ESSAYS ON BANK BAILOUTS: PREDICTIVE FACTORS, GENDER INFLUENCE ON BANK PERFORMANCE, AND RISK ASPECTS

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Abstract

This thesis provides comprehensive research on the banking industry, beginning with examining the predictability of bank bailouts. Following that, it proceeds to investigate the influence of gender diversity on the banking sector, closely examining the relationship between the involvement of women on the board of directors and the performance of banks. In addition, the study expands its range to evaluate the impact of gender diversity on different risk aspects in banks, such as credit, market, and operational risks. This offers an in-depth overview of how gender balance can influence risk management strategies in the banking sector.

This study provides an empirical investigation of the impact of tail risk measures, namely value-at-risk (VaR), Cornish-Fisher Value-at-Risk (VaRCF), and Expected Shortfall (ES), on the probability of bank bailouts for publicly traded bank holding companies (BHCs) in the United States. Our findings reveal a significant and positive association between tail risk measures and bank bailouts, indicating that BHCs with a higher incidence of extreme negative daily equity returns are exposed to greater tail risks, which increase their likelihood of receiving government assistance. These outcomes underscore the importance of prudential regulatory frameworks that promote market discipline to mitigate against potential tail risks.

In addition, this thesis investigates the impact of gender diversity on the performance of the US banks after the government's bailout initiatives. Based on critical mass theory, the study provides comprehensive empirical evidence that the relationship between board gender diversity and bank performance is contingent on a specific level of gender diversity on the board. Specifically, the optimal proportion of women positively affecting performance is under the tilted groups, which is between 20% and 40% of the board members.

This thesis not only investigates the ideal proportion of women on the board in relation to bank performance, but it also examines its impact on credit, market, and operational risks on the US

banks after the government's bailout efforts. The research presents empirical data that supports the critical mass theory, indicating that the association between board gender diversity and bank risk depends on a certain level of gender diversity on the board. More precisely, the ideal ratio of women that has a negative impact on risk is also within the range of 20% to 40% of the board members in the tilted groups. These findings resolve the conflicting results from prior studies on this issue.

Chapter One: Introduction

1.1 The Importance of Studying Bank Bailout

The global financial crisis, which started between 2007 and 2008, led to several worldwide bailout programmes. Due to the enormous budget, the ambiguity surrounding the selection of recipient institutions, and the overall impact on banking systems, these bailout programmes were debatable (Barbu et al., 2021). According to Fernandes et al. (2017), the global financial crisis was the worst since the Great Depression. The efficacy and stability of the banking industry became major concerns in many countries due to the global financial crisis that occurred from 2007 to 2009 (Al-Magharem et al., 2019; Ashraf et al., 2020; Dikko et al., 2021).

Little attention has been paid to the impact of bailouts on maintaining the banking sector's stability (Calabrese et al., 2017). Due to the financial crisis, which resulted in unusual policy interventions (Laeven & Valencia, 2010), various papers have studied the impact of these policies on the stability of a banking system. However, it is still unclear whether these policies are beneficial or detrimental to banks' performance (Calabrese et al., 2017).

The bank bailout events not only signal acute problems within specific institutions but also reveal broader weaknesses across the entire financial system. These critical periods provide a unique perspective for examining the mechanisms predicting a bank's slide into crisis and the possible routes to resilience and recovery. The anticipation and handling of such bailouts are the highest priority to policymakers, investors, and stakeholders due to their major consequences for financial stability and economic health.

These bailout events have a wider significance beyond just financial rescue operations. They provide an opportunity to critically examine the dynamics of risk management and corporate governance. Cardillo et al. (2021) confirm that it is worth noting that bank bailouts are considered a more reliable indicator of bank risk and performance when compared to other measures. The clarity of this situation is due to the binary nature of bailout events. Bailouts can either happen or not happen, reducing ambiguity. This reduces the risk of data mining and the influence of different banking models and managerial decisions on financial reporting. Therefore, the bailout period is more than just a crisis management phase; it is an essential opportunity to assess the effectiveness of risk assessment methods and the policy choices made before bailout events.

Considering these circumstances, predicting bank bailouts becomes critical to understanding bank stability, as any bank that gets bailed out is regarded as a failed bank. Additionally, examining the impact of gender diversity in bank leadership during the bailout period becomes an essential field of study. Analysing the period after a bailout allows for a specific timeframe to analyse the influence of gender diversity on bank performance and risk aspects. This investigation is based on the wider discussion surrounding corporate governance and risk management. It suggests that having a diverse leadership can contribute to more balanced decision-making, which may result in improved stability and performance. Thus, the bailout event and its aftermath provide a valuable perspective on how gender diversity can affect bank resilience. This shed light on the potential for more inclusive governance models to strengthen banks in the face of future crises.

1.2 Motivation

Understanding what led us to study the topic of bank bailouts is essential. Reflecting on the words of Timothy Geithner, former U.S. Secretary of the Treasury, during the tenth anniversary of the Global Financial Crisis, he remarked: "It was not about saving one institution but saving the whole system. Not until the Troubled Asset Relief Program (TARP) was passed and a second wave of authority was granted in early 2009 did I have a sense that there might be light at the end of the tunnel" (McCaffrey, 2018). This quote underscores the broader economic implications of such interventions, beyond the maintenance of individual institutions. Motivated by this perspective, our research aims to understand the determinants of bank bailouts and how gender diversity in bank leadership influences these critical financial events, specifically examining how it affects bank performance and risk during and after these interventions.

In Chapter Two, we are motivated to study the hypothesis that an increase in the frequency of extremely negative daily equity returns indicates larger tail risks, putting banks at a greater probability of bailouts. Specifically, we seek to address the following questions to bridge the existing gap in the literature: Does an increase in the frequency of extremely negative daily equity returns indicate larger tail risks, putting banks at a greater probability of bailouts? Do our results support the extreme value theory?

Several key papers, such as Lagarde (2010), Palvia et al. (2014), Berger et al. (2021), Cardillo et al. (2021), and Adams and Ragunathan (2017), have led us to think deeply about the causes of bank failure and have shifted our focus on the Third and Fourth Chapters to study the impact of women on the banking industry. More specifically, examining women's impact on bank performance, credit, market, and operational risk. Ms. Christine Lagarde of the IMF famously said in 2010: "If Lehman Brothers had been Lehman Sisters, today's economic crisis clearly would look quite different" (Lagarde, 2010; Palvia et al., 2014). Berger et al. (2021) confirm the causes behind the increase in the probability of bank failures, such as individualism and masculinity. Cardillo et al. (2021) investigate the influence of gender diversity on bank boards on the likelihood and size of public bailouts.[1] They propose that banks with a higher level of gender diversity on their boards have a reduced likelihood of requiring a public bailout. Furthermore, these banks receive a smaller proportion of bailout funds in relation to their total assets compared to banks with less gender diversity on their boards. Sapienza et al. (2009) show that testosterone levels influence career choices and risk preferences, with higher testosterone linked to finance career selection and lower risk aversion, suggesting that women in finance roles may have risk profiles

[1] Their findings are derived from an analysis of a sample of European banks that were publicly listed between 2005 and 2017.

comparable to those of their male peers. Adams and Ragunathan (2017) indicate that women in the financial industry may exhibit similar or lower risk aversion than their male counterparts in finance. Furthermore, their findings emphasise their incomplete understanding of the mechanisms and significance of gender diversity on corporate performance and the circumstances in which diversity is impactful. They confirm that further investigation is required to provide a comprehensive understanding of the impact of gender on corporate management.

To achieve effective outcomes, we focus Chapters Three and Four on investigating the period after the global financial crisis. We use this treatment period as motivation to explore and take advantage of unique opportunities for analysis. Additionally, the primary impetus behind Chapter Three is the existence of disparities in the field where some research reveals a positive relationship between gender diversity and bank performance such as García-Meca et al. (2015), Owen and Temesvary (2018), and Tampakoudis et al. (2022), while others, such as Berger et al. (2014), Farag and Mallin (2017), Liao et al. (2019), and Pathan and Faff (2013), find negative or mixed effects.

Thus, to resolve these contradictory results, we study whether such diversity significantly affects bank performance. The Third Chapter aims to investigate the following questions to fill the current gap in the literature: Does gender diversity, specifically the presence of females on a bank's board of directors, enhance bank performance after the financial crisis, and what is the optimal ratio of women on the board that leads to positive effects on performance? Does critical mass theory effectively describe the impact of board gender diversity on bank performance?

In Chapter Four, we extend our analysis to investigate how women influence bank risk, thereby providing a more complete picture of their contribution to the banking sector. Several studies, such as those by Abou-El-Sood (2021), Arango and Gaitan (2021), Manello et al. (2023), Sila et al. (2016), Tran et al. (2020), and Valls Martínez and Soriano Román (2022), suggest that there is little evidence to support the view that having female board members effectively reduces excessive risk-taking in banks. Thus, we are motivated to investigate the relationship between gender diversity and the risk of banks in the United States after the government's rescue efforts to determine the impact of such diversity. To the best of our knowledge, this is the first empirical study concentrating on the three types of bank risk after the bailout: credit, market, and operational risk. Chapter Four examines the following questions to fill the current gap in the literature: Firstly, does gender diversity, particularly the inclusion of women on a bank's board of directors, decrease credit, market, and operational risk post-financial crisis periods? Secondly, what is the ideal proportion of female representation on the board that negatively affects these forms of risk? Thirdly, does critical mass theory effectively describe the impact of board gender diversity on banks' credit, market, and operational risk?

1.3 Contribution

In this study, a bailout is treated as an indicator of financial failure that necessitates external support, which we refer to as a form of bank failure. Therefore, we define any bank that has been bailed out in any way as a failed bank. This study focuses on bailouts as an outcome of financial failure. This definition is straightforward, obvious, and objective. Our thesis provides an in-depth look at the banking sector's difficulties. This includes providing an essential understanding of predicting bank failure and studying the impact of governance elements, particularly gender diversity, on performance and risk after a bailout.

Based on the Chapter Two, we contribute to establishing a causal link between the tail risk measures of banks and their likelihood of being bailed out. Studying the bailout events as an external preventive method helps mitigate the endogeneity issue, reducing ambiguity. Cardillo et al. (2021) confirm that it is worth noting that bank bailouts are considered a more reliable indicator of bank risk and performance when compared to other measures due to their binary external nature. Thus, it reduces the risk of data mining and the influence of different banking models and managerial decisions on financial reporting. To the best of our knowledge, this is the first empirical study concentrating on this link. The Chapter Two findings clarify that when determining bank bailouts, it is essential to consider market factors, particularly tail risk indicators and accounting variables. Moreover, it examines the support for extreme value theory and its essential opportunity to assess the effectiveness of risk assessment methods. Thus, it increases awareness about the importance of early prevention mechanisms, which might strengthen the policies and regulations.

Chapter Three has served to clarify prior ambiguities within the literature and provide a definitive assessment of the relationship between gender diversity and bank performance. This study significantly contributes to the current literature on board diversity by addressing key research questions and filling an important gap in understanding the influence of women directors on bank performance. Firstly, it presents extensive empirical evidence based on the critical period after bank bailouts, demonstrating that the association between gender diversity on a board and a bank's performance depends on achieving a certain level of gender diversity. This empirical study addresses a crucial gap in the literature by assessing the support for the critical mass theory in corporate governance. The prevailing consensus in literature asserts that a linear relationship exists between gender diversity and performance. Nevertheless, our study validates a U-shaped relation between the proportion of women on the board and bank performance, which is consistent with the empirical findings reported by Joecks et al. (2013). Their investigation of German firms demonstrated that a critical mass of female representation on boards is achieved when the women's ratio ranges between 20% and 40%. Our research provides a lucid image and establishes an optimal proportion of women on boards under the tilted groups that enhance bank performance. Our results support the primary hypothesis that post-bailout, banks with a specific percentage of women on their boards outperform those without female representation or with a lower percentage of women.

Chapter Four presents the first empirical study concentrating on three types of bank risk after the bailout: credit, market, and operational risk, thereby filling an essential gap in the literature. This chapter clarifies uncertainties in previous research and offers a clear evaluation of the relationship between gender diversity and risk in the banking sector. Furthermore, it evaluates the support for the critical mass theory in corporate governance, consistent with the finding of Joecks et al. (2013), who confirm that female board representation reaches a critical mass when the percentage of women on boards falls between 20% and 40%. Chapter Four offers a clear and precise assessment, establishing the optimal proportion of women on boards within the specified categories to effectively reduce bank risk. Our analysis's findings validate the hypothesis that banks with a certain percentage of women on their boards reduce risk more effectively than banks without female representation or with a lower percentage of women in the following years of the bailout.

1.4 Significance of the Study

This thesis provides a comprehensive understanding of analysing the ability to predict financial bailouts and examining the impact of governance elements, particularly the influence of gender diversity on bank performance and risk post-bailout. Although several studies have concentrated on the causes of bank failure and others have focused on the impact of gender diversity on bank performance and risk, our study still effectively builds a coherent and rational storyline. Beginning with this definition, any bank that has been bailed out in any way is considered a failed bank. In this study, bailouts are conceptualised as an outcome of financial distress that demands external support, representing a type of bank failure. This definition is straightforward, obvious, and objective. It enables the inclusion of predictive aspects of bank bailouts. Furthermore, the knowledge gained from our study, specifically addressing the contribution of women in enhancing bank performance and reducing risk, may provide valuable guidance for policy-making and governance enhancements within the banking industry. In addition, our thesis enhances academic discussion by establishing connections across three papers. Specifically, we contribute to the academic debate on bank bailouts, risk management, and gender diversity in corporate governance.

To the best of our knowledge, Chapter Two is the first empirical study to establish a causal link between the tail risk measures of banks and their likelihood of being bailed out.[2] It seeks to address this gap in the literature by analysing a sample of bank holding companies (BHCs) in the United States.[3] Our first hypothesis is well backed by the Extreme Value Theory (Rocco, 2011), which argues that bank stocks are priced efficiently, indicating that significant price declines may indicate their financial distress. Furthermore, the combined use of accounting-based and market-based indicators produces a distinct set of evidence supporting the idea that they are more effective in predicting bank failures (Coffinet et al., 2013; Nguyen, 2011).

The significance of Chapter Three is the resolution of disparities in the field. While some research reveals a positive relationship between gender diversity and firm performance, such as García-Meca et al. (2015), Owen and Temesvary (2018), and Tampakoudis, et al. (2022), others find negative or mixed effects, such as Berger et al. (2014), Farag and Mallin (2017), Liao et al. (2019), and Pathan and Faff (2013). These findings have prompted us to investigate the impact of gender diversity on the performance of banks in the United States, specifically during and after the government's bailout actions, to ascertain whether such diversity has a significant effect.

Multiple studies indicate a lack of evidence about the impact of having female board members on reducing excessive risk-taking in banks, as shown by Abou-El-Sood (2021), Arango and Gaitan (2021), Manello et al. (2023), Sila et al. (2016), Tran et al. (2020), and Valls Martínez and Soriano Román (2022). Therefore, we extend our analysis to investigate how women influence bank risk, providing a more complete picture of their role in the banking sector. The significance of Chapter Four resides in its uniqueness in studying the relationship between the impact of women on the

[2] We differ from Gupta and Chaudhry's (2019) research since they use data from a wide range of publicly traded companies on three separate stock exchanges. Financial firms, however, are not mentioned in their research. In addition, we follow Alzugaiby et al. (2019), who use Z-score, Value at Risk, and Expected Shortfall in predicting bank distress.

[3] We use the terms BHC and bank interchangeably throughout the paper.

board of directors and the three types of bank risk: credit, market, and operational risk, specifically during and after the government's bailout to determine whether such diversity has a meaningful impact.

In both Chapter Three and Chapter Four, we apply the framework based on Critical mass theory, as used by Kanter (1977a ,1977b); the behaviour and impact of a subgroup are determined by its size. More precisely, it suggests that when the subgroup hits a certain level, referred to as the "critical mass", it acquires the capacity to substantially impact the wider group (Torchia et al., 2011). In line with Kanter's (1977b) framework, the representation of women on corporate boards can be categorised into four distinct groups. Based on our data, these chapters illustrate the trend of women on bank boards from 2003 to 2019, highlighting the significance of our research. Figure (1) shows women's overall proportion and distribution across different categories (uniform, skewed, tilted, balanced).

Figure 1.1: Trend of Women on Bank Boards (2003-2019) by Category

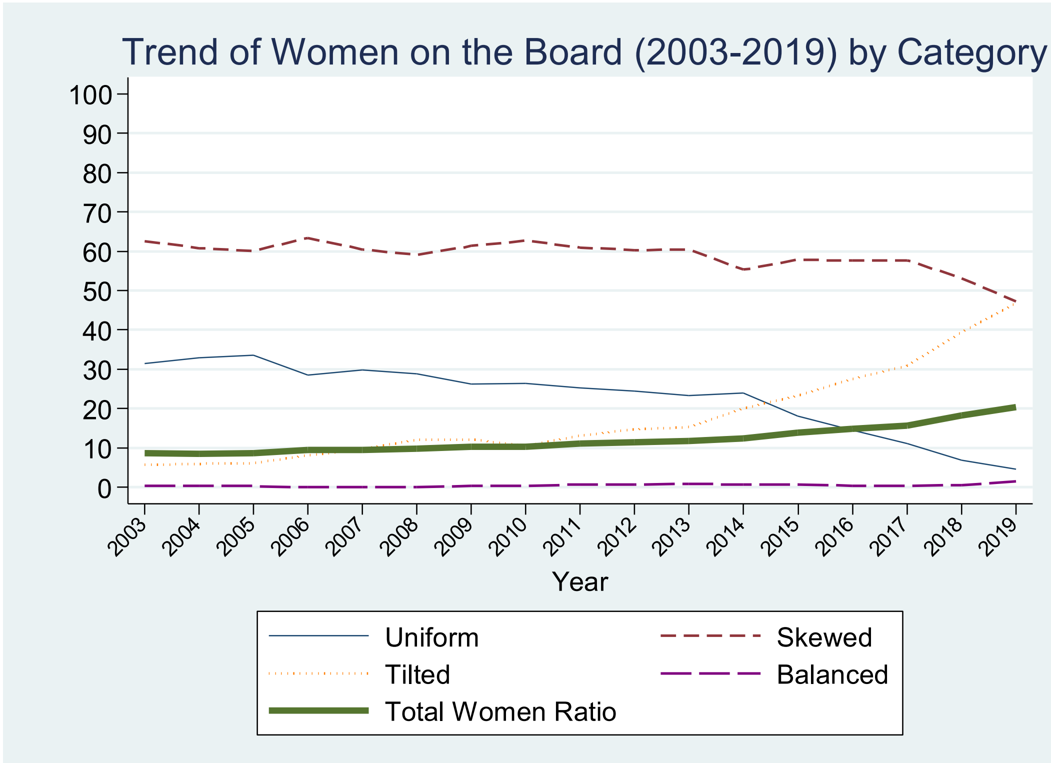


Figure (1): This figure illustrates the trend of women on bank boards from 2003 to 2019, highlighting both the overall proportion of women and their distribution across different categories (uniform, skewed, tilted, balanced). The increasing trend in the overall women ratio emphasises the growing gender diversity on bank boards. The separate lines for each category provide a detailed view of how women representation is distributed, supporting the analysis of critical mass theory in this study. The skewed group consistently comprises the largest proportion of observations, indicating that most banks have more than 0% but up to 20% women on their boards.

1.5 The Structure of the Thesis

1.5.1 Chapter One: Introduction, which includes the importance of studying bank bailout, motivation, contribution, and significance of the study.

1.5.2 Chapter Two: "Predicting Bank Bailout Using Market Measures".

This chapter studies the link between banks' tail risk measures and their likelihood of being bailed out using market measures, namely Value at Risk (VaR) and Expected Shortfall (ES). We restrict our sample to BHCs in the US due to the nature of our research. The final dataset shows 9,519 bank-quarter observations of 202 bailout BHCs and 13,995 bank-quarter observations of 674

BHCs that have not been bailed out. We hypothesise that an increase in the frequency of extremely negative daily equity returns is indicative of larger tail risks, putting banks at a greater probability of bailouts. To test this hypothesis, we use the correlated random-effects logistic regression. The tail risk indicators are critical in predicting whether or not the bank will be bailed out. Our research indicates a significant positive association between the VaR, VaRCF, ES estimates, and the bank's bailout. Our research findings suggest that it is essential to consider market variables, particularly tail risk indicators, besides accounting variables, when determining bank bailouts.

1.5.3 Chapter Three: "Do Females Perform Better During Crises: An Analysis of Bank Performance After Bailouts".

This chapter investigates women's impact on bank performance using accounting measures: return on equity (ROE) and return on assets (ROA). Our analysis is based on a robust dataset comprising 2,317 bank-year observations of 179 bailout BHCs and 2,766 bank-year observations of 434 BHCs that have not received bailouts, providing more extended coverage than prior studies. We hypothesise that post-bailout, banks with a specific percentage of women on their boards outperform those without female representation or with a lower percentage of women. We use the multivariate fixed effect regression technique to test our hypothesis and estimate a multivariate model for all BHC samples with accounting-based covariates. The fixed effects approach accounts for unobserved, time-invariant differences between banks and mitigates serial correlation issues. By the classification proposed by Kanter (1977b), we categorise the ratio of women into four main groups. Using this classification enables us to determine the ideal female representation on the bank's board of directors, which appears to enhance the bank's performance. The majority of previous research papers conclude that there is a linear relationship between gender diversity and performance. However, our research confirms a U-shaped relationship between the proportion of women on a board and a bank's performance. The critical mass is achieved when a significant presence of women on boards, namely within the range of 20% to 40%. Our findings provide a distinct representation and define an ideal ratio among the tilted groups that improve the performance of banks.

1.5.4 Chapter Four: "Do Females Manage Risk Better During Crises: An Analysis of Bank Risk After Bailouts".

This chapter investigates women's impact on credit, market, and operational risk. Our analysis is based on a robust dataset comprising 2,317 bank-year observations of 179 bailout BHCs and 2,766 bank-year observations of 434 BHCs that have not received bailouts, providing more extended coverage than prior studies. We hypothesise that banks with a certain percentage of women on their boards reduce risk more effectively than banks without female representation or with a lower percentage of women in the following years of the bailout.

As we have done in Chapter Three, we use the multivariate fixed effect regression approach to examine our hypothesis and estimate a multivariate model for all BHC samples, including accounting-based and market-based variables. The fixed effects technique mitigates the impact of serial correlation by considering unobserved, time-invariant changes across banks. Kanter (1977b) classifies the proportion of women into four primary categories. The use of categorisation led us to find an appropriate range for the percentage of female bank board members, namely the tilted group, which is within the range of 20% to 40%. This range is thought to efficiently reduce banks' risks, such as credit, market, and operational risks. Tilted group results show a significant negative impact on all six risk measures under the credit, market, and operational risks, indicating that this range of women's representation is most helpful in lowering risk. The balanced group has a limited influence on risk measures, which are significant only for CR and VaR, suggesting that the protective effect is still there but less so than in the tilted group. The results of this chapter provide an in-depth understanding and identify an ideal proportion within tilted groups, which successfully reduces the risk banks face.

1.5.5 Chapter Five: Conclusion

1.5.5.1 Key Outcomes and Implications

This section combines the empirical knowledge from the research in Chapters Two, Three, and Four. This combination is essential in presenting and answering the fundamental research questions that form the basis of this thesis. This chapter examines the empirical evidence in-depth, explaining how the findings contribute to the study field.

1.5.5.2 Limitations and Future Research

This part not only provides a summary of the main results but also recognises the inherent limitations in the research methods and scope of the study. We present potential areas for further investigation, providing recommendations that are intended to guide future researchers in investigating topics that are still unexplored or offer new research opportunities.

Chapter Two: Predicting Bank Bailouts Using Market Measures

2.1 Introduction

Since the start of the financial crisis, regulators have bailed out several banks to lower the banking system's instability and rebuild trust in the financial industries. Many financial institutions have failed during this time. As a result of these events, plenty of new research on the causes and implications of bank failures and bailouts has appeared, such as Bayazitova and Shivdasani, (2012), Berger and Bouwman (2013), Calabrese et al. (2017), Cole and White (2012), Dam and Koetter (2012), and Demyanyk and Hasan (2010).

Defining bank failure: Traditional perspectives and a new approach

A failed bank has been defined in several different ways in the literature. Calabrese and Giudici (2015) define failed banks as bankrupt or liquidated. Alternatively, Koetter et al. (2007) define failed banks as those closed by the FDIC (Federal Deposit Insurance Corporation) or with tier 1 capital ratios of less than 2% (i.e., critically undercapitalised under bank regulatory laws). Calabrese et al. (2017) define financial support provided by regulators to a bank as a distressing event, even if the bank survives.

Furthermore, a distressed bank is defined as one that has defaulted or is on the edge of defaulting by Koetter et al. (2007). According to Mare (2015), when a bank is placed under special administration or faces compulsory liquidation, it is considered a defaulted one. Banks are declared as failed when they are unable to meet their commitments.

As several banks were bailed out during the global financial crisis of 2007-08, this provides us a natural way of defining a failed bank. We define any bank that has been bailed out in any way as a failed bank. Our analysis treats bailouts as a direct consequence of financial instability necessitating external assistance, which we define as a form of bank failure. This is a clean and direct definition of a failed bank. Therefore, we differ from the earlier literature in this respect.

Factors influencing bank stability and failure probabilities

Many authors, such as Demyanyk and Hasan (2010) and Oshinsky and Olin (2005), have extensively tried to answer the reasons behind financial institutions' failure. However, the majority of these papers focus on banks' features, such as Capital adequacy, Asset quality, Management skills, Earnings, Liquidity, and Sensitivity (CAMELS) rating components. In fact, accounting measures, such as CAMEL, have received a lot of attention in the empirical literature as predictors of financial distress. Earlier papers have shown that a decrease in profitability or capitalisation, an increase in non-performing loans, which indicates poor asset quality, an increase in cost, and a reduction in liquidity are the main causes of bank default in the United States (Wheelock & Wilson, 2000).

Aside from looking at the financial characteristics of banks, some scholars investigate other possible causes of bank failures. Berger et al. (2012) look into the effects of managerial hierarchy and bank ownership on the likelihood of bank failure and that governance is important. Overall, these findings show that regulators acted logically with regard to struggling banks by using Capital Purchase Program (CPP)[4] funding differently depending on the quality of a bank's asset portfolio (Lu & Whidbee, 2016). Also, low-quality assets increase bank failure while decreasing the possibility of a bank bailout, like obtaining CPP, which implies that regulators used CPP funds differently, depending on the asset's quality. According to the findings of CPP injection studies, bailout or receiving CPP funds depends on the following features: bigger size, increase in political connectedness, more capital capability, higher-performing loans, higher systemic risk, an

[4] The Capital Purchase Program (CPP), which was the largest bank program under the Troubled Asset Relief Program (TARP), is one of the Treasury's five different bank programs created as part of the larger effort to stabilise America's banking system. Around $205 billion had been invested by Treasury under the CPP. The United States Department of the Treasury infused capital into a total of 707 financial institutions situated across 48 states, among which over 450 were small and community banks, and 22 were certified community development financial institutions (CDFIs). The magnitude of capital injections ranged from a substantial $25 billion to a minimum of $301,000, according to Bank Investment Programs | U.S. Department of the Treasury.

increase in liquidity demands, heightened tendency towards funding risks, and reduced sensitivity to real estate lending (Lu & Whidbee, 2016).

Recent studies reveal key factors that increase the risk of bank failures, highlighting the challenges of financial stability. These factors include individualism and masculinity (Berger et al., 2021); negative banking market frictions (Contreras et al., 2021); the inefficiency of US commercial banks and greater loan-to-asset and real-estate-loan-to-total-loan ratios (Sanchez González et al., 2021); tighter risk-weighted capital requirements (Mankart et al., 2020); separated CEO positions (Harkin et al., 2020); a decrease in retained earnings (Carmona et al., 2019); and wealth inequality, and low bank screening capacity (Tzur & Jacobi, 2019).

Avoiding bank failure by concentrating on bank stability is one of the most crucial challenges that banking regulators face. A recent study shows one of the aspects that support the strength and stability of banks. It suggested that an L-shaped wealth distribution, defined as a distribution in which a small number of people own the majority of the country's wealth, is linked to bank stability. It revealed that the average failure rate of nations with unimodal-shape wealth distribution, defined as a wealth distribution in which the lower and middle classes have a larger share of the total wealth, is around two to nine times that of countries with L-shaped wealth distribution (Jacobi & Tzur, 2021). Moreover, lower competition and new regulations have increased the banking system's safety margins in recent years, resulting in a stronger financial sector as banks become fewer in number but act more wisely (Papadimitriou et al., 2020).

Newly published research identifies essential strategies for reducing bank failure risks, proposing techniques for improved security, such as the Troubled Asset Relief Program (TARP) (Contreras et al., 2021); having a remuneration committee, and non-executive directors (NEDs) overseeing the bank (Harkin et al., 2020); liquidity creation (Zheng et al., 2019); cost efficiency (Assaf et al., 2019); and effective corporate governance mechanisms (Mili et al., 2019).

Bank failure resolution strategies

In circumstances where a bank failure occurs, two prevailing approaches for addressing such a situation are the "purchase-and-assumption" and the "deposit payoff" methods. The former involves the transfer of insured deposits from the failed bank to another institution, with the failed bank subsequently closing.

On the other hand, the latter method involves depositors of the bank that failed would receive the entire amount of insured deposits from the Federal Deposit Insurance Corporation (FDIC), and the bank would then close without being replaced. The deposit payoff option is typically utilised when no other financial institution is willing to assume the assets and liabilities of the failed bank. These mechanisms are critical in ensuring the financial system's stability and safeguarding the interests of depositors, as they provide a structured process for managing the failure of a financial institution and mitigating potential contagion effects (Papanikolaou, 2018).

Approaches to measuring and predicting bank failure

Numerous studies have utilised various metrics to examine instances of bank failures that occurred within the United States during the most recent financial crisis, such as corporate governance (Jin et al., 2011); the quality of auditing (Jin et al., 2011); direct investments in real estate (Cole & White, 2012); and cash flow generated from non-traditional banking revenues (DeYoung & Torna, 2013). Berger et al. (2016) find that the CAMEL ratios are still effective at clarifying bank failure.[5] Additionally, under the CAMELS evaluation framework, profitability and capital measures contribute the most to the forecast of bank failures (Petropoulos et al., 2020). A combination of accounting-based with market-based measures yields a different body of evidence arguing that they performed better in bank failure prediction (Coffinet et al., 2013; Nguyen, 2011).

[5] US authorities in 1979 created CAMEL rating to assess banks' financial health.

Recently, different techniques have been employed to predict bank failure, such as using Bayesian model averaging (BMA), which enhances out-of-sample predictions (Goenner, 2020); using Lasso regression to select vital bank-failure-specific indicators; and the Synthetic Minority Oversampling Technique (SMOTE) for transforming unbalanced into balanced data(Shrivastava et al., 2020). Furthermore, the random forests (RF) method has superior out-of-sample and out-of-time prediction performance, with neural networks doing almost as well as RF in out-of-time samples (Petropoulos et al., 2020).

However, useful additional evidence on the possibility of future bank difficulties might be generated by market-based measures. In fact, the employment of market-based factors improves the accuracy of bank failure prediction models. As a result, to get a complete understanding of bank fragility, researchers must consider possible market-based drivers, particularly bank stock prices. In practice, bank regulators in the US have lately begun to supervise public banks using market data in addition to standard early warning models (Coffinet et al., 2013).

Adopted frameworks and methodological critique

This study is guided by Alzugaiby et al. (2019) and Gupta and Chaudhry (2019) in evaluating the marginal explanatory power of downside risk metrics, such as Value at Risk and Expected Shortfall. Given our focus on the banking sector, particular attention is paid to Alzugaiby et al. (2019), who utilise the Z-score, Value at Risk, and Expected Shortfall to predict bank distress. However, using the Z-score as a dependent variable had many limitations. Despite its benefits, the Z-score is not without its drawbacks. To begin with, like other accounting-based indicators, its accuracy is dependent on the integrity of the accounting data, which is a major concern in developing nations. Furthermore, because banks smooth accounting data over time, the Z-score may provide an overly optimistic evaluation of the danger of bank failure (Laeven & Majnoni, 2003). Second, according to Cihak's (2007) analysis, the Z-score and distance-to-default are limited in their ability to capture the interdependence of financial institutions within the system.

These measures focus solely on each bank independently, disregarding the potential spillover effects that a distressed bank could have on other institutions. Third, the inclusion of the Z-score variable in the baseline prediction model yields a relatively small coefficient, suggesting that this measure does not significantly improve the predictive accuracy of bank distress (Chiaramonte et al., 2015; Poghosyan & Cihák, 2009).

Moreover, Alzugaiby et al. (2019) use annual data; however, when the Z-score is calculated using annual data, it has a much higher value than those calculated using quarterly data. The discrepancy is due to the ROA standard deviation. The standard deviation calculated from four annual numbers is substantially smaller than the standard deviation calculated from sixteen quarterly numbers, indicating that a standard deviation of four numbers is unlikely to give a meaningful estimate. This promotes the use of quarterly data to calculate the Z-score to give a more reliable series of Z-score estimates (Li & Malone, 2016).

Rationale and motivation behind exploring bank stability and tail risk

There are various reasons to investigate the association between bank bailout and tail risk metrics, which assess the likelihood of significant losses. Literature suggests that tail risk increases bank fragility (Ellul & Yerramilli, 2010; Kashyap et al., 2008). Additionally, financial firms frequently use tail risk measurements to meet their objectives, and the importance of these metrics is increasing. Moreover, stock returns exhibit fat-tailed, suggesting a higher rate of occurrence of extreme negative values (Conrad et al., 2013). Our motivation for this research is to enhance our understanding of bank bailouts by using market metrics to meet the needs of stakeholders such as regulators and managers. The study explores the important role of tail risk in bank stability, highlighting the need to appropriately evaluate risks to avoid bank failures. The primary focus is to improve the financial system's resilience by emphasising the need for efficient risk management and the application of proactive actions to prevent possible banking crises.

Original insights and contributions

To the best of our knowledge, this is the first empirical study to establish a causal link between the tail risk measures of banks and their likelihood of being bailed out. The present research seeks to address this gap in the literature by analysing a sample of bank holding companies (BHCs) in the United States. An increase in the frequency of extremely negative daily equity returns is indicative of larger tail risks, putting banks at a greater probability of bailouts. This hypothesis is well backed by the Extreme Value Theory (Rocco, 2011), which argues that bank stocks are efficiently priced, indicating that dramatic drops in their prices may reflect their financial difficulty. More particularly, the Extreme Value Theory (EVT) model posits that significant daily losses in bank equities represent not just temporary events but rather indicators of financial crises. Moreover, the potential for crisis contagion, i.e., the spread of a crisis from one bank to others, is evident through simultaneous sharp declines in multiple bank stocks. Lastly, an individual bank's high sensitivity to systematic risks arising from aggregate shocks is demonstrated through concurrent steep losses in the bank's stock and non-diversifiable risk factors, such as the market index (Straetmans & Chaudhry, 2015).

In this paper, we investigate the role of tail risk indicators in conjunction with CAMEL rating measurement in forecasting bank bailouts using the correlated random-effects logistic regression. The tail risk indicators are critical in predicting whether or not the bank will be bailed out. According to our findings, all VaR, VaRCF, and ES estimations are substantial and positively associated with the bank's rescue. The results of our study indicate that in the determination of bank bailouts, market variables, specifically tail risk indicators, should be accorded significant priority in conjunction with accounting variables.

This chapter is organised into several sections. Firstly, we describe our methodology, covering the research data, sample construction, and measurement of dependent and independent variables. Secondly, we provide a detailed explanation of our empirical model and method, which includes descriptive statistics, correlation, and the correlated random-effects logistic analysis. Afterward, we demonstrate the application of the robustness checks. Lastly, we conclude the study in the final section of this chapter.

2.2 Methodology

Our dataset sources are discussed first, followed by the formation of the sample to be examined. Finally, we specify the important dependent and independent variables used in our regression estimates.

2.2.1 Research Data

We utilise accounting and market data to conduct our empirical study. First, the accounting data related to Bank Holding Companies (BHCs) in the United States originates exclusively from the Federal Reserve Bank (FRB) located in Chicago[6]. Second, The Center for Research in Security Prices (CRSP) is the primary source for market-related information concerning publicly traded Bank Holding Companies (BHCs), comprising a range of data points such as daily stock returns, stock prices, and the volume of outstanding shares. Third, the US Treasury Department is used as the source of bailout data.

2.2.2 Sample Construction

We restrict our sample to BHCs in the US due to the nature of our research. We use the CRSP-FRB Link (provided by the Federal Reserve Bank of New York) to connect entity numbers (rssd9001) in the FR Y-9C to PERMCO numbers in CRSP[7] in order to merge the data, which is an effective method utilised by previous papers Gandhi et al. (2019) and Goetz et al. (2014). In order to accurately estimate the bailout risk, it is essential that the model detects the bailout early enough. We develop bailout prediction models using quarterly bank data provided as of the end

[6] The website of the Federal Reserve Bank of Chicago (www.chicagofed.org) provides access to the information under consideration.

[7] The website of the Federal Reserve Bank of New York, where the relevant information can be accessed, is accessible via the following hyperlink: (https://www.newyorkfed.org/research/banking_research/datasets.html).

of March, June, September, and December of each calendar year during the period of investigation spanning from 2001 to 2014. The final dataset includes 9,519 bank-quarter observations for 202 bailed-out BHCs and 13,995 bank-quarter observations for 674 BHCs that have not been bailed out.

2.2.3 Measurement of Dependent Variable

This study defines a bank bailout as the dependent variable. A bank bailout is a binary variable that takes a value of 1 if the bank has been bailed out and 0 otherwise.

2.2.4 Measurements of Independent Variables

In order to estimate a bank's potential exposure to tail risks, we utilise tail risk metrics such as Value at Risk (VaR) and Expected Shortfall (ES), guided by the Extreme Value Theory (EVT) and following the work of Alzugaiby et al. (2019)[8]. To forecast the likelihood of a bank bailout within the upcoming period, we employ rolling windows of daily stock returns spanning short periods of 3 months and long periods of 36 months for each bank. Specifically, for each quarter, risk measures are computed one month before the quarter ends using these rolling windows of 3 months and 36 months of daily stock returns. This ensures that the most recent data informs the prediction, enhancing the accuracy of bailout forecasts.[9]

2.2.4.1 Downside Risk Measures

Value-at-Risk: VaR has been frequently utilised in the literature and is an essential metric in measuring market risk. To estimate the Value at Risk (VaR), which is the maximum potential loss that could occur over a specific time period at a given level of confidence, it is necessary to determine two numerical metrics: the confidence level $(1-\alpha)$ and the time horizon (τ). These parameters are utilised in the estimation of VaR. We follow Hagendorff et al. (2018) in computing

[8] EVT is a good tool for analysing extreme negative events, such as sharp stock price drops (Pais & Stork, 2013).
[9] We get same results when we use daily stock returns for 6 months and 12 months individually in a given year for each bank.

VaR and ES using 252 days, the number of trading days in a year instead of the number of calendar days. There are no clear criteria or comprehensive standards in terms of the time range. As a response, we follow Gupta and Chaudhry (2019) and assess the risk's liquidity as well as the duration of exposure. The poorer the liquidity of the assets, the longer it will take to hedge the risk completely. It is advisable to use a wider time horizon when measuring VaR in a market with a bigger variety (Gupta & Chaudhry, 2019). We estimate VaR using two distinct time scopes to capture any changes over time in light of the previous considerations. We use the daily stock returns for the past 3-month and 36-month to predict bank bailouts in the coming period. Similarly, the chosen confidence level is determined by the users' attitude toward risk. For example, the Basel II Accord requires commercial banks to calculate their minimum capital needs using a high confidence level of 99%, whereas a greater confidence level of (99.97%) is a requirement from rating agencies to get a good credit rating of AA or above (Gupta & Chaudhry, 2019; Jorion, 2000). Consequently, we estimate the tail risk estimates at a 99% confidence level, as the Basel Accord suggested.

To calculate the VaR, we start by considering the theoretical framework where time is represented by τ, a firm's return between the period *t* and $t + \tau$ *is represented by* $R_{t+\tau}$. The cumulative distribution function (CDF) of $R_{t+\tau}$ based on the information set accessible at time *t is represented by* $F_{R,t}$ with its inverse function being $F_{R,t}^{-1}$. The VaR is then theoretically defined as:

$$\mathrm{VaR}_t(\alpha, \tau) = -\mathrm{F}_{\mathrm{R,t}}^{-1}(\alpha) \tag{1}$$

However, our calculations employ the historical method, which does not assume a specific distribution for returns. We use historical return data to compute VaR by identifying the appropriate percentile corresponding to the desired confidence level.

Cornish-Fisher expansion Value-at-Risk (VaRCF): To adjust for non-normality in the return distribution by incorporating higher moments, namely skewness (S) and excess kurtosis (K), we utilise the Cornish-Fisher expansion Value-at-Risk (VaRCF). Equation 2 shows the fourth-order (Cornish & Fisher, 1938) expansion for the α percentile of $(R-\mu)/\sigma$, which calculates $\Omega(\alpha)$ to adjust the critical value $Z(\alpha)$, whereas Equation 3 shows the VaRCF (VaR_{CF}).

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

$$VaR_{CF} = -(\mu + \Omega(\alpha) \times \sigma) \quad (3)$$

Where $Z(\alpha)$ denotes the critical value from the standard normal distribution, μ is the mean return, σ is the standard deviation of returns, S represents the skewness, K represents the excess kurtosis of past n-month daily returns, and $(1-\alpha)$ indicating the level of confidence. [10]

Expected Shortfall: ES estimates the expected loss given that the VaR threshold is exceeded. Artzner et al. (1999) confirm that the ES has advantages over historical VaR due to its mathematical features such as continuity and sub-additivity. ES is represented in terms of return, and it is stated as follows:

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

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

$$= -\frac{\int_{\nu=-\infty}^{-VaR_t(\alpha,t)} \nu f_{R,t}(\nu) d\nu}{\alpha} \quad (4)$$

Our calculation of ES involves averaging the historical returns that exceeded the VaR threshold, providing an estimate of the expected loss in extreme scenarios. Thus, by employing the historical method and adjusting for skewness and kurtosis using the Cornish-Fisher expansion, we capture

[10] Typically, VaR and ES are negative. In the previous equations, we multiply the original VaR and ES values by -1 to avoid confusion, as suggested by Gupta and Chaudhry (2019). As a result, the VaR and ES figures in this study are almost always positive.

a comprehensive picture of downside risk that reflects the empirical characteristics of the return distribution.

2.2.4.2 Baseline Factors

Accounting-based indicators of banks relating to capitalisation, asset quality, managerial skills, earnings, and liquidity (CAMEL), among other things, have proved successful in predicting bank failure. We employed established measures for the CAMEL components as standard predictive factors of bank bailouts, as recommended by the banking literature and supervisory practice.

It is reasonable to use factors commonly used to predict bank failure to predict bank bailouts, as financial distress indicators like CAMEL are widely recognised as strong indicators of a bank's health and risk profile. Galil et al. (2023) support this approach by including bailouts as one possible outcome in their distress model, showing that CAMEL indicators and financial fundamentals help identify banks likely to experience distress, whether through closure or bailout. Similarly, Berger et al. (2020) examine the effects of government intervention (TARP) on financial stability, using CAMELS indicators as proxies for financial health to assess how bailouts influence systemic risk.

By using CAMEL indicators as control variables, this study aligns with established literature, supporting the relevance of financial health measures in assessing bailout likelihood.

Capital (C): The most important factor in the CAMEL list is capital, as it serves as an early warning indicator in the models used by regulators. It assesses bank health and guarantees the financial system's stability. Furthermore, numerous academic papers use it as the main indicator (Berger & Bouwman, 2007). A bank's ability to meet its financial obligations is measured by its level of capital. As a result, a drop in capital could be a warning sign of impending financial trouble. Capital can be proxied by taking the ratio of total equity to total gross assets (Capital Ratio) (Berger et al., 2012). To avoid giving the largest institutions more weight and to make the variables comparable across banks, GTA normalisation of the equity is required (Berger & Bouwman, 2007). Therefore, as indicated by Acharya et al. (2016) and Mehran and Thakor (2011), there is a positive association between capital and a bank's survival (Berger & Bouwman, 2013).

Asset quality (A): This parameter is evaluated through the comparison of the present-period net loan losses, derived by subtracting the total loan recoveries from the loan charge-offs, with the prior-period allowances for loan losses, encompassing the supplementary allowance for loans and leases. Imbierowicz and Rauch (2014) developed this measure, which is utilised to evaluate Credit Risk. The proposed measure serves to determine the unanticipated occurrences of loan defaults and their impact on the risk profile of the loan portfolio, which can be substantially influenced by the actions of the bank's administration within a brief timeframe. A larger ratio, represented by values below 1, serves as an indicator of suboptimal asset quality or an escalation in credit risk, whereas values exceeding 1 suggest the emergence of unanticipated losses. The utilisation of this metric has enabled us to scrutinise the precision of banks' managerial forecasts concerning short-term loan losses that may threaten their long-term viability. Furthermore, we anticipate a positive association between low asset quality and the probability of banks requiring bailouts.

Management (M): The efficacy of bank managers is a crucial determinant of operational performance and overall success. However, the complexity involved in evaluating this metric through financial data has limited its utilisation in previous research studies (Wheelock & Wilson, 2000). Nevertheless, Mayes et al. (2014) assert that earnings can serve as a proxy for measuring managerial quality. Consequently, we measure earnings as the return on equity (ROE) ratio, computed as the net income divided by shareholders' equity, to assess managerial effectiveness. We contend that inadequate managerial expertise can lead to suboptimal decision-making and significant losses, thus heightening the likelihood of requiring bailout measures.

Earnings (E): This metric serves as a comprehensive gauge of a bank's performance, encompassing its overall profitability. Empirical research has employed various indicators to evaluate this category, including return on assets (ROA), net income divided by gross total assets (GTA), and return on equity (ROE), among others. Given that net income and equity encompass both on- and off-balance-sheet operations, we adopt the approach advanced by Berger and Bouwman (2013) and utilise ROE as a comprehensive profitability indicator.

Liquidity (L): The ability of a bank to meet its present and unforeseen financial obligations, particularly deposit and creditor withdrawals, is contingent on its liquidity. Betz et al. (2014) have suggested the employment of the interest expense-to-total-liabilities ratio as a prevalent gauge of liquidity. An increase in this ratio is anticipated to be associated with the occurrence of a bank bailout.

Real Estate Loans: The proportion of real estate loans to gross total assets (GTA) is considered a significant metric in predicting the probability of a bank bailout. An increase in this measure is believed to indicate greater distress faced by the bank (Berger et al., 2012).

Bank Size: According to research conducted by Berger and Bouwman (2013), bank size notably impacts bank failure. Smaller banks are more likely to fail compared to larger banks, highlighting the importance of bank size as a factor expected to exert a negative influence on the likelihood of failure. In this regard, the logarithm of gross total assets (GTA) serves as a proxy for bank size (Cole & White, 2012).

To reduce the impact of extreme values on our statistical estimations, we winsorise all variables at a 1% level, as recommended by the literature.

Table 2.1 provides a comprehensive description of all variables utilised in the study.

Table 2.1: Description of the Variables

Variable	Description	Data source
Dependent Variables		
Bailout	A binary variable that has a value of one if the bank has been bailed out and zero otherwise	The US Treasury Department
Independent Variables		
SVaR3M1	Short Value-at-Risk calculated using daily returns over the previous 3 months at a 1% significance level.	CRSP
LVaR36M1	Long Value-at-Risk calculated using daily returns over the previous 36 months at 1% significance level.	CRSP
SVaRCF3M1	Short Cornish-Fisher Value-at-Risk calculated using daily returns over the previous 3 months at 1% significance level.	CRSP
LVaRCF36M1	Long Cornish-Fisher Value-at-Risk calculated using daily returns over the previous 36 months at 1% significance level.	CRSP
SES3M1	Short Expected Shortfall calculated using daily returns over the previous 3 months at 1% significance level.	CRSP
LES36M1	Long Expected Shortfall calculated using daily returns over the previous 36 months at 1% significance level.	CRSP
Control Variables		
Capital Ratio	Capital: total equity / Gross Total Asset (GTA).	Federal Reserve Bank (FRB) of Chicago
Credit Risk	Asset quality: credit risk = the net loan charge-offs / the loan loss allowance in the previous period.	Federal Reserve Bank (FRB) of Chicago
ROE	Earning quality: return on equity = net Income / total equity.	Federal Reserve Bank (FRB) of Chicago
IETL	Liquidity: IETL = total Interest expenses / total Liabilities.	Federal Reserve Bank (FRB) of Chicago
RELGTA	Real-estate loans: Real-estate loans / (GTA).	Federal Reserve Bank (FRB) of Chicago
LGTA	Bank size: natural logarithm of (GTA).	Federal Reserve Bank (FRB) of Chicago
ER	Capital Adequacy: equity ratio = equity/total assets	Federal Reserve Bank (FRB) of Chicago
LLRR	Asset Quality: loan loss reserves ratio = loan loss reserves/gross loans	Federal Reserve Bank (FRB) of Chicago
OR	Management: overheads ratio = overheads/total assets	Federal Reserve Bank (FRB) of Chicago
ROAE	Earning Quality: return on average equity = net income/average equity	Federal Reserve Bank (FRB) of Chicago
EDR	Service Quality: employee-deposit ratio = number of employees/customer deposits	Federal Reserve Bank (FRB) of Chicago

Notes: The set of independent variables, as well as control variables, that we use in our empirical study are listed in this table. The names of variables are listed in the first column, while their definitions are listed in the second column. The data sources are listed in the third column.

2.3 Empirical Model and Method

In this section, we provide summary statistics for our variables and essential information about the correlation among the variables. Then, we analyse the statistical significance of each tail risk measure using the correlated random-effects logistic regression and explain the major findings.

2.3.1 Descriptive Statistics and Correlation

To understand our variables, we divide the sample into two groups: *bailed-out and non-bailed-out banks*. Table 2.2 shows the summary statistics for these variables.

Significant distinctions are observed between banks that have received a bailout and those that have not. Bailed-out banks exhibit lower capital ratios, return on equity, proportions of real-estate loans, and levels of liquidity risk as indicated by the total interest cost to total liabilities (IETL) ratio.

Bailed-out banks demonstrate higher mean values across all tail risk measures compared to non-bailed-out banks. This aligns with the increased volatility typically associated with bailed-out banks. A higher VaR value indicates a greater risk of losing money. For instance, the mean LVaR36M1 value of bailed-out banks is 7.49%, as shown in Table 2.2. This implies that we are 99% confident the average loss for bailed-out banks over one period will not exceed 7.49%. In contrast, Expected Shortfall is the predicted loss if the loss exceeds a certain level over a specified period (Hull, 2018). Table 2.2 shows that the average LES36M1 value for bailed-out banks is 9.67%. Indicating that, on average, the bailed-out loss would be 9.67% during one period. Table 2.2 also highlights Intertemporal variations among extreme measures with longer rolling periods exhibiting larger mean values compared to shorter ones.

Table 2.2: Summary Statistics[11]

Variable	Banks that have not been bailed out					Banks that have been bailed out				
	Mean	Sd	Min	Median	Max	Mean	Sd	Min	Median	Max
Capital Ratio	0.0961	0.0314	0.0368	0.0912	0.2070	0.0930	0.0219	0.0368	0.0912	0.2070
Credit Risk	0.1476	0.1993	-0.0622	0.0776	1.0541	0.1784	0.2074	-0.0622	0.1083	1.0541
ROE	0.0479	0.0792	-0.3696	0.0493	0.2020	0.0439	0.0819	-0.3696	0.0472	0.2020
IETL	0.0123	0.0094	0.0006	0.0097	0.0582	0.0115	0.0088	0.0006	0.0089	0.0582
RELGTA	0.4946	0.1631	0.0055	0.5086	0.7994	0.4832	0.1437	0.0055	0.4952	0.7994
LGTA	14.3086	1.4372	10.9342	13.9527	20.6819	15.0259	1.7103	12.0520	14.5393	21.6053
SVaR3M1	0.0612	.05322	.00164	0.0462	0.788	0.0665	0.0538	0.0041	0.0492	0.6992
LVaR36M1	0.0676	0.0354	0.0156	0.0575	0.3333	0.0749	0.0393	0.0172	0.0615	0.2444
SVaRCF3M1	0.0677	0.0774	-0.2505	0.0471	1.4557	0.0718	0.0687	-0.4836	0.0507	1.2657
LVaRCF36M1	0.1236	0.1756	-4.2793	0.0811	2.0689	0.1289	0.1369	0.0191	0.0851	1.8205
SES3M1	0.0612	0.0532	0.0016	0.0462	0.788	0.0665	0.0538	0.0041	0.0492	0.6992
LES36M1	0.0870	0.0477	0.0201	0.0734	0.4388	0.0967	0.0521	0.0200	0.0789	0.3278

Notes: From 2001 through 2014, this table offers descriptive data for all variables across bailout banks and non-bailout bank holding companies (BHCs). The categorisation variable is a binary variable. If a BHC bailed out within our sample period, the binary indication for that period is “1”, and otherwise, it is “0”. Table 1 has more information on the definitions of the various variables.

The pairwise correlation analysis presented in Table 2.3 provides initial insights into the relationships among accounting measures, market risk measures, and the dependent variable (bailout). Most accounting measures in Panel A exhibit significant correlations with a bailout at the 1% level, highlighting their relevance in explaining bailout likelihood. Panel B shows that tail risk measures (VaR, VaRCF, and ES) generally have low correlations with accounting variables, indicating that these metrics capture distinct dimensions of bank risk. The CAMEL variables, presented in Rows (2)–(7), are applied in the main regression, while the modified CAMELS variables, shown in Rows (8)–(12), are used as part of the robustness checks. Separating these variables ensures clarity and avoid multicollinearity, enhancing the reliability and interpretability of the results.

[11] The sample includes 202 banks that were bailed out and 674 banks that were not bailed out during the study period.

Table 2.3: Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Correlation among Accounting Variables												
(1) bailout	1.0000											
(2) Capital Ratio	0.0090	1.0000										
(3) Credit Risk	0.0896***	-0.0134**	1.0000									
(4) ROE	-0.0711***	0.0803***	-0.3057***	1.0000								
(5) IETL	0.0505***	-0.1943***	0.2184***	0.1182***	1.0000							
(6) RELGTA	0.0181***	-0.1288***	-0.0540***	-0.1361***	0.1162***	1.0000						
(7) LGTA	0.0310***	0.0952***	0.1526***	0.0715***	-0.1239***	-0.4272***	1.0000					
(8) ER	0.0099	0.9998***	-0.0097	0.0752***	-0.1954***	-0.1263***	0.0961***	1.0000				
(9) LLRR	0.0269***	-0.0447***	0.2533***	-0.4290***	-0.0981***	-0.0329***	0.0872***	-0.0300***	1.0000			
(10) OR	0.0269***	0.1349***	0.4008***	0.0297***	0.3135***	-0.1619***	0.0566***	0.1359***	0.0919***	1.0000		
(11) ROAE	-0.0699***	0.0924***	-0.3090***	0.9793***	0.1173***	-0.1393***	0.0730***	0.0872***	-0.4434***	0.0304***	1.0000	
(12) EDR	0.0054	0.1799***	0.1054***	-0.0022	0.0538***	-0.2735***	0.1513***	0.1789***	-0.0135***	0.2913***	-0.0005***	1.0000
Panel B: Correlation among Accounting and Tail Risk Variables												
(13) SVaR3M1	0.1828***	-0.1761***	0.3248***	-0.4379***	0.1224***	0.0998***	-0.0572***	-0.1713***	0.3669***	0.0921***	-0.4506***	0.0294***
(14) LVaR36M1	0.0610***	-0.1050***	0.3591***	-0.4656***	-0.0744***	0.0499***	-0.0406***	-0.0968***	0.5821***	0.0880***	-0.4764***	0.0483***
(15) SVaRCF3M1	0.1548***	-0.1891***	0.2916***	-0.4159***	0.1083***	0.1169***	-0.0819***	-0.1849***	0.3400***	0.0659***	-0.4282***	0.0185***
(16) LVaRCF36M1	0.0410***	-0.1199***	0.2138***	-0.3066***	-0.0153**	0.0563***	-0.0695***	-0.1158***	0.3176***	0.0465***	-0.3145***	0.0301***
(17) SES3M1	0.1828***	-0.1761***	0.3248***	-0.4379***	0.1224***	0.0998***	-0.0572***	-0.1713***	0.3669***	0.0921***	-0.4506***	0.0294***
(18) LES36M1	0.0695***	-0.1017***	0.3595***	-0.4659***	-0.0660***	0.0395***	-0.0344***	-0.0937***	0.5684***	0.0889***	-0.4769***	0.0517***

Note 1: Table 2.3 demonstrates the correlations between the variables. Panel A presents the accounting measures, while Panel B shows the correlations between accounting variables and tail risk measures (VaR, VaRCF, and ES).
Note 2: Row (1) represents the dependent variable (bailout). Rows (2)-(7) present the CAMEL variables, while Rows (8)-(12) represent the modified CAMELS variables. Rows (13)-(18) display the market risk measures.

2.3.2 The Correlated Random-Effects Logistic Analysis

Schunck and Perales (2017) confirm that it is possible to consistently estimate level-one effects while including level-two variables by using flexible modelling specifications, such as hybrid and correlated random-effects models, which distinguish between within-cluster and between-cluster effects.[12] Random-effects models assume that the random effects (e.g., the level-two error) are uncorrelated with the observed covariates, allowing researchers to examine the impact of cluster-invariant factors (level-two variables) on the outcome variable. However, if this assumption is violated, the coefficients may be biased.

In contrast, fixed-effects models do not require this assumption and can provide unbiased estimates even with unobserved cluster-level heterogeneity. These models estimate effects based only on within-cluster variation of the explanatory and outcome variables, making them well-suited for studying within-group dynamics. However, this focus on within-cluster variation limits fixed-effects models, as they cannot estimate the effects of time-invariant or level-two variables (which remain constant within each group over time).

We use the correlated random-effects model (Wooldridge, 2010), also known as the Mundlak (1978) model, in place of fixed-effects models. This choice is motivated by the model's ability to incorporate time-invariant variables and address unobserved heterogeneity, a limitation of fixed-effect models. Supported by Li and Yang (2021) and Schunck and Perales (2017), this methodology enables more robust estimations by including both time-varying and invariant predictors, thereby improving the model's accuracy and efficiency.

The correlated random-effects model combines the advantages of both random and fixed-effects models, providing unbiased estimates for within-cluster variables while also accounting for

[12] prominent examples of such models include the hybrid model proposed by Allison (2009) and correlated random-effects models suggested by Wooldridge (2010), the latter of which is also referred to as the Mundlak model (Baltagi, 2006; Mundlak, 1978).

between-cluster invariants. This approach allows for a more comprehensive understanding of the data structure and dynamics. Additionally, it enables the inclusion of banks that did not experience the event (zero outcomes), thereby mitigating potential biases that might arise from excluding such observations and effectively addressing limitations associated with fixed-effects models.

The following is the model's specification:

$$\mathrm{Bailout}_{\mathrm{b,t}} = \beta \mathrm{w} \mathrm{X}_{\mathrm{b,t}} + \tau \overline{\mathrm{X}}_{\mathrm{b}} + \gamma c_{\mathrm{b}} + \upsilon_{\mathrm{b}} \quad (5)$$

where $bailout_{\mathrm{b,t}}$ is a binary variable that has a value of 1 if the bank has been bailed out and 0 otherwise during t. The bailout variable is coded as 1 for the quarter in which a bank received a bailout (typically in 2008 or 2009) and is set to 0 for all quarters after that. $X_{b,t}$ is a bank-specific characteristic vector. This model presents the assumption that the level-two error $u_b = \tau \overline{\mathrm{X}}_{\mathrm{b}} + \upsilon_{\mathrm{b}}$ and $\upsilon_{\mathrm{b}} \sim N(0, \sigma^2_{\upsilon \mathrm{b}})$. This means that the level-two error can depend on $\mathrm{X}_{\mathrm{b,t}}$ through its cluster means. Any association between this variable and the unobserved random effect is detected by including $\overline{\mathrm{X}}_{\mathrm{b}}$. In this model, $\tau = \beta_{Between} - \beta_{Within}$[13]. The advantages of random- and fixed-effects models are combined in these estimate procedures, which also distinguish between within- and between-cluster effects. We use the xthybrid command with (cre) and (logit) link in the Stata program to run this model.

All financial ratios are extremely significant with expected signs, according to the baseline model's results displayed in column (1) of Table 2.4. An increase in capital ratio is associated with a higher probability of bailout. Specifically, the regression coefficient indicates that a one percentage point increase in the capital ratio is linked to a 27.48% increase in bailout likelihood, holding other factors constant. This finding aligns with Berger and Bouwman (2013), who suggest that higher capital levels contribute to a bank's resilience and survival. However, in the context of this study,

[13] Refer to Schunck and Perales (2017) to more details about the implementation of these models and a through discussion about Hybrid and correlated random-effects models.

higher capital levels might indicate a bank's capacity to sustain itself through riskier exposures, making it more likely to attract intervention during financial distress. From a policy perspective, this result highlights that highly capitalised banks might not always be safer; instead, they may engage in behaviours that increase bailout probability. This underscores the need for regulators to consider capitalisation not only as a sign of strength but also as a potential indicator of systemic risk due to moral hazard dynamics.

The regression results indicate that ROE significantly and negatively affects the probability of a bailout. Specifically, the coefficient of -4.613 suggests that a one percentage point increase in ROE reduces the likelihood of a bailout by approximately 4.61 percentage points, holding other factors constant. This finding highlights the importance of profitability as a safeguard against financial failure. Higher profitability strengthens a bank's financial position, reducing its reliance on external intervention during economic stress.

Other primary variables have significantly positive coefficients, suggesting that banks with poor asset quality, higher liquidity risk, and greater real-estate loan exposure are more likely to be bailed out. The coefficient of 1.255 for asset quality indicates that a one-unit increase in the asset quality ratio is associated with a 125.5% increase in the likelihood of a bailout, holding other factors constant. This underscores the critical role of asset quality in predicting financial failure that necessitates government intervention. For liquidity risk, the coefficient of 81.662 highlights that banks with greater liquidity risk are significantly more likely to be bailed out. This reflects the consequences of liquidity mismatches, where an imbalance between liquid assets and liabilities can quickly lead to financial instability requiring external support. The coefficient of 8.197 for real-estate loans indicates that a one percentage point increase in the proportion of real-estate loans increases the likelihood of a bailout by approximately 8.20 percentage points. This finding aligns with the greater risk of real-estate loans, particularly during market downturns.

From a policy perspective, these results emphasise the need for regulatory frameworks that address vulnerabilities associated with poor asset quality, liquidity management, and concentrated real-estate exposures. Strengthening oversight in these areas could reduce the likelihood of bailouts and enhance financial system stability.

Bank size is positively associated with bank risk and bailout probability, which can be understood through the “too-big-to-fail” (TBTF) argument. This perspective suggests that larger banks may engage in riskier behaviour due to moral hazard, expecting government support in times of distress. The regression coefficient for bank size is 1.486, indicating that a one-unit increase in the logarithm of total assets is associated with a 148.6% increase in bailout probability, holding other factors constant. This finding aligns with Tsafack et al. (2020), confirming that size is a significant factor, as larger institutions are more likely to receive bailouts when facing financial challenges. From a practical perspective, these results highlight the need for regulatory frameworks that address the risks caused by larger institutions. Policymakers should consider stricter oversight or capital requirements for systemically important banks to mitigate moral hazard behaviours and reduce the likelihood of bailouts.

Overall, these variables are significant in explaining the BHC bank bailout.

Subsequently, we add our tail risk metrics—VaR, VaRCF, and ES—to this baseline multivariate model to determine their effectiveness in predicting bank bailout. To account for potential intertemporal changes, we run separate multivariate correlated random-effects logistic regression for daily 3-month and 36-month tail risk estimates.

The findings across all tail risk measures—VaR, VaRCF, and ES—demonstrate their significant and positive relationships with bank bailouts. Specifically, short-duration measures consistently exhibit stronger predictive power compared to their long-duration counterparts, underscoring the importance of capturing near-term vulnerabilities in assessing bailout likelihood.

For VaR, as shown in columns (2)–(3) of Table 2.4, the coefficient for SVaR3M1 is 13.094, indicating that a one-unit increase in this metric is associated with a 1309.4% increase in the likelihood of a bailout, holding other factors constant. The coefficient for LVaR36M1 is 12.616, reflecting a 1261.6% increase in bailout probability per unit increase. Although both metrics show strong effects, the larger magnitude of the SVaR3M1 coefficient suggests that short-term VaR estimates are more effective predictors of bank bailouts compared to long-term VaR measures.

For VaRCF, as presented in columns (4)–(5) of Table 2.4, the coefficient for SVaRCF3M1 is 7.400, indicating that a one-unit increase in this short-duration rolling estimate is associated with a 740% increase in bailout likelihood, holding other factors constant. In contrast, the coefficient for LVaRCF36M1 is 1.881, reflecting a much smaller effect, a 188.1% increase in bailout likelihood per unit increase. These results demonstrate that short-duration VaRCF measure, Specifically SVaRCF3M1, is a more effective predictor of bailouts compared to long-duration measures like LVaRCF36M1. This suggests that short-term risk metrics capture more immediate vulnerabilities that may trigger bailouts.

For ES, as shown in Table 2.4, columns (6)–(7), the SES3M1 rolling coefficients are slightly stronger than the LES36M1 rolling coefficients, meaning that the ES of short-duration rolling estimates is better at anticipating bank bailouts than that of long-duration rolling estimates. Specifically, the coefficient for SES3M1 is 13.094, indicating that a one-unit increase in this short-duration measure is associated with a 1309.4% increase in the likelihood of a bailout, holding other factors constant. In comparison, the coefficient for LES36M1 is 11.703, reflecting an 1170.3% increase in bailout likelihood per unit increase.

From an economic perspective, the results emphasise that short-term risk measures across all three tail risk metrics—VaR, VaRCF, and ES—are more effective in capturing early warning signals of financial failure. Regulators and policymakers should prioritise monitoring these short-term measures as they provide actionable insights into the urgent risks facing financial institutions.

By incorporating these metrics into predictive models, authorities can strengthen early intervention mechanisms, mitigating the likelihood of systemic crises and reducing the need for costly bailouts.

These results back our main hypothesis that tail risk measures can positively predict bank bailouts. Overall, combining accounting-based measures with market-based measures in the prediction model enhances the power of classical bank stability models.

Table 2.4: The Correlated Random-Effects Logistic Regression Model With Bailout As Dependent Variable

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SVaR3M1		13.094***					
		(15.11)					
LVaR36M1			12.616***				
			(5.29)				
SVaRCF3M1				7.400***			
				(12.38)			
LVaRCF36M1					1.881***		
					(4.28)		
SES3M1						13.094***	
						(15.11)	
LES36M1							11.703***
							(6.50)
Capital Ratio	27.480***	33.570***	28.375***	33.961***	29.504***	33.570***	27.791***
	(6.77)	(8.00)	(6.55)	(8.36)	(6.90)	(8.00)	(6.42)
Credit Risk	1.255***	0.713**	0.861**	0.905 ***	1.147***	.713**	0.741**
	(3.79)	(1.97)	(2.45)	(2.59)	(3.36)	(1.97)	(2.10)
ROE	-4.613***	-1.161	-3.092***	-2.212***	-4.041***	-1.161	-2.624***
	(-5.93)	(-1.30)	(-3.59)	(-2.62)	(-4.92)	(-1.30)	(-3.03)
IETL	81.662***	78.823***	97.701***	79.673***	87.610***	78.823***	100.256***
	(9.31)	(8.48)	(10.22)	(8.65)	(9.64)	(8.48)	(10.47)
RELGTA	8.197***	7.373***	9.073***	7.500***	8.639***	7.373***	9.270***
	(5.63)	(4.77)	(6.01)	(4.95)	(5.71)	(4.77)	(6.09)
LGTA	1.486***	1.400***	1.597***	1.372***	1.468***	1.400***	1.639***
	(5.44)	(4.68)	(5.46)	(4.74)	(5.06)	(4.68)	(5.55)
Observations	22,012	21,951	20,604	21,951	20,604	21,951	20,604
Number of groups	795	789	749	789	749	789	749

Notes: The table presents the findings of the correlated random-effects logistic regression model using our sample of bank bailouts from 2001 to 2014. The dependent variable is the bailout. Column (1) reports CAMEL measures as a baseline regression. Columns (2) to (3) report historical VaR as the tail risk. Columns (4) to (5) show Cornish-Fisher VaR as the tail risk measure. Columns (6) to (7) show ES as the tail risk measure. A full description of each variable is provided in Table 1. The table's last two rows show the total number of bank-quarter observations and the number of groups. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

2.4 Robustness Checks

Several robustness checks are presented in this part to support our hypothesis. First, we rerun the correlated random-effects logistic regression using return on assets instead of return on equity. Second, we rerun the correlated random-effects logistic regression using the modified CAMELS. Third, we divide our sample into small, medium, and large banks. Fourth, to overcome the reverse causality problem, we rerun our regression with lag-market measures. Fifth, we use the System Generalised Method of Moment (GMM) to mitigate the probability of endogeneity. Sixth, we use the Receiver Operating Characteristic (ROC) curve to evaluate the predictive power of market risk measures for bank bailouts. The robustness checks support the essential results.

2.4.1 ROA Instead of ROE

We rerun the correlated random-effects logistic regression using return on assets (ROA) instead of return on equity (ROE) to evaluate the reliability of the profitability indicator in predicting bank bailouts. The results, presented in Table 2.5, are nearly identical to the primary outcomes shown in Table 2.4. However, the coefficients of the tail risk are slightly weaker when ROA is used instead of ROE in the CAMEL framework. In terms of significance and associations with bank risk, the baseline specification results in column (1) of Table 2.5 and tail risk results in columns (2)–(7) of Table 2.5 remain consistent with our main findings in Table 2.4.

Table 2.5: The Correlated Random-Effects Logistic Regression Model With Bailout As Dependent Variable Using ROA

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SVaR3M1		12.819***					
		(14.78)					
LVaR36M1			11.777***				
			(4.96)				
SVaRCF3M1				7.170***			
				(12.08)			
LVaRCF36M1					1.815***		
					(4.08)		
SES3M1						12.819***	
						(14.78)	
LES36M1							10.991***
							(6.14)
Capital Ratio	29.140***	35.050***	30.032***	35.747***	31.020***	35.050***	29.540***
	(7.16)	(8.35)	(6.97)	(8.79)	(7.27)	(8.35)	(6.86)
Credit Risk	0.936***	0.475	0.600*	0.612*	0.842**	0.475	0.496
	(2.74)	(1.27)	(1.67)	(1.69)	(2.40)	(1.27)	(1.37)
ROA	-76.290***	-30.233**	-56.612***	-45.909***	-68.731***	-30.233**	-50.465***
	(-7.22)	(-2.50)	(-4.91)	(-3.97)	(-6.24)	(-2.50)	(-4.54)
IETL	86.157***	82.289***	100.463***	84.213***	91.663***	82.289***	102.705***
	(9.71)	(8.73)	(10.45)	(9.01)	(9.99)	(8.73)	(10.68)
RELGTA	8.050***	7.213***	8.843***	7.303***	8.438***	7.213***	9.020***
	(5.51)	(4.67)	(5.84)	(4.82)	(5.56)	(4.67)	(5.92)
LGTA	1.504***	1.373***	1.586***	1.360***	1.475***	1.373***	1.619***
	(5.48)	(4.59)	(5.40)	(4.70)	(5.06)	(4.59)	(5.47)
Observations	22,012	21,951	20,604	21,951	20,604	21,951	20,604
Number of groups	795	789	749	789	749	789	749

Notes: The table presents the findings of the correlated random-effects logistic regression model using our sample of bank bailouts from 2001 to 2014. The dependent variable is the bailout. Column (1) reports CAMEL measures as a baseline regression. Columns (2) to (3) report historical VaR as the tail risk. Columns (4) to (5) show Cornish-Fisher VaR as the tail risk measure. Columns (6) to (7) present ES as the tail risk measure. A full description of each variable is provided in Table 1. The table's last two rows show the total number of bank-quarter observations and the number of groups. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

2.4.2 Using Modified CAMELS

We rerun the correlated random-effects logistic regression using the modified CAMELS framework, following Naqvi et al. (2018), instead of the CAMEL framework used in the main regression to evaluate the reliability of the modified CAMELS measure in predicting bank bailouts. The results in Table 2.6 show that the findings across all tail risk measures—VaR, VaRCF, and ES—demonstrate significant and positive relationships with bank bailouts.

The long-duration VaR (LVaR36M1) and long-duration ES (LES36M1) coefficients are higher, indicating that these measures are better at anticipating bank bailouts. Similarly, the short-duration VaRCF (SVaRCF3M1) shows a higher coefficient, suggesting that it predicts bank bailouts better than long-duration VaRCF.

In terms of significance and associations with bank risk, the baseline specification results in column (1) of Table 2.6 and the tail risk results in columns (2)–(7) of Table 2.6 remain consistent with our main findings in Table 2.4, except for the overheads ratio (OR) and the loan loss reserves ratio (LLRR). OR has a significantly negative coefficient, indicating that the likelihood of a bailout decreases as the overheads ratio increases. Similarly, the significantly negative coefficient for the loan loss reserves ratio (LLRR) indicates that banks with higher LLRR ratios are better equipped to manage financial distress, thereby reducing the likelihood of requiring a bailout.

Table 2.6: The Correlated Random-Effects Logistic Regression Model With Bailout As Dependent Variable Using the Modified CAMELS

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SVaR3M1		14.847***					
		(16.62)					
LVaR36M1			23.068***				
			(8.38)				
SVaRCF3M1				8.374***			
				(13.30)			
LVaRCF36M1					2.399***		
					(5.53)		
SES3M1						14.847***	
						(16.62)	
LES36M1							18.828***
							(9.56)
ER	31.754***	35.963***	33.539***	35.967***	34.454***	35.963***	32.444***
	(8.77)	(9.47)	(8.63)	(9.71)	(8.98)	(9.47)	(8.27)
LLRR	-23.392***	-41.430***	-57.147***	-34.087***	-29.094***	-41.430***	-56.150***
	(-3.01)	(-4.89)	(-6.47)	(-4.09)	(-3.59)	(-4.89)	(-6.69)
OR	-24.067***	-25.962***	-27.198***	-23.789***	-24.668***	-25.962***	-30.206***
	(-2.95)	(-2.83)	(-3.19)	(-2.70)	(-2.94)	(-2.83)	(-3.51)
ROAE	-10.164***	-6.324***	-8.684***	-7.233***	-9.406***	-6.324***	-8.326***
	(-11.35)	(-6.24)	(-9.45)	(-7.44)	(-10.20)	(-6.24)	(-9.00)
IETL	98.421***	88.427***	112.261***	91.007***	103.825***	88.427***	114.877***
	(10.31)	(8.23)	(11.08)	(8.80)	(10.51)	(8.23)	(11.24)
EDR	27.428***	30.926***	28.111***	30.749***	28.105***	30.926***	27.723***
	(2.84)	(3.07)	(2.95)	(3.15)	(2.90)	(3.07)	(2.95)
Observations	21,836	21,775	20,440	21,775	20,440	21,775	20,440
Number of groups	786	780	741	780	741	780	741

Notes: The table presents the findings of the correlated random-effects logistic regression model using our sample of bank bailouts from 2001 to 2014. The dependent variable is the bailout. Column (1) reports the modified CAMEL measures as a baseline regression. Columns (2) to (3) report historical VaR as the tail risk. Columns (4) to (5) show Cornish-Fisher VaR as the tail risk measure. Columns (6) to (7) display ES as the tail risk measure. A full description of each variable is provided in Table 1. The table's last two rows show the total number of bank-quarter observations and the number of groups. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

2.4.3 Bank Size

While our main result accounts for bank size through the inclusion of the logarithm of gross total assets (GTA), there remains the possibility that variations over time in certain banks may not be fully captured. In addition, it is essential to determine if the variables have different significance or economic interpretations based on different samples and to examine their behaviour to see if they are consistent across various samples. To clarify this, we follow Berger and Bouwman (2013) and divide our sample into small banks (GTA of less than $1 billion), medium banks (GTA of more than

$1 billion but less than $3 billion), and large banks (GTA of more than $3 billion). Subsequently, the regression analysis is conducted separately for each of the three bank size categories. Specifically, the outcomes for small, medium, and large banks are presented in Tables 2.7, 2.8, and 2.9, respectively.

With the exception of the Credit Risk variable among small and medium banks, all factors for small, medium, and large banks are significant. Another exception is that small banks have an insignificant real estate loans (RELGTA) variable. Ultimately, most of the coefficients for large banks exhibit the highest magnitude, followed closely by those for medium banks, while small banks show the lowest coefficients. The empirical findings suggest a positive association between the effectiveness of tail risk measures and the size of a bank. In other words, tail risk metrics are more effective in larger banks compared to smaller ones.

Table 2.7: The Correlated Random-Effects Logistic Regression Model With Bailout As Dependent Variable For Small Banks

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SVaR3M1		12.707***					
		(7.84)					
LVaR36M1			30.010***				
			(4.99)				
SVaRCF3M1				6.574***			
				(7.16)			
LVaRCF36M1					1.352**		
					(1.84)		
SES3M1						12.707***	
						(7.84)	
LES36M1							22.063***
							(5.10)
Capital Ratio	24.990**	36.364***	32.969***	38.371***	27.564**	36.364***	31.145***
	(2.23)	(3.26)	(3.16)	(3.43)	(2.38)	(3.26)	(2.94)
Credit Risk	0.233	0.045	-1.055	-0.032	0.002	0.045	-1.046
	(0.28)	(0.05)	(-1.09)	(-0.04)	(0.00)	(0.05)	(-1.08)
ROE	-4.570**	-2.393	-1.411	-3.256	-4.126*	-2.393	-1.528
	(-2.17)	(-1.07)	(-0.65)	(-1.45)	(-1.86)	(-1.07)	(-0.71)
IETL	61.603***	52.700**	91.593***	64.956**	72.282***	52.700**	93.280***
	(3.07)	(2.47)	(4.32)	(3.03)	(3.51)	(2.47)	(4.36)
RELGTA	1.710	0.023	4.863	0.758	2.213	0.023	4.532
	(0.54)	(0.01)	(1.42)	(0.23)	(0.65)	(0.01)	(1.31)
LGTA	3.935***	3.999***	4.741***	3.946***	4.087***	3.999***	4.431***
	(4.20)	(3.99)	(4.50)	(4.10)	(3.97)	(3.99)	(4.25)
Observations	7,940	7,918	7,072	7,918	7,072	7,918	7,072
Number of groups	441	439	400	439	400	439	400

Notes: The table presents the findings of the correlated random-effects logistic regression model using our sample of bank bailouts from 2001 to 2014. The dependent variable is the bailout. Column (1) reports CAMEL measures as a baseline regression. Columns (2) to (3) report historical VaR as the tail risk. Columns (4) to (5) show Cornish-Fisher VaR as the tail risk measure. Columns (6) to (7) present ES as the tail risk measure. A full description of each variable is provided in Table 1. The table's last two rows show the total number of bank-quarter observations and the number of groups. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

Table 2.8: The Correlated Random-Effects Logistic Regression Model With Bailout As Dependent Variable For Medium Banks

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SVaR3M1		14.517***					
		(8.37)					
LVaR36M1			17.250***				
			(3.77)				
SVaRCF3M1				7.340***			
				(6.20)			
LVaRCF36M1					2.058**		
					(2.36)		
SES3M1						14.517***	
						(8.37)	
LES36M1							15.978***
							(4.59)
Capital Ratio	39.758***	50.020***	45.144***	48.200***	46.173***	50.020***	46.294***
	(5.62)	(6.73)	(5.72)	(6.65)	(5.83)	(6.73)	(5.89)
Credit Risk	0.390	-0.231	-0.123	0.012	0.343	-0.231	-0.273
	(0.65)	(-0.35)	(-0.19)	(0.02)	(0.56)	(-0.35)	(-0.41)
ROE	-5.319***	-2.115	-3.615**	-3.222**	-4.856***	-2.115	-2.941*
	(-3.87)	(-1.36)	(-2.37)	(-2.11)	(-3.31)	(-1.36)	(-1.88)
IETL	72.025***	65.804***	92.027***	66.161***	76.667***	65.804***	93.659***
	(4.80)	(4.14)	(5.45)	(4.25)	(4.83)	(4.14)	(5.56)
RELGTA	11.301***	9.966***	10.232***	10.818***	10.510***	9.966***	10.496***
	(4.31)	(3.65)	(3.75)	(4.12)	(3.83)	(3.65)	(3.81)
LGTA	2.952***	2.479***	3.196***	2.592***	3.062***	2.479***	3.227***
	(3.55)	(2.84)	(3.59)	(3.04)	(3.54)	(2.84)	(3.61)
Observations	6,964	6,941	6,543	6,941	6,543	6,941	6,543
Number of groups	368	365	344	365	344	365	344

Notes: The table presents the findings of the correlated random-effects logistic regression model using our sample of bank bailouts from 2001 to 2014. The dependent variable is the bailout. Column (1) reports CAMEL measures as a baseline regression. Columns (2) to (3) report historical VaR as the tail risk. Columns (4) to (5) show Cornish-Fisher VaR as the tail risk measure. Columns (6) to (7) show ES as the tail risk measure. A full description of each variable is provided in Table 1. The table's last two rows show the total number of bank-quarter observations and the number of groups. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

Table 2.9: The Correlated Random-Effects Logistic Regression Model With Bailout As Dependent Variable For Large Banks

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SVaR3M1		14.805***					
		(9.77)					
LVaR36M1			9.519***				
			(2.56)				
SVaRCF3M1				12.214***			
				(8.61)			
LVaRCF36M1					5.368***		
					(4.58)		
SES3M1						14.805***	
						(9.77)	
LES36M1							10.175***
							(3.50)
Capital Ratio	24.327***	25.694***	22.688***	28.731***	21.872***	25.694***	21.008***
	(3.62)	(3.61)	(3.34)	(4.11)	(3.27)	(3.61)	(3.06)
Credit Risk	2.183***	1.462**	1.831***	1.541***	1.781***	1.462**	1.659***
	(4.23)	(2.52)	(3.45)	(2.72)	(3.37)	(2.52)	(3.09)
ROE	-4.649***	0.175	-3.149**	-0.889	-2.942**	0.175	-2.596*
	(-3.84)	(0.12)	(-2.38)	(-0.63)	(-2.39)	(0.12)	(-1.94)
IETL	110.890***	112.830***	123.246***	115.265***	122.434***	112.830***	128.445**
	(7.53)	(7.20)	(7.76)	(7.23)	(7.98)	(7.20)	(8.00)
RELGTA	6.010**	5.603*	6.732**	3.037	5.968***	5.603*	7.150***
	(2.21)	(1.90)	(2.45)	(1.03)	(2.17)	(1.90)	(2.58)
LGTA	1.566***	1.726***	1.718***	1.563***	1.727***	1.726***	1.806***
	(3.15)	(3.13)	(3.39)	(2.88)	(3.36)	(3.13)	(3.50)
Observations	7,108	7,092	6,989	7,092	6,989	7,092	6,989
Number of groups	269	268	258	268	258	268	258

Notes: The table presents the findings of the correlated random-effects logistic regression model using our sample of bank bailouts from 2001 to 2014. The dependent variable is the bailout. Column (1) reports CAMEL measures as a baseline regression. Columns (2) to (3) report historical VaR as a measure of tail risk. Columns (4) to (5) show Cornish-Fisher VaR as a measure of tail risk. Columns (6) to (7) display ES as a measure of tail risk. A full description of each variable is provided in Table 1. The table's last two rows show the total number of bank-quarter observations and the number of groups. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

2.4.4 Endogeneity

Endogeneity issues, such as reverse causality and omitted variable bias, sometimes confuse empirical results. This study notes the possibility of endogeneity challenges that might impact the results. Reverse causality arises from the two-way association between bank bailouts and stock market tail risk. Before the bailout, banks were likely sensitive to significant financial risk, as seen by their increased tail risk. Furthermore, the bailout itself has the potential to further enhance tail risk through changing market views and operations. This is a challenge in distinguishing whether high tail risk causes bailouts or whether bailouts escalate tail risk.

Furthermore, there is an appearance of omitted variable bias. Unobserved variables may influence the relationship between tail risk metrics and the occurrence of bank failure. These variables may include bank-specific characteristics such as governance and risk management, market circumstances including liquidity and investor mood, and macroeconomic elements such as GDP growth and interest rates. Determining whether these issues have been appropriately identified might be challenging.

We follow Cavallo and Frankel (2008) and Jean et al. (2016) as they use the lag of the independent variables to deal with the endogeneity issue. We lag all market measures by one period. This method decreases the potential effect of endogeneity of predicting bank bailout and market risk measures association. Table 2.10 illustrates the results of running the regression.

When we rerun all lagged market measures, the results remain consistent with the primary findings, except for the long-duration VaR, VaRCF, and ES, which show an insignificant relationship. Table 2.10 indicates that the endogeneity issue does not significantly affect our main results.

Table 2.10: The Correlated Random-Effects Logistic Regression Model With Lagged Market Measures

Variable	(1)	(2)	(3)	(4)	(5)	(6)
SVaR3M1	9.534***					
	(10.58)					
LVaR36M1		-3.561				
		(-1.35)				
SVaRCF3M1			6.269***			
			(9.74)			
LVaRCF36M1				-0.141		
				(-0.21)		
SES3M1					9.534***	
					(10.58)	
LES36M1						-2.264
						(-1.13)
Capital Ratio	30.864***	28.502***	31.646***	28.096***	30.864***	28.500***
	(7.54)	(6.54)	(7.76)	(6.47)	(7.54)	(6.53)
Credit Risk	0.861**	1.373***	1.011***	1.293***	0.861**	1.358***
	(2.49)	(3.96)	(2.95)	(3.78)	(2.49)	(3.92)
ROE	-2.473***	-5.353***	-2.844***	-5.038***	-2.473***	-5.312***
	(-3.01)	(-6.36)	(-3.51)	(-6.15)	(-3.01)	(-6.28)
IETL	89.127***	79.569***	85.741***	84.285***	89.127***	80.370***
	(9.88)	(8.30)	(9.52)	(9.13)	(9.88)	(8.41)
RELGTA	8.097***	8.265***	8.140***	8.485***	8.097***	8.264***
	(5.45)	(5.35)	(5.48)	(5.53)	(5.45)	(5.36)
LGTA	1.569***	1.399***	1.546***	1.455***	1.569***	1.414***
	(5.44)	(4.79)	(5.39)	(4.95)	(5.44)	(4.84)
Observations	21,529	20,018	7,092	20,018	21,529	20,018
Number of groups	785	738	268	738	785	738

Notes: The table presents the findings of the correlated random-effects logistic regression model using our sample of bank bailouts from 2001 to 2014. The dependent variable is the bailout. Columns (1)-(2) report lagged historical VaR as a measure of tail risk, including all control variables. Columns (3)-(4) show lagged Cornish-Fisher VaR as a measure of tail risk, including all control variables. Columns (5)-(6) display lagged ES as a measure of tail risk, including all control variables. A full description of each variable is provided in Table 1. The table's last two rows show the total number of bank-quarter observations and the number of groups. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

2.4.5 The System Generalised Method of Moment (GMM)

We use the System Generalised Method of Moment (GMM) to mitigate the probability of endogeneity. The market risk measures are assumed to be endogenous because causality may run in both directions – from bailout to market risk measures and vice versa – these regressors may be correlated with the error term.

Addressing the endogeneity problem in panel data analysis, especially in studies predicting bank bailouts using market measures, requires a strong econometric method. The Generalised Method of Moments (GMM), developed by Arellano and Bond (1991) and expanded by Arellano and Bover (1995) and Blundell and Bond (1998), is made for such complex scenarios. It works well where independent variables might not be strictly exogenous and could correlate with past and current error terms, a common issue in dynamic financial data analysis (Roodman, 2009). Ullah et al. (2018) mention that this method effectively deals with challenges like unobserved heterogeneity, simultaneity, and dynamic endogeneity (Wintoki et al., 2012).

Avom et al. (2022) clarify that system GMM's approach, using lagged levels and differences of variables as instruments, allows for a comprehensive strategy that addresses both the equation in differences and the equation in levels. The GMM approach considered common estimates to address endogeneity concerns (Arellano & Bover, 1995; Blundell & Bond, 1998). GMM also avoids simultaneity or reverse causality problems (Avom et al., 2022).

We employ a System GMM estimation method, following the approach Roodman (2009) used. Using past values of the dependent variables as explanatory variables, we introduce a way to deal with endogenous relationships within the data. In other words, as Ullah et al. (2018) have mentioned in their paper, the GMM model addresses endogeneity through an 'internal transformation' of the data, a process where each variable's past value is subtracted from its current value, as (Roodman, 2009) explains. This transformation effectively decreases the number of observations and highlights the GMM framework's efficiency (Wooldridge, 2012).

To reduce the possibility of data loss caused by internal transformation concerns in the first-step GMM, Arellano and Bover (1995) proposed using a second-order transformation called the two-step GMM. This method employs 'forward orthogonal deviations,' which involves utilising the mean of all future observations of a variable rather than only subtracting previous observations from its current value, as explained by Roodman (2009).

The reliability of System GMM estimations depends on two essential conditions: no serial correlation in the error term (AR(2)) and the right choice of instruments (Hansen tests), which confirm the instruments' reliability (Avom et al., 2022). Table 2.11 shows that the AR(2) test result does not indicate significant second-order autocorrelation, supporting our model's specification that the error terms are not serially correlated beyond the first lag. This absence of second-order autocorrelation is crucial for the validity of our GMM estimation, as it suggests that our lagged variables are appropriately serving as instruments and are not correlated with the error term. In addition, the Hansen test results from columns (1)–(6) indicate that our instruments can be considered exogenous, confirming our instruments' validity.

Our results in Table 2.11 confirm our main results and the conclusion that VaR, VaRCF, and ES are positive significant predictors of bank bailouts under varying conditions and specifications. Therefore, the results of Table 2.11 indicate that our primary findings are not affected by the endogeneity issue.

Table 2.11: The System Generalised Method of Moment (System GMM) model

Variable	(1)	(2)	(3)	(4)	(5)	(6)
L3. bailout	0.044	0.044	0.045	0.044	0.044	0.041
	(1.39)	(1.27)	(1.36)	(1.28)	(1.39)	(1.21)
SVaR3M1	0.404***					
	(10.27)					
LVaR36M1		0.093***				
		(2.90)				
SVaRCF3M1			0.232***			
			(7.53)			
LVaRCF36M1				0.016**		
				(2.33)		
SES3M1					0.404***	
					(10.27)	
LES36M1						0.106***
						(4.02)
Capital Ratio	0.939***	0.340***	0.863***	0.417***	0.939***	0.336***
	(9.67)	(4.69)	(9.47)	(5.80)	(9.67)	(4.45)
Credit Risk	0.011**	0.019***	0.013**	0.023***	0.011**	0.016***
	(2.09)	(3.31)	(2.28)	(4.11)	(2.09)	(3.02)
ROE	0.024	-0.057***	-0.003	-0.067***	0.024	-0.048***
	(1.40)	(-3.49)	(-0.23)	(-4.17)	(1.40)	(-3.05)
IETL	0.496***	0.973***	0.706***	0.891***	0.496***	1.004***
	(3.79)	(7.19)	(5.33)	(6.34)	(3.79)	(7.60)
RELGTA	0.033**	0.078***	0.033**	0.054***	0.033**	0.082***
	(2.05)	(4.30)	(2.50)	(2.85)	(2.05)	(4.13)
LGTA	-0.005*	0.011***	-0.0008	0.008***	-0.005*	0.012***
	(-1.89)	(4.67)	(-0.34)	(3.63)	(-1.89)	(4.86)
Observations	19,965	19,098	19,965	19,098	19,965	19,098
Number of groups	740	714	740	714	740	714
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	0.475	0.628	0.714	0.612	0.475	0.663
Hansen	0.318	0.275	0.204	0.450	0.318	0.375

Notes: The table presents the findings of the System Generalised Method of Moment (System GMM) model using our sample of bank bailouts from 2001 to 2014 are presented in this table. Columns (1) to (2) report historical VaR as a measure of tail risk. Columns (3) to (4) show Cornish-Fisher VaR as a measure of tail risk. Columns (5) to (6) show ES as a measure of tail risk. The table's last five rows show the total number of bank-quarter observations, the number of groups, the p-value of the Arellano-Bond tests for first-order and second-order autocorrelation, and the Hansen test for overidentification restrictions. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) represent significance at 10%, 5%, and 1%, respectively.

2.4.6 The Receiver Operating Characteristic (ROC) curve

This section evaluates the predictive power of various market risk measures in identifying banks that are at risk of receiving a bailout. Each measure is individually tested within a logistic regression model, and the predictive accuracy of each model is assessed using the area under the ROC curve (AUC). AUC values close to 1.0 indicate strong predictive power, and the individual coefficients provide insight into the influence of each risk measure on bailout likelihood.

Table 2.12 summarises each model's predictive accuracy; all six models yielded AUC values above 0.78, confirming that each risk measure possesses strong predictive power for bailout likelihood. Specifically, the models using SVaR3M1 and SES3M1 achieved the highest AUCs (0.8832), indicating that these measures are particularly robust predictors. Other models also performed well, with SVaRCF3M1 achieving an AUC of 0.8510.

Additionally, six figures displaying the ROC curves for each market risk measure as a predictor of bank bailouts are included to illustrate the models' performance. These results show that various market risk measures can effectively predict the likelihood of a bailout, providing flexibility in selecting risk indicators while maintaining model accuracy.

Table 2.12: Summarise Each Model's Predictive Accuracy

Variable	SVaR3M1	LVaR36M1	SVaRCF3M1	LVaRCF36M1	SES3M1	LES36M1
AUC	0.8832	0.7940	0.8510	0.7814	0.8832	0.8007
Pseudo R-squared	0.1924	0.1056	0.1557	0.1021	0.1924	0.1086
Risk Measure Coefficient	11.504***	7.553***	5.996***	1.146***	11.504***	6.354***
Control Variables	Included	Included	Included	Included	Included	Included

Notes:
- AUC: Area Under the ROC Curve; higher values indicate better discriminatory power.
- Pseudo R-squared: Higher values suggest a better model fit.
- *** indicates significance at the 1% level.

Figure 2.1: ROC Curve for SVaR3M1 as a Predictor of Bank Bailout

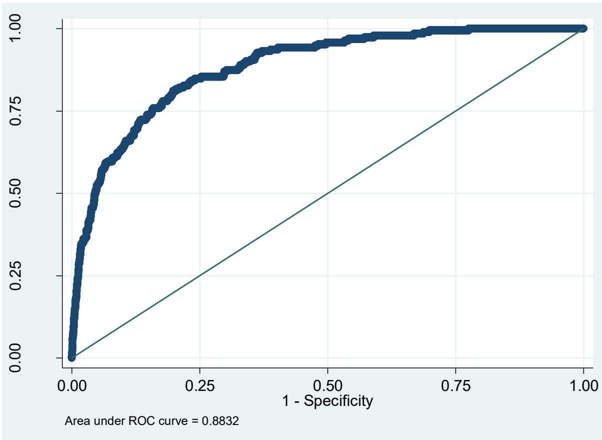


Figure 2.2: ROC Curve for LVaR36M1 as a Predictor of Bank Bailout

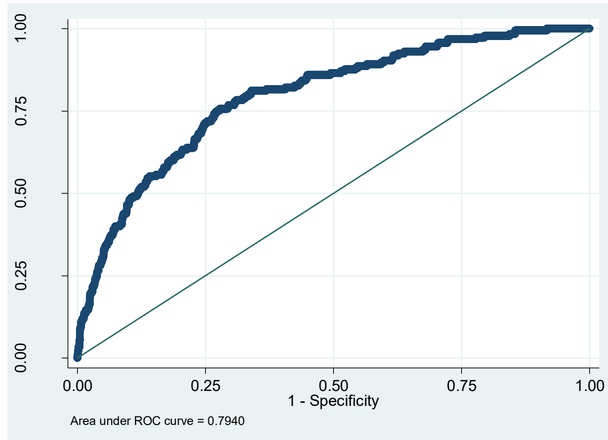


Figure 2.3: ROC Curve for SVaRCF3M1 as a Predictor of Bank Bailout

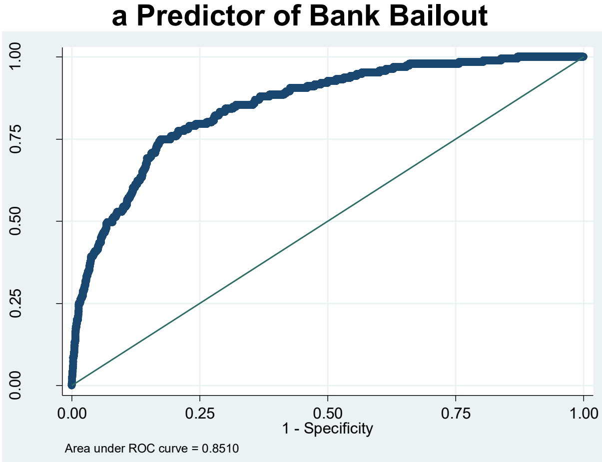


Figure 2.4: ROC Curve for LVaRCF36M1 as a Predictor of Bank Bailout

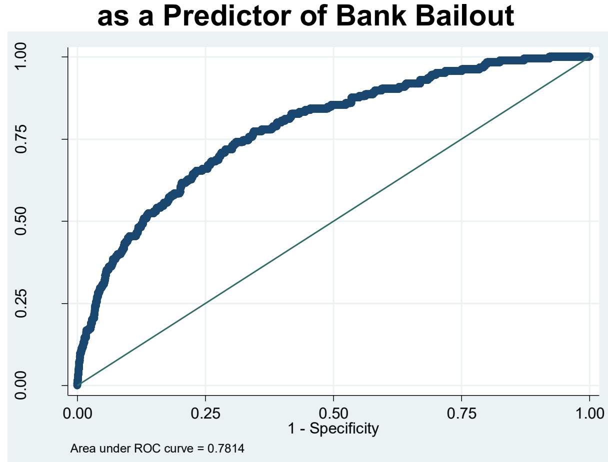


Figure 2.5: ROC Curve for SES3M1 as a Predictor of Bank Bailout

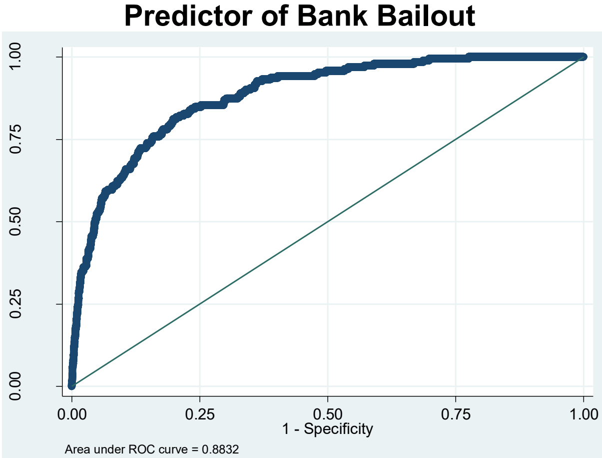
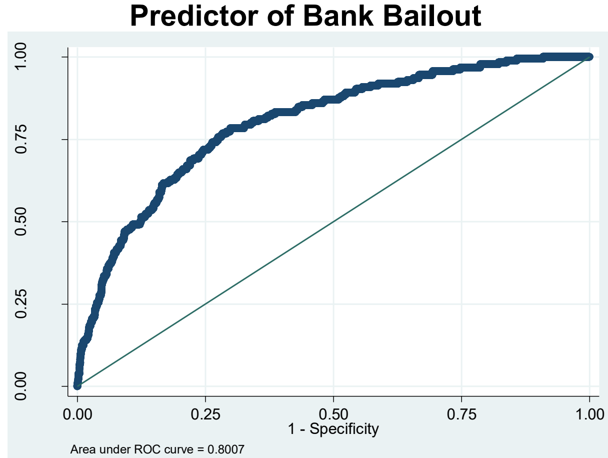


Figure 2.6: ROC Curve for LES36M1 as a Predictor of Bank Bailout



2.5 Conclusion

In this chapter, the information content of market variables is investigated to see if they can be used as indicators of bank bailouts. We empirically evaluate the influence of downside risk measures such as value-at-risk, Cornish-Fisher expansion value-at-risk, and Expected Shortfall in predicting the bailout of US BHCs between 2001 and 2014. We hypothesise that an increase in the frequency of extremely negative daily equity returns is indicative of larger tail risks, putting banks at a greater probability of bailouts.

We utilise the correlated random-effects logistic regression to investigate the role of tail risk measures in conjunction with CAMEL rating measurement in predicting bank bailouts. The tail risk indicators are crucial in anticipating the bank’s bailout. Our research findings demonstrate that every estimate of VaR, VaRCF, and ES measurements show significant positive associations with the bank's bailout. Moreover, our results are robust to endogeneity, ensuring the reliability of our findings.

Our research underscores the significance of incorporating market-based variables, such as tail risk metrics and accounting-based variables, to assess the likelihood of a bank bailout. This is particularly relevant in the banking industry, where the consequences of a bank failure can be severe and widespread. In addition, including market variables in the analysis of bank bailouts can help provide a more comprehensive assessment of a bank's financial health and risk exposure. This can assist regulators in making more informed decisions regarding allocating resources and implementing corrective measures in the event of a bank's financial distress. Overall, our research contributes to the ongoing discussion surrounding the use of tail risk metrics in the banking industry and emphasises the importance of considering these variables alongside traditional accounting-based measures in assessing the risk of a bank bailout.

Chapter Three: Do Females Perform Better During Crises: An Analysis of Bank Performance After Bailouts

3.1 Introduction

"Companies with more gender-balanced workforces outperformed their least-balanced peers by as much as 2 percentage points annually between 2013 and 2022, according to a BlackRock study of the MSCI World index" (Khalaf, 2023). The importance of gender diversity in leadership has received growing emphasis in recent years. While some research reveals a positive relationship, such as García-Meca et al. (2015), Owen and Temesvary (2018), and Tampakoudis et al. (2022), others find negative or mixed effects, such as Berger et al. (2014), Farag and Mallin (2017), Liao et al. (2019), and Pathan and Faff (2013). Brahma et al. (2021), Joecks et al. (2013), and Liu et al. (2014) use critical mass theory to explore the influence of women on firms' performance. Our analysis has similarities with Joecks et al. (2013) in that we also use the ratio of women instead of the absolute number of women. However, we distinguish our research based on several important considerations. Initially, our attention is directed at the banking sector, which has distinct regulatory and operational challenges. Furthermore, we expand our research to include data until 2019, including times of the financial crisis. Additionally, our focus is on the US market, where we provide valuable insights that are relevant to a distinct regulatory and market environment. Moreover, we enhance the accuracy of our study by using data on gender diversity sourced from BoardEx.

Thus, we are prompted to investigate the impact of gender diversity on the performance of banks in the United States, during and after the government's bailout initiatives, to ascertain whether such diversity has a significant effect.

Our study serves to clarify prior ambiguities within the literature and provide a definitive assessment of the relationship between gender diversity and banking industry performance.

Furthermore, our study motivates us to examine the sources of gender diversity's effects to enrich the literature.

The present study investigates several fundamental questions: Does gender diversity, specifically the presence of females on a bank's board of directors, enhance bank performance after the financial crisis, and what is the optimal ratio of women on the board that leads to positive effects on performance? Does critical mass theory effectively describe the impact of board gender diversity on bank performance? In addressing these questions, this study makes several significant contributions to the existing literature on board diversity, thereby bridging a critical gap in understanding the impact of women directors on bank performance. Firstly, it provides comprehensive empirical evidence that the relationship between board gender diversity and bank performance is contingent on a specific level of gender diversity on the board. Secondly, this study helps to reconcile the mixed findings from previous research on this topic. Thirdly, by examining support for the critical mass theory in corporate governance, this empirical investigation addresses a notable gap in the literature. Finally, our analysis is based on a robust dataset comprising 2,317 bank-year observations of 179 bailout BHCs and 2,766 bank-year observations of 434 BHCs that have not received bailouts, providing a longer period of coverage than prior studies.

Drawing on Critical mass theory, as used by Kanter (1977a, 1977b), we posit that the behavior and influence of a subgroup are a function of its size. Specifically, it proposes that once the subgroup reaches a certain threshold, known as the "critical mass", it gains the ability to exert more significant influence within the larger group (Torchia et al., 2011). In line with Kante's (1977b) framework, the representation of women on corporate boards can be categorised into four distinct groups. These groups include uniform groups, where there is a complete absence of female representation (0% women); skewed groups, where there is minimal representation of women (up to 20% women); tilted groups, where there is moderate representation of women (20-40%

women); and balanced groups, where there is substantial representation of women (40-60% women).

The prevailing consensus in literature asserts that a linear relationship exists between gender diversity and performance. Nevertheless, our study validates a U-shaped relation between the proportion of women on the board and bank performance, which is consistent with the empirical findings reported by Joecks et al. (2013). Their investigation of German firms demonstrated that a critical mass of female representation on boards is achieved when the women's ratio ranges between 20% and 40%. Our research provides a lucid image and establishes an optimal proportion of women on boards under the tilted groups that enhance bank performance.

In addition, we apply bank size as a robustness check following the methodology of Berger and Bouwman (2013), and we find that medium and large banks are consistent with the main results and confirm that the tilted groups has a significant and positive effect on bank performance. Moreover, we follow the methodology outlined by Huang and Kisgen (2013) to apply the instrumental variable approach and address the endogeneity issue. The Instrumental variable regression results are consistent with the main results that we get previously using the woman ratio. Our results support the primary hypothesis that post-bailout, banks with a specific percentage of women on their boards outperform those without female representation or with a lower percentage of women.

The organisation of this chapter proceeds as follows. Initially, we offer an overview of the current literature concerning the influence of gender diversity on bank performance. Next, we delineate our methodology, including research data, sample construction, and the measurement of both dependent and independent variables. We then provide a comprehensive account of our empirical model and method, including descriptive statistics, correlation, and the multivariate fixed effect regression analysis. After that, we apply the robustness checks to support our primary results. Finally, we present the study's conclusion in the last section of this chapter.

3.2 Literature Review

The importance of the banking industry and board governance

We focus on our study on the impact of gender diversity on banking holding companies' performance after the bailout in the United States. Banks are a major aspect of every nation's financial system and play a significant role in maintaining sustainable economic growth and development (Dikko et al., 2021). Macey and O'Hara (2003) and Tampakoudis et al. (2022) concentrate on the banking sector because bank directors have a particular responsibility to depositors, creditors, and regulators compared to directors in other industries. In addition, the bank's board of directors is an integral element of corporate governance, which plays an essential role in shaping the bank's financial behaviour and responses to complicated situations. In addition, other stakeholders lack the authority to establish adequate and effective governance in banks (Elsharkawy et al., 2018; Levine, 2004).

The importance of gender diversity

There is accumulating evidence that board gender diversity influences organisational outcomes (Sila et al., 2016; Tampakoudis et al., 2022). Research suggests that gender diversity on the board of directors may be an effective internal corporate governance tool for encouraging managers to make decisions that maximise shareholder wealth (Denis & McConnell, 2003; Tampakoudis et al., 2022). However, including more gender-diverse monitors can have either positive or negative consequences (Adams & Ferreira, 2009; Carter et al., 2010; Tampakoudis et al., 2022). Moreover, the empirical evidence on the relationship between board diversity and firm value, primarily in the United States, is inconclusive as to whether the link is positive, negative, or neutral (Adams & Ferreira, 2009; Bøhren & Strøm, 2010; García-Meca et al., 2015; Levi et al., 2014; Pathan & Skully, 2010; Tampakoudis et al., 2022).

The primary argument in favour of diversity is that a more diversified management team tends to be more creative, innovative, and open to a larger variety of decision-making choices. In addition, boards with greater diversity should support minorities, ensure different perspectives, and protect against manipulation (Arnaboldi et al., 2020). Gender and nationality differences are most likely to provide distinct datasets that management may use to make better decisions (Berger & Neugart, 2012; Carter et al., 2010; García-Meca et al., 2015). To enhance corporate governance and business ethics, gender diversity on boards of directors has received a great deal of attention from regulatory authorities, firms, and academics (Bertrand et al., 2019; Seierstad et al., 2017; Tampakoudis et al., 2022).

The impact of gender diversity on banks and firms in general

A few studies have examined the effect of board gender composition on the banking industry, yielding conflicting results, including Adams and Mehran (2012), Berger et al. (2014), García-Meca et al. (2015), Owen and Temesvary (2018), and Pathan and Faff (2013). Female directors are likely to be more risk-averse than their male counterparts, which might contribute to a reduction in financial distress costs and systemic risk (Bayazitova & Shivdasani, 2012) and, thus, a reduction in the likelihood that the bank would require a public bailout (Cardillo et al., 2021). Besides that, gender diversity seems to increase the sensitivity of executive compensation and CEO turnover to firm performance. Female directors tend to supervise more carefully than male directors. In addition, gender diversity tends to improve the performance of companies with inadequate governance procedures (Adams & Ferreira, 2009; Cardillo et al., 2021). Chakrabarty and Bass (2014) find that microfinance institutions indicate that more women are better able to reduce operational expenses, and Strøm et al. (2014) find that more women enhance financial performance (García-Meca et al., 2015). Moreover, as they are not part of "old boys' networks" and are less tolerant of opportunistic activity, women directors are more independent and careful monitors (Fan et al., 2019).

Gender-based differences in behavior and actions are widely recognised in the fields of cognitive psychology and behavioral economics. These differences have been extensively documented and are believed to be linked to various factors such as information processing, diligence, conservatism, overconfidence, and risk tolerance. It is commonly observed that women and men exhibit varying patterns of behavior, which have significant implications for various aspects of life, including decision-making, financial management, and social interactions (Byrnes et al., 1999; Costa et al., 2001; Croson & Gneezy, 2009; Eckel & Grossman, 2002; Feingold, 1994; Nettle, 2007; Palvia et al., 2014; Powell & Ansic, 1997; Schmitt et al., 2008).

Many papers mention the positive impact of a woman on mitigating the risk of banks and firms. For example, Palvia et al. (2014) demonstrate that banks led by female CEOs tend to maintain more conservative capital levels, even after accounting for the size of their assets. Such banks also exhibit a lower likelihood of failure during financial crises, and their leaders tend to make cautious and conservative decisions, as Barua et al. (2010) and Krishnan and Parsons (2008) noted. Additionally, these banks tend to pursue less risky financing and investment decisions, as highlighted by Faccio et al. (2016), and are less likely to engage in acquisitions or debt issuance, as noted by Huang and Kisgen (2013). Moreover, the existing body of research suggests that gender diversity in corporate leadership leads to a more risk-averse decision-making approach, as highlighted by Adams and Ragunathan (2017) and Croson and Gneezy (2009). This approach, in turn, can positively impact the risk profile of banks, as Farag and Mallin (2017) noted, resulting in a reduced probability of a public bailout and higher payout ratios, as observed by Cardillo et al. (2021). Female leaders also exhibit a greater tendency to monitor organisational activities and are more averse to risk, as evidenced by Del Prete and Stefani (2021). Furthermore, the presence of at least one woman on the board is associated with a 20% lower likelihood of bankruptcy, as demonstrated by Ghosh (2017), and can help prevent earnings management, according to Fan et al. (2019). These findings highlight the potential benefits of gender diversity in corporate leadership, particularly in the financial sector.

The impact of gender diversity on bank performance

The existing body of empirical research on the impact of gender diversity on bank performance has yielded conflicting results. Several studies have reported a positive association between gender diversity and bank performance, such as Adams and Ragunathan (2017), Andrieș et al. (2020), Belhaj and Mateus (2016), Cardillo et al. (2021), Del Prete and Stefani (2021), Elsharkawy et al. (2018), García-Meca et al. (2015), Geyfman et al. (2018), Hoang et al. (2021), Owen and Temesvary (2018), Pathan and Faff (2013), and Romano et al. (2012).

Some studies have found that gender diversity has an insignificant or little impact on the performance of banks or firms. For example, Farrell and Hersch (2005), Fernández-Temprano and Tejerina-Gaite (2020), Ferrari et al. (2016), Gregory-Smith et al. (2014), and Marinova et al. (2015). In addition, Issa et al. (2021) illustrate an insignificant relationship between gender diversity in educational levels and bank performance.

In contrast to studies highlighting the benefits of gender diversity or reporting insignificant effects, some research identifies a negative association between bank gender diversity and firm performance, such as Ahern and Dittmar (2012), Haslam et al. (2010), Hoang et al. (2021), and Jadah et al. (2016). In a separate paper, Adams and Ferreira (2009) show that corporations with a high level of board diversity are more likely to pay higher incentives, hold more board meetings, and experience worse operating performance. According to Ramly et al. (2015), a larger proportion of women on bank boards in five Asian nations reduces bank efficiency. In addition, Tampakoudis et al. (2022) show a negative association between female board membership and shareholder wealth in acquiring US banks after the banking crisis.

Performance measures

There are several performance measures, but the most common is the return on asset (ROA), which is net income divided by gross total assets (GTA), as employed by numerous studies, such as Adams and Ragunathan (2017), El-Chaarani et al. (2019), Ghosh (2017), Marimuthu (2020), Neely (2007), Nouaili et al. (2015), and Stefanovic and Barjaktarovic (2021). The second common performance measure is the return on equity (ROE), which is net income divided by total equity. Examples of papers that use (ROE) to measure performance are El-Chaarani et al. (2019), Neely (2007), and Nouaili et al. (2015). The third measure of performance is (Tobin's Q), which is the ratio of the firm's market value of assets to its book value of assets, as utilised by Adams and Ragunathan (2017), Ghosh (2017), and Stefanovic and Barjaktarovic (2021).

Several studies concentrate on other performance measures. Abaenewe et al. (2013) illustrate that stock prices and their behaviour indicate a firm's performance. Additionally, the number of deposits, the size of the bank, and its profitability may be seen as more reliable measures of bank performance. Moreover, profit growth, sales growth, and competitive reaction are used to measure financial performance (Bontis et al., 2000). Seçme et al. (2009) assess performance by utilising capital adequacy, asset quality, profitability, and liquidity. Wu et al. (2009) employ sales, debt ratio, return on assets, earnings per share, net profit margin, and return on investment as indexes. Also, Hamann et al. (2013) use stock market performance and accounting return to evaluate the financial performance of the firms (Dikko & Alifiah, 2020).

Owen and Temesvary (2018) employ four performance measures for banks. The first measure is the revenue to expense ratio, which is the ratio of a bank's operating revenue to its operating expenses and it serves as a measure of its operational efficiency.[14] The second measure is the return on assets (ROA), which is a bank profitability measure. The third measure is the Sharpe ratio on a bank's books, which is a risk indicator, accounting for the impact of a risky activity on bank performance. The first three measures are based on bank financial statements. The fourth measure is the annual stock price growth, which is based on a market-based measure.

[14] This measure is the opposite of the efficiency ratio, a common performance indicator in banking.

Gender diversity measures

The measure of board gender diversity used in the literature is the percentage of women board members. Independence is the proportion of independent board members. To categorise directors' gender percentage and independence, some literature relies on Boardex's categories (Adams & Ragunathan, 2017).

Owen and Temesvary (2018) use the Blau Index as the primary indicator of gender diversity on boards (Bear et al., 2010; Blau, 1977). This measure has a maximum value of 50 when gender equality on boards is achieved when men and women have equal representation at 50%. Lower Blau Index scores imply higher gender disparity. In addition, they contain the spread of bank board tenure, board experience, and overall board time frame to represent the dispersion of board members' expertise. Spread is defined for each variable as the logarithm of the difference between the average and median board experience metric, divided by the median value.

To the best of our knowledge, this is the first empirical study to investigate the impact of different categories of female board representation on bank performance over an extended period following the financial crisis in the United States, using accounting measures such as return on equity (ROE) and return on assets (ROA). This chapter examines how these categories influence bank performance during the post-crisis recovery, offering valuable insights into the long-term impact of board diversity. Specifically, our final data includes 179 bailout BHCs and 434 BHCs that have not received bailouts from 2003 to 2019, providing a more extended coverage period than prior studies. We hypothesise that post-bailout, banks with a specific percentage of women on their boards outperform those without female representation or with a lower percentage of women. We use the multivariate fixed effect regression technique to test our hypothesis and estimate a multivariate model for all BHC samples with accounting-based covariates. The fixed effects approach accounts for unobserved, time-invariant differences between banks and mitigates serial correlation issues. By the classification proposed by Kanter (1977b), we have categorised the ratio of women into four main groups. By using this classification, we determine the ideal female representation on the bank's board of directors, which appears to enhance the bank's performance.

3.3 Methodology

In this section, we provide an overview of our dataset's sources. Subsequently, we proceed to elaborate on the methodology employed for forming the sample under examination. Finally, we describe the key independent and dependent variables utilised in our regression estimate.

3.3.1 Research Data

This empirical study gathers data from various sources to conduct our analysis. Specifically, accounting data from 2003 to 2019 are obtained from the Federal Reserve Bank (FRB) of Chicago, which served as the primary source of accounting information for US Bank Holding Companies (BHCs). Second, we use the CRSP-FRB link (provided by the Federal Reserve Bank of New York) to obtain PERMCO IDs. We obtain bailout data from the US Treasury Department. The US bank board data from 2003 to 2019 are sourced from BoardEx. Finally, we use the BoardEx-CRSP Compustat Link to merge CRSP with BoardEX. These sources are selected to provide a comprehensive examination of the data.

3.3.2 Sample Construction

Our sample selection is limited to US-based bank holding companies (BHCs) due to the specific focus of our research. First, we gather accounting data from the Federal Reserve Bank (FRB) of Chicago and link it with the bailout data obtained from the US Treasury Department. Then, we use the CRSP-FRB link (provided by the Federal Reserve Bank of New York) [15] to connect entity IDs (RSSD9001) in the FR Y-9C to PERMCO IDs in CRSP to merge the data, which is an effective

[15] The link (https://www.newyorkfed.org/research/banking_research/datasets.html) will take you to the website of the Federal Reserve Bank (FRB) of New York.

method utilised by previous papers (Gandhi et al., 2019; Goetz et al., 2016). After that, we use the BoardEx-CRSP Compustat Link to match the FRB dataset with BoardEx using PERMCOs.[16]

Our sample starts in 2003 because BoardEx data coverage before 2003 is limited, and it ends in 2019 to avoid the effect of the COVID-19 pandemic. We exclude companies that have missing data points or missing reporting periods between their first and last years in the sample. The final dataset includes 2,317 bank-year observations of 179 bailout BHCs and 2,766 bank-year observations of 434 BHCs that have not been bailed out.

3.3.3 Measurement of Dependent Variables

In the empirical research, various metrics have been employed to assess performance category, with common choices including return on equity (ROE), computed as net income divided by total equity, and return on assets (ROA), calculated as net income divided by gross total assets (GTA).

3.3.3.1 Return on Equity (ROE)

The metric is indicative of a bank's general performance, with a particular emphasis on its profitability. As both net income and equity encapsulate a bank's on- and off-balance-sheet activities, we adopt the approach of Berger and Bouwman (2013) and employ Return on Equity (ROE) as a comprehensive indicator of profitability. We anticipate that a higher proportion of female representation in leadership positions will be positively correlated with profitability.

3.3.3.2 Return on Asset (ROA)

We utilise the return on assets as a measure that permits the evaluation of the reliability of profitability indicators when there is an increase in the proportