983 (FDIC data). This transition from traditional interest income sources has been facilitated by innovations in information, communications and financial technologies, and supported banks to grow faster and confront the high competition from other financial institutions (Demirgüç-Kunt and Huizinga, 2010). Thus, I expect successive cohorts of new banks to strongly focus on these activities. However, revenues from these activities tend to be more volatile than traditional interest-based income (DeYoung and Torna, 2013). De Jonghe (2010) concludes that "the heterogeneity in extreme bank risk is attributed to differences in the scope of non-traditional banking activities: non-interest generating activities increase banks' tail beta". Stiroh (2004) argues that even a small exposure to non-interest income, particularly trading revenue, increases risk. Similarly, Demirgüç-Kunt and Huizinga (2010) find that the very risky banks are reliant on generating non-interest income. Recently, DeYoung and Torna (2013) report that the probability of distressed bank failure increased with noninterest income from asset-based non-traditional activities such as investment banking, insurance underwriting and venture capital. Based on the discussion above, I hypothesise the followings:

> **H3.5a**: Successive cohorts exhibit increasing non-interest income.
>
> **H3.5b**: The cohort risk effect becomes insignificant once non-interest income is accounted for.

3.2.3.6 All Five Bank-Specific Factors

The theoretical and empirical studies discussed above suggest that brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income are closely related to bank risk. Hence, I expect these factors jointly affect the increasing risks in successive cohorts of new banks. To investigate this, I test the following hypothesis:

> **H3.6**: The cohort risk effect becomes insignificant once brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income are jointly accounted for.

3.3 Data and Descriptive Analysis

3.3.1 Sample

My dataset includes virtually all chartered banks in the United States from the beginning of 1980 through to the end of 2017. The year 1980 is selected as the starting point due to the introduction of the Depository Institutions Deregulation and Monetary Control Act, which liberalised several constraints on the banking system and strengthened the Federal Reserve Bank's control over monetary policy (Kane, 1981). For all banks in my sample, I construct financial variables using data from the annual Report of Condition and Income (Call Report) at the end of the fourth quarter, which is 31 December of each year.[19] The Call Report is a report that all

[19] All explanatory variables have been winsorised at the 1st and 99th percentile which is widely used in the literature (e.g., Acharya and Mora, 2015; Berg and Gider, 2017) to mitigate the effect of possible outliers.

banks regulated by the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve, or the Office of the Comptroller of the Currency are required to file with the Federal Financial Institutions Examination Council (FFIEC) on a quarterly basis, and contains information on banks' balance sheets and income statements. Due to mergers and acquisitions, new entry, and failures, the dataset is an unbalanced panel and consists of 418,796 bank-year observations for 23,074 banks. To obtain a more homogeneous dataset, banks must meet three conditions to be included in the final sample. First, I exclude banks with zero or missing information on gross total assets (GTA), total equity capital, total loans and total deposits. Second, following Berger and Bouwman (2009), I exclude very small banks with average GTA below $25 million because they argue that these banks are not likely to be viable commercial banks in equilibrium. This exclusion reduces my sample by 24,084 bank-year observations but does not substantially affect the results. Third, I drop banks established after the year 2009 to ensure that my sample contains comparatively settled banks that have had enough time to form their strategies.[20] The final sample contains 375,006 bank-year observations for 19,963 banks. In all my analyses, I classify the banks as established banks and new banks according to their founding year. The established banks (consisting of 306,180 bank-year observations on 14,848 banks) are banks that started operations before 1980 and are considered as a benchmark for assessing the risk of new banks. The new banks (consisting of 68,826 bank-year observations on 5,190 banks) contain all banks that started after 1980. They are subsequently split into three ten-year groups: a cohort of 2,532 banks that started between 1980 and 1989, a cohort of 1,342 banks that started between 1990 and 1999, and a cohort of 1,323 banks that started between 2000 and 2009. I select the 10-year cohorts as a base in my analysis to be consistent with prior research (Brown and Kapadia, 2007; Fama and French, 2004; Srivastava, 2014) and to be exposed to comparable effects such as economic, technological, and innovation changes.

[20] I re-ran the analyses including all banks established after 2009 and the results remain qualitatively unchanged.

Panel A in Table 1 presents the annual distribution of observations for all banks, established (pre-1980s) banks, and new banks (1980s, 1990s, and 2000s cohorts). The total number of banks drops sharply from around 14,000 in the early 1980s to 5,646 in 2017. This fall can be attributed to the consolidation of the banking industry (Berger and Bouwman, 2009). Panel B in Table 1 presents the annual distribution of observations for established (pre-1980s) banks, and new banks (1980s, 1990s, and 2000s cohorts). The number of banks for each new cohort (1980s, 1990s, and 2000s) grows in the first ten years and then diminishes over time. Most banks in my sample are established (pre-1980 banks); therefore, they are highly comparable to the pattern for all banks.

Table 1: Summary Statistics

Panel A: Annual Averages of Risks				*Panel B: Annual Observations of Cohorts*			
Year	All Banks	Liquidity Risk	Credit Risk	Pre-1980 Banks	1980s Cohort	1990s Cohort	2000s Cohort
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1980	13,812	0.93%		13,632	180		
1981	13,850	1.44%		13,484	366		
1982	13,886	3.12%		13,268	618		
1983	13,938	8.09%		13,007	931		
1984	13,795	16.09%		12,543	1,252		
1985	13,837	16.05%		12,306	1,531		
1986	13,716	16.48%		11,986	1,730		
1987	13,492	16.76%		11,593	1,899		
1988	13,065	16.39%		11,093	1,972		
1989	12,644	15.99%		10,633	2,011		
1990	12,299	16.65%		10,235	1,910	154	
1991	11,994	17.41%		9,920	1,820	254	
1992	11,671	19.27%	57.3%	9,639	1,721	311	
1993	11,341	20.75%	57.7%	9,373	1,625	343	
1994	10,940	22.37%	59.5%	9,050	1,514	376	
1995	10,418	20.52%	59.8%	8,535	1,412	471	
1996	10,060	21.70%	61.9%	8,155	1,311	594	
1997	9,735	22.32%	62.4%	7,781	1,202	752	
1998	9,300	22.25%	62.4%	7,285	1,111	904	
1999	9,019	24.54%	64.5%	6,925	995	1,099	
2000	8,779	24.78%	65.7%	6,607	912	1,074	186
2001	8,462	25.94%	66.0%	6,288	832	1,031	311
2002	8,206	26.94%	66.0%	6,067	772	975	392
2003	8,083	28.49%	66.2%	5,924	728	936	495
2004	7,957	30.54%	67.7%	5,788	686	876	607
2005	7,858	31.04%	68.9%	5,612	639	836	771
2006	7,759	30.31%	69.8%	5,434	606	779	940
2007	7,632	30.60%	71.1%	5,265	568	710	1,089
2008	7,421	30.34%	71.2%	5,080	526	668	1,147
2009	7,178	29.89%	69.2%	4,936	499	619	1,124
2010	7,608	28.32%	66.0%	5,311	542	630	1,125
2011	7,260	28.62%	63.8%	5,156	492	562	1,050
2012	7,031	29.30%	62.9%	5,101	427	522	981
2013	6,758	31.42%	64.2%	4,956	401	488	913
2014	6,478	32.66%	64.9%	4,803	379	452	844
2015	6,179	34.26%	66.7%	4,625	355	415	784
2016	5,899	35.96%	67.6%	4,470	330	384	715
2017	5,646	37.02%	68.1%	4,314	311	358	663
Total	**375,006**			**306,180**	**37,116**	**17,573**	**14,137**

Notes: This table reports the annual distribution of banks and cohorts as well as the annual averages of liquidity risk and credit risk. U.S. banks started to report risk-weighted assets, as a proxy for credit risk in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992. All variables are defined in Table 2 and 3.

3.3.2 Covariates

In this section, I discuss the key dependent and independent variables.

3.3.2.1 Dependent Variables

Since the great majority of banks in my sample are not publicly listed and hence market-based measures of risk (e.g., return volatility) are not obtainable, I exploit accounting-based information to assess bank risk. I measure banks' risk using liquidity risk and credit risk.

3.3.2.1.1 Liquidity Risk

To measure banks liquidity risk, I employ a liquidity creation indicator introduced by Berger and Bouwman (2009), which has been widely used as a key measure of liquidity risk in the banking literature (e.g., Berger et al., 2016; Distinguin et al., 2013; Khan et al., 2017). The advantages of using this indicator are that it includes the different sources and uses of liquidity in one measure (Berger and Bouwman, 2016) and provides information about the liquidity profile of each bank, about the cash value of assets that could be monetised, and about the availability of market funding to assess bank liquidity (Distinguin et al., 2013). To construct the liquidity risk measure, I follow Berger and Bouwman's (2009) three-step procedure. In step 1, I classify the bank, based on balance sheet and off-balance sheet activities, as liquid or illiquid. I exclude equity for two reasons. First, theories argue that banks do not create liquidity when illiquid assets are transformed into equity (Berger and Bouwman, 2009). Second, my alternative measure of liquidity risk, as a robustness check, defined by Imbierowicz and Rauch (2014), does not take into account equity when calculating the liquidity risk indicator. I also ignore semiliquid activities as in Khan et al. (2017) because these activities produce roughly zero net liquidity creation. In step 2, I apply weights to the classified activities in the first step. In step 3, I combine the classified and weighted activities in the first and second steps, respectively, to compute the liquidity-creation (liquidity risk) measure which is normalised by GTA as follows:

$$\textit{Liquidity Creation} = [0.5\ (\textit{Illiquid Assets} + \textit{Liquid Liabilities} + \textit{illiquid guarantees}) - 0.5\ (\textit{Liquid Assets} + \textit{Illiquid Liabilities} + \textit{Liquid guarantees and derivatives})]/GTA$$

The definition of liquidity risk measure along with its calculation is provided in Tables 2 and 3, respectively.

3.3.2.1.2 Credit Risk

The second measure to gauge bank risk is credit risk defined as the bank's Basel I risk-weighted assets. This is a weighted sum of the bank's assets and off-balance-sheet activities, divided by GTA, and it is used in several banking studies as a measure of bank risk (e.g., Berger et al., 2016; Berger and Bouwman, 2009, 2013; Khan et al., 2017).[21] All banks report their risk-weighted assets in Call Reports from 1990 because Basel I risk-based capital requirements became effective in December 1990.[22] The description of credit risk measure is provided in Table 2.

3.3.2.2 Independent Variables

Likewise, I do not consider market-based covariates because my sample is dominated by unlisted banks. I use several explanatory variables including brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income, that are derived from banks' balance sheets and income statements; and motivated by prior literature discussed in Section 2. All variables are expressed as a ratio with respect to the bank's GTA except non-interest income, which is divided by total operating income. A description of these variables is provided in Table 2.

[21] According to Berger and Bouwman (2009), it is essential to divide the dependent variable by GTA to make it meaningful and comparable across banks and to avoid assigning excessive weight to large banks.
[22] This variable is available on the FDIC website, https://www5.fdic.gov/sdi/download_large_list_outside.asp, only from 1992. Thus, I use it from that time onward.

Table 2: Description of variables

Variable	Discerption
Gross Total Assets (GTA)	Total assets + the allowance for loan and the lease losses + the allocated transfer risk reserve (a reserve for certain foreign loans).
Profitability (ROA)	Return on assets (ROA) is net income divided by GTA.
Growth	The growth rate of gross total assets.
Credit Risk (RWAGTA)	Risk-weighted Assets and off-balance-sheet activities divided by GTA. A higher value indicates higher riskiness.
Credit Risk (Z-score)	The Z-score is the natural logarithm of ROA + TEGTA divided by the standard deviation of the ROA for rolling 5-year windows. It measures a bank's distance to default. I use the natural logarithm of Z-score due to its high skewness (Laeven and Levine, 2009). A higher z-score indicates lower riskiness and greater bank stability.
Liquidity Risk (BB)	The BB measure (as proposed by Berger and Bouwman, 2009) represents a bank's liquidity creation, which considers several on and off balance sheet items shown in Table 3. It measures to what degree a bank can finance illiquid assets with liquid liabilities. It is standardised by GTA. A high value indicates high liquidity risk.
Liquidity Risk (IR)	The IR measure is introduced by Imbierowicz and Rauch (2014) and calculated as [(Demand Deposits + Transaction Deposits + Brokered Deposits + NOW Accounts + Unused Loan Commitments) - (Cash + Currency & Coin + Trading Assets + Fed Funds Purchased + Commercial Paper + Securities available for Sale) ± Net Inter-Bank Lending Position ± Net Inter-Bank Acceptances ± Net Derivative Position] divided by GTA. It measures the ability of bank to handle unforeseen liquidity demand. Values above zero indicate that the bank cannot deal with unexpected bank default.
BDGTA	Brokered Deposits divided by GTA
CRELGTA	Commercial Real Estate Loans (construction and land development loans + real estate loans secured by multi-family (5 or more) residential properties + real estate loans secured by nonfarm non-residential properties) divided by GTA
Capital ratio (TEGTA)	Total Equity divided by GTA
OBSGTA	Off-balance sheet (Unused Commitments + Derivatives) divided by GTA
NIIOI	Non-Interest Income divided by total operating income (interest income + non-interest income)
Dum pre-1980s	Dummy variable equals 1 if the bank opened prior to 1980
Dum1980s	Dummy variable equals 1 if the bank opened in the 1980-1989 cohort
Dum1990s	Dummy variable equals 1 if the bank opened in the 1990-1999 cohort
Dum2000s	Dummy variable equals 1 if the bank opened in the 2000-2009 cohort

Table 3: Methodology to construct liquidity creation measure

Panel A: Liquidity classification of bank activities	
Assets	
Illiquid assets (weight = ½)	Liquid assets (weight = -½)
Commercial real estate loans (CRE). Loans to finance agricultural production. Commercial and industrial loans (C&I). Other loans and lease financing receivables. Other real estate owned (OREO). Investment in unconsolidated subsidiaries. Customers' liability on bankers' acceptances. Intangible assets. Premises. Other assets.	Cash and due from other institutions. All securities (regardless of maturity). Trading assets. Fed funds sold.
Liabilities	
Liquid liabilities (weight = ½)	Illiquid liabilities + equity (weight = -½)
Transactions deposits. Savings deposits. Overnight federal funds purchased Trading. Trading liabilities.	Bank's liability on bankers' acceptances. Subordinated debt. Other liabilities.
Off-Balance Sheet	
Illiquid guarantees (weight = ½)	Liquid guarantees & derivatives (weight = -½)
Unused commitment. Net standby letters of credit. Commercial and similar letters of credit. All other off-balance sheet liabilities.	Net participations acquired. Interest rate derivatives. Foreign exchange derivatives. Equity and commodity derivatives.
Panel B: Calculation of liquidity creation measure	
Cat fat = (1/2 * illiquid assets + 1/2 * liquid liabilities + 1/2 * illiquid guarantees) – (1/2 * liquid assets + 1/2 * illiquid liabilities + 1/2 * Liquid guarantees and derivatives)	

This table explains Berger and Bouwman (2009) methodology to construct liquidity creation measure in three steps:
Step 1: Bank activities are classified as liquid and illiquid, based on the bank activities category in Panel A.
Step 2: I assign weights to all bank activities classified in Step 1.
Step 3: I combine the bank activities classification in Step 1 with weights in Step 2 in two ways to construct liquidity creation measure (*cat fat*) shown in Panel B.

3.4 Tests of Hypotheses

3.4.1. Hypothesis 1

To identify any systematic trend in banks' risks, I compute the annual averages of liquidity risk and credit risk for all banks over the period 1980-2017. Panel A in Table 1 reports that the average of liquidity risk and credit risk increased for all banks over the sample period. Figures

1 and 2 graphically display the same information as Panel A in Table 1 and can be interpreted as the time trend for liquidity risk and credit risk for all U.S. banks. They clearly show that the average for liquidity risk increased steadily from 0.93% in 1980 to 37% in 2017, and the average for credit risk increased from 57% in 1992 to a peak of 71% in 2008, but fell sharply between 2008 and 2012, and then accelerated strongly from about 2012 onward. This supports the hypothesis that the liquidity risk and credit risk in banks are increasing over time. In addition, it is consistent with the arguments of Berger and Bouwman (2009) and Delis et al. (2014).

3.4.2. Hypothesis 2

To test the power of successive cohorts in explaining the positive systematic trend in liquidity risk and credit risk, I split my sample by banks' age into two subsamples: young banks subsample and old "established" banks. The young subsample contains all banks that were started from 1980 and I separate them into three ten-year groups: a cohort of banks that started between 1980 and 1989, a cohort of banks that started between 1990 and 1999, and a cohort of banks that started between 2000 and 2009. The old "established" banks consist of all banks that started operations before 1980 and are considered as the benchmark group for assessing the riskiness of young banks. Subsequently, I estimate pooled regressions at the bank level with and without dummy variables for each cohort of new banks. The dummies allow each cohort to have different means, while the time trend is the same across cohorts (Brown and Kapadia, 2007). The results are reported in Table 4. Columns (2) and (6) show that the time trends in liquidity risk and credit risk across all banks are 0.1% per year and significant when I am not accounting for founding year. Column (4) shows that the time trend in credit risk is decreased and insignificantly different from zero once the cohort dummy variables are included.[23]

[23] The time trend in credit risk is strongly decreased from 1.72e-07 to 1.34e-09 and converted to be insignificant, while time trend in liquidity risk is decreased from 2.28e-07 to 1.11e-08 but still significant.

Columns (7) and (9) show that the t-statistic for time trend is decreased from around 160 to approximately 8. This suggests that the significance of time trend in liquidity risk fell sharply when accounting for the cohort specific dummy variables. As expected, coefficients of cohort dummy variables are large, increasing over time, and statistically significant (Columns 4 and 8). The results show that there is mostly no trend in liquidity risk and credit risk for individual banks. Instead, the observed increases in average liquidity risk and credit risk are simply the result of successive cohorts of riskier banks.

Table 4: Pooled regression with and without cohort dummy variables

Variable	Credit Risk				Liquidity Risk			
	β	t	β	t	β	t	β	t
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Time trend	0.001[a]	200.2	0.001	1.60	0.001[a]	159.5	0.001[a]	7.8
Dum1980s			0.037[a]	141.6			0.089[a]	194.6
Dum1990s			0.083[a]	255.4			0.155[a]	224.0
Dum2000s			0.105[a]	296.2			0.187[a]	244.7
Adjusted R^2	15.73%		46.88%		6.35%		28.72%	
Observations	214,678		214,678		375,006		375,006	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. This table reports the time trend in annual estimates of credit risk and liquidity risk using bank-level observations. All variables are defined in Table 2 and 3.

To demonstrate the existence of risk phenomenon in successive cohorts and the risk differences between the cohorts, I first compute cross-sectional averages of risk measures, growth, and profitability on a cohort–year basis.[24] This yields a sample that contains 122 cohort–year observations: 38 annual observations for the pre-1980 banks (1980 to 2017), 38 annual observations for the 1980s cohort (1980 to 2017), 28 annual observations for the 1990s cohort (1990 to 2017), and 18 annual observations for the 2000s cohort (2000 to 2017).[25] Using the averages of data has two key advantages. First, it reduces potential endogeneity issues

[24] I provide summary data of growth and profitability for confirmation, but they are beyond the scope of my study.

[25] An exception is the ratio of risk-weighted assets, as a proxy for credit risk, which has 96 cohort–year observations (26 annual observations for the pre-1980 banks, 1980s cohort, and 1990s cohort; and 18 annual observations for the 2000s cohort) because US banks started to report it in Call Reports from 1990. In addition, the growth ration has 118 cohort–year observations.

(Berger and Bouwman, 2009). Second, it mitigates the impact of survivor bias on results (DeYoung and Hasan, 1998).

Panel A in Table 5 reports the overall averages of the growth, profitability, liquidity risk, and credit risk by calculating the average of annual cohort-year averages for both established and new banks. The growth averages are 0.045, 0.161, 0.198, and 0.232 for pre-1980 banks, 1980s, 1990s, and 2000s cohorts respectively, and the profitability averages are 0.094, 0.041, 0.042, and -0.012 for pre-1980 banks, 1980s, 1990s, and 2000s cohorts respectively. In addition, the liquidity risk averages are 0.181, 0.270, 0.338, and 0.370 for pre-1980 banks, 1980s, 1990s, and 2000s cohorts respectively; and the credit risk averages are 0.634, 0.672, 0.704, and 0.724 for pre-1980 banks, 1980s, 1990s, and 2000s cohorts, respectively. Furthermore, in Panel A of Table 5, I test the statistical significance of risk differences between the averages of each successive cohort and its predecessor. I use 38 annual differences between pre-1980 and the 1980s cohort, 28 annual differences between the 1980s and 1990s cohorts, and 18 annual differences between the 1990s and 2000s cohorts.[26] Several results are apparent in Panel A of Table 5. First and foremost, the liquidity risk and credit risk levels increase with successive cohorts. Second, the growth of each successive cohort is larger than its predecessor. These results confirm that successive cohorts of new banks adopt riskier business strategies to grow faster. Third, the profitability is decreasing in successive cohorts. Finally, the differences between the successive cohorts are statistically significant.

Next, I estimate the following ordinary least squares (OLS) regression on a cohort-year basis:

$$\boldsymbol{Risk_{cy} = \beta_0 + \gamma_1\, Dum1980s + \gamma_2\, Dum1990s + \gamma_3\, Dum2000s + \varepsilon_{cy}} \qquad \textbf{(1)}$$

[26] For credit risk, I use 26 annual differences between pre-1980 and the 1980s cohort, 26 annual differences between the 1980s and 1990s cohorts, and 18 annual differences between the 1990s and 2000s cohorts.

where $Risk_{cy}$ is the liquidity risk (or credit risk) calculated on a cohort-year basis. The *Dum1980s, Dum1990s,* and *Dum2000s* are dummy variables equal to one if the cohort–year observations are for the 1980s, 1990s and 2000s cohorts respectively, and zero otherwise. The dummy variable for pre-1980s banks is considered as the reference category; therefore, it is excluded from Equation (1). ε_{cy} is the error term.

Panel B in Table 5 reports results for Equation (1). The Table shows that each cohort has significantly higher risks (liquidity risk or credit risk) than its predecessor. Particularly, the F-tests on the differences in coefficients of the cohort dummies are also significant at a p-value of 10% or better. The only exception is that the difference in liquidity risk between the 1990s and 2000s cohorts is insignificant.

In summary, the successive cohorts of new banks provide an adequate explanation for the positive trend in average liquidity risk and credit risk.

Table 5: Successive cohorts of banks and inter-cohort differences

Panel A: Averages and inter-cohort differences								
Cohort	Growth		Profitability		Credit Risk		Liquidity Risk	
(1)	(2)		(3)		(4)		(5)	
	Average	Difference	Average	Difference	Average	Difference	Average	Difference
Pre 1980s	0.045		0.094		0.634		0.181	
1980s	0.161	0.115[a]	0.041	-0.053[a]	0.672	0.037[a]	0.270	0.088[a]
1990s	0.198	0.037[a]	0.042	0.001	0.704	0.032[a]	0.338	0.068[a]
2000s	0.232	0.034[a]	-0.012	-0.054[a]	0.724	0.020[c]	0.370	0.032[a]
Panel B: Control for Cohorts								
Variable	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
Dum1980s	0.108[a]	0.035	-0.041[a]	0.012	0.037[a]	0.010	0.067[a]	0.019
Dum1990s	0.149[a]	0.038	-0.056[a]	0.013	0.070[a]	0.010	0.114[a]	0.021
Dum2000s	0.233[a]	0.044	-0.104[a]	0.015	0.089[a]	0.011	0.148[a]	0.024
Constant	0.044[c]	0.025	0.092[a]	0.008	0.634[a]	0.007	0.210[a]	0.013
Observations	118		122		96		122	
F-value	11.03[a]		18.25[a]		23.47[a]		15.78[a]	
Adjusted R^2	20.45%		29.96%		41.50%		26.81%	
F-test								
1980s > Pre-1980s (γ_1>0)	9.58[a]		12.26[a]		12.34[a]		11.81[a]	
1990s > 1980s (γ_2> γ_1)	1.20		1.40		8.87[a]		4.71[b]	
2000s > 1990s (γ_3> γ_2)	3.33[c]		9.86[a]		2.80[c]		1.66	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A reports the overall averages on a cohort–year basis and the significance of differences across cohorts. I use 38 annual differences between pre-1980 and the 1980s cohorts, 28 annual differences between the 1980s and 1990s cohorts, and 18 annual differences between the 1990s and 2000s cohorts to estimate the significance of differences across cohorts. Panel B shows the OLS regression results after controlling for cohorts. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regression is estimated by using 122 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because US banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

Figures 3 and 4 plot the cross-sectional averages of liquidity risk and credit risk, respectively, for each cohort by year. They demonstrate that each cohort has relatively higher risk than its predecessor. This phenomenon is strongly noticeable following the recent global financial crisis of 2008 and onward, indicating that banks, particularly new banks, have been taking excessive risks following the crisis to offset their losses.

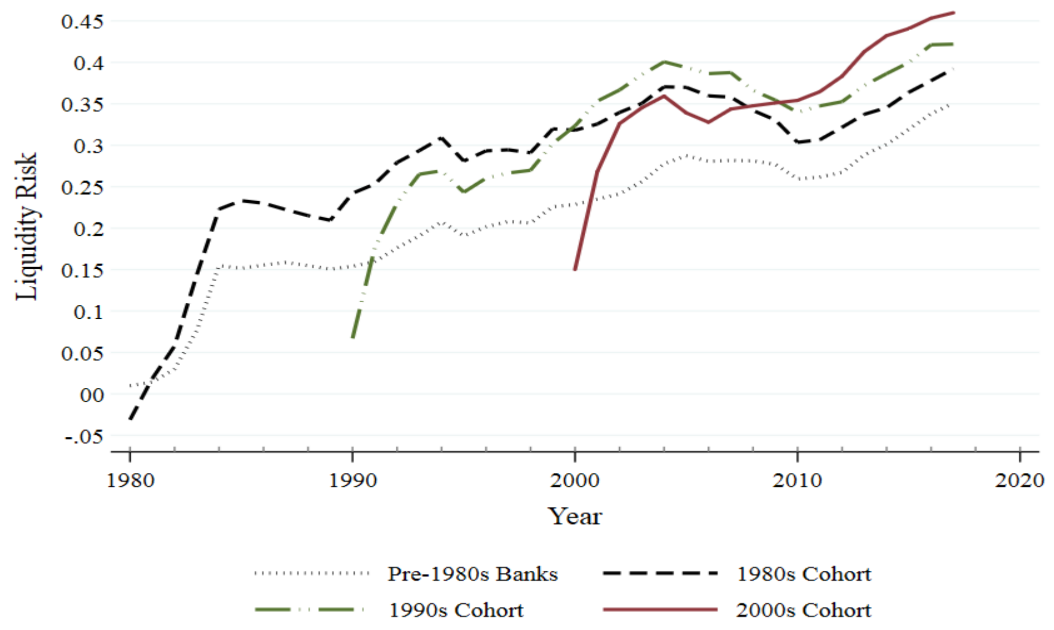


Fig. 3. Liquidity Risk

This figure illustrates the liquidity risk for each year by cohort. The banks are sorted into four cohorts based on their year of opening: prior to 1980, 1980-1989, 1990-1999, and 2000-2009. The definition of liquidity risk is provided in Table 2 and calculated as overall average on a cohort–year basis.

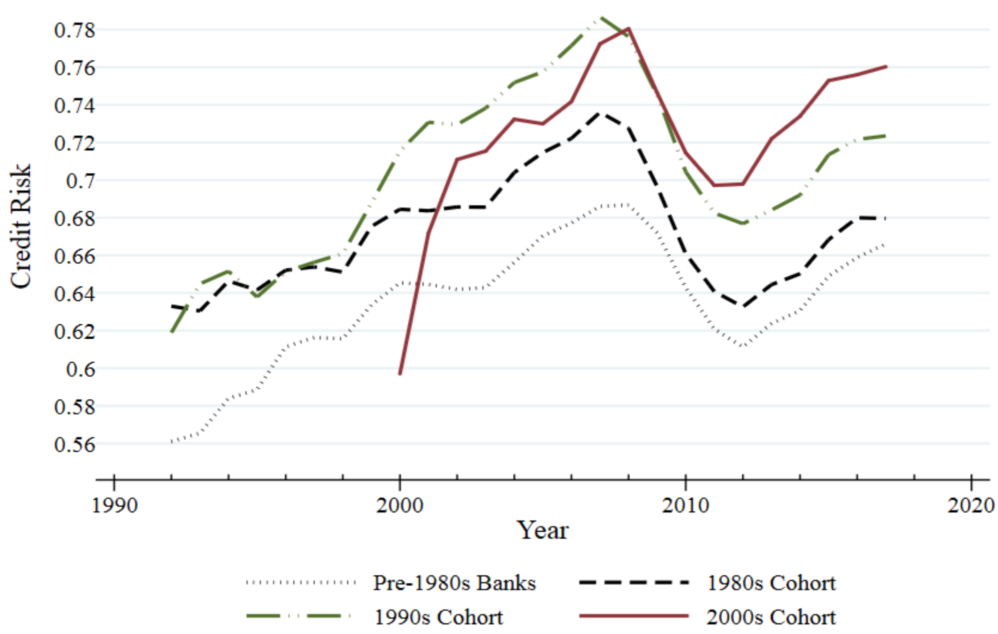


Fig. 4. Credit Risk

This figure illustrates the credit risk for each year by cohort. The banks are sorted into four cohorts based on their year of opening: prior to 1980, 1980-1989, 1990-1999, and 2000-2009. The credit risk is measured as the risk-weighted assets divided by Gross Total Assets (GTA) and calculated as overall average on a cohort–year basis.

3.4.3. Hypothesis 3

To observe the trend in bank-specific factors across the successive cohorts, I calculate, individually, the overall averages of brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income for each cohort by averaging their cohort–year observations. I also test differences in averages between the cohorts.[27] Panel A of Table 6 shows that the earliest to the latest cohorts have increasing brokered deposits of 0.005, 0.011, 0.030, and 0.049; increasing commercial real estate loans of 0.129, 0.201, 0.250, and 0.322; increasing capital of 0.094, 0.101, 0.111, and 0.124; increasing off-balance sheet items of 0.076, 0.105, 0.146, and 0.147; and increasing non-interest income of 0.080, 0.116, 0.118, and

[27] I follow an identical approach described in Section 4.2 to test the risk phenomenon in successive cohorts.

0.095, respectively (figures not presented for brevity).[28] Next, I estimate the following ordinary least squares (OLS) regression on a cohort–year basis:

$$\boldsymbol{Characteristic_{cy} = \beta_0 + \gamma_1\, Dum1980s + \gamma_2\, Dum1990s + \gamma_3\, Dum2000s + \varepsilon_{cy}} \quad \textbf{(2)}$$

The $Characteristic_{cy}$ refers to one of the bank-specific factors (brokered deposits, commercial real estate loans, capital, off-balance sheet items, or non-interest income) calculated on a cohort–year basis.

The results for Equation (2) presented in Panel B of Table 6, show that the differences between each bank-specific factor for the new cohorts and the preceding cohorts are positively significant. All these results support my third hypothesis (H3.1a to H3.5a) that new banks in successive cohorts focus more on brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income than their predecessors. In addition, the results are in line with certain researchers (e.g., Demirgüç-Kunt and Huizinga, 2010; Stiroh, 2004).

[28] The only exception is that the difference in non-interest income between the 1990s and 2000s cohorts is decreasing but insignificant.

Table 6: Bank-specific characteristics of successive cohorts and inter-cohort differences

Panel A: Averages and inter-cohort differences										
Cohort	**BDGTA**		**CRELGTA**		**TEGTA**		**OBSGTA**		**NIIOI**	
(1)	(2)		(3)		(4)		(5)		(6)	
	A	D	A	D	A	D	A	D	A	D
Pre 1980s	0.005		0.129		0.094		0.076		0.080	
1980s	0.011	0.006[a]	0.201	0.072[a]	0.101	0.007[a]	0.105	0.028[a]	0.116	0.036[a]
1990s	0.030	0.019[a]	0.250	0.049[a]	0.111	0.010[a]	0.146	0.041[a]	0.118	0.002[a]
2000s	0.049	0.019[a]	0.322	0.072[a]	0.124	0.013[a]	0.147	0.001	0.095	-0.023
Panel B: Control for Cohorts										
Variable	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
Dum1980s	0.007[b]	0.003	0.072[a]	0.016	0.011[b]	0.005	0.028[a]	0.007	0.027[a]	0.009
Dum1990s	0.021[a]	0.003	0.120[a]	0.017	0.017[a]	0.006	0.069[a]	0.008	0.025[a]	0.009
Dum2000s	0.036[a]	0.003	0.192[a]	0.019	0.034[a]	0.007	0.070[a]	0.009	0.001	0.011
Constant	0.008[a]	0.002	0.129[a]	0.011	0.098[a]	0.004	0.076[a]	0.005	0.094[a]	0.006
Observations	122		122		122		122		122	
F-value	34.84[a]		35.59[a]		7.98[a]		29.67[a]		4.30[a]	
Adjusted R^2	45.62%		46.17%		17.28%		41.55%		7.57%	
F-test										
1980s > Pre-1980s (γ_1>0)	5.42[b]		20.19[a]		4.16[b]		13.36[a]		8.96[a]	
1990s > 1980s (γ_2> γ_1)	17.20[a]		7.82[a]		0.75		23.08[a]		0.06	
2000s > 1990s (γ_3> γ_2)	13.27[a]		11.70[a]		5.08[b]		0.01		3.87[b]	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A reports the overall averages on a cohort–year basis and the significance of differences across cohorts. I use 38 annual differences between pre-1980 and the 1980s cohorts, 28 annual differences between the 1980s and 1990s cohorts, and 18 annual differences between the 1990s and 2000s cohorts to estimate the significance of differences across cohorts. Panel B shows the OLS regression results after controlling for cohorts. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regression is estimated by using 122 cohort–year observations, composed of 38 annual observations for the pre-1980-bank category (1980–2017), 38 annual observations for the 1980s cohort (1980–2017), 28 annual observations for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

Prior to estimating the main regressions, I examine the correlation coefficients of the variables used in this study. Table 7 reports correlations between bank-specific factors and risk measures. The table shows that the liquidity risk shows strong positive correlation with the credit risk. This positive relationship is supported by both theoretical and empirical banking literature (e.g., Acharya and Viswanathan, 2011; Diamond and Dybvig, 1983; Imbierowicz and Rauch, 2014). The table also shows that the brokered deposits, commercial real estate loans, and off-balance sheet items are strongly and positively correlated with two measures of risk (liquidity risk and credit risk), as well as with each other. This suggests that these factors are most likely responsible for the increase in liquidity risk and credit risk. The capital, measured by total equity to GTA, is positively correlated with credit risk but insignificant; and is weakly negatively correlated with liquidity risk. These different correlations are consistent with the divergent theories in the literature (e.g., Allen et al., 2011; Besanko and Kanatas, 1996; Koehn and Santomero, 1980; Mehran and Thakor, 2011). In contrast, the non-interest income ratio is negatively correlated with credit risk but insignificant, and is significantly positively correlated with liquidity risk. This is in line with the different findings in prior studies (e.g., Demirgüç-Kunt and Huizinga, 2010; DeYoung and Roland, 2001; Kwast, 1989). Finally, some of the variables exhibit moderate to strong correlation with other variables. To address the issues associated with multicollinearity, the highest correlated variables (brokered deposits, commercial real estate loans, and off-balance sheet items) have been orthogonalised which is technique adopted in the banking literature (e.g., Berger and Bouwman, 2009; Distinguin et al., 2013).[29]

[29] I also orthogonalise the highest two variables and the results remain unchanged.

Table 7: Correlation Test

Variable	RWAGTA	LCGTA	BDGTA	CRELGTA	TETA	OBSGTA	NIIOI
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RWAGTA	1						
LCGTA	0.823[a]	1					
BDGTA	0.838[a]	0.746[a]	1				
CRELGTA	0.924[a]	0.895[a]	0.912[a]	1			
TETA	0.023	-0.198[b]	0.138	-0.021	1		
OBSGTA	0.754[a]	0.846[a]	0.614[a]	0.822[a]	0.143	1	
NIIOI	-0.072	0.769[a]	0.168[c]	0.513[a]	-0.304[a]	0.593	1

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level.

I now turn to my main regressions to test whether the bank-specific factors of successive cohorts separately explain the cohort risk phenomenon. I regress the risk on one of the five bank-specific factors while controlling for cohorts, as follows:

$$\boldsymbol{Risk_{cy} = \beta_0 + \beta_1 X_{cy} + \gamma_1\ Dum1980s + \gamma_2\ Dum1990s + \gamma_3\ Dum2000s + \varepsilon_{cy}} \qquad \textbf{(3)}$$

where X_{cy} is one of bank level factors, specifically brokered deposits, commercial real estate loans, capital, off-balance sheet items, or non-interest income.

Then, I regress the risk on all five bank-specific factors and control for cohorts to investigate the extent to which the bank-specific factors of successive cohorts jointly explain the cohort risk phenomenon, as follows:

$$\boldsymbol{Risk_{cy} = \beta_0 + \beta_1 \sum X_{cy} + \gamma_1\ Dum1980s + \gamma_2\ Dum1990s + \gamma_3 Dum2000s + \varepsilon_{cy}} \qquad \textbf{(4)}$$

where $\sum X_{cy}$ are all bank level factors (brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income).[30]

[30] All regressions are estimated by using 122 cohort–year observations (except for risk-weighted assets, as a proxy for credit risk, which uses 96 cohort–year observations because US banks started to report it in Call Reports from 1990), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980s banks (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Tables 2 and 3.

My main results are reported in Table 8. Panel A (columns 2 to 6) shows that brokered deposits, commercial real estate loans, off-balance sheet items, and non-interest income have a positive and significant impact on credit risk as a dependent variable.[31] Nonetheless, capital has a negative and significant relationship with credit risk. The results are similar to the correlation analysis in Table 7 except in the case of capital which has a contrary relationship. The coefficients on cohort dummies are generally smaller, but still increasing, than my findings for credit risk in Panel B of Table 5.[32] Furthermore, the differences in cohort dummies remain significant in most cases suggesting less persuasive results for the hypothesis that a singular variable is a principal factor behind the persistence of risk across cohorts. Most importantly, the last column of Panel A in Table 8 shows that the coefficients of cohort dummies are generally decreasing and much smaller than those in Panel B of Table 5, and, additionally, that F-tests on the differential coefficients on cohort dummies are no longer statistically significant, indicating that the increasing credit risk of successive cohorts is no longer evident once I control for all five bank-specific variables (brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income). This result supports the hypothesis (H3.6) that all these variables are responsible for the observed cohort risk phenomenon.

Panel B in Table 8 reports the results for liquidity risk after controlling for bank-specific characteristics and cohorts. The relationships between liquidity risk and bank-specific characteristics are identical to the correlation analysis in Table 7. The key results are that only brokered deposits and commercial real estate loans, separately (columns 2 and 3), explain the increase in liquidity risk across successive cohorts, because the coefficients of the cohort dummies declined, and F-tests of their differences are insignificant.

[31] An exception is non-interest income which has an insignificant relationship with credit risk.
[32] The capital, however, has higher values than those in Equation (1).

Overall these findings broadly suggest that the increasing of brokered deposits, commercial real estate loans, off-balance sheet items, and non-interest income, as well as decreasing capital, account for the cohort risk phenomenon.

Table 8: Differences in financial risks after controlling for cohorts and bank-specific characteristics

Panel A: Credit Risk												
Variable	**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all variables & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)	
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA	2.047[a]	0.191									0.033[a]	0.003
CRELGTA			0.625[a]	0.032							0.012[a]	0.002
TEGTA					-0.708[a]	0.199					-0.449[a]	0.101
OBSGTA							1.157[a]	0.177			0.033[a]	0.004
NIIOI									0.177	0.178	-0.261[a]	0.061
Dum1980s	0.019[a]	0.007	-0.020[a]	0.006	0.035[a]	0.010	0.001	0.010	0.031[a]	0.012	-0.023[a]	0.005
Dum1990s	0.027[a]	0.008	0.003	0.006	0.073[a]	0.010	0.009	0.012	0.068[a]	0.010	-0.018[a]	0.005
Dum2000s	0.020[b]	0.010	-0.015[b]	0.008	0.109[a]	0.012	0.032[b]	0.013	0.092[a]	0.012	-0.024[a]	0.007
Constant	0.611[a]	0.005	0.537[a]	0.006	0.708[a]	0.022	0.521[a]	0.018	0.614[a]	0.021	0.684[a]	0.012
Observations	96		96		96		96		96		96	
F-value	67.65[a]		184.00[a]		22.98[a]		36.20[a]		17.84[a]		195.57[a]	
Adjusted R^2	73.73%		88.51%		48.07%		59.71%		41.49%		94.25%	
F-test												
1980s > Pre-1980s (γ_1>0)	7.05[a]		13.27[a]		12.60[a]		0.00		6.65[a]		22.26[a]	
1990s > 1980s (γ_2> γ_1)	1.23		24.45[a]		13.64[a]		0.88		9.77[a]		1.38	
2000s > 1990s (γ_3> γ_2)	0.76		10.84[a]		8.74[a]		5.46[b]		3.70[c]		0.77	
Panel B: Liquidity Risk												
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA	3.921[a]	0.450									0.025[a]	0.003
CRELGTA			1.068[a]	0.056							0.006[b]	0.003
TEGTA					-1.805[a]	0.267					-0.689[a]	0.101
OBSGTA							1.995[a]	0.142			0.028[a]	0.005
NIIOI									1.893[a]	0.094	0.969[a]	0.078
Dum1980s	0.039[b]	0.015	-0.009	0.005	0.089[a]	0.017	0.010	0.012	0.015[c]	0.009	0.008	0.006

Dum1990s	0.029	0.019	-0.014	0.012	0.145[a]	0.018	-0.024	0.016	0.066[a]	0.010	0.013[c]	0.007
Dum2000s	0.003	0.025	-0.058[a]	0.016	0.210[a]	0.022	0.007	0.018	0.145[a]	0.011	0.053[a]	0.010
Constant	0.178[a]	0.011	0.070[a]	0.010	0.378[a]	0.028	0.057[a]	0.013	0.032[a]	0.011	0.187[a]	0.013
Observations	122		122		122		122		122		122	
F-value	38.27[a]		135.29[a]		27.75[a]		80.07[a]		152.98[a]		328.33[a]	
Adjusted R^2	55.20%		81.62%		46.93%		72.33%		83.40%		95.88%	
F-test												
1980s > Pre-1980s (γ_1>0)	6.10[a]		0.71		27.19[a]		0.71		2.63[c]		2.11	
1990s > 1980s (γ_2> γ_1)	0.26		0.24		9.48[a]		5.86[b]		24.95[a]		0.38	
2000s > 1990s (γ_3> γ_2)	1.46		10.19[a]		8.14[a]		3.98[b]		38.93[a]		23.24[a]	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A shows the OLS regression results for credit risk after controlling for cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regressions are estimated by using 122 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because U.S. banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

3.5 Robustness Tests

In this section, I perform a set of robustness checks on my findings in Section 4. First, I split my sample into small, medium, and large banks and re-estimate my regressions separately for these three groups. Second, I control for time trend. Third, I exclude mergers and acquisitions and bank failures. Fourth, I control for two banking crises. Fifth, I limit my sample to "true" commercial banks. Sixth, I use two alternative measures of liquidity risk and credit risk. Seventh, I apply an alternative cohort measurement period of five years. In all cases, I show that my main results remain qualitatively unchanged.

3.5.1 Heterogeneity in Bank Size

Several empirical studies have shown that bank size has an impact on liquidity risk (e.g., (Berger and Bouwman, 2009; Kashyap et al., 2002) and credit risk (e.g., Hakenes and Schnabel, 2011; Stiroh, 2004). To account for size differences in banks, I follow Imbierowicz and Rauch (2014) and define the bottom 25 percentile of GTA as small banks, the top 25 percentile as large banks, and the rest as medium banks, as threshold in each year. I then run the analysis separately for each bank size. This gives me a sample of 93,755 bank-year observations for 5,320 small banks, 187,506 bank-year observations for 9,785 medium banks, and 93,745 bank-year observations for 4,858 large banks.

Table 9 and Panel A of Table 10 report the overall averages and the significance of cohort risk and bank-specific characteristic differences for both established and new banks across bank size classes. Consistent with the summary data in Sections 4.2 and 4.3, the average levels of liquidity risk, credit risk, and bank-specific factors for small, medium, and large banks generally increase with successive cohorts and the differences are significant.[33] Panel B of Table 10 displays the regression results for bank-specific factors while controlling for cohort

[33] An exception is non-interest income which decreases in the 1990s and 2000s for small and medium banks, but the differences are not significant.

dummies. I find results similar to my main findings in Section 4 and prior results in Panel A of Table 10.

Panels A and B of Table 11 provide the estimation results for the three different bank sizes. The basic results are hold for small, medium, and large banks, with a few notable exceptions. Specifically, non-interest income has a significant and negative association with the credit risk for small banks; the coefficients on cohort dummies while controlling for all five bank-specific variables are tremendously small, but still increasing, compared to coefficients on cohort dummies for credit risk without control variables for large banks; the liquidity risk cohort phenomenon is explained by all bank-specific factors for large banks only.

Table 9: Averages and differences across bank size categories

Cohort	Profitability		Credit Risk		Liquidity Risk	
(1)	(2)		(3)		(4)	
	Average	Difference	Average	Difference	Average	Difference
Small Banks						
Pre 1980s	0.008		0.610		0.135	
1980s	-0.001	-0.009[a]	0.628	0.018[b]	0.212	0.077[a]
1990s	0.001	0.002[a]	0.655	0.027[a]	0.249	0.037[a]
2000s	-0.009	-0.010[a]	0.700	0.044[a]	0.312	0.062[a]
Observations	93,755		93,755		93,755	
Medium Banks						
Pre 1980s	0.009		0.630		0.172	
1980s	0.004	-0.005[a]	0.675	0.044[a]	0.281	0.109[a]
1990s	0.003	-0.001[a]	0.694	0.019[b]	0.329	0.047[a]
2000s	-0.003	-0.006[a]	0.722	0.027[c]	0.363	0.034[a]
Observations	187,506		187,506		187,506	
Large Banks						
Pre 1980s	0.008		0.668		0.247	
1980s	0.007	-0.001[a]	0.690	0.022[a]	0.332	0.084[a]
1990s	0.005	-0.002[a]	0.728	0.038[a]	0.406	0.073[a]
2000s	0.001	-0.004[a]	0.736	0.008	0.421	0.015[a]
Observations	93,745		93,745		93,745	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. I consider small banks corresponding to the bottom 25 percentile of average Gross Total Assets (GTA), those in the top 25 percentile as large banks, and the rest medium banks. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. I use 38 annual differences (26 annual observations for credit risk) between pre-1980 and the 1980s cohorts, 28 annual differences (26 annual observations for credit risk) between the 1980s and 1990s cohorts, and 18 annual differences between the 1990s and 2000s cohorts to estimate the significance of differences across cohorts. All financial characteristics are calculated as overall averages on a cohort–year basis to estimate the significance of differences across cohorts. All variables are defined in Table 2 and 3.

Table 10: Bank-specific characteristics of cohorts and inter-cohort differences across bank size categories

Panel A: Averages and inter-cohort differences										
Cohort	**BDGTA**		**CRELGTA**		**TEGTA**		**OBSGTA**		**NNIOI**	
(1)	(2)		(3)		(4)		(5)		(6)	
	A	D	A	D	A	D	A	D	A	D
Small Banks										
Pre 1980s	0.003		0.076		0.100		0.047		0.077	
1980s	0.004	0.001^{a}	0.145	0.069^{a}	0.103	0.003^{a}	0.060	0.013^{a}	0.116	0.038^{a}
1990s	0.012	0.008^{a}	0.186	0.040^{a}	0.125	0.022^{a}	0.086	0.025^{a}	0.103	-0.013
2000s	0.031	0.019^{a}	0.283	0.097^{a}	0.142	0.017^{a}	0.096	0.100^{c}	0.098	-0.004
Medium Banks										
Pre 1980s	0.004		0.130		0.094		0.064		0.089	
1980s	0.009	0.005^{a}	0.215	0.085^{a}	0.098	0.004^{a}	0.090	0.025^{a}	0.109	0.020^{b}
1990s	0.025	0.015^{a}	0.255	0.040^{b}	0.109	0.011^{a}	0.119	0.028^{a}	0.108	-0.001
2000s	0.044	0.019^{a}	0.332	0.077^{a}	0.122	0.013^{a}	0.129	0.010^{c}	0.087	-0.020
Large Banks										
Pre 1980s	0.009		0.183		0.087		0.154		0.121	
1980s	0.027	0.018^{a}	0.208	0.025^{c}	0.107	0.020^{a}	0.248	0.094^{a}	0.147	0.026^{b}
1990s	0.049	0.022^{a}	0.255	0.046^{b}	0.112	0.005^{a}	0.371	0.122^{a}	0.148	0.001
2000s	0.072	0.023^{a}	0.312	0.056^{a}	0.132	0.013^{a}	0.265	-0.105	0.109	-0.038
Panel B: Control for Cohorts										
Small Banks										
Variable	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
Dum1980s	0.001	0.001	0.066^{a}	0.009	0.006	0.006	0.013^{b}	0.005	0.037^{a}	0.007
Dum1990s	0.007^{a}	0.002	0.107^{a}	0.010	0.021^{a}	0.006	0.039^{a}	0.005	0.023^{a}	0.008
Dum2000s	0.020^{a}	0.002	0.204^{a}	0.011	0.044^{a}	0.007	0.048^{a}	0.006	0.019^{b}	0.006
Constant	0.005	0.001	0.078^{a}	0.006	0.104^{a}	0.004	0.047^{a}	0.004	0.078^{a}	0.004
Observations		122		122		122		122		122
F-value		35.75^{a}		114.41^{a}		13.61^{a}		27.09^{a}		7.73^{a}
Adjusted R^2		46.28%		73.77%		23.81%		39.28%		**14.31%**
F-test										
1980s > Pre-1980s (γ_1>0)		0.04		53.24^{a}		1.12		6.25^{a}		22.79^{a}

1990s > 1980s ($\gamma_2 > \gamma_1$)	15.08^{a}		16.57^{a}		5.53^{b}		21.28^{a}		2.61^{c}	
2000s > 1990s ($\gamma_3 > \gamma_2$)	29.18^{a}		62.56^{a}		7.96^{a}		1.67		0.11	
Medium Banks										
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
Dum1980s	0.005^{c}	0.002	0.080^{a}	0.016	0.008	0.005	0.026^{a}	0.006	0.018^{b}	0.008
Dum1990s	0.016^{a}	0.003	0.121^{a}	0.018	0.015^{b}	0.006	0.054^{a}	0.007	0.018^{b}	0.009
Dum2000s	0.032^{a}	0.003	0.198^{a}	0.020	0.032^{a}	0.007	0.064^{a}	0.008	-0.002	0.010
Constant	0.007^{a}	0.002	0.134^{a}	0.011	0.097^{a}	0.003	0.065^{a}	0.004	0.090^{a}	0.005
Observations	122		122		122		122		122	
F-value	34.18^{a}		34.13^{a}		7.19^{a}		29.24^{a}		2.74^{b}	
Adjusted R^2	45.13%		45.10%		13.31%		41.18%		4.13%	
F-test										
1980s > Pre-1980s ($\gamma_1 > 0$)	2.93^{c}		22.66^{a}		2.37		15.01^{a}		4.71^{b}	
1990s > 1980s ($\gamma_2 > \gamma_1$)	13.81^{a}		5.10^{b}		0.98		15.30^{a}		0.00	
2000s > 1990s ($\gamma_3 > \gamma_2$)	20.24^{a}		12.06^{a}		5.20^{b}		1.43		3.48^{b}	
Large Banks										
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
Dum1980s	0.014^{a}	0.004	0.025	0.018	0.025^{a}	0.005	0.094^{a}	0.018	0.026^{b}	0.011
Dum1990s	0.031^{a}	0.005	0.072^{a}	0.020	0.026^{a}	0.006	0.216^{a}	0.020	0.026^{b}	0.012
Dum2000s	0.054^{a}	0.005	0.129^{a}	0.023	0.038^{a}	0.007	0.110^{a}	0.023	-0.011	0.014
Constant	0.013^{a}	0.003	0.183^{a}	0.013	0.092^{a}	0.004	0.154^{a}	0.013	0.121^{a}	0.008
Observations	122		122		122		122		122	
F-value	33.75^{a}		12.01^{a}		11.85^{a}		36.99^{a}		3.92^{a}	
Adjusted R^2	44.81%		21.44%		21.19%		47.16%		6.75%	
F-test										
1980s > Pre-1980s ($\gamma_1 > 0$)	10.32^{a}		1.87		18.39^{a}		24.65^{a}		5.25^{b}	
1990s > 1980s ($\gamma_2 > \gamma_1$)	11.43^{a}		5.32^{b}		0.01		35.12^{a}		0.00	
2000s > 1990s ($\gamma_3 > \gamma_2$)	13.46^{a}		5.30^{b}		2.73^{c}		17.90^{a}		6.48^{a}	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. I consider small banks corresponding to the bottom 25 percentile of average Gross Total Assets (GTA), those in the top 25 percentile as large banks, and the rest medium banks. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A reports the overall averages **(A)** on a cohort–year basis and the significance of differences **(D)** across cohorts. I use 38 annual differences between pre-1980 and the 1980s cohorts, 28 annual differences between the 1980s and 1990s cohorts, and 18 annual differences between the 1990s and 2000s cohorts to estimate the significance of differences across cohorts. Panel B shows the OLS regression results after controlling for cohorts. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regression is estimated by using 122 cohort–year observations, composed of 38 annual observations for the pre-1980-bank category (1980–2017), 38 annual observations for the 1980s cohort (1980–2017), 28 annual observations for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

Table 11: Financial risks after controlling for cohorts and bank-specific characteristics across bank size categories

Panel A: Credit Risk														
Variable	**Control for Cohorts**		**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Small Banks														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			1.977[a]	0.334									0.042[a]	0.003
CRELGTA					0.695[a]	0.069							0.036[a]	0.004
TEGTA							-0.132	0.160					-0.134	0.103
OBSGTA									1.053[a]	0.169			0.024[a]	0.003
NIIOI											-0.292[c]	0.175	-0.562[a]	0.086
Dum1980s	0.017[b]	0.008	0.019[a]	0.007	-0.036[a]	0.007	0.016[b]	0.008	0.007	0.007	0.030[a]	0.011	-0.023[a]	0.006
Dum1990s	0.045[a]	0.008	0.033[a]	0.007	-0.023[a]	0.009	0.047[a]	0.008	0.020[b]	0.008	0.049[a]	0.008	-0.039[a]	0.007
Dum2000s	0.089[a]	0.009	0.053[a]	0.010	-0.042[a]	0.014	0.094[a]	0.011	0.054[a]	0.009	0.090[a]	0.009	-0.067[a]	0.013
Constant	0.611[a]	0.005	0.595[a]	0.005	0.545[a]	0.008	0.625[a]	0.018	0.544[a]	0.012	0.638[a]	0.017	0.727[a]	0.013
Observations		96		96		96		96		96		96		96
F-value		35.18[a]		43.78[a]		78.32[a]		25.72[a]		45.72[a]		26.83[a]		119.25[a]
Adjusted R^2		51.16%		64.30%		76.50%		51.00%		65.32%		52.10%		90.87%
F-test														
1980s > Pre-1980s ($\gamma_1>0$)		4.33[b]		7.19[a]		20.54[a]		3.83[b]		0.93		7.14[a]		13.09[a]
1990s > 1980s ($\gamma_2>\gamma_1$)		10.78[a]		3.16[c]		3.99[b]		11.37[a]		2.50		3.14[c]		10.02[a]
2000s > 1990s ($\gamma_3>\gamma_2$)		20.98[a]		4.93[b]		4.57[b]		20.29[a]		18.84[a]		18.94[a]		11.73[a]
Medium Banks														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			2.420[a]	0.227									0.064[a]	0.002
CRELGTA					0.639[a]	0.032							0.039[a]	0.002
TEGTA							-0.811[a]	0.208					-0.466[a]	0.101
OBSGTA									1.114[a]	0.200			0.018[a]	0.002
NIIOI											0.154	0.205	-0.209[a]	0.068

Dum1980s	0.043[a]	0.011	0.031[a]	0.007	-0.022[a]	0.006	0.039[a]	0.010	0.015	0.011	0.040[a]	0.012	-0.022[a]	0.005
Dum1990s	0.063[a]	0.011	0.027[a]	0.008	-0.004	0.006	0.066[a]	0.010	0.020	0.012	0.063[a]	0.011	-0.020[a]	0.004
Dum2000s	0.090[a]	0.012	0.018[c]	0.010	-0.019[b]	0.007	0.112[a]	0.012	0.039[a]	0.014	0.094[a]	0.013	-0.029[a]	0.007
Constant	0.631[a]	0.008	0.606[a]	0.006	0.528[a]	0.006	0.715[a]	0.022	0.538[a]	0.018	0.614[a]	0.024	0.740[a]	0.012
Observations		96		96		96		96		96		96		96
F-value		19.54[a]		60.79[a]		172.15[a]		20.68[a]		27.11[a]		14.72[a]		213.29[a]
Adjusted R^2		36.93%		71.57%		87.81%		45.32%		52.37%		36.62%		94.70%
F-test														
1980s > Pre-1980s (γ_1>0)		14.43[a]		15.70[a]		13.49[a]		13.10[a]		1.97		10.20[a]		19.01[a]
1990s > 1980s (γ_2> γ_1)		2.79[c]		0.17		12.49[a]		6.28[a]		0.18		3.33[c]		0.39
2000s > 1990s (γ_3> γ_2)		4.69[b]		0.97		6.02[a]		12.69[a]		2.83[c]		5.22[b]		3.23[c]
Large Banks														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			1.493[a]	0.131									0.060[a]	0.003
CRELGTA					0.526[a]	0.030							0.032[a]	0.002
TEGTA							-0.663[a]	0.223					-0.356[a]	0.091
OBSGTA									-0.066	0.087			0.026[a]	0.004
NIIOI											0.161	0.149	-0.165[a]	0.061
Dum1980s	0.022[b]	0.010	-0.005	0.007	-0.001	0.005	0.028[a]	0.010	0.030[b]	0.015	0.018	0.011	-0.025[a]	0.007
Dum1990s	0.060[a]	0.010	0.014[c]	0.008	0.033[a]	0.005	0.067[a]	0.010	0.071[a]	0.018	0.060[a]	0.010	-0.010	0.009
Dum2000s	0.067[a]	0.011	-0.006	0.010	0.017[a]	0.006	0.087[a]	0.013	0.072[a]	0.013	0.074[a]	0.013	-0.002	0.008
Constant	0.678[a]	0.007	0.640[a]	0.005	0.553[a]	0.007	0.734[a]	0.023	0.681[a]	0.018	0.643[a]	0.024	0.748[a]	0.014
Observations		96		96		96		96		96		96		96
F-value		15.89[a]		60.55[a]		122.07[a]		15.14[a]		12.01[a]		12.23[a]		115.97[a]
Adjusted R^2		31.98%		71.49%		83.60%		37.31%		31.67%		32.11%		90.64%
F-test														
1980s > Pre-1980s (γ_1>0)		4.40[b]		0.47		0.00		7.24[a]		4.17[b]		2.26		13.03[a]
1990s > 1980s (γ_2> γ_1)		12.23[a]		7.88[a]		40.98[a]		14.82[a]		12.24[a]		13.27[a]		8.93[a]
2000s > 1990s (γ_3> γ_2)		0.41		6.83[a]		6.79[a]		2.68		0.00		1.14		1.53
Panel B: Liquidity Risk														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
Small Banks														

BDGTA			3.763[a]	0.773									0.036[a]	0.005
CRELGTA					1.478[a]	0.086							0.027[a]	0.006
TEGTA							-1.403[a]	0.212					-0.587[a]	0.118
OBSGTA									2.003[a]	0.218			0.023[a]	0.004
NIIOI											1.719[a]	0.100	0.777[a]	0.100
Dum1980s	0.060[a]	0.015	0.059[a]	0.014	-0.038[a]	0.011	0.068[a]	0.013	0.034[a]	0.012	-0.004	0.010	-0.014	0.008
Dum1990s	0.083[a]	0.017	0.054[a]	0.017	-0.075[a]	0.014	0.114[a]	0.015	0.005	0.015	0.043[a]	0.009	-0.016	0.011
Dum2000s	0.139[a]	0.020	0.062[a]	0.024	-0.163[a]	0.022	0.200[a]	0.019	0.042[b]	0.018	0.104[a]	0.010	-0.010	0.020
Constant	0.166[a]	0.011	0.145[a]	0.011	0.049[a]	0.008	0.312[a]	0.024	0.069[a]	0.013	0.030[a]	0.009	0.225[a]	0.018
Observations		122		122		122		122		122		122		122
F-value		18.10[a]		22.10[a]		121.31[a]		29.31[a]		44.07[a]		119.64[a]		172.80[a]
Adjusted R^2		29.78%		41.09%		79.91%		48.35%		58.74%		79.68%		91.91%
F-test														
1980s > Pre-1980s ($\gamma_1>0$)		14.09[a]		16.08[a]		14.13[a]		24.94[a]		7.39[a]		0.22		2.71
1990s > 1980s ($\gamma_2>\gamma_1$)		1.80		0.07		13.54[a]		8.56[a]		3.87[b]		24.77[a]		0.11
2000s > 1990s ($\gamma_3>\gamma_2$)		6.70[a]		0.13		38.52[a]		20.95[a]		5.16[b]		28.52[a]		0.31
Medium Banks														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			4.113[a]	0.521									0.051[a]	0.003
CRELGTA					1.009[a]	0.053							0.025[a]	0.003
TEGTA							-1.844[a]	0.266					-0.729[a]	0.105
OBSGTA									2.158[a]	0.185			0.017[a]	0.002
NIIOI											2.003[a]	0.107	1.064[a]	0.082
Dum1980s	0.079[a]	0.019	0.059[a]	0.016	-0.001	0.010	0.095[a]	0.016	0.023[c]	0.014	0.042[a]	0.010	0.025[a]	0.006
Dum1990s	0.107[a]	0.021	0.040[b]	0.019	-0.015	0.012	0.135[a]	0.018	-0.009	0.017	0.070[a]	0.010	0.015[b]	0.007
Dum2000s	0.147[a]	0.024	0.012	0.026	-0.052[a]	0.016	0.207[a]	0.022	0.008	0.020	0.153[a]	0.012	0.049[a]	0.011
Constant	0.204[a]	0.013	0.173[a]	0.011	0.068[a]	0.009	0.384[a]	0.028	0.063[a]	0.015	0.023[b]	0.011	0.229[a]	0.015
Observations		122		122		122		122		122		122		122
F-value		15.61[a]		33.34[a]		134.83[a]		28.27[a]		58.99[a]		133.20[a]		313.81[a]
Adjusted R^2		26.59%		51.67%		81.56%		47.41%		65.72%		81.38%		95.39%
F-test														
1980s > Pre-1980s ($\gamma_1>0$)		16.44[a]		13.75[a]		0.02		32.64[a]		2.81[c]		17.96[a]		15.72[a]

1990s > 1980s ($\gamma_2 > \gamma_1$)	1.67		1.09		1.67		4.62[b]		4.86[b]		6.80[a]		2.78[c]	
2000s > 1990s ($\gamma_3 > \gamma_2$)	2.46		1.52		7.49		10.46[a]		1.02		38.83[a]		18.74[a]	
Large Banks														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			2.810[a]	0.343									0.041[a]	0.003
CRELGTA					0.949[a]	0.060							0.024[a]	0.003
TEGTA							-1.739[a]	0.302					-0.720[a]	0.091
OBSGTA									0.723[a]	0.080			0.017[a]	0.003
NIIOI											1.693[a]	0.076	0.920[a]	0.073
Dum 1980s	0.038[c]	0.021	-0.003	0.018	0.014	0.012	0.081[a]	0.020	-0.029	0.018	-0.005	0.009	0.006	0.007
Dum1990s	0.115[a]	0.023	0.025	0.021	0.046[a]	0.014	0.159[a]	0.022	-0.041	0.025	0.070[a]	0.010	0.042[a]	0.011
Dum2000s	0.127[a]	0.026	-0.024	0.028	0.050	0.017	0.193[a]	0.026	0.047[b]	0.022	0.147[a]	0.011	0.096[a]	0.012
Constant	0.278[a]	0.015	0.239[a]	0.013	0.104[a]	0.014	0.438[a]	0.030	0.166[a]	0.017	0.072[a]	0.011	0.266[a]	0.015
Observations	122		122		122		122		122		122		122	
F-value	12.09[a]		30.92[a]		89.36[a]		19.78[a]		35.12[a]		167.17[a]		304.72[a]	
Adjusted R^2	21.57%		49.72%		74.50%		38.30%		53.01%		84.60%		95.26%	
F-test														
1980s > Pre-1980s ($\gamma_1 > 0$)	3.17[c]		0.04		1.29		15.81[a]		2.64		0.37		0.71	
1990s > 1980s ($\gamma_2 > \gamma_1$)	10.72[a]		2.16		5.58[b]		13.98[a]		0.32		54.04[a]		22.01[a]	
2000s > 1990s ($\gamma_3 > \gamma_2$)	0.19		4.41[b]		6.23[b]		1.84		14.24[a]		35.82[a]		41.14[a]	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. I consider small banks corresponding to the bottom 25 percentile of average Gross Total Assets (GTA), those in the top 25 percentile as large banks, and the rest medium banks. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009.Panel A shows the OLS regression results for credit risk after controlling for cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regression is estimated by using 122 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because U.S. banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

3.5.2 Time Trend

The averages of cohorts are calculated over different periods. For example, the cohort average for the 2000s banks is calculated using only 18 observations from 2000 to 2017, while the cohort average for the pre-1980 banks is calculated using 38 observations from 1980 to 2017. Since the cohorts might not have comparable averages, one may argue that this could represent overall time trends. To test this possibility, I follow (Brown and Kapadia, 2007) and Srivastava (2014) and include a variable, which controls for the secular time trend, in my regression analysis. Table 12 presents the results. While credit risk has similar results to those presented in Panel B of Table 5, liquidity risk has marginally different results. The difference is that the 2000s cohort slightly decreased but it is still larger than the 1980s cohort and the F-test is insignificant. Other results are broadly consistent with my main conclusion previously obtained in Table 8.

3.5.3 Excluding M&As and Failures

Banks typically exit the market if failing, are acquired by another institution, or merged with another bank. This can lead to a re-evaluation of financial statements which may affect my analysis. To investigate whether the main results are influenced by these exit states, I exclude from the sample the non-surviving banks that failed, were acquired, or merged. I find that the results presented in Table 13 are robust to the impact of mergers, acquisitions, or failures; and they leave my main conclusion unchanged.

Table 12: Financial risks after controlling for time trend, cohorts and bank-specific characteristics

Panel A: Credit Risk														
Variable	**Control for Cohorts**		**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			2.152[a]	0.250									0.035[a]	0.004
CRELGTA					0.756[a]	0.038							0.012[a]	0.002
TEGTA							-0.563[a]	0.186					-0.412[a]	0.1113
OBSGTA									1.059[a]	0.160			0.032[a]	0.005
NIIOI											-0.855[a]	0.223	-0.189[a]	0.112
Time trend	0.001[a]	0.001	-0.001	0.001	-0.001[a]	0.001	0.001[a]	0.001	0.001[a]	0.001	0.001[a]	0.001	-0.001	0.001
Dum1980s	0.037[a]	0.009	0.018[a]	0.007	-0.032[a]	0.005	0.035[a]	0.009	0.003	0.009	0.065[a]	0.012	-0.026[a]	0.006
Dum1990s	0.068[a]	0.009	0.025[a]	0.008	-0.010[c]	0.006	0.072[a]	0.009	0.013	0.011	0.073[a]	0.009	-0.020[a]	0.005
Dum2000s	0.078[a]	0.010	0.018[c]	0.010	-0.030[a]	0.007	0.095[a]	0.011	0.027[b]	0.012	0.052[a]	0.012	-0.025[a]	0.007
Constant	0.591[a]	0.011	0.616[a]	0.009	0.545[a]	0.005	0.655[a]	0.023	0.493[a]	0.017	0.653[a]	0.019	0.678[a]	0.014
Observations	96		96		96		96		96		96		96	
F-value	27.14[a]		53.87[a]		194.09[a]		25.50[a]		40.65[a]		27.88[a]		173.08[a]	
Adjusted R^2	52.40%		73.56%		91.04%		56.32%		67.61%		58.59%		94.22%	
F-test														
1980s > Pre-1980s (γ_1>0)	14.67[a]		6.23[b]		34.92[a]		14.83[a]		0.10		31.34[a]		14.93[a]	
1990s > 1980s (γ_2> γ_1)	10.48[a]		0.87		27.74[a]		14.72[a]		1.46		0.57		1.86	
2000s > 1990s (γ_3> γ_2)	0.86		0.77		16.72[a]		4.36[b]		2.58		2.68		0.56	

Panel B: Liquidity Risk														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			0.619	0.444									0.029[a]	0.003
CRELGTA					0.687[a]	0.085							0.021[a]	0.002
TEGTA							-1.279[a]	0.134					-1.174[a]	0.119
OBSGTA									1.123[a]	0.131			0.012[a]	0.001
NIIOI											1.293[a]	0.143	0.305[a]	0.114
Time trend	0.002[a]	0.001	0.001[a]	0.001	0.001[a]	0.001	0.001[a]	0.001	0.001[a]	0.001	0.001[a]	0.001	0.001[a]	0.001
Dum1980s	0.067[a]	0.011	0.063[a]	0.011	0.019[c]	0.010	0.082[a]	0.008	0.034[a]	0.009	0.033[a]	0.009	0.033[a]	0.006
Dum1990s	0.077[a]	0.012	0.067[a]	0.014	0.015	0.012	0.102[a]	0.009	0.011	0.012	0.067[a]	0.009	0.035[a]	0.006
Dum2000s	0.070[a]	0.014	0.053[a]	0.018	-0.019	0.016	0.120[a]	0.012	0.017	0.012	0.114[a]	0.012	0.070[a]	0.009
Constant	0.098[a]	0.010	0.102[a]	0.010	0.069[a]	0.009	0.234[a]	0.025	0.049[a]	0.009	0.041[a]	0.010	0.264[a]	0.014
Observations	122		122		122		122		122		122		122	
F-value	103.13[a]		83.56[a]		141.05[a]		163.89[a]		148.30[a]		155.43[a]		296.90[a]	
Adjusted R^2	77.15%		77.33%		85.27%		87.07%		85.89%		86.45%		95.86%	
F-test														
1980s > Pre-1980s (γ_1>0)	37.34[a]		30.20[a]		3.33[c]		94.51[a]		13.50[a]		12.52[a]		24.03[a]	
1990s > 1980s (γ_2> γ_1)	0.69		0.11		0.16		4.82[b]		4.91[b]		12.01[a]		0.18	
2000s > 1990s (γ_3> γ_2)	0.27		0.80		8.07[a]		2.48		0.20		13.38[a]		21.92[a]	

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A shows the OLS regression results for credit risk after controlling for cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regressions are estimated by using 122 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because U.S. banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

Table 13: Financial risks after controlling for cohorts and bank-specific characteristics (Without M&A and Failures)

Panel A: Credit Risk

Variable	**Control for Cohorts**		**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			2.171[a]	0.193									0.064[a]	0.003
CRELGTA					0.566[a]	0.036							0.032[a]	0.002
TEGTA							-0.878[a]	0.171					-0.622[a]	0.107
OBSGTA									1.099[a]	0.201			0.024[a]	0.003
NIIOI											0.429[a]	0.171	-0.414[a]	0.086
Dum1980s	0.030[a]	0.010	0.011	0.007	-0.011[c]	0.006	0.031[a]	0.009	-0.008	0.011	0.010	0.013	-0.012[b]	0.005
Dum1990s	0.068[a]	0.010	0.020[b]	0.008	0.011[c]	0.007	0.078[a]	0.009	-0.001	0.016	0.061[a]	0.010	-0.024[a]	0.007
Dum2000s	0.090[a]	0.012	0.014	0.010	-0.004	0.008	0.118[a]	0.011	0.028[c]	0.015	0.097[a]	0.011	-0.023[a]	0.009
Constant	0.629[a]	0.007	0.606[a]	0.005	0.547[a]	0.007	0.724[a]	0.019	0.528[a]	0.019	0.581[a]	0.020	0.790[a]	0.016
Observations	96		96		96		96		96		96		96	
F-value	23.87[a]		73.53[a]		124.52[a]		29.41[a]		30.91[a]		20.50[a]		136.53[a]	
Adjusted R^2	41.93%		75.33%		83.87%		54.47%		55.74%		45.08%		91.94%	
F-test														
1980s > Pre-1980s ($\gamma_1>0$)	7.77[a]		2.51		3.48[c]		10.93[a]		0.49		0.60		5.19[b]	
1990s > 1980s ($\gamma_2>\gamma_1$)	12.45[a]		1.33		16.49[a]		22.46[a]		0.36		18.98[a]		3.62[c]	
2000s > 1990s ($\gamma_3>\gamma_2$)	3.31[c]		0.55		5.88[b]		13.06[a]		8.17[a]		7.59[a]		0.01	

Panel B: Liquidity Risk														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			4.743[a]	0.440									0.070[a]	0.004
CRELGTA					1.134[a]	0.047							0.031[a]	0.003
TEGTA							-1.845[a]	0.284					-0.455[a]	0.113
OBSGTA									2.232[a]	0.153			0.015[a]	0.003
NIIOI											1.908[a]	0.101	0.767[a]	0.102
Dum1980s	0.056[a]	0.021	0.028[c]	0.015	-0.002	0.009	0.083[a]	0.018	-0.016	0.013	-0.016	0.011	-0.013[b]	0.006
Dum1990s	0.118[a]	0.023	0.019	0.018	-0.006	0.010	0.159[a]	0.020	-0.064[a]	0.018	0.051[a]	0.012	-0.008	0.009
Dum2000s	0.164[a]	0.026	-0.009	0.024	-0.053[a]	0.014	0.232[a]	0.024	-0.007	0.019	0.152[a]	0.013	0.022[c]	0.012
Constant	0.195[a]	0.014	0.154[a]	0.011	0.057[a]	0.008	0.385[a]	0.031	0.037[a]	0.014	0.020[c]	0.011	0.233[a]	0.019
Observations		122		122		122		122		122		122		122
F-value		16.54[a]		54.48[a]		215.09[a]		27.30[a]		87.35[a]		138.56[a]		295.77[a]
Adjusted R^2		27.81%		63.43%		87.62%		46.51%		74.06%		81.97%		95.12%
F-test														
1980s > Pre-1980s (γ_1>0)		7.28[a]		3.44[c]		0.09		20.15[a]		1.56		2.11		4.43[b]
1990s > 1980s (γ_2> γ_1)		7.12[a]		0.25		0.19		14.42[b]		9.03[a]		34.29[a]		0.34
2000s > 1990s (γ_3> γ_2)		2.70[c]		1.84		14.54[a]		8.92[a]		11.28[a]		49.45[a]		9.45[a]

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017 excluding mergers and acquisitions and failures banks. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A shows the OLS regression results for credit risk after controlling for cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regressions are estimated by using 122 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because U.S. banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

3.5.4 Banking Crises

During my sample period, the banking industry encountered two banking crises: first, the credit crunch that occurred in the U.S. between 1990 and 1992, due to poorly capitalised institutions from the loan loss incidents of the late 1980s (e.g., Peek and Rosengren, 1995), the increase in risk-based capital and supervisory requirements (e.g., Thakor, 1996), and the reduction in loan demand associated with macroeconomic and regional recessions (Berger and Bouwman, 2013); second, the subprime mortgage crisis that started in the U.S. between early 2008 and the end of 2009 and that spread to the rest of the world. It was mainly triggered by the meltdown of real estate prices, leading to a high number of foreclosures and the collapse of large and complex banks.

These crises have had a significant impact on the health of the U.S. banking system and on the soundness of individual banks. To control for possible effects on the reliability of my findings, I re-ran my main analyses while excluding the years of the banking crises (1990, 1991, 1992, 2008, and 2009). Table 14 contains the results for liquidity risk and credit risk. As can be seen, the results are similar to the main results presented in Tables 5 and 8.

3.5.5 "True" Commercial Banks

Following Distinguin et al. (2013), I limit my sample to "true" commercial banks defined by Berger and Bouwman (2009) as banks that have commercial real estate or commercial and industrial loans outstanding, have deposits, have positive equity capital, have average GTA above $25 million, have unused commitments below four times GTA, have residential real estate loans below 50% of GTA, and are not classified as credit card banks.[34] Table 15 shows that the results are in line with those earlier presented in Tables 5 and 8 on my full sample of banks.

[34] A credit card bank as defined by the Federal Reserve Board is a bank that has 50% or more of its total assets in the form of loans to individuals, 90% or more of its loans to individuals in the form of credit card payments outstanding, and $200 million or more in loans to individuals.

Table 14: Financial risks after controlling for banking crises, cohorts and bank-specific characteristics

Panel A: Credit Risk														
Variable	**Control for Cohorts**		**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			2.165[a]	0.251									0.056[a]	0.002
CRELGTA					0.609[a]	0.037							0.033[a]	0.001
TEGTA							-0.692[a]	0.186					-0.455[a]	0.096
OBSGTA									1.293[a]	0.168			0.017[a]	0.002
NIIOI											0.229	0.170	-0.190[a]	0.059
Dum1980s	0.036[a]	0.010	0.019[b]	0.008	-0.019[a]	0.006	0.034[a]	0.009	-0.006	0.010	0.028[b]	0.012	-0.029[a]	0.005
Dum1990s	0.069[a]	0.010	0.028[a]	0.009	0.005	0.006	0.073[a]	0.009	-0.001	0.012	0.067[a]	0.010	-0.017[a]	0.005
Dum2000s	0.084[a]	0.011	0.019[c]	0.011	-0.013	0.008	0.105[a]	0.012	0.019	0.012	0.088[a]	0.011	-0.017[a]	0.007
Constant	0.634[a]	0.007	0.610[a]	0.006	0.540[a]	0.006	0.706[a]	0.020	0.506[a]	0.017	0.607[a]	0.021	0.750[a]	0.012
Observations	85		85		85		85		85		85		85	
F-value	22.54[a]		50.69[a]		140.77[a]		23.04[a]		43.85[a]		17.53[a]		197.93[a]	
Adjusted R^2	43.48%		70.29%		86.94%		51.21%		67.11%		44.04%		94.94%	
F-test														
1980s > Pre-1980s (γ_1>0)	11.87[a]		5.74[b]		10.41[a]		12.57[a]		0.46		5.56[b]		35.32[a]	
1990s > 1980s (γ_2> γ_1)	9.46[a]		1.29		24.11[a]		14.90[a]		.54		11.37[a]		7.58[b]	
2000s > 1990s (γ_3> γ_2)	1.87		0.96		9.51[a]		7.50[a]		4.96[b]		3.10[c]		0.01	

Panel B: Liquidity Risk														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			4.144[a]	0.406									0.043[a]	0.002
CRELGTA					1.132[a]	0.061							0.016[a]	0.001
TEGTA							-1.718[a]	0.302					-0.748[a]	0.159
OBSGTA									1.919[a]	0.149			0.008[a]	0.002
NIIOI											1.825[a]	0.088	0.852[a]	0.078
Dum1980s	0.062[a]	0.021	0.042[a]	0.011	-0.011	0.010	0.086[a]	0.019	0.007	0.013	0.016[c]	0.009	0.008	0.005
Dum1990s	0.130[a]	0.023	0.026[c]	0.014	-0.012	0.013	0.151[a]	0.020	-0.014	0.018	0.076[a]	0.010	0.016[b]	0.007
Dum2000s	0.146[a]	0.026	-0.005	0.018	-0.060[a]	0.016	0.207[a]	0.025	0.007	0.019	0.139[a]	0.011	0.048[a]	0.011
Constant	0.213[a]	0.014	0.194[a]	0.008	0.063[a]	0.010	0.383[a]	0.032	0.065[a]	0.014	0.039[a]	0.010	0.219[a]	0.018
Observations		105		105		105		105		105		105		105
F-value		15.47[a]		56.54[a]		136.13[a]		23.26[a]		71.52[a]		166.38[a]		211.42[a]
Adjusted R^2		29.46%		69.39%		83.86%		46.13%		73.06%		86.41%		94.50%
F-test														
1980s > Pre-1980s (γ_1>0)		8.66[a]		12.72[a]		1.15		20.64[a]		0.30		2.96[c]		1.80
1990s > 1980s (γ_2> γ_1)		7.12[a]		1.38		0.00		10.11[a]		1.80		34.05[a]		1.38
2000s > 1990s (γ_3> γ_2)		0.32		4.25[b]		12.06[a]		4.76[b]		1.57		24.90[a]		10.22[a]

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A shows the OLS regression results for credit risk after controlling for banking crises, cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for banking crises, cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regressions are estimated by using 122 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because U.S. banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

Table 15: Financial risks after controlling for cohorts and bank-specific characteristics (Commercial banks only)

Panel A: Credit Risk														
Variable	**Control for Cohorts**		**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			2.167[a]	0.198									0.060[a]	0.002
CRELGTA					0.643[a]	0.031							0.035[a]	0.002
TEGTA							-0.865[a]	0.240					-0.495[a]	0.113
OBSGTA									1.316[a]	0.179			0.015[a]	0.002
NIIOI											0.317[c]	0.189	-0.209[a]	0.066
Dum1980s	0.031[a]	0.011	0.016[b]	0.007	-0.035[a]	0.005	0.026[b]	0.010	-0.001	0.010	0.023[c]	0.012	-0.032[a]	0.005
Dum1990s	0.064[a]	0.011	0.025[a]	0.008	-0.013[b]	0.006	0.066[a]	0.010	0.013	0.011	0.066[a]	0.011	-0.025[a]	0.005
Dum2000s	0.089[a]	0.012	0.020[b]	0.010	-0.025[a]	0.007	0.109[a]	0.013	0.031[b]	0.012	0.098[a]	0.013	-0.027[a]	0.008
Constant	0.640[a]	0.008	0.615[a]	0.006	0.539[a]	0.006	0.730[a]	0.025	0.511[a]	0.018	0.603[a]	0.023	0.760[a]	0.012
Observations	96		96		96		96		96		96		96	
F-value	20.09[a]		64.18[a]		188.74[a]		20.26[a]		37.20[a]		16.07[a]		203.24[a]	
Adjusted R^2	37.61%		72.68%		88.77%		44.78%		60.39%		38.81%		94.45%	
F-test														
1980s > Pre-1980s ($\gamma_1>0$)	7.50[a]		4.64[b]		36.31[a]		6.16[b]		0.03		3.73[c]		35.87[a]	
1990s > 1980s ($\gamma_2>\gamma_1$)	8.30[a]		1.23		19.04[a]		13.01[a]		2.51		11.26[a]		2.80[c]	
2000s > 1990s ($\gamma_3>\gamma_2$)	4.02[b]		0.25		4.48[b]		11.54[a]		3.12[c]		5.93[b]		0.16	

Panel B: Liquidity Risk														
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			3.290[a]	0.380									0.048[a]	0.003
CRELGTA					1.078[a]	0.057							0.025[a]	0.003
TEGTA							-2.075[a]	0.309					-0.957[a]	0.149
OBSGTA									2.166[a]	0.150			0.013[a]	0.002
NIIOI											2.048[a]	0.100	1.009[a]	0.091
Dum1980s	0.068[a]	0.021	0.054[a]	0.013	-0.019[c]	0.011	0.086[a]	0.017	0.018	0.013	0.029[a]	0.010	0.010	0.007
Dum1990s	0.107[a]	0.023	0.028[c]	0.015	-0.039[a]	0.013	0.133[a]	0.020	-0.014	0.016	0.085[a]	0.010	0.019[b]	0.008
Dum2000s	0.148[a]	0.026	0.018	0.020	-0.072[a]	0.017	0.210[a]	0.024	0.006	0.018	0.162[a]	0.012	0.061[a]	0.012
Constant	0.218[a]	0.014	0.205[a]	0.010	0.077[a]	0.010	0.419[a]	0.032	0.050[a]	0.014	0.021[c]	0.011	0.274[a]	0.017
Observations		122		122		122		122		122		122		122
F-value		13.57[a]		38.37[a]		130.36[a]		25.21[a]		79.83[a]		148.41[a]		221.70[a]
Adjusted R^2		23.77%		56.52%		81.05%		44.46%		72.27%		82.97%		93.88%
F-test														
1980s > Pre-1980s (γ_1>0)		10.84[a]		15.84[a]		2.87[c]		23.08[a]		1.99		7.46[a]		1.97
1990s > 1980s (γ_2> γ_1)		2.91[c]		3.01[c]		2.91[c]		6.04[b]		5.09[b]		29.05[a]		2.01
2000s > 1990s (γ_3> γ_2)		2.29		0.29		5.63[b]		10.33[a]		1.66		35.15[a]		24.25[a]

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. commercial banks only over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A shows the OLS regression results for credit risk after controlling for cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regressions are estimated by using 122 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because U.S. banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992), composed of 38 annual observations (26 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (26 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (26 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

3.5.6 Alternative Risk Proxies

To verify my main results, I use two alternative risk measures: one measure of liquidity risk, and one of credit risk. The description and calculation for each measure is provided in Table 2. The first is liquidity risk developed by Imbierowicz and Rauch (2014) which measures the relationship of short-term obligations to short-term assets, including off-balance sheet items and shows to what degree a bank exposes itself to the interbank lending and derivative markets. The second is credit risk measured by Z-score, which represents the number of standard deviations below the mean by which profits would have to fall so as to deplete the bank's equity capital (Houston et al., 2010). The Z-score is considered a measure of a bank's distance to insolvency and has been widely used in the empirical banking literature for measuring bank risk (e.g., Bertay et al., 2013; Boyd and Runkle, 1993; Delis et al., 2014). Estimation results, reported in Panel A of Table 16, show that each new cohort is less stable than its predecessor. In Panel B, the liquidity risk increases in successive cohorts but with smaller values than for my main results presented in Table 5. Other findings are comparable to those presented in Tables 5 and 8.

3.5.7 Alternative Cohort Period

To examine the sensitivity of my results to different cohort measurement periods, I split the new banks into six 5-year groups: a cohort of 1,375 banks that started between 1980 and 1984, a cohort of 1,161 banks that started between 1985 and 1989, a cohort of 447 banks that started between 1990 and 1994, a cohort of 895 banks that started between 1995 and 1999, a cohort of 655 banks that started between 2000 and 2004, and a cohort of 668 banks that started between 2005 and 2009. The results are presented in Table 17 and show that the trends I find for 10-year periods are generally present in the shorter time periods as well. This indicates that my main findings reported in Tables 5 and 8 are relatively not sensitive to alternative cohort periods.

Table 16: Financial risks after controlling for cohorts and bank-specific characteristics (Using alternative measures)

Panel A: Credit Risk														
Variable	**Control for Cohorts**		**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			15.370[a]	2.981									0.275[a]	0.069
CRELGTA					4.534[a]	0.534							0.155[a]	0.052
TEGTA							-2.349	2.350					2.321	0.250
OBSGTA									8.533[a]	1.101			0.064	0.096
NIIOI											6.010[a]	1.028	0.311	1.343
Dum1980s	-0.610[a]	0.108	-0.726[a]	0.100	-0.948[a]	0.093	-0.590[a]	0.110	-0.860[a]	0.093	-0.780[a]	0.100	-1.037[a]	0.104
Dum1990s	-0.783[a]	0.118	-1.128[a]	0.126	-1.350[a]	0.113	-0.751[a]	0.122	-1.378[a]	0.122	-0.932[a]	0.107	-1.427[a]	0.126
Dum2000s	-1.157[a]	0.137	-1.748[a]	0.168	-2.069[a]	0.149	-1.092[a]	0.010	-1.739[a]	0.134	-1.163[a]	0.120	-2.109[a]	0.187
Constant	3.773[a]	0.076	3.643[a]	0.073	3.176[a]	0.091	4.004[a]	0.022	3.099[a]	0.107	3.190[a]	0.120	3.518[a]	0.278
Observations	118		118		118		118		118		118		118	
F-value	29.05[a]		33.32[a]		54.69[a]		22.04[a]		48.05[a]		36.65[a]		30.05[a]	
Adjusted R^2	41.83%		52.49%		64.73%		41.83%		61.67%		54.93%		66.52%	
F-test														
1980s > Pre-1980s (γ_1>0)	31.51[a]		51.49[a]		103.56[a]		28.59[a]		83.78[a]		60.85[a]		98.19[a]	
1990s > 1980s (γ_2> γ_1)	2.14		12.04[a]		17.51[a]		1.83		23.91[a]		2.13		10.26[a]	
2000s > 1990s (γ_3> γ_2)	6.68[a]		19.84[a]		36.22[a]		5.26[b]		9.44[b]		3.18[c]		21.10[a]	

Panel B: Liquidity Risk

	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			2.487[a]	0.655									2.228[a]	0.598
CRELGTA					0.926[a]	0.106							-1.039[a]	0.174
TEGTA							-1.458[a]	0.353					-1.213[a]	0.159
OBSGTA									2.629[a]	0.139			2.775[a]	0.191
NIIOI											2.132[a]	0.134	1.066[a]	0.123
Dum1980s	0.002	0.023	-0.016	0.023	-0.064[a]	0.020	0.019	0.022	-0.073[a]	-0.056[a]	0.029[a]	0.013	-0.033[a]	0.009
Dum1990s	0.075[a]	0.025	0.022	0.028	-0.036	0.023	0.101[a]	0.024	-0.106[a]	0.016	0.022	0.014	-0.045[a]	0.011
Dum2000s	0.086[a]	0.029	-0.005	0.036	-0.092[a]	0.031	0.136[a]	0.030	-0.098[a]	0.017	0.083[a]	0.016	0.050[a]	0.017
Constant	0.197[a]	0.016	0.177[a]	0.016	0.077[a]	0.019	0.340[a]	0.038	-0.004	0.013	-0.003	0.015	0.119[a]	0.022
Observations		122		122		122		122		122		122		122
F-value		5.58[a]		8.26[a]		25.66[a]		9.02[a]		106.17[a]		75.83[a]		148.57[a]
Adjusted R^2		10.19%		19.36%		44.91%		20.95%		77.66%		71.21%		90.70%
F-test														
1980s > Pre-1980s ($\gamma_1>0$)		0.01		0.50		10.34[a]		0.73		34.37[a]		16.49[a]		12.13[a]
1990s > 1980s ($\gamma_2> \gamma_1$)		8.20[a]		2.15		1.89		11.36[a]		5.74[b]		29.18[a]		1.10
2000s > 1990s ($\gamma_3> \gamma_2$)		0.11		0.78		4.89[b]		1.39		0.27		11.49[a]		53.13[a]

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1989, 1990-1999, and 2000-2009. Panel A shows the OLS regression results for credit risk after controlling for cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regressions are estimated by using 122 cohort–year observations (except Z-score, as a proxy for credit risk, is 118 cohort–year observations because the first annual observation of each cohort is exempt of calculations), composed of 38 annual observations (37 annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (37 annual observations for credit risk) for the 1980s cohort (1980–2017), 28 annual observations (27 annual observations for credit risk) for the 1990s cohort (1990–2017), and 18 annual observations (17 annual observations for credit risk) for the 2000s cohort (2000–2017). All variables are defined in Table 2 and 3.

Table 17: Financial risks after controlling for cohorts and bank-specific characteristics (Alternative cohort period of 5 years)

Panel A: Credit Risk														
Variable	**Control for Cohorts**		**Control for BDGTA & Cohorts**		**Control for CRELGTA & Cohorts**		**Control for TEGTA & Cohorts**		**Control for OBSGTA & Cohorts**		**Control for NIIOI & Cohorts**		**Control for all & Cohorts**	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	β	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*	*β*	*SE*
BDGTA			1.99^{a}	0.157									0.050^{a}	0.002
CRELGTA					0.625^{a}	0.025							0.028^{a}	0.001
TEGTA							-0.813^{a}	0.120					-0.639^{a}	0.056
OBSGTA									1.109^{a}	0.144			0.013^{a}	0.001
NIIOI											0.164	0.139	-0.274^{a}	0.044
Dum1980s	0.018	0.012	0.009	0.008	-0.028^{a}	0.006	0.017^{c}	0.010	-0.003	0.010	0.013	0.013	-0.016^{a}	0.004
Dum1985s	0.042^{a}	0.012	0.024^{a}	0.008	-0.009^{c}	0.006	0.039^{a}	0.010	-0.002	0.011	0.036^{a}	0.013	-0.015^{a}	0.004
Dum1990s	0.060^{a}	0.012	0.036^{a}	0.008	0.001	0.006	0.061^{a}	0.010	-0.011	0.014	0.056^{a}	0.012	-0.022^{a}	0.005
Dum1995s	0.066^{a}	0.012	0.019^{b}	0.009	0.004	0.006	0.077^{a}	0.011	0.015	0.012	0.066^{a}	0.012	-0.007	0.004
Dum2000s	0.086^{a}	0.013	0.019^{c}	0.010	-0.005	0.007	0.100^{a}	0.011	0.033^{a}	0.013	0.088^{a}	0.013	-0.008^{c}	0.005
Dum2005s	0.080^{a}	0.015	0.009	0.012	-0.030^{a}	0.008	0.114^{a}	0.014	0.031^{b}	0.014	0.085^{a}	0.016	-0.012^{c}	0.007
Constant	0.642^{a}	0.008	0.614^{a}	0.006	0.535^{a}	0.006	0.727^{a}	0.014	0.530^{a}	0.016	0.623^{a}	0.018	0.716	0.008
Observations		158		158		158		158		158		158		158
F-value		12.50^{a}		44.70^{a}		135.60^{a}		20.38^{a}		23.19^{a}		10.94^{a}		221.41^{a}
Adjusted R^2		30.54%		66.08%		85.72%		46.35%		49.73%		30.71%		93.92%
F-test														
1980s > Pre-1980s ($\gamma_1>0$)		2.47		1.16		25.33^{a}		2.86^{c}		0.10		1.03		15.39^{a}
1985s > 1980s ($\gamma_2>\gamma_1$)		4.13^{b}		3.36^{c}		12.28^{a}		4.46^{b}		0.03		4.05^{b}		0.22
1990s > 1985s ($\gamma_3>\gamma_2$)		2.36		1.98		4.08^{b}		4.58^{b}		0.85		2.82^{c}		3.86^{c}
1995s > 1990s ($\gamma_4>\gamma_3$)		0.24		3.46^{c}		0.21		1.97		6.11^{a}		0.59		14.52^{a}
2000s > 1995s ($\gamma_5>\gamma_4$)		2.18		0.00		2.13		3.92^{b}		2.54		2.56		0.13
2005s > 2000s ($\gamma_6>\gamma_5$)		0.15		0.74		11.54^{a}		0.99		0.02		0.02		0.57
Panel B: Liquidity Risk														

	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE	β	SE
BDGTA			3.026[a]	2.981									0.045[a]	0.002
CRELGTA					0.998[a]	0.043							0.025[a]	0.002
TEGTA							-1.586[a]	0.178					-0.676[a]	0.072
OBSGTA									1.916[a]	0.128			0.007[a]	0.001
NIIOI											1.834[a]	0.090	0.785[a]	0.060
Dum1980s	0.052[a]	0.019	0.042	0.013	-0.006	0.010	0.067[a]	0.016	0.016	0.013	-0.001	0.011	-0.009[c]	0.005
Dum1985s	0.089[a]	0.020	0.047[a]	0.014	0.006	0.011	0.102[a]	0.017	0.004	0.014	0.016	0.012	-0.004	0.005
Dum1990s	0.125[a]	0.021	0.067[a]	0.015	0.014	0.012	0.145[a]	0.017	-0.030[c]	0.017	0.053[a]	0.012	0.005	0.007
Dum1995s	0.116[a]	0.022	0.019	0.017	-0.012	0.012	0.146[a]	0.019	-0.012	0.017	0.077[a]	0.012	0.014[b]	0.007
Dum2000s	0.144[a]	0.024	0.017	0.019	-0.030[b]	0.014	0.181[a]	0.020	0.013	0.018	0.125[a]	0.013	0.032[a]	0.008
Dum2005s	0.133[a]	0.028	0.000	0.022	-0.072[a]	0.017	0.210[a]	0.025	0.009	0.021	0.154[a]	0.016	0.041[a]	0.010
Constant	0.221[a]	0.013	0.204[a]	0.010	0.080[a]	0.009	0.377[a]	0.021	0.068[a]	0.014	0.047[a]	0.011	0.221[a]	0.011
Observations		191		191		191		191		191		191		191
F-value		11.44[a]		31.08[a]		112.27[a]		25.27[a]		53.70[a]		90.54[a]		261.02[a]
Adjusted R^2		24.80%		53.36%		80.39%		47.20%		66.01%		76.74%		93.96%
F-test														
1980s > Pre-1980s (γ_1>0)		7.53[a]		9.84[a]		0.37		17.42[a]		1.45		0.01		2.85[c]
1985s > 1980s (γ_2> γ_1)		3.54[c]		0.15		1.43		4.61[b]		0.75		2.38		1.06
1990s > 1985s (γ_3> γ_2)		2.76[c]		1.71		0.47		5.67[b]		4.83[b]		9.40[a]		2.29
1995s > 1990s (γ_4> γ_3)		0.15		8.44[a]		4.57[b]		0.00		1.2		3.35[c]		2.32
2000s > 1995s (γ_5> γ_4)		1.16		0.02		1.69		2.55		2.08		10.74[a]		6.51[a]
2005s > 2000s (γ_6> γ_5)		0.13		0.62		6.56[a]		1.13		0.04		2.76[c]		1.29

Notes: a (b) [c] significant at the 1 % (5 %) [10 %] level. The sample is based on annual data of U.S. banks over the period 1980-2017. The banks are sorted into four cohorts based on their year of opening: prior to 1980, between 1980-1985, 1985-1989, 1990-1994, 1995-1999, 2000-2004, and 2005-2009. Panel A shows the OLS regression results for credit risk after controlling for cohorts and bank-specific characteristics. Panel B shows the OLS regression results for liquidity risk after controlling for cohorts and bank-specific characteristics. I consider the dummy variable for pre-1980s as base case; therefore, I exclude it from the regression. The regressions are estimated by using 191 cohort–year observations (except risk-weighted assets, as a proxy for credit risk, is 96 cohort–year observations because U.S. banks started to report it in Call Reports from 1990, but it is available in Bank Regulatory database by WRDS from 1992, composed of 38 annual observations (annual observations for credit risk) for the pre-1980-bank category (1980–2017), 38 annual observations (annual observations for credit risk) for the 1980s cohort (1980–2017), 33 annual observations for the 1985s cohort, 28 annual observations (annual observations for credit risk) for the 1990s cohort, 23 annual observations (annual observations for credit risk) for the 1995s cohort (1990–2017), 18 annual observations (27 annual observations for credit risk) for the 2000s cohort (2000–2017), and 13 annual observations (17 annual observations for credit risk) for the 2005s cohort (2005–2017). All variables are defined in Table 2 and 3.

3.6 Conclusion

According to Allen and Santomero (1997), the role of banks has changed from reducing transaction costs and asymmetric information to risk management over the last few decades. This transformation can be attributed to major regulatory changes (e.g., deregulation), financial innovations, and technology. Although, this role is pivotal for many banks, it has a significant impact on banks' riskiness. Thus, this study sheds light on the systematic trend in bank risk measured by liquidity risk and credit risk, and examines potential explanations for this trend.

My main results are as follow. First, there is strong evidence of a positive trend in bank risk over my sample period, 1980-2017. Second, the increase in bank risk is the result of successive cohorts of young and riskier banks. Third, the risk differences across successive cohorts persist. Fourth, the cohort risk phenomenon is significantly attenuated once I account for new cohorts' bank-specific characteristics including brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income. In other words, the adoption of business strategy that is based on higher brokered deposits, commercial real estate loans, off-balance sheet items, and non-interest income and lower capital by each new cohort is responsible for the cohort risk phenomenon. I perform a set of robustness checks and the main results are qualitatively unchanged.

My results offer deeper insights into the understanding of bank risk and support recent regulatory requirements to enhance the stability of the banking industry to avoid the adverse effects on whole economy. In addition, my results should interest bank managers, supervisors, policy makers, and researchers who attempt to prevent upcoming banking crises.

4. THE LONGER THE TAIL, THE SHORTER THE SAIL

4.1 Introduction

In the aftermath of the Global Financial Crisis of 2008, the information content of market-based indicators has drawn increased attention in the domain concerned with systemic risk and financial stability (Milne, 2014). This crisis, considered to be one of the most acute financial crises in terms of costs to society (Atkinson et al., 2013), raised scepticism about our understanding of the vulnerability of financial institutions to black swan (low probability and high impact) events, in particular, the vulnerability of banking institutions. Anecdotal evidence also suggests that this crisis was the alarm bell that augmented global awareness about the vulnerability that financial institutions face due to unforeseen tail risk events (Cohen et al., 2014). This calls for an improved understanding of the factors affecting bank failure, so that pre-emptive measures can be undertaken to reduce their failure likelihood and, in turn, reduce costs associated with such failures. Thus, in this study, I hypothesise that more frequent extreme negative daily equity returns result in higher tail risk, and this subsequently increases banks' likelihood of experiencing distress risk.

The empirical literature on the determinants of bank distress has focused heavily on financial ratios based on accounting information. Early studies have documented that the United States (U.S.) banks' default risk is mainly driven by low profitability, low capitalisation, weak asset quality (nonperforming loans), cost inefficiency and/or poor management, and illiquidity (e.g., Cole and Gunther, 1995; Martin, 1977; Meyer and Pifer, 1970; Wheelock and Wilson, 2000). Recent studies have mostly applied these proxies to U.S. bank failures during the financial crisis of 2007-08 supplemented with some information related to banks' audit quality (Jin et al., 2011), real estate investments (Cole and White, 2012), income from non-traditional banking activities

(DeYoung and Torna, 2013), or corporate governance (Berger et al., 2016). Generally, they find that the CAMEL indicators are still efficient in explaining the bank failure.[35]

However, a separate strand of literature argues for the superior performance of accounting-based bank failure prediction models when supplemented with market price-based factors (e.g., Coffinet et al., 2010; Curry et al., 2007; Evanoff and Wall, 2002; Flannery, 1998; Gropp et al., 2006). While these studies focus on individual bank risk, others explicitly take into account the systemic aspect (e.g., Adrian and Brunnermeier, 2016; De Jonghe, 2010; Hartmann et al., 2005; Straetmans et al., 2008). The general finding across these studies is that the use of market-based variables plays a significant role in explaining bank failure and can enhance the prediction performance of bank failure prediction models.

However, relative to market indicators, existing literature on the determinants of bank distress has primarily focused on the information content of financial statements in predicting bank failure/distress. But market-based indicators derived from banks' stock prices may signal useful marginal information on the future distress likelihood of banks. Hence, a thorough understanding of bank fragility should also focus equally on potential market-based determinants, especially banks' stock prices. In practice, U.S. bank supervisors have recently started to use market data combined with traditional early warning models to monitor publicly traded federally insured institutions (Coffinet et al., 2013; Curry et al., 2007).

Notwithstanding that prior studies have clearly established a strong link between the information content of market indicators and individual bank risk (e.g., Coffinet et al., 2010; Curry et al., 2007; Evanoff and Wall, 2002; Flannery, 1998; Gropp et al., 2006), they do not focus on the

[35] Demyanyk and Hasan (2010) provide a comprehensive survey by reviewing the results obtained in several economics, finance and operations studies that attempt to explain financial crises and bank defaults.

relationship between banks' extreme negative daily equity returns (tail risk) and their likelihood of experiencing a distress event. In this study, I address this important gap in the literature by exploring whether increase in tail risk exposure is associated with an increased likelihood of financial distress in banks. I hypothesise that more frequent extreme negative daily equity returns result in higher tail risk, and this subsequently increases banks' likelihood of entering financial distress. Specifically, I explore the information content of tail risk measures, namely Value-at-risk (VaR) and Expected Shortfall (ES), in explaining banks' likelihood of financial distress.

There are several reasons for considering the relationship between downside risk measures, which focus only on the risk of underperforming a defined benchmark return, and the financial distress of banks. First, a new body of research, focusing mainly on the determinants of individual bank tail risk, find that the tail risk is higher for banks with a weak risk management function, greater earnings management, small inside debt holdings, non-traditional activities (securities held for-sale, trading assets and derivatives used for trading purposes), and a large relative size (e.g., Cohen et al., 2014; Ellul and Yerramilli, 2013; Hagendorff et al., 2018; Kashyap et al., 2008; Knaup and Wagner, 2010; Srivastav et al., 2017; Van Bekkum, 2016). In addition, they suggest that excessive exposure to tail risk can enhance banks' short-term performance, but it can also be associated with a small probability of large losses to these banks. Second, the recent literature also argues that tail risk could cause a serious threat to banks' stability (e.g., Ellul and Yerramilli, 2013; Kashyap et al., 2008), thus leading me to hypothesise that banks with higher extreme negative daily equity returns lead to higher tail risk, thereby increasing their likelihood of financial distress. Third, there is an extensive literature on safety-first investors who minimise the probability of large negative outcomes. Such investors are intended to select portfolios that have maximum expected returns with limited downside risks (see, among others, Roy, 1952; Arzac and Bawa, 1977). Fourth, financial firms routinely apply tail risk measures for their risk-management objectives, and firms are increasingly adopting these measures to manage their risk as well. Finally, empirical evidence generally finds that the stock returns are fat tailed, implying that the rate of occurrence of negative extreme events is more frequent than suggested by the normal distribution (see, among others, Jansen and De Vries, 1991; Conrad et al., 2013). Thus, traditional market risk measures might be insufficient for explaining the probability of maximum loss that a bank may face, especially during highly volatile periods.

Considering the above discussion, I assess the marginal discriminatory power of tail risk measures, namely VaR and ES, in predicting the financial distress of publicly-traded BHCs in the United States. In particular, I use tail risk estimates reported in Ellul and Yerramilli (2013) and Gupta and Chaudhry (2019) as my primary measures of tail risk, generated using three-month, six-month, one-year, three-year, and five-year daily returns. Following Liang and Park (2010), I include the Cornish and Fisher (1938) expansion in these risk measures. The advantage of adding this expansion is to bring skewness and kurtosis into the equation, which is more appropriate for non-normal financial returns (Gupta and Chaudhry, 2019). I estimate the tail risk measure of each bank at the year-end to predict banks' financial distress in the following year. To proxy banks' distress risk, I use the celebrated Z-score, which is widely used in banking literature to proxy financial distress of banks (e.g., Beck et al., 2013; Berger and Bouwman, 2009; Goetz et al., 2016; Imbierowicz and Rauch, 2014 and many others).

To test my hypothesis, I empirically analyse an unbalanced panel of publicly-traded BHCs in the U.S. during the period 1987 to 2017.[36] I start the empirical validation by estimating separate

[36] Throughout the paper, I will use BHC and bank interchangeably.

one-year distress prediction models using respective tail risk estimates (three-month, six-month, one-year, three-year, and five-year at a 99% confidence level) to assess their statistical significance in explaining the likelihood of banks' distress in a univariate framework. The results of univariate regression are in line with my hypothesis, and show a significantly positive relationship between banks' extreme negative equity returns and their likelihood of experiencing financial distress. In the second part of my analysis, I develop multivariate models to test the marginal discriminatory power of tail risk measures. First, I estimate a one-year financial distress prediction model (baseline model), using the OLS regression technique, with accounting-based variables, as well as bank and year fixed effects. Specifically, I use the standard proxies of the CAMEL components along with measures of bank size and real estate loans.[37] I then supplement respective tail risk measures with my baseline distress model and investigate their significance in the presence of competing variables.

Empirical results verify the finding of extant bank default literature that traditional proxies for the CAMEL are essential determinants of bank distress (e.g., Cole and Gunther, 1995; Cole and White, 2012). Specifically, the capital ratio and return on equity have significant and negative effects, suggesting that more capital and high profitability reduce default probability of banks. On the other hand, weak assets quality (high credit risk), high liquidity risk, more reliance on real-estate loans, and large bank size significantly increase the chances of a bank's default. More importantly, I find that all rolling estimates of VaR and ES measures at a 99% confidence level are significantly and positively linked to the probability of bank distress. These results strongly support my hypothesis that banks with more frequent extreme negative daily equity returns are

[37] The CAMEL ratings system was introduced by the US regulators in 1979 to evaluate the financial health of individual banks, where the letters refer to Capital adequacy, Asset quality, Management skills, Earnings, Liquidity.

more likely to experience financial distress. Moreover, my results are consistent with the findings of previous studies that market-based measures can efficiently signal bank fragility (e.g., Curry et al., 2007; Gropp et al., 2006).

To validate the main results, I perform a range of robustness checks. First, I use the Merton distance to default (DD) model as an alternative measure for banks' distress risk. Second, I use a confidence level of 95% instead of 99% to estimate tail risk measures. Third, I divide my overall sample into small, medium, and large banks. Fourth, I include additional variables to control for competition and macroeconomic conditions. Fifth, I add dummy variables to control for financial crises. Sixth, I exclude mergers and acquisitions. Seventh, I drop "Too big To Fail" banks. Eighth, I lag my explanatory variables by 3 years to further mitigate the impact of potential endogeneity issues (i.e., simultaneity). In general, my main results stand up to all these tests and analyses.

The rest of the chapter is organised as follows: Section 4.2 discusses data and financial covariates; Section 4.3 presents my empirical methods and main results; Section 4.4 presents additional results on robustness checks; and Section 4.5 concludes this chapter.

4.2 Data, Sample and Covariates

In this section, I first discuss the sources of my datasets, followed by construction of the sample analysed. Finally, I define key dependent and independent covariates employed in my regression estimates.

4.2.1 Data Sources

To perform my empirical analysis, I use accounting, market and macroeconomic data. First, all accounting information on the U.S. Bank Holding Companies (BHCs) are obtained from the Federal Reserve Bank (FRB) of Chicago.[38] Since June of 1986, the FRB of Chicago has collected data from the FR Y-9 reports that are filed by BHCs on a quarterly basis. The FR Y-9C reports contain basic financial data on a consolidated basis in the form of a balance sheet, income statement, and detailed supporting schedules. Second, market data including daily stock returns, stock prices, and number of shares outstanding for publicly traded BHCs are collected from the Centre for Research in Security Prices (CRSP). Finally, I collect macroeconomic data consisting of daily risk-free rate, which is 1-year U.S. Treasury Constant Maturity series offered by the Federal Reserve Bank of St. Louis, House Price Indices (HPIs) acquired from the Federal Housing Finance Agency, and state personal income data sourced from the Bureau of Economic Analysis.[39]

4.2.2 Sample Construction

Considering the nature of my study, I limit my sample to publicly traded BHCs in the United States. I match accounting information on BHCs with their market counterparts by using CRSP-FRB Link, that has been successfully used by several studies in the literature (e.g., Carmichael and Coën, 2018; Gandhi et al., 2019; Goetz et al., 2016) (provided by the Federal Reserve Bank of New York to link entity numbers (rssd9001) in the FR Y-9C to PERMCO numbers in CRSP).[40] To efficiently predict the likelihood of financial distress in a bank, it is important that the prediction model identifies any distress sufficiently ahead of time. Hence, I use annual bank data reported as

[38] Available on the Federal Reserve Bank of Chicago website (www.chicagofed.org).

[39] Board of Governors of the Federal Reserve System (U.S.). 1-Year Treasury Constant Maturity Rate [DGS1] is retrieved from FRED, Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/DGS1).

[40] Available at the New York Federal Reserve Bank (FRB) website, specifically on the following link (https://www.newyorkfed.org/research/banking_research/datasets.html).

of December 31 of each calendar year over a relatively long analysis period from 1987 to 2017, to develop one-year distress prediction models. Since the starting date of both CRSP-FRB Link and FRB Chicago data is June 1986, and my sample employs annual information, I start my sample from 1987 to align with both. The final sample contains 11,980 bank-year observations of 1,095 unique BHCs.

4.2.3 Dependent Variables

4.2.3.1 Measuring Distress Risk

To measure the overall distress risk of banks, I mainly employ Z-score, which is an accounting-based distress risk indicator originally proposed by Roy (1952). Since then, the Z-score has remained a popular choice in the empirical banking literature for measuring banks' distress risk (e.g., Beck et al., 2013; Berger and Bouwman, 2009; Goetz et al., 2016; Imbierowicz and Rauch, 2014 and many others). It is calculated as the sum of the return on assets plus the ratio of total equity to gross total assets (GTA) divided by the standard deviation of return on assets. It can be interpreted as the number of standard deviations below the mean by which profits would have to fall so as to deplete the bank's equity capital (Houston et al., 2010). It indicates the bank's distance from default (Goetz, 2018). According to Laeven and Levine (2009), default is defined as a state in which losses overcome equity ($E < -\pi$) (where E is equity and π is profit). Thus, the probability of default can be expressed as prob ($-ROA < CAR$), where ROA ($= \pi/GTA$) is the return on gross total assets, and CAR ($= E/GTA$) is the capital assets ratio. I calculate each bank's Z-score (following Laeven and Levine, 2009) as:

$$Z\text{-}score = \frac{(ROA+CAR)}{\sigma_{ROA}} \tag{1}$$

where σ_{ROA} is the standard deviation of ROA. I calculate the σ_{ROA} using a 3-year rolling window to allow for time variation in the Z-score's denominator, and to avoid the possibility that Z-score values are entirely driven by variation in the levels of capital and profitability (Danisewicz et al., 2017). I use the Z-score's natural logarithm, which is suggested to smooth out its high skewness (Beck et al., 2013; Laeven and Levine, 2009).

I also proxy banks' distress risk using the Merton distance to default (DD) model (Merton, 1974) as a robustness check, and report the results in Section 4.1. The Merton DD model has also been widely used in empirical literature as a market-based indicator of the soundness of publicly listed financial institutions (e.g., Bennett et al., 2015; Fu et al., 2014; Pereira and Rua, 2018). This model assumes that the capital structure primarily consists of equity and debt. The equity is viewed as a call option on the value of assets. The strike price of the call option is the face value of debt maturing at time T. When the value of assets at the maturity date falls below the strike price, the value of equity equals zero and the default occurs.

To estimate the bank default risk measure using the Merton DD model, I follow the iterative process that is very similar to the one used by Moody's KMV and outlined in Bharath and Shumway (2008). First, I use daily stock returns over the past year to calculate the volatility of equity returns, and use this as a proxy for asset volatility σ_V in the first iteration. Second, I infer the value of bank assets (V) for each trading day over the past 12 years using the following standard Black–Scholes formula:

$$\mathrm{E} = \mathrm{V}\mathcal{N}(\mathrm{d}_1) - \mathrm{e}^{-\mathrm{rT}}\mathrm{F}\mathcal{N}(\mathrm{d}_2) \tag{2}$$

where E is the market value of the bank's equity, F is the debt's face value, T is the time until the debt matures (one-year horizon), r is the risk-free interest rate, $\mathcal{N}$ is the cumulative standard normal distribution function, and, d_1 and d_2 are estimated as follows:

$$d_1 = \frac{\ln\left(\frac{V}{F}\right)+\left(r+0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}},\ d_2 = d_1 - \sigma_V\sqrt{T} \tag{3}$$

This generates a daily time series V, which is used to obtain the next estimate of σ_V. Third, I repeat the iterative procedure until the values of σ_V converge within a small tolerance level. After convergence, the distance to default can be calculated as

$$DD = \frac{\ln\left(\frac{V}{F}\right)+\ \left(\mu-0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \tag{4}$$

where μ is the mean of the instantaneous rate of return on the assets. Finally, I assume that the expected frequency of default follows the theoretical distribution implied by Merton's model, which is the normal distribution. Thus, the probability of default (PD) is given by:

$$PD = \mathcal{N}(-DD) \tag{5}$$

I repeat this procedure at the end of each year for each respective bank, resulting in a yearly time series of *PD*s for each bank. The main advantage of this *PD* is that it responds quickly to new information, and is not subject to misrepresentation by 'regulatory arbitrage' (Milne, 2014). To facilitate a more consistent interpretation with the probability of default (the Merton distance to default model), I follow Khan et al. (2017) and multiply the natural logarithm of Z-score values by −1. This implies that the higher the Z-score, the higher is the distress risk of the bank.

2.4 Independent Variables

2.4.1 Downside Risk Measures

Following Van Bekkum (2016), I use tail risk measures, namely value at risk (VaR) and expected shortfall (ES) to proxy a bank's tail risk exposure. Employing a similar approach to Liang and Park (2010), I generate these measures by using daily stock returns for three-month, six-month, one-year, three-year, and five-year periods separately for each bank as of the month-end (of the latest available daily return data) in a given year to predict bank' financial distress in the next year. For example, if the date on which a bank's financial statements were filed is June 2015, I compute its risk measures as of May 2015 to predict the probability of the bank's financial distress in the next year.

Value-at-risk: VaR has become a standard measure for determining market risk of financial and non-financial firms (Berkowitz and O'Brien, 2002). To estimate VaR, I need to define two quantitative parameters, the confidence level $(1-\alpha)$ and the time horizon (τ), along with the estimation model. Then, I use these parameters to estimate the maximum loss that may occur over a target horizon and at a specified confidence level. I follow Hagendorff et al. (2018) and use the number of trading days in the year (set at 252 trading days), rather than the number of calendar days, to compute VaR and ES. In terms of time horizon, there are no defined rules or detailed guidelines. Therefore, I follow Gupta and Chaudhry (2019) and consider the liquidity of the risk and the duration of exposure to that risk. The lower the assets' liquidity, the higher the time required to totally hedge the exposure. Considering a longer time horizon when measuring VaR in market with a greater range of movements is recommended (Gupta and Chaudhry, 2019). In the light of the above arguments, I estimate VaR using five different time horizons to capture any intertemporal differences. I estimate the risk of each bank as of the month-end (of the latest available daily return data) in a given year using the past three-month, six-month, twelve-month, three-year, and five-year daily returns to predict banks' financial distress in the next year. Likewise, the selection of confidence level relies on the attitude of users towards risk and the nature of application. For instance, commercial banks are required by the Basel II Accord to apply a high confidence level of 99% for calculating their minimum capital requirements, while rating authorities require an even higher confidence level (99.97%) to achieve a high credit rating (AA or above) (Gupta and Chaudhry, 2019; Jorion, 2000). Additionally, using a lower confidence level (95%) with a shorter risk horizon (1 day) might be acceptable for a risk manager while setting VaR bases trading limits. Accordingly, I follow the recommended practice by authorities (e.g., the Basel Accord), and estimate the downside risk measures at 99% confidence levels. I also apply a confidence level of 95% as a robustness check and report the results in Section 4.2.

To compute the VaR, let τ denote the time horizon, $R_{t+\tau}$ denote a firm's return between the time period *t* and *t* + τ, and let $F_{R,t}$ represent the cumulative distribution function (CDF) of $R_{t+\tau}$ conditional upon the set of information available at time t. Then, $F_{R,t}^{-1}$ represents the inverse function of $F_{R,t}$. Given this, the VaR of a bank's return as of time t with a time horizon τ and at $(1-\alpha)$ confidence level can be estimated as follows:

$$\mathrm{VaR_t}(\alpha,\tau) = -\mathrm{F_{R,t}^{-1}}(\alpha) \tag{6}$$

The semi-parametric Cornish-Fisher VaR (VaR_{CF}) is different to normal VaR. It allows higher moments (skewness and kurtosis) to be considered, thus, accounting for non-normality in the return distribution (Cornish and Fisher,1938). This was first introduced by Zangari (1996) to estimate the VaR of option portfolios, because distributions can be approximated with these known moments (Johnson et al., 1994; Jaschke, 2002). Therefore, I use VaR_{CF}[41] to adapt non-symmetrical and fat-tailed returns distribution. The fourth order Cornish and Fisher (1938) expansion for α percentile of $(R-\mu)/\sigma$ is shown in Equation 7, while Equation 8 defines the Cornish-Fisher VaR (VaR_{CF}).

[41] I use VaR and $\mathrm{VaR_{CF}}$ interchangeably in this study.

$$\Omega(\alpha) = Z(\alpha) + \frac{1}{6}(Z(\alpha)^2 - 1)S + \frac{1}{24}\big(Z(\alpha)^3 - 3Z(\alpha)\big)K - \frac{1}{36}\big(2Z(\alpha)^3 - 5Z(\alpha)\big)S^2 \quad (7)$$

$$VaR_{CF} = -(\mu + \Omega(\alpha) \times \sigma) \quad (8)$$

where σ is the standard deviation, μ is the average return, S is the measure of skewness, K is the excess kurtosis of past n-month daily returns, $(1-\alpha)$ is the confidence level, and $Z(\alpha)$ is the critical value obtained from the standardised normal distribution.[42]

Expected Shortfall: Unlike VaR, Expected Shortfall (ES) provides information about the size of the loss in the event when that level is breached. Theoretically, Artzner et al. (1999) argue that ES is superior to VaR in possessing mathematical properties such as continuity and sub-additivity, which are needed for a coherent measure of risk. ES is the conditional expected loss that is greater than or equal to the VaR. It is expressed in terms of return rather than dollar amount and formulated as follows:

$$ES_t(\alpha,\tau) = -E_t[R_{t+\tau}|R_{t+\tau} \leq -VaR_t(\alpha,\tau)]$$

$$= -\frac{\int_{\nu=-\infty}^{-VaR_t(\alpha,t)} \nu f_{R,t}(\nu)d\nu}{F_{R,t}[-VaR_t(\alpha,\tau)]}$$

$$= -\frac{\int_{\nu=-\infty}^{-VaR_t(\alpha,t)} \nu f_{R,t}(\nu)d\nu}{\alpha} \quad (9)$$

Here, $R_{t+\tau}$ represents a firm's return in the time period t, and $t+\tau$ and $f_{R,t}$ denotes the conditional probability density function (PDF) of $R_{t+\tau}$. $F_{R,t}$ is the conditional CDF of $R_{t+\tau}$ conditional upon the information set available at time t, $F_{R,t}^{-1}$ represents the inverse function of $F_{R,t}$, and $(1-\alpha)$ is

[42] The original VaR and ES are usually negative. To avoid confusion, I follow Gupta and Chaudhry (2019) and multiply the original VaR and ES numbers by −1 in Equations 7 and 8. Hence, the VaR and ES numbers presented in this paper are usually positive.

the confidence level. I use Cornish-Fisher VaR (VaR_{CF}) calculated using Equations 7 and 8 to estimate Expected Shortfall, denoted as ES_{CF}.[43]

4.2.4.2 Baseline Factors

As discussed in the introduction, banks' failure risk has traditionally been explained using indicators other than downside risk measures discussed in Section 2.4.1. Specifically, accounting-based determinants that are related to capitalisation, asset quality, managerial skills, earnings, and liquidity (CAMEL) of banks and several others have been successfully employed in explaining banks' failure risk. Following the banking literature and supervisor practice, I use standard proxies for the CAMEL as baseline explanatory variables of bank distress. Furthermore, I include a measure of real estate loans, as well as the log of GTA for controlling bank size. I also include other factors to control for competition and macroeconomic conditions as a robustness check and report the results in Section 4.4.[44]

Capital (C): Capital is the first in the CAMEL list and foremost factor in virtually all early warning models adopted by regulatory and supervisory agencies (e.g., Basel) to evaluate the soundness of banks, and to ensure that the financial system is secure and healthy. Moreover, it has been employed as a main variable in the majority of academic studies (e.g., Berger and Bouwman, 2009; Betz et al., 2014; Cole and White, 2012). The level of capital is considered as the mirror image of the capacity of banks to meet their financial obligations. Thus, a deterioration of capital could be a critical indicator of potential financial distress and vice-versa. To measure capital adequacy, I use the ratio of total equity to gross total assets (TEGTA), which is largely used in the literature

[43] I use ES and ES_{CF} interchangeably in this paper.
[44] I include Herfindahl-Hirschman Index (HHI), house price index, and state personal income for controlling competition, inflation, and GDP, respectively.

and is a highly valuable proxy of capital (e.g., Berger et al., 2016; Berger and Bouwman, 2013; DeYoung and Torna, 2013). Normalisation of the equity by GTA is essential to make the dependent variables meaningful and comparable across banks and to avoid assigning excessive weight to the largest institutions (Berger and Bouwman, 2009). Following Poghosyan and Čihak (2011), I do not use the regulatory capital ratio, namely the Tier 1 and Total risk-based capital ratios, for three reasons: first, to avoid any risk assessment; second, the calculation of these ratios is based on relatively arbitrary weights; third, these ratios became fully effective a few years into my sample period. Although some theories argue that higher capital may hurt bank safety (e.g., Calem and Rob, 1999; Koehn and Santomero, 1980), I believe that a solid TEGTA ratio reduces the probability of default because equity counts as a buffer between the value of the bank's assets and the value of its liabilities (Cole and White, 2012); additionally, most theories, particularly the recent ones (e.g., Acharya et al., 2016; Mehran and Thakor, 2011), predict that capital is positively related to bank survival (Berger and Bouwman, 2013).

A*sset quality (A):* Asset quality is represented by net loan losses (loan charge-offs minus loan recoveries) in the current year against the allowances for these loan losses (including the excess allowance on loans and leases) recorded in the previous year. This measure was developed by Imbierowicz and Rauch (2014) and is similar to the measures used by Angbazo (1997) and Dick (2006) to assess credit risk. According to Imbierowicz and Rauch (2014), this indicator not only measures the current riskiness of a banks' loan portfolio, because it can be affected by bank management in a short-term period, but also captures the unexpected loan losses. Therefore, a higher ratio indicates weak asset quality or higher credit risk, and values above 1 imply unexpected losses. I follow Imbierowicz and Rauch (2014) and employ this proxy variable to evaluate the accuracy of banks' risk management to predict short-term loan losses and to observe the unexpected loan losses that may face banks and affect their soundness. Overall, poor quality of assets is expected to have a positive relationship with the probability of bank default.

Management (M): Management proficiency is essential to enhance the performance and success of a bank. However, it has rarely been used in the literature because it is hard to observe and measure with financial data (Wheelock and Wilson, 2000). Some researchers have employed other CAMELS categories such as earnings and asset quality to capture the quality of management (Mayes and Stremmel, 2014). Thus, I consider earnings proxied by return on equity (ROE) ratio, net income divided by stockholders' equity, to approximate to management skills. I believe that insufficient management capability leads to wrong decisions and high losses, thereby increasing the probability of default.

Earnings (E): Earnings reflects the performance, in general, and the profitability of a bank, in particular. Numerous indicators have been applied in the empirical literature to measure this category but the most frequently employed are return on assets (ROA), net income divided by GTA, and return on equity (ROE). I follow Berger and Bouwman (2013) and use ROE, which is a comprehensive profitability measure, because both net income and equity reflect the bank's on- and off-balance-sheet activities. I use ROA, as a robustness check, and obtain similar results. Similar to management competence, I expect that higher earnings enhance banks' performance. Accordingly, the relationship between profitability and the likelihood of distress is expected to be negative.

Liquidity (L): Liquidity determines whether the bank is able to meet its current obligations and unexpected withdrawals of depositors and creditors. Following Betz et al. (2014), I assess a bank's liquidity by the ratio of interest expenses to total liabilities. A higher share of interest expenses to total liabilities is expected to be positively associated with bank distress.

Real Estate Loans: Real-estate loans play a significant role in determining bank distress. This is supported by a new body of literature which focuses on the recent financial crisis (e.g., Berger et al., 2016; Cole and White, 2012; Imbierowicz and Rauch, 2014). Hence, I include the ratio of real-estate loans to GTA for this purpose.

Bank Size: The literature documents that bank size has a vital impact on banks' distress (Berger and Bouwman, 2013; Bertay et al., 2013). Bank size matters and is expected to have a negative effect on the probability of default, because it is well-known that small banks are likely to fail more easily than large banks (Cole and White, 2012). Due to the importance of bank size and the advantages generated by size heterogeneity, I include a proxy to control for bank size represented by the logarithm of GTA.[45]

Following conventions in the literature, I winsorize all independent variables at the 1% level to limit the influence of extreme values on my statistical estimates. I also lag all independent variables (including VaR and ES) by 1 year to alleviate the impact of potential concerns endogeneity (i.e., simultaneity) (Hagendorff et al., 2018; Srivastav et al., 2017). All covariates are defined in detail in Table 1.

[45] As a robustness check, I rerun my main regression separately for small, medium, and large banks. A detailed discussion and the results are provided in Section 4.3 of the paper.

Table 1: Description of the variables

Variable	Description	Data source
Dependent Variables		
Z-score	The sum of the return on assets and the ratio of total equity to total assets divided by the standard deviation of the return on assets. I use its log due to its high skewness.	Federal Reserve Bank
PD	The bank-level probability of default.	Federal Reserve Bank & CRSP
Independent Variables		
LGTA	Natural Logarithm of Gross Total Assets (GTA).	Federal Reserve Bank
TEGTA	Total Equity divided by GTA.	Federal Reserve Bank
CR	The net loan charge-offs divided by the loan loss allowance in the previous year.	Federal Reserve Bank
ROA	Return on Assets; Net Income divided by GTA.	Federal Reserve Bank
ROE	Return on Equity; Net Income divided by Total Equity.	Federal Reserve Bank
RELGTA	Real-estate loans divided by GTA.	Federal Reserve Bank
IETL	Total Interest Expenses divided by Total Liabilities.	Federal Reserve Bank
VAR3M1	Value-at-Risk estimated using daily returns over past 3 months at 1% significance level.	CRSP
VAR6M1	Value-at-Risk estimated using daily returns over past 6 months at 1% significance level.	CRSP
VAR1Y1	Value-at-Risk estimated using daily returns over past 1 year at 1% significance level.	CRSP
VAR3Y1	Value-at-Risk estimated using daily returns over past 3 years at 1% significance level.	CRSP
VAR5Y1	Value-at-Risk estimated using daily returns over past 5 years at 1% significance level.	CRSP
VAR3M5	Value-at-Risk estimated using daily returns over past 3 months at 5% significance level	CRSP
VAR6M5	Value-at-Risk estimated using daily returns over past 6 months at 5% significance level.	CRSP
VAR1Y5	Value-at-Risk estimated using daily returns over past 1 year at 5% significance level.	CRSP
VAR3Y5	Value-at-Risk estimated using daily returns over past 3 years at 5% significance level.	CRSP
VAR5Y5	Value-at-Risk estimated using daily returns over past 5 years at 5% significance level.	CRSP
ES3M1	Expected Shortfall estimated using daily returns over past 3 months at 1% significance level.	CRSP
ES6M1	Expected Shortfall estimated using daily returns over past 6 months at 1% significance level.	CRSP
ES1Y1	Expected Shortfall estimated using daily returns over past 1 year at 1% significance level.	CRSP
ES3Y1	Expected Shortfall estimated using daily returns over past 3 years at 1% significance level.	CRSP
ES5Y1	Expected Shortfall estimated using daily returns over past 5 years at 1% significance level.	CRSP
ES3M5	Expected Shortfall estimated using daily returns over past 3 months at 5% significance level.	CRSP
ES6M5	Expected Shortfall estimated using daily returns over past 6 months at 5% significance level.	CRSP
ES1Y5	Expected Shortfall estimated using daily returns over past 1 year at 5% significance level.	CRSP
ES3Y5	Expected Shortfall estimated using daily returns over past 3 years at 5% significance level.	CRSP
ES5Y5	Expected Shortfall estimated using daily returns over past 5 years at 5% significance level.	CRSP
Control Variables		
GHPI	Growth of State-level House Price Indices (HPIs).	Federal Housing Finance Agency
GCPI	Growth of State-level personal income.	Bureau of Economic Analysis
HHI	Market concentration based on the bank's weighted deposits in the state.	constructed
SL	Dummy variable indicating whether the year is on saving and loans crisis (credit crunch) that occurred between 1990 and 1992.	constructed

GFC	Dummy variable indicating whether the year is on subprime lending crisis (Global Financial Crisis) that occurred between 2007 and 2009.	constructed
Dot	Dummy variable indicating whether the year is on the dot.com bubble and the September 11 terrorist attack that occurred between 2000 and 2002.	constructed

Notes: This table reports the set of accounting- and market-based covariates, as well as control variables that I use in my empirical analysis. The first column lists names of covariates, while the second column provides their respective definitions. The third column provides the data sources.

4.3 Empirical Methods

In this section, I provide summary statistics of my covariates along with relevant discussion pertaining to correlation among the covariates. Next, I perform univariate regression analysis of each tail risk covariate in turn using Z-score to understand any unexpected behaviour in their discriminatory performance, and discuss the results. Finally, I develop multivariate regression models using the fixed effects to examine the marginal explanatory power of downside risk measures, and discuss the main results.

4.3.1 Descriptive Statistics and Correlation

To gain a preliminary understanding of the variability of my covariates, I split the sample in a given year into two groups: financially distressed and non-distressed/healthy banks. Following Curry et al. (2007), I consider BHC is distressed if the final year of exit was during my sample period and the reason for termination was voluntary liquidation, inactivity, or failure. Table 2 provides summary statistics of the variables discussed earlier. It shows clear disparities between distressed and non-distressed banks. Not surprisingly, distressed banks are, on average, smaller than non-distressed banks, have lower capital ratios, lower earnings, weak performance, poor assets quality (higher credit risk), and greater real-estate loans. Interestingly, distressed banks have, on average, marginally lower total interest expenses to total liabilities (IETL) than non-distressed banks, implying that liquidity risk is lower in distressed banks.

On the tail risk side (i.e. VaR and ES), distressed banks exhibit higher mean values compared to non-distressed banks. This is expected because distressed banks tend to have extreme movements. The VaR indicates the loss that will not surpass a certain amount over a target time span with a fixed confidence level (Hull, 2015). The greater magnitude of VaR indicates a greater likelihood of loss. As shown in Table 2, the mean value of VAR1Y1 for financially distressed banks is 22.7%. It implies that I am 99% confident that the mean loss for financially distressed banks over a one-year period will not exceed 22.7%. On the other hand, ES is the expected loss conditional on the loss being larger than a specific threshold over a target time (Hull, 2015). For example, in Table 2, the mean value of ES1Y1 for financially distressed banks is 30.07%. It suggests that the average loss for financially distressed banks will be 30.07% over a one-year period with the assumption that the loss is greater than 99% of the loss distribution. Table 2 also shows intertemporal differences among extreme measures. Specifically, the mean values at longer rolling windows are higher than those at shorter ones.

Table 2: Summary statistics

Variable	**Healthy Banks**					**Distressed Banks**				
	N	Mean	Sd	Min	Max	N	Mean	Sd	Min	Max
Z-score	11119	4.076	1.275	-4.968	7.006	43	2.863	1.752	-2.354	7.006
PD	11868	0.300	0.192	0.000	0.701	59	0.153	0.189	0.000	0.701
TEGTA	11921	0.090	0.026	0.028	0.188	59	0.070	0.040	0.028	0.188
CR	10768	0.295	0.328	-0.073	1.783	57	0.321	0.381	-0.073	1.783
ROE	11921	0.080	0.127	-0.747	0.252	59	-0.052	0.324	-0.747	0.252
ROA	11921	0.008	0.009	-0.038	0.023	59	-0.005	0.017	-0.038	0.023
IETL	11921	0.027	0.016	0.001	0.068	59	0.024	0.015	0.002	0.064
RELGTA	11921	0.433	0.163	0.011	0.785	59	0.477	0.156	0.011	0.785
LGTA	11921	14.51	1.663	11.198	21.674	59	13.777	1.045	11.515	17.013
VAR3M1	11759	0.059	0.048	0.320	0.010	59	0.127	0.125	0.320	0.010
VAR6M1	11737	0.066	0.054	0.362	0.015	54	0.156	0.141	0.362	0.015
VAR1Y1	11698	0.075	0.080	1.000	0.006	48	0.227	0.263	1.000	0.006
VAR3Y1	11864	0.097	0.106	1.000	0.010	57	0.232	0.244	1.000	0.023
VAR5Y1	11890	0.112	0.122	1.000	0.023	58	0.238	0.232	1.000	0.034
ES3M1	11878	0.079	0.087	0.641	0.014	59	0.188	0.205	0.641	0.014
ES6M1	11835	0.088	0.088	0.630	0.017	55	0.209	0.206	0.630	0.017
ES1Y1	11771	0.104	0.119	1.000	0.007	50	0.307	0.308	1.000	0.011
ES3Y1	11885	0.123	0.129	1.000	0.004	58	0.357	0.304	1.000	0.052
ES5Y1	11904	0.128	0.126	1.000	0.022	59	0.277	0.246	1.000	0.051

Notes: This table shows descriptive statistics for all variables across healthy and distressed bank holding companies (BHCs) over the period 1987–2017. The classification variable is binary. If a BHC voluntary liquidates, be inactive, or fails in final year *t* during my sample period, the BHC's binary indicator is '1' in that year *t* and '0' otherwise. Further information on definition of respective variables is provided in Table 1.

Table 3 reports the results for the pair-wise correlation analysis. Panel A shows that all correlations among accounting variables have low to moderate values, except ROE which shows strong positive correlation with ROA (0.892). This is expected, as both are competing indicators of banks' profitability. However, I deal with this issue by including these measures separately. Specifically, I use ROE in regressions with Z-score; for the robustness check, I use ROA in regression with the alternative risk measure (distance to default). Panel B shows that all estimates of tail risk measures (VaR and ES) exhibit low to moderate correlations with accounting variables.

Table 3: Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Correlation among Accounting Variables									
(1) Z-score	1.000								
(2) PD	0.150	1.000							
(3) TEGTA	-0.215	0.072	1.000						
(4) CR	0.395	0.133	-0.181	1.000					
(5) ROE	-0.565	-0.215	0.149	-0.471	1.000				
(6) ROA	-0.577	-0.180	0.319	-0.514	0.892	1.000			
(7) IETL	0.032	-0.067	-0.330	0.226	0.016	-0.030	1.000		
(8) RELGTA	0.037	0.059	0.106	-0.095	-0.152	-0.152	-0.216	1.000	
(9) LGTA	0.017	0.026	-0.001	0.099	0.065	0.063	-0.158	-0.326	1.000
Panel B: Correlation among Accounting and Tail Risk Variables									
(10) VAR3M1	0.339	0.189	0.206	-0.389	0.467	0.504	-0.171	-0.064	0.146
(11) VAR6M1	0.355	0.196	0.231	-0.400	0.486	0.524	-0.191	-0.044	0.127
(12) VAR1Y1	0.315	0.197	0.212	-0.332	0.431	0.469	-0.131	-0.040	0.084
(13) VAR3Y1	0.304	0.189	0.179	-0.306	0.384	0.418	-0.126	-0.050	0.056
(14) VAR5Y1	0.289	0.166	0.151	-0.251	0.335	0.365	-0.104	-0.063	0.044
(15) ES3M1	0.266	0.162	0.170	-0.289	0.375	0.406	-0.124	-0.042	0.104
(16) ES6M1	0.287	0.176	0.196	-0.310	0.417	0.446	-0.135	-0.052	0.127
(17) ES1Y1	0.284	0.184	0.195	-0.271	0.388	0.422	-0.089	-0.069	0.108
(18) ES3Y1	0.298	0.208	0.182	-0.250	0.370	0.406	-0.082	-0.083	0.084
(19) ES5Y1	0.304	0.172	0.164	-0.248	0.338	0.368	-0.106	-0.069	0.073

Notes: This table reports correlation among the set of covariates. Panel A displays correlations among accounting variables. Panel B provides correlations among accounting variables and the respective tail risk measures (VaR and ES).

4.3.2 Univariate Regression Analysis

To get an initial insight into the statistical significance of respective tail risk measure, I perform univariate regression analysis with Z-score as the dependent variable. The results in Table 4 show that all rolling estimates (generated using daily three-month, six-month, one-year, three-year, and five-year returns) of tail risk measures (VaR and ES) are highly significant at the 1% significance level. This implies that the extreme risk measures can predict financial distress, even with a longer horizon.

The results also show intertemporal differences and that short-duration rolling coefficients of VaR have higher values than long-duration rolling coefficients. For example, three-month VaR (VAR3M1), estimated at the 1% level of significance, has the highest coefficient value of 8.81%, while five-year VaR (VAR5Y1) has the lowest coefficient value of 3.53%. This suggests that shorter duration rolling estimates of VaR perform better in predicting the financial distress of banks. On the other hand, coefficients of some of the long-duration rolling ES are slightly higher than some of the short-duration rolling coefficients. For instance, the coefficient value for three-year ES (ES3Y1), estimated at the 1% level of significance, equals 4.19% which is marginally higher than the coefficient value for three-month ES (ES3M1) that equals 3.63%. This generally indicates that longer term rolling estimates of ES perform better in predicting the financial distress of banks. Overall, these results clearly reveal the strong relationship between banks' distress risk and downside risk measures. These results also support my hypothesis that banks with higher frequent extreme negative daily equity returns are more likely to experience financial distress.

Table 4: Univariate Regression

Variable	N	Coef.	SE	t-value
VAR3M1	10,574	8.810***	0.421	20.94
VAR6M1	10,590	7.624***	0.395	19.30
VAR1Y1	10,622	4.857***	0.507	9.57
VAR3Y1	10,684	4.464***	0.402	11.11
VAR5Y1	10,689	3.525***	0.310	11.38
ES3M1	10,676	3.637***	0.238	15.28
ES6M1	10,660	4.141***	0.248	16.68
ES1Y1	10,654	3.231***	0.230	14.05
ES3Y1	10,693	4.194***	0.334	12.56
ES5Y1	10,698	3.537***	0.313	11.30

Notes: This table reports the univariate regression results of respective tail risk measures using Z-score as the dependent variable over the period 1987–2017. The regressions are estimated using fixed effects models. Standard errors are clustered at the BHC-level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

4.3.3 Multivariate Regression Analysis

In this section, I examine whether downside risk measures found significant in the previous section have any marginal explanatory power above the baseline covariates discussed in Section 2.4.2. I begin my multivariate empirical analysis by estimating a baseline multivariate model for the full sample of BHCs with accounting-based covariates using the Ordinary Least Square (OLS) regression technique. The model is specified as follows:

$$\mathrm{Risk}_{\mathrm{b,t}} = \beta \mathrm{X}_{\mathrm{b,t-1}} + \delta_{\mathrm{b}} + \delta_{\mathrm{t}} + \varepsilon_{\mathrm{b,t}}\ , \tag{10}$$

where $Risk_{\mathrm{b,t}}$ is bank distress risk represented by the natural logarithm of Z-Score of BHC b during year t, $X_{b,t-1}$ is a vector of bank-specific characteristics lagged by 1 year, δ_b are BHC fixed effects, δ_t are year fixed effects and $\varepsilon_{\mathrm{b,t}}$ is an error term that is adjusted for heteroskedasticity. My motivation for using the fixed effects model is to account for time-invariant unobserved heterogeneity at the bank level.[46] All reported standard errors are robust and adjusted for clustering at the bank level to control for heteroskedasticity.

The results of the baseline model, shown in column (1) of Table 5, indicate that all financial ratios are strongly significant with expected signs. An exception is that bank size has a positive relationship with bank risk which is opposite to my expectation based on the suggestions of some recent studies (e.g., Berger and Bouwman, 2013; Cole and White, 2012) In more detail, the capital ratio (TEGTA) and return on equity (ROE) have significant and negative effects, implying that more capital and high profitability reduce banks' default probability. Conversely, other main variables exhibit significantly positive coefficients, suggesting that weak assets quality (high credit

[46] I also perform the Hausman test to choose between the fixed effects model and random effects model in panel data. The result suggests using the fixed effects model.

risk (CR)), high liquidity risk (IETL), more reliance on real-estate loans (RELGTA), and large bank size (LGTA) increase their likelihood of default risk. Overall, all these covariates are jointly significant in explaining the financial distress of BHCs and are consistent with a broad body of research (e.g., Betz et al., 2014; Cole and White, 2012; Imbierowicz and Rauch, 2014).

Subsequently, I supplement this baseline multivariate model with respective tail risk measures (VaR and ES) to gauge their marginal discriminatory power in predicting banks' failure. I run separate multivariate models for daily three-month, six-month, one-year, three-year, and five-year tail risk estimates to account for any intertemporal differences that may exist. Columns (2) to (6) of Table 5 report my multivariate regression results with VaR measures estimated at a 1% significance level. I find that all rolling estimates of VaR measures are significant, and positively linked to default probability across all model specifications. Second, I observe that the magnitudes of short-duration rolling coefficients are mostly stronger than those of long-duration rolling coefficients, implying that short-duration rolling estimates have superior performance in predicting the financial distress of banks.

Now I turn to multivariate regression with ES measures estimated at a 1% significance level, reported in columns (7) to (11) of Table 5. Similar to multivariate regression results with VaR, I find that all rolling estimates of ES measures have significantly positive influence on the probability of default in all model specifications. However, the magnitudes of short-duration rolling coefficients are generally weaker than those of long-duration rolling coefficients, implying that long-duration rolling estimates perform better in predicting the financial distress of banks.

In general, the results of all rolling estimates of VaR and ES measures support my hypothesis that banks with more frequent extreme negative daily equity returns experience higher probability of financial distress. These results broadly reinforce the findings of Gropp et al. (2006) who show that market-based measures (distance to default and subordinated bond spreads) have some forecasting power at a horizon of 6-18 months. Furthermore, my results with respect to the long-term horizons (3 and 5 years) are consistent with the findings of Curry et al. (2007), that stock market data has significant predictive ability for up to 4 years in terms of predicting bank failure. Overall, the addition of tail risk measures (VaR and ES), as market-based indicators, to multivariate analysis with accounting-based proxies represented by CAMEL improves the power of traditional models for bank stability. This strongly supports the limited empirical literature on the use of market-based indicators in assessing banks distress (e.g., Coffinet et al., 2010; Curry et al., 2007; Evanoff and Wall, 2002; Flannery, 1998; Gropp et al., 2006; Milne, 2014)

Table 5: Multivariate Regression Models

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		4.460***									
		(0.352)									
VAR6M1			4.135***								
			(0.338)								
VAR1Y1				2.486***							
				(0.288)							
VAR3Y1					2.966***						
					(0.304)						
VAR5Y1						2.289***					
						(0.208)					
ES3M1							1.829***				
							(0.171)				
ES6M1								2.169***			
								(0.181)			
ES1Y1									1.718***		
									(0.146)		
ES3Y1										2.804***	
										(0.241)	
ES5Y1											2.322***
											(0.209)
TEGTA	-2.256**	-1.932*	-1.760*	-1.754*	-1.936*	-2.196**	-2.117**	-1.901*	-1.773*	-1.674*	-2.145**
	(1.081)	(1.074)	(1.078)	(1.086)	(1.047)	(1.035)	(1.068)	(1.080)	(1.078)	(1.041)	(1.021)
CR	0.750***	0.654***	0.654***	0.695***	0.654***	0.697***	0.709***	0.700***	0.706***	0.666***	0.695***
	(0.054)	(0.053)	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)	(0.053)
ROE	-3.135***	-2.608***	-2.570***	-2.677***	-2.676***	-2.848***	-2.800***	-2.721***	-2.770***	-2.572***	-2.814***
	(0.145)	(0.157)	(0.157)	(0.156)	(0.150)	(0.144)	(0.149)	(0.150)	(0.149)	(0.150)	(0.143)
IETL	12.679***	9.817***	10.011***	10.960***	8.560***	9.057***	11.271***	10.920***	11.296***	9.052***	9.396***
	(1.475)	(1.507)	(1.501)	(1.479)	(1.473)	(1.450)	(1.477)	(1.482)	(1.471)	(1.443)	(1.431)
RELGTA	1.221***	1.096***	1.114***	1.146***	1.031***	0.980***	1.152***	1.175***	1.160***	0.952***	0.951***
	(0.231)	(0.230)	(0.231)	(0.232)	(0.226)	(0.222)	(0.229)	(0.230)	(0.229)	(0.226)	(0.221)
LGTA	0.231***	0.214***	0.213***	0.219***	0.182***	0.178***	0.222***	0.218***	0.217***	0.194***	0.193***
	(0.038)	(0.038)	(0.037)	(0.037)	(0.036)	(0.036)	(0.037)	(0.037)	(0.037)	(0.036)	(0.035)
_cons	-8.023***	-7.940***	-7.972***	-8.015***	-7.431***	-7.300***	-7.995***	-8.002***	-7.976***	-7.663***	-7.569***
	(0.542)	(0.543)	(0.540)	(0.538)	(0.519)	(0.508)	(0.540)	(0.536)	(0.536)	(0.520)	(0.508)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9618	9500	9511	9537	9597	9605	9593	9571	9564	9604	9611
R-squared	0.230	0.251	0.251	0.245	0.272	0.264	0.244	0.247	0.248	0.277	0.265

Notes: This table reports results of multivariate OLS regressions estimated using my sample of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

4.4 Robustness Checks

This section presents numerous robustness checks in support of my hypothesis. First, I use an alternative bank failure risk measure. Second, I use an alternative confidence level to estimate tail risk measures. Third, I split my sample into small, medium, and large banks. Fourth, I control for competition and macroeconomic conditions. Fifth, I control for financial crises. Sixth, I exclude mergers and acquisitions. Seventh, I exclude “Too big To Fail” banks. Eighth, I use long lags (3 years) for my explanatory variables to reduce the impact of endogeneity. Generally, my main results are robust to all these tests, and remain qualitatively and quantitatively unaffected.

4.4.1 Alternative Bank Risk Measure

To assess the reliability of the main results in Section 3.3, I use a different dependent variable as an alternative risk measure, the Merton distance to default (DD) model, already introduced in Section 2.3.1 of this paper. I rerun the same OLS regression models (replacing ROE with ROA[47]) discussed in Section 3.3 and report the results in Table 6. The results are basically comparable to the main results reported in Table 5. Interestingly, the magnitudes of tail risk coefficients are generally stronger than my findings using Z-score as a dependent variable in predicting bank distress (see Table 5). This suggests that applying market-based indicator (DD) as a dependent variable is superior compared to the accounting-based measure (Z-score) when I use tail risk estimates as the main independent variables to investigate bank stability. However, I do not regress the DD, as a main measure of bank risk in my study, on downside risk measures (VaR and ES) to further avoid potential simultaneity, as all these measures are based on market information. Thus, I prefer to use

[47] I exclude the ROA in the model specifications using the Z-score because the Z-score is mainly calculated using the return on assets and its standard deviation. However, I include the ROA as a substitute for ROE in the model specification using the DD to test the robustness of the profitability proxy in explaining the bank risk.

the DD as a robustness test. The baseline specification results in column (1) are different to my main results, in terms of significances and relationships with bank risk. Specifically, the effects of capital (TEGTA), liquidity risk (IETL), and credit risk (CR) are not significant anymore, and CR even turns negative. These results are persistent across all model specifications.

4.4.2 Alternative Confidence Level

The choice of confidence level in tail risk estimations is fundamental for the assessment of a capital cushion only. This implies that a greater amount of capital should cover potential losses, thereby leading to a higher confidence level. It will be less important if the tail risk estimations are just used as a benchmark to compare risks across different markets. As Dennis Weatherstone, former CEO, JP Morgan, said: “VaR gets me to 95% confidence. I pay my Risk Managers good salaries, to look after the remaining 5%.” 1 use a less strict confidence level at 95% to estimate VaR and ES. Table 7 shows that the results are strongly consistent with my main findings, and show even stronger magnitudes of respective coefficients in all model specifications. This indicates that the multivariate models estimated using tail risk measures at the 95% confidence interval are more resilient than those estimated using tail risk measures at the 99% confidence interval. However, 1 do not use the 95% confidence interval, as a main confidence level in my study, to be consistent with the suggested practice by the authorities (e.g., the Basel Accord) as highlighted in Section 2.4.1.

Table 6: Multivariate Regression Models with Merton distance to default (DD)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		4.396***									
		(0.548)									
VAR6M1			4.323***								
			(0.535)								
VAR1Y1				2.817***							
				(0.596)							
VAR3Y1					3.124***						
					(0.469)						
VAR5Y1						2.459***					
						(0.307)					
ES3M1							1.910***				
							(0.253)				
ES6M1								2.531***			
								(0.289)			
ES1Y1									2.194***		
									(0.319)		
ES3Y1										3.133***	
										(0.447)	
ES5Y1											2.501***
											(0.322)
TEGTA	-0.075	-0.082	-0.062	-0.040	-0.069	-0.076	-0.076	-0.050	-0.028	-0.048	-0.081
	(0.148)	(0.149)	(0.149)	(0.148)	(0.147)	(0.148)	(0.147)	(0.148)	(0.147)	(0.146)	(0.147)
CR	-0.008	-0.019**	-0.018**	-0.014	-0.015	-0.011	-0.012	-0.013	-0.013	-0.014	-0.012
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
ROA	-1.834***	-1.019**	-1.007**	-1.072**	-1.113***	-1.374***	-1.301***	-1.182***	-1.099**	-1.057**	-1.333***
	(0.408)	(0.445)	(0.443)	(0.438)	(0.417)	(0.414)	(0.428)	(0.431)	(0.428)	(0.416)	(0.414)
IETL	0.312	0.066	0.106	0.206	0.006	0.057	0.189	0.192	0.215	0.052	0.070
	(0.242)	(0.246)	(0.246)	(0.242)	(0.243)	(0.246)	(0.242)	(0.243)	(0.242)	(0.242)	(0.245)
RELGTA	0.186***	0.174***	0.179***	0.182***	0.171***	0.169***	0.182***	0.183***	0.183***	0.165***	0.167***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
LGTA	0.024***	0.022***	0.022***	0.022***	0.019***	0.019***	0.023***	0.022***	0.022***	0.020***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
_cons	-0.707***	-0.702***	-0.698***	-0.705***	-0.655***	-0.650***	-0.702***	-0.705***	-0.702***	-0.673***	-0.669***
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.074)	(0.074)	(0.075)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9676	9557	9567	9595	9654	9662	9651	9629	9622	9662	9669
R-squared	0.020	0.027	0.026	0.026	0.030	0.027	0.024	0.026	0.029	0.031	0.028

Notes: This table reports results of multivariate OLS regressions estimated using my sample of bank-year observations over the period 1987–2017. The dependent variable is the probability of default estimated using Merton distance to default (DD). Column (1) reports regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

Table 7: Multivariate Regression Models with 95% confidence level of tail risk measures

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M5		8.158***									
		(0.617)									
VAR6M5			9.109***								
			(0.673)								
VAR1Y5				5.613***							
				(1.258)							
VAR3Y5					5.584**						
					(2.637)						
VAR5Y5						4.836*					
						(2.547)					
ES3M5							5.159***				
							(0.386)				
ES6M5								4.626***			
								(0.359)			
ES1Y5									2.472***		
									(0.329)		
ES3Y5										2.667***	
										(0.383)	
ES5Y5											2.068***
											(0.377)
TEGTA	-2.256**	-2.029*	-1.879*	-1.904*	-2.424**	-2.637**	-2.006*	-1.753*	-1.970*	-2.358**	-2.513**
	(1.081)	(1.067)	(1.071)	(1.099)	(1.085)	(1.078)	(1.066)	(1.075)	(1.093)	(1.089)	(1.084)
CR	0.750***	0.637***	0.620***	0.682***	0.699***	0.718***	0.654***	0.663***	0.705***	0.715***	0.725***
	(0.054)	(0.053)	(0.053)	(0.056)	(0.061)	(0.058)	(0.052)	(0.053)	(0.054)	(0.054)	(0.054)
ROE	-3.135***	-2.544***	-2.480***	-2.661***	-2.750***	-2.885***	-2.566***	-2.586***	-2.779***	-2.856***	-2.990***
	(0.145)	(0.157)	(0.160)	(0.171)	(0.202)	(0.173)	(0.153)	(0.154)	(0.153)	(0.153)	(0.149)
IETL	12.679***	9.267***	9.310***	10.709***	10.001***	10.722***	9.785***	10.331***	11.514***	10.673***	11.310***
	(1.475)	(1.512)	(1.523)	(1.555)	(1.776)	(1.703)	(1.500)	(1.500)	(1.499)	(1.475)	(1.476)
RELGTA	1.221***	1.074***	1.063***	1.126***	1.116***	1.174***	1.096***	1.114***	1.169***	1.181***	1.213***
	(0.231)	(0.229)	(0.230)	(0.235)	(0.236)	(0.234)	(0.229)	(0.229)	(0.233)	(0.232)	(0.232)
LGTA	0.231***	0.212***	0.213***	0.225***	0.224***	0.230***	0.215***	0.215***	0.222***	0.209***	0.217***
	(0.038)	(0.037)	(0.038)	(0.038)	(0.038)	(0.038)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
_cons	-8.023***	-7.932***	-7.994***	-8.104***	-8.025***	-8.106***	-7.955***	-7.980***	-8.021***	-7.792***	-7.874***
	(0.542)	(0.542)	(0.545)	(0.550)	(0.547)	(0.544)	(0.539)	(0.541)	(0.542)	(0.538)	(0.534)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9618	9521	9487	9440	9368	9348	9597	9578	9548	9451	9435
R-squared	0.230	0.254	0.257	0.246	0.250	0.248	0.253	0.251	0.241	0.246	0.240

Notes: This table reports results of multivariate OLS regressions estimated using my sample of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 95% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 95% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

4.4.3 Bank Size

The variances in banks' incentives, engendered by size heterogeneity, may cloud the interpretation of my main results. This issue is addressed partly in my empirical analysis because bank size is controlled by including the log of gross total assets (GTA). Yet, this might not be enough due to intertemporal differences in some of these banks. To address this, I follow Berger and Bouwman (2013) and split my sample into small banks (gross total assets, or GTA, up to $1 billion), medium banks (GTA exceeding $1 billion and up to $3 billion), and large banks (GTA exceeding $3 billion). Next, I rerun my regressions separately for these three groups. Tables 8, 9, and 10 show the results for small, medium and large banks, respectively. As can be seen, these results are broadly similar to the results of all banks because the log of GTA might capture the size effects (see Table 5).

In more detail, all variables across small, medium, and large banks are significant, except the capital (TEGTA), with signs similar to those I report in Table 5. An exception also is that the real estate loans (RELGTA) variable among small banks is insignificant, and the sign turns negative across most of the model specifications. This suggests that small banks do not heavily rely on such loans in their business strategies. Finally, among the tail risk variables, the highest magnitude of coefficients is generally across medium banks, followed slightly by large banks, and the lowest is across small banks. This implies that tail risk measures broadly perform better when bank size is increased.

Table 8: Multivariate Regression Models for Small BHCs

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		3.469***									
		(0.596)									
VAR6M1			3.421***								
			(0.573)								
VAR1Y1				1.788***							
				(0.312)							
VAR3Y1					2.019***						
					(0.455)						
VAR5Y1						1.534***					
						(0.319)					
ES3M1							1.226***				
							(0.241)				
ES6M1								1.563***			
								(0.283)			
ES1Y1									1.241***		
									(0.210)		
ES3Y1										1.970***	
										(0.402)	
ES5Y1											1.513***
											(0.296)
TEGTA	-1.385	-0.753	-0.504	-0.607	-1.120	-1.300	-1.223	-1.001	-0.931	-0.930	-1.311
	(1.956)	(1.893)	(1.877)	(1.944)	(1.838)	(1.841)	(1.942)	(1.923)	(1.903)	(1.819)	(1.838)
CR	0.473***	0.418***	0.400***	0.438***	0.421***	0.467***	0.470***	0.452***	0.457***	0.424***	0.461***
	(0.099)	(0.100)	(0.097)	(0.097)	(0.097)	(0.097)	(0.100)	(0.100)	(0.097)	(0.097)	(0.097)
ROE	-2.994***	-2.517***	-2.502***	-2.610***	-2.704***	-2.791***	-2.735***	-2.677***	-2.690***	-2.657***	-2.806***
	(0.290)	(0.319)	(0.322)	(0.301)	(0.302)	(0.292)	(0.299)	(0.303)	(0.301)	(0.302)	(0.291)
IETL	11.652***	9.277***	9.453***	10.796***	8.759***	9.233***	10.576***	10.205***	10.761***	9.249***	9.476***
	(2.844)	(2.812)	(2.843)	(2.828)	(2.819)	(2.761)	(2.836)	(2.861)	(2.827)	(2.818)	(2.771)
RELGTA	0.002	-0.045	-0.123	-0.196	-0.186	-0.140	-0.045	-0.016	-0.131	-0.236	-0.172
	(0.453)	(0.433)	(0.433)	(0.444)	(0.436)	(0.437)	(0.446)	(0.449)	(0.443)	(0.436)	(0.436)
LGTA	0.447***	0.456***	0.473***	0.452***	0.409***	0.383***	0.452***	0.442***	0.424***	0.416***	0.392***
	(0.119)	(0.115)	(0.115)	(0.117)	(0.114)	(0.115)	(0.118)	(0.118)	(0.118)	(0.115)	(0.115)
_cons	-9.876***	-10.217***	-10.442***	-10.069***	-9.456***	-9.125***	-10.033***	-9.972***	-9.698***	-9.601***	-9.256***
	(1.585)	(1.545)	(1.534)	(1.561)	(1.529)	(1.529)	(1.579)	(1.569)	(1.575)	(1.537)	(1.531)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2551	2503	2511	2516	2539	2542	2542	2534	2530	2543	2547
R-squared	0.193	0.215	0.219	0.206	0.223	0.214	0.203	0.210	0.208	0.225	0.216

Notes: This table reports results of multivariate OLS regressions estimated using subsample (small BHCs with less than $1B of GTA) of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

Table 9: Multivariate Regression Models for Medium BHCs

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		5.775***									
		(0.710)									
VAR6M1			4.890***								
			(0.669)								
VAR1Y1				3.350***							
				(0.770)							
VAR3Y1					3.941***						
					(0.582)						
VAR5Y1						2.939***					
						(0.422)					
ES3M1							2.361***				
							(0.406)				
ES6M1								2.484***			
								(0.355)			
ES1Y1									1.626***		
									(0.273)		
ES3Y1										3.021***	
										(0.351)	
ES5Y1											3.178***
											(0.441)
TEGTA	-0.754	0.655	0.587	0.161	0.288	-0.230	-0.397	0.304	0.058	0.530	-0.046
	(2.141)	(2.172)	(2.174)	(2.136)	(2.053)	(2.047)	(2.101)	(2.148)	(2.134)	(2.031)	(1.957)
CR	0.782***	0.634***	0.677***	0.715***	0.681***	0.731***	0.717***	0.727***	0.762***	0.722***	0.723***
	(0.101)	(0.094)	(0.096)	(0.102)	(0.100)	(0.100)	(0.097)	(0.098)	(0.101)	(0.099)	(0.099)
ROE	-3.200***	-2.579***	-2.524***	-2.627***	-2.602***	-2.881***	-2.736***	-2.737***	-2.804***	-2.494***	-2.763***
	(0.250)	(0.268)	(0.265)	(0.276)	(0.257)	(0.248)	(0.263)	(0.255)	(0.273)	(0.269)	(0.255)
IETL	15.926***	13.131***	13.317***	13.727***	10.707***	11.884***	14.477***	14.161***	14.659***	13.188***	12.869***
	(3.040)	(3.164)	(3.160)	(3.095)	(3.137)	(3.074)	(3.040)	(3.042)	(3.024)	(2.950)	(2.956)
RELGTA	1.294***	0.931**	1.140***	1.190***	1.073***	1.077***	1.184***	1.261***	1.247***	1.136***	1.068***
	(0.386)	(0.400)	(0.411)	(0.403)	(0.404)	(0.391)	(0.402)	(0.405)	(0.384)	(0.388)	(0.386)
LGTA	0.551***	0.529***	0.515***	0.520***	0.453***	0.449***	0.515***	0.506***	0.506***	0.457***	0.464***
	(0.105)	(0.104)	(0.105)	(0.106)	(0.102)	(0.101)	(0.104)	(0.105)	(0.105)	(0.102)	(0.100)
_cons	-12.653***	-12.576***	-12.477***	-12.460***	-11.512***	-11.391***	-12.292***	-12.296***	-12.230***	-11.696***	-11.726***
	(1.467)	(1.448)	(1.461)	(1.472)	(1.416)	(1.403)	(1.453)	(1.459)	(1.474)	(1.415)	(1.388)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2999	2959	2958	2971	2991	2995	2986	2980	2979	2993	2996
R-squared	0.262	0.293	0.288	0.281	0.309	0.295	0.281	0.285	0.277	0.314	0.301

Notes: This table reports results of multivariate OLS regressions estimated using subsample (medium BHCs with GTA between $1B and $3B) of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

Table 10: Multivariate Regression Models for Large BHCs

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		4.396***									
		(0.548)									
VAR6M1			4.323***								
			(0.535)								
VAR1Y1				2.817***							
				(0.596)							
VAR3Y1					3.124***						
					(0.469)						
VAR5Y1						2.459***					
						(0.307)					
ES3M1							1.910***				
							(0.253)				
ES6M1								2.531***			
								(0.289)			
ES1Y1									2.194***		
									(0.319)		
ES3Y1										3.133***	
										(0.447)	
ES5Y1											2.501***
											(0.322)
TEGTA	0.249	0.138	0.269	0.402	0.079	-0.438	0.255	0.140	0.185	0.152	-0.258
	(1.936)	(1.921)	(1.936)	(1.925)	(1.899)	(1.873)	(1.906)	(1.937)	(1.908)	(1.913)	(1.877)
CR	0.861***	0.754***	0.740***	0.785***	0.714***	0.764***	0.793***	0.774***	0.765***	0.724***	0.768***
	(0.086)	(0.086)	(0.088)	(0.087)	(0.087)	(0.085)	(0.085)	(0.086)	(0.084)	(0.086)	(0.085)
ROE	-2.782***	-2.358***	-2.291***	-2.287***	-2.336***	-2.511***	-2.516***	-2.360***	-2.419***	-2.258***	-2.486***
	(0.220)	(0.228)	(0.233)	(0.232)	(0.213)	(0.209)	(0.221)	(0.227)	(0.213)	(0.214)	(0.206)
IETL	14.430***	10.829***	11.054***	11.866***	9.729***	9.876***	12.607***	12.144***	12.085***	9.149***	10.017***
	(2.314)	(2.327)	(2.281)	(2.268)	(2.227)	(2.215)	(2.291)	(2.281)	(2.244)	(2.217)	(2.205)
RELGTA	1.717***	1.471***	1.474***	1.630***	1.375***	1.225***	1.571***	1.560***	1.612***	1.227***	1.202***
	(0.410)	(0.409)	(0.409)	(0.411)	(0.405)	(0.400)	(0.403)	(0.405)	(0.410)	(0.415)	(0.405)
LGTA	0.143**	0.104*	0.104*	0.119**	0.088	0.089	0.124**	0.123**	0.120**	0.093*	0.100*
	(0.060)	(0.057)	(0.056)	(0.056)	(0.055)	(0.054)	(0.058)	(0.057)	(0.057)	(0.055)	(0.054)
_cons	-7.411***	-6.829***	-6.870***	-7.151***	-6.518***	-6.412***	-7.139***	-7.160***	-7.132***	-6.594***	-6.637***
	(0.943)	(0.905)	(0.892)	(0.895)	(0.860)	(0.848)	(0.918)	(0.910)	(0.898)	(0.861)	(0.847)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4068	4038	4042	4050	4067	4068	4065	4057	4055	4068	4068
R-squared	0.212	0.232	0.233	0.233	0.263	0.254	0.227	0.230	0.237	0.267	0.255

Notes: This table reports results of multivariate OLS regressions estimated using subsample (small BHCs with more than $3B of GTA) of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

4.4.4 Additional Control Variables

I augment the multivariate models by introducing additional control variables to ensure robustness of my main results, and test whether these variables significantly affect the probability of bank distress. Following Berger et al. (2016), I include the Herfindahl–Hirschman Index (HHI) of market concentration based on each bank's weighted deposits at state level to proxy for the competition.[48] I also include economic variables at the state level—GDP growth proxied by annual personal income and inflation rate measured using house price index growth—the latter of which could affect bank stability because real estates are used by banks as collaterals, thereby changes in real estate prices allow banks to partially recover the collaterals in case of defaulted mortgage loans (Berger et al., 2016). These variables are broadly used in the empirical literature on bank risk (e.g., Berger and Bouwman, 2013; Buch et al., 2014; Khan et al., 2017). Table 11 reports the results. As shown, they are very similar to the results without these factors (see Table 5). These results also indicate that the market power of banks has an insignificant positive influence on bank stability. This can be supported by the "competition-stability" view, more market power in the loan market may result in higher bank risk and a higher probability of failure (e.g., Boyd and De Nicoló, 2005; Schaeck et al., 2009). However, house price inflation and GDP growth show significantly negative values, suggesting that declining real estate prices and negative GDP growth increase the likelihood of banks' default. This is consistent with the findings by Berger et al. (2016).

[48] HHI is calculated by summing the squared percentage of deposits share of each bank in the market (State).

Table 11: Multivariate Regression Models with Control Variables

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		3.807***									
		(0.358)									
VAR6M1			3.610***								
			(0.346)								
VAR1Y1				2.167***							
				(0.262)							
VAR3Y1					2.671***						
					(0.297)						
VAR5Y1						2.007***					
						(0.208)					
ES3M1							1.573***				
							(0.168)				
ES6M1								1.875***			
								(0.182)			
ES1Y1									1.571***		
									(0.139)		
ES3Y1										2.554***	
										(0.236)	
ES5Y1											2.046***
											(0.208)
TEGTA	-3.582***	-3.125***	-2.995***	-3.076***	-3.090***	-3.334***	-3.356***	-3.175***	-3.058***	-2.832***	-3.294***
	(1.065)	(1.069)	(1.072)	(1.077)	(1.036)	(1.023)	(1.060)	(1.070)	(1.066)	(1.031)	(1.009)
CR	0.646***	0.585***	0.582***	0.609***	0.583***	0.618***	0.622***	0.616***	0.615***	0.593***	0.616***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.053)	(0.053)	(0.054)	(0.053)	(0.053)	(0.053)
ROE	-2.834***	-2.428***	-2.388***	-2.460***	-2.485***	-2.641***	-2.568***	-2.509***	-2.524***	-2.389***	-2.610***
	(0.141)	(0.154)	(0.153)	(0.151)	(0.147)	(0.141)	(0.145)	(0.147)	(0.146)	(0.147)	(0.141)
IETL	7.911***	5.963***	6.045***	6.734***	5.133***	5.787***	6.961***	6.689***	6.853***	5.560***	6.093***
	(1.504)	(1.538)	(1.534)	(1.510)	(1.501)	(1.481)	(1.506)	(1.513)	(1.498)	(1.473)	(1.463)
RELGTA	0.626***	0.598**	0.611***	0.609**	0.576**	0.544**	0.612***	0.641***	0.610***	0.511**	0.518**
	(0.236)	(0.234)	(0.235)	(0.236)	(0.231)	(0.228)	(0.234)	(0.234)	(0.234)	(0.230)	(0.227)
LGTA	0.166***	0.165***	0.165***	0.164***	0.139***	0.130***	0.166***	0.165***	0.161***	0.150***	0.144***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.036)	(0.035)	(0.037)	(0.037)	(0.037)	(0.036)	(0.035)
GHPI	-2.821***	-2.679***	-2.712***	-2.722***	-2.212***	-2.090***	-2.740***	-2.712***	-2.759***	-2.183***	-2.082***
	(0.279)	(0.275)	(0.272)	(0.274)	(0.272)	(0.279)	(0.274)	(0.273)	(0.273)	(0.267)	(0.276)
GCPI	-3.323***	-1.805***	-1.797***	-2.515***	-2.777***	-3.355***	-2.557***	-2.388***	-2.649***	-2.756***	-3.362***
	(0.468)	(0.476)	(0.477)	(0.469)	(0.463)	(0.462)	(0.472)	(0.472)	(0.459)	(0.464)	(0.462)
HHI	0.040	0.046	0.036	0.048	-0.005	0.030	0.046	0.023	0.027	-0.005	0.035
	(0.146)	(0.146)	(0.145)	(0.146)	(0.143)	(0.141)	(0.145)	(0.145)	(0.145)	(0.142)	(0.140)
_cons	-6.320***	-6.604***	-6.633***	-6.524***	-6.156***	-5.970***	-6.478***	-6.537***	-6.451***	-6.376***	-6.207***
	(0.536)	(0.546)	(0.543)	(0.539)	(0.521)	(0.511)	(0.541)	(0.538)	(0.535)	(0.524)	(0.511)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9618	9500	9511	9537	9597	9605	9593	9571	9564	9604	9611
R-squared	0.230	0.251	0.251	0.245	0.272	0.264	0.244	0.247	0.248	0.277	0.265

Notes: This table reports results of multivariate OLS regressions estimated using my sample of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients (except competition, and macroeconomic variables) are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

4.4.5 Financial Crises

Berger and Bouwman (2013) recognise that the influence of financial crises most likely varies and depends on the source of crisis. For instance, a crisis that started in the banking sector is different in impact from one that started in the capital markets. Thus, it is interesting to investigate the extent to which my results hold during crises. I follow Berger and Bouwman (2013) in defining periods for banking crises (the credit crunch 1990–1992 and subprime lending crisis 2007– 2009) and market crises (the 1987 stock market crash, the dot.com bubble and the September 11 terrorist attack 2000–2002).[49]

These crises have had a significant impact on the health of the U.S. banking system and on the soundness of individual banks. To control for possible effects on the reliability of my findings, Ire-estimate my main analyses controlling for the years of crises.[50] Table 12 reports the results. As can be seen, these results verify my main findings, suggesting that my main results are not affected by the financial crises. In addition, I find that both banking crises have positive relationships with bank risk, and only the recent crisis is significant, whereas the market crises have negative relationships with bank risk, and are only significant in some model specifications. These findings are generally intuitive as defaulted banks (banking crises) have direct and adverse effects on other banks in the sector but vary in terms of significance levels. Nonetheless, market crashes most likely have an indirect and less stringent impact on banks' failure risk. This is in line with Berger and Bouwman (2013), who show that higher capital helps banks improve the probability of surviving during banking crises.

[49] Note that stock market crash omitted due to collinearity.

[50] I use dummy variables indicating whether the years are on crises. See Table 1 for further information on definition of all variables.

Table 12: Multivariate Regression Models with Financial Crises

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		3.519***									
		(0.357)									
VAR6M1			3.363***								
			(0.335)								
VAR1Y1				2.116***							
				(0.252)							
VAR3Y1					2.628***						
					(0.290)						
VAR5Y1						1.911***					
						(0.191)					
ES3M1							1.504***				
							(0.162)				
ES6M1								1.825***			
								(0.173)			
ES1Y1									1.543***		
									(0.135)		
ES3Y1										2.506***	
										(0.231)	
ES5Y1											1.963***
											(0.195)
TEGTA	-2.516**	-2.248**	-2.123**	-2.093**	-2.196**	-2.386**	-2.402**	-2.248**	-2.112**	-1.968*	-2.361**
	(1.038)	(1.046)	(1.048)	(1.050)	(1.019)	(1.011)	(1.033)	(1.044)	(1.039)	(1.016)	(1.000)
CR	0.783***	0.698***	0.695***	0.731***	0.683***	0.725***	0.745***	0.734***	0.737***	0.694***	0.724***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.053)	(0.054)	(0.054)
ROE	-3.110***	-2.679***	-2.637***	-2.708***	-2.697***	-2.872***	-2.828***	-2.752***	-2.774***	-2.601***	-2.841***
	(0.143)	(0.157)	(0.156)	(0.154)	(0.150)	(0.143)	(0.148)	(0.149)	(0.148)	(0.150)	(0.143)
IETL	4.953**	5.494**	5.262**	4.868**	2.836	3.470	5.147**	5.121**	4.938**	3.684*	3.709*
	(2.201)	(2.211)	(2.211)	(2.213)	(2.203)	(2.189)	(2.207)	(2.214)	(2.195)	(2.163)	(2.169)
RELGTA	0.663***	0.693***	0.688***	0.667***	0.637***	0.618***	0.667***	0.702***	0.664***	0.575**	0.588***
	(0.232)	(0.231)	(0.231)	(0.232)	(0.228)	(0.225)	(0.230)	(0.230)	(0.230)	(0.227)	(0.224)
LGTA	0.115***	0.137***	0.132***	0.123***	0.101***	0.100***	0.125***	0.126***	0.119***	0.116***	0.112***
	(0.038)	(0.039)	(0.038)	(0.038)	(0.037)	(0.037)	(0.038)	(0.038)	(0.037)	(0.037)	(0.036)
SL	0.055	0.025	0.032	0.045	0.088	0.084	0.039	0.042	0.049	0.071	0.079
	(0.056)	(0.057)	(0.057)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)	(0.056)
GFC	0.633***	0.471***	0.494***	0.554***	0.481***	0.467***	0.558***	0.539***	0.568***	0.465***	0.469***
	(0.054)	(0.055)	(0.054)	(0.054)	(0.054)	(0.053)	(0.054)	(0.054)	(0.053)	(0.053)	(0.053)
Dot	-0.037	-0.093**	-0.094**	-0.067	-0.046	-0.025	-0.064	-0.078*	-0.074*	-0.053	-0.022
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.044)	(0.045)
_cons	-5.925***	-6.490***	-6.441***	-6.237***	-5.923***	-5.856***	-6.204***	-6.285***	-6.169***	-6.192***	-6.066***
	(0.555)	(0.572)	(0.566)	(0.561)	(0.547)	(0.540)	(0.563)	(0.561)	(0.556)	(0.546)	(0.539)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9618	9500	9511	9537	9597	9605	9593	9571	9564	9604	9611

R-squared	0.254	0.265	0.267	0.265	0.285	0.276	0.263	0.266	0.268	0.290	0.277

Notes: This table reports results of multivariate OLS regressions estimated using my sample of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients (except financial crises dummy variables) are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. ∗, ∗∗, ∗∗∗ denote significance at 10%, 5%,

4.4.6 Excluding Mergers and Acquisitions

Numerous banks typically exit my sample because they were acquired by another institution or merged with another bank. This can lead to a re-evaluation of financial statements which may affect the analysis (Goetz, 2018). To investigate the impact of mergers and/or acquisitions on the main results, I exclude the non-surviving banks that were acquired or merged. The results from this sample are presented in Table 13. I find that the main results presented in Table 5 are robust to the impact of mergers and/or acquisitions and remain unchanged.

4.4.7 Excluding TBTF Banks

To avoid potential safety net issues associated with "Too Big to Fail" (TBTF) policies involving large organisations (Curry et al., 2007), I re-estimate my main analyses while excluding these banks. In the absence of a formal definition of TBTF, I follow Berger and Bouwman (2013) and consider all banks with gross total assets (GTA) exceeding $50 billion to be TBTF, which is consistent with the definition of systemically-important banks in the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. The results summarised in Table 14 indicate that the main results in Table 5 are still strongly significant. An exception is the capital ratio (TEGTA); it is insignificant in most model specifications.

Table 13: Multivariate Regression Models without Mergers and Acquisitions

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		4.363***									
		(0.434)									
VAR6M1			3.955***								
			(0.431)								
VAR1Y1				2.148***							
				(0.351)							
VAR3Y1					2.709***						
					(0.379)						
VAR5Y1						2.113***					
						(0.242)					
ES3M1							1.854***				
							(0.234)				
ES6M1								2.249***			
								(0.261)			
ES1Y1									1.574***		
									(0.208)		
ES3Y1										2.749***	
										(0.352)	
ES5Y1											2.190***
											(0.251)
TEGTA	-2.454*	-2.122	-1.963	-2.034	-2.056	-2.245*	-2.321*	-2.140	-1.971	-1.700	-2.172*
	(1.363)	(1.347)	(1.348)	(1.356)	(1.325)	(1.313)	(1.348)	(1.354)	(1.355)	(1.326)	(1.294)
CR	0.844***	0.729***	0.733***	0.785***	0.728***	0.775***	0.786***	0.775***	0.793***	0.731***	0.774***
	(0.068)	(0.066)	(0.067)	(0.069)	(0.070)	(0.068)	(0.067)	(0.068)	(0.067)	(0.069)	(0.068)
ROE	-3.398***	-2.863***	-2.814***	-2.992***	-2.964***	-3.122***	-3.043***	-2.957***	-3.041***	-2.817***	-3.074***
	(0.181)	(0.198)	(0.202)	(0.195)	(0.192)	(0.182)	(0.191)	(0.193)	(0.192)	(0.202)	(0.184)
IETL	14.634***	11.650***	11.926***	12.969***	10.421***	10.643***	12.967***	12.559***	13.095***	10.477***	10.851***
	(2.068)	(2.080)	(2.079)	(2.059)	(2.067)	(2.040)	(2.068)	(2.077)	(2.063)	(2.031)	(2.018)
RELGTA	1.250***	1.112***	1.166***	1.186***	1.050***	0.991***	1.183***	1.214***	1.205***	0.975***	0.967***
	(0.272)	(0.272)	(0.273)	(0.272)	(0.269)	(0.264)	(0.271)	(0.271)	(0.270)	(0.270)	(0.263)
LGTA	0.206***	0.189***	0.191***	0.201***	0.163***	0.156***	0.199***	0.195***	0.200***	0.174***	0.170***
	(0.049)	(0.048)	(0.048)	(0.048)	(0.047)	(0.047)	(0.048)	(0.048)	(0.048)	(0.047)	(0.046)
_cons	-7.780***	-7.687***	-7.767***	-7.854***	-7.257***	-7.090***	-7.770***	-7.783***	-7.850***	-7.489***	-7.331***
	(0.712)	(0.712)	(0.711)	(0.712)	(0.691)	(0.677)	(0.707)	(0.707)	(0.710)	(0.689)	(0.677)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5792	5752	5759	5777	5788	5788	5787	5780	5783	5789	5791
R-squared	0.245	0.265	0.264	0.258	0.283	0.277	0.258	0.262	0.258	0.287	0.279

Notes: This table reports results of multivariate OLS regressions estimated using my sample (exclude Mergers and Acquisitions) of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

Table 14: Multivariate Regression Models without Too-Big-To-Fail

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		4.709***									
		(0.375)									
VAR6M1			4.303***								
			(0.363)								
VAR1Y1				2.693***							
				(0.325)							
VAR3Y1					3.122***						
					(0.356)						
VAR5Y1						2.406***					
						(0.252)					
ES3M1							1.925***				
							(0.186)				
ES6M1								2.209***			
								(0.194)			
ES1Y1									1.744***		
									(0.153)		
ES3Y1										2.835***	
										(0.269)	
ES5Y1											2.431***
											(0.252)
TEGTA	-2.034*	-1.598	-1.485	-1.459	-1.531	-1.766	-1.897*	-1.662	-1.512	-1.295	-1.715
	(1.125)	(1.119)	(1.119)	(1.131)	(1.095)	(1.076)	(1.112)	(1.123)	(1.123)	(1.090)	(1.061)
CR	0.762***	0.667***	0.668***	0.704***	0.669***	0.709***	0.723***	0.715***	0.719***	0.684***	0.707***
	(0.057)	(0.056)	(0.056)	(0.057)	(0.057)	(0.056)	(0.056)	(0.057)	(0.056)	(0.056)	(0.056)
ROE	-3.136***	-2.580***	-2.545***	-2.651***	-2.672***	-2.862***	-2.787***	-2.711***	-2.770***	-2.581***	-2.828***
	(0.151)	(0.164)	(0.164)	(0.165)	(0.159)	(0.150)	(0.156)	(0.157)	(0.155)	(0.158)	(0.150)
IETL	11.772***	8.805***	9.028***	10.095***	7.730***	8.319***	10.346***	9.997***	10.524***	8.413***	8.768***
	(1.555)	(1.589)	(1.577)	(1.557)	(1.559)	(1.531)	(1.559)	(1.564)	(1.550)	(1.525)	(1.509)
RELGTA	1.117***	0.980***	1.018***	1.053***	0.955***	0.922***	1.057***	1.083***	1.061***	0.887***	0.894***
	(0.241)	(0.240)	(0.241)	(0.242)	(0.237)	(0.232)	(0.240)	(0.240)	(0.239)	(0.237)	(0.231)
LGTA	0.241***	0.229***	0.226***	0.228***	0.190***	0.187***	0.232***	0.228***	0.226***	0.203***	0.205***
	(0.041)	(0.042)	(0.041)	(0.041)	(0.041)	(0.040)	(0.041)	(0.041)	(0.041)	(0.040)	(0.040)
_cons	-8.077***	-8.092***	-8.094***	-8.092***	-7.514***	-7.408***	-8.059***	-8.072***	-8.043***	-7.756***	-7.711***
	(0.576)	(0.589)	(0.583)	(0.585)	(0.568)	(0.557)	(0.583)	(0.578)	(0.578)	(0.568)	(0.556)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8913	8800	8811	8836	8892	8900	8888	8868	8862	8899	8906
R-squared	0.232	0.255	0.254	0.248	0.272	0.264	0.247	0.250	0.250	0.276	0.265

Notes: This table reports results of multivariate OLS regressions estimated using my sample (exclude Too-Big-To-Fail with $50B of GTA or more) of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 4.2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 1 year. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. $*$, $**$, $***$ denote significance at 10%, 5%, and 1%, respectively.

4.4.8 Endogeneity Issues

It is well-known that endogeneity problems often cloud empirical results. However, it may be difficult to know whether I have detected these problems. Following Hagendorff et al. (2018) and others, I address simultaneity, as a notorious type of endogeneity issues, by regressing the bank failure risk on longer lagged values of tail risk based on the argument that such historical values are largely predetermined (Faleye, 2007). I lag the values of tail risk and all other bank characteristics by 3 years. This further reduces the potential impact of endogeneity on the bank distress risk-tail risk relationship. As Table 15 shows, I obtain similar results to the findings reported in Table 5. This suggests that it is highly unlikely that my main results are clouded by endogeneity issues (i.e., simultaneity).

4.5 Conclusion

This paper explores the extent to which the information content of market variables may be useful as signals of financial fragility in banks. Using a sample of the U.S. listed bank holding companies (BHCs) between 1987 and 2017, I empirically investigate the impact of tail risk measures namely, value-at-risk (VaR) and expected shortfall (ES), on bank distress. I hypothesise that BHCs with higher extreme negative daily equity returns experience higher tail risk, thereby a higher likelihood of financial distress.

In support of my hypothesis, the univariate regression results show a significant and positive relationship between banks' distress likelihood and respective tail risk measures (estimated using daily returns for three-month, six-month, one-year, three-year, and five-year rolling windows). Subsequently, I develop multivariate regression models using the fixed effects to examine the role of tail risk measures alongside accounting-related indicators, typically based on traditional CAMEL categories, in predicting banks' financial distress.

Empirical results show that proxies for capital adequacy, asset quality, management, earnings and liquidity, as well as real estate loans, are still central determinants of bank distress risk as documented in the literature (e.g., Cole and White, 2012). However, the tail risk measures play a substantial role in explaining the likelihood of banks' distress risk. More precisely, I find that all rolling estimates of VaR and ES measures are significant and positively linked to the probability of banks' distress risk. These results also support my hypothesis that banks with more frequent extreme negative daily equity returns are more likely to experience financial distress.

The main results are robust to endogeneity issues (i.e., simultaneity) and numerous other robustness analyses, including the heterogeneity of bank size, the use of an alternative dependent variable, the employment of an alternative confidence level to estimate tail risk measures, and other control variables (e.g., financial crises and macroeconomic factors).

My study suggests that it is crucial to assign strong emphasis to market-based variables, especially tail risk measures, alongside accounting-based variables in determining bank stability. This provides clear implications, which might assist regulators, supervisors, managers, and other market participants in understanding the default risk across listed banks.

Table 15: Multivariate Regression Models With 3-Year Lag

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VAR3M1		1.613***									
		(0.364)									
VAR6M1			1.197***								
			(0.337)								
VAR1Y1				0.679***							
				(0.242)							
VAR3Y1					1.732***						
					(0.279)						
VAR5Y1						2.351***					
						(0.343)					
ES3M1							0.709***				
							(0.193)				
ES6M1								0.555**			
								(0.218)			
ES1Y1									0.479***		
									(0.183)		
ES3Y1										1.693***	
										(0.265)	
ES5Y1											2.327***
											(0.339)
TEGTA	-1.003	-0.869	-0.886	-0.884	-0.950	-1.255	-0.892	-0.971	-0.870	-0.768	-1.117
	(1.570)	(1.567)	(1.569)	(1.574)	(1.551)	(1.530)	(1.564)	(1.566)	(1.567)	(1.538)	(1.513)
CR	0.084	0.040	0.049	0.065	0.026	0.036	0.061	0.063	0.067	0.024	0.032
	(0.062)	(0.063)	(0.063)	(0.063)	(0.062)	(0.061)	(0.063)	(0.063)	(0.062)	(0.062)	(0.061)
ROE	-0.732***	-0.566***	-0.598***	-0.636***	-0.512**	-0.464**	-0.619***	-0.658***	-0.649***	-0.459**	-0.446**
	(0.199)	(0.206)	(0.204)	(0.202)	(0.201)	(0.197)	(0.204)	(0.202)	(0.200)	(0.198)	(0.196)
IETL	28.193***	27.274***	27.386***	27.653***	25.931***	24.934***	27.615***	27.715***	27.728***	25.984***	25.341***
	(1.992)	(1.972)	(1.978)	(1.988)	(1.990)	(2.003)	(1.965)	(1.979)	(1.987)	(1.977)	(1.977)
RELGTA	2.522***	2.516***	2.528***	2.490***	2.417***	2.293***	2.504***	2.538***	2.503***	2.376***	2.277***
	(0.342)	(0.344)	(0.345)	(0.344)	(0.338)	(0.331)	(0.341)	(0.341)	(0.341)	(0.337)	(0.331)
LGTA	0.476***	0.472***	0.468***	0.472***	0.452***	0.429***	0.473***	0.471***	0.473***	0.459***	0.447***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.052)	(0.052)	(0.053)	(0.053)	(0.053)	(0.052)	(0.052)
_cons	-12.745***	-12.763***	-12.708***	-12.725***	-12.452***	-12.103***	-12.743***	-12.721***	-12.747***	-12.593***	-12.412***
	(0.774)	(0.775)	(0.775)	(0.772)	(0.758)	(0.755)	(0.770)	(0.771)	(0.772)	(0.759)	(0.752)
Time fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BHC fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7699	7650	7666	7687	7695	7697	7691	7686	7694	7696	7698
R-squared	0.116	0.120	0.119	0.117	0.128	0.145	0.118	0.118	0.117	0.128	0.144

Notes: This table reports results of multivariate OLS regressions estimated using my sample of bank-year observations over the period 1987–2017. The dependent variable is the natural logarithm of Z-score. Column (1) reports multivariate regression estimates (baseline model) that employ only accounting variables discussed in Section 2.4.2. Columns (2) to (6) report respective multivariate regression estimates supplementing VaR as the tail risk measure (3-month, 6-month, 1-year, 3-year and 5-year) at 99% confidence level. Columns (7) to (11) report respective multivariate regression estimates supplementing ES as the tail risk measure (3-month, 6-month, 1-year, 3-year, and 5-year) at 99% confidence level. The last 2 rows of this table provide total number of bank-year observations and R-squared. See Table 1 for further information on definition of respective variables. All coefficients are winsorized at the 1% level and are lagged by 3 years. All regression models include year and BHC fixed effects as indicated. Standard errors are clustered at the BHC-year level and reported in parentheses. *, **, *** denote significance at 10%, 5%, and 1%, respectively.

5. THESIS CONCLUSION

5.1 Summary

Inspired by the aftermath of financial crises, the serious threat of risks to bank stability, the large number of bank failures, the authorities requirements (e.g., the Dodd-Frank Act of 2010 and the Basel III framework), and the demand to focus on some aspects that have not been fully investigated in the empirical literature of bank risk, this thesis analyses distinctive lines of research on risks in banks. The primary objectives of this thesis are to address the important gaps in the literature and enhance the understanding about the bank risk. To that end, three empirical essays are pursued.

In *first essay* (chapter 2), I provide a comprehensive analysis of bank failures by developing separate early-warning models for small, medium, and large banks, and report any differences in comparison to all bank failure prediction models, irrespective of bank size. I apply univariate regression analysis as a variable selection technique to examine the relative importance of accounting-based variables that have been used in bank failure literature and compare the consistency (statistical significance and average marginal effects (AMEs)) of these covariates across size categories. I also propose an econometric method on multivariate model building strategy based on variables' AMEs and their inter-temporal discrimination ability.

Empirical results show that factors affecting bank failure and the magnitudes of mutually significant factors (AMEs) vary across small, medium, and large banks. Further interesting results of this essay are as follows. First, credit risk has a significant impact on bank failure probability across size classes and for the three-time lagged periods, implying that weak assets quality, represented by net charge off, past due 90+ days, loan loss reserves, and other real estate owned, increases the risk of failure. Second, small banks are most likely to fail if they have high deposit ratios, are more cost inefficient, and have a high liquidity risk, while medium and large banks with poor capital and low net interest margins are more likely to fail.

Finally, I perform several robustness tests and the main results remain valid. Moreover, the AUROC of all multivariate models developed across bank size classes for out-of-sample have an excellent performance for different forecast horizons.

My *second essay* (chapter 3) explores the systematic trend in bank risk measured by liquidity risk and credit risk, and examines potential explanations for this trend. I find a strong evidence of a positive trend in bank risk over the sample period, 1980-2017. I explain the increase in bank risk is the result of successive cohorts of young and riskier banks, and the risk differences across these cohorts persist. Moreover, the cohort risk phenomenon is significantly attenuated once I account for new cohorts' bank-specific characteristics including brokered deposits, commercial real estate loans, capital, off-balance sheet items, and non-interest income. In other words, the adoption of business strategy that is based on higher brokered deposits, commercial real estate loans, off-balance sheet items, and non-interest income and lower capital by each new cohort is responsible for the cohort risk phenomenon. I perform a set of robustness checks and the main results are qualitatively unchanged.

The *third essay* (chapter 4) empirically investigates the impact of tail risk measures namely, value-at-risk (VaR) and expected shortfall (ES), on bank distress. I hypothesise that BHCs with higher extreme negative daily equity returns experience higher tail risk, thereby a higher likelihood of financial distress.

In support of my hypothesis, the univariate regression results show a significant and positive relationship between banks' distress likelihood and respective tail risk measures (estimated using daily returns for three-month, six-month, one-year, three-year, and five-year rolling windows). Subsequently, I develop multivariate regression models using the fixed effects to examine the role of tail risk measures alongside accounting-related indicators, typically based on traditional CAMEL categories, in predicting banks' financial distress.

Empirical results show that proxies for capital adequacy, asset quality, management, earnings and liquidity, as well as real estate loans, are still central determinants of bank distress risk as documented in the literature (e.g., Cole and White, 2012). However, the tail risk measures play a substantial role in explaining the likelihood of banks' distress risk. More precisely, I find that all rolling estimates of VaR and ES measures are significant and positively linked to the probability of banks' distress risk. These results also support my hypothesis that banks with more frequent extreme negative daily equity returns are more likely to experience financial distress. The main results are robust to numerous sensitivity analyses. Finally, this essay suggests that it is crucial to assign strong emphasis to market-based variables, especially tail risk measures, alongside accounting-based variables in determining bank stability.

Overall, my thesis makes a crucial contribution to the literature by providing new and deeper insights into the understanding of bank risk. It also strongly supports recent regulatory reforms to enhance the stability of the banking sector to avoid the adverse effects on whole economy. In addition, my thesis should interest all parties including bank managers, supervisors, policy makers, and researchers who attempt to prevent future banking crises.

5.2 Limitations and Future Research

Although this thesis presents strong results and offers several policy implications, it has its limits as other empirical studies.

The key limit to the *first essay* (chapter 2) is the information content of market-based indicators. Due to the great majority of commercial banks in the United States are not publicly traded, I focus on financial ratios based on accounting data. This limitation presents an opportunity for future work by using sample of publicly listed banks in developed and/or developing countries, and replicating my analysis supplemented with market-based measures.

The potential limit to the *second essay* (chapter 3) is the suggested reasons for cohort risk phenomenon. While this essay provides several valuable explanations for this phenomenon, I believe there are more factors may explain the phenomenon. Thus, number of avenues for further research on this topic can be considered. An interesting area for future research would be to explain the observed cohort risk phenomenon according to competition and/or macroeconomic (e.g., interest rate) factors.

The main limit to the *third essay* (chapter 4) is the scarcity of actual failures among publicly traded bank holding companies (BHCs) in the United States. This restricts the methodology choices to apply ordinary least squares (OLS) regression when analysing the impact of tail risk exposure on the probability of bank distress. Therefore, I suggest a possible direction for future research by using logit regression, which is a common model for predicting individual bank distress, based on distress events introduced by Betz et al. (2014), including bankruptcies, liquidations, defaults, state interventions, and mergers.

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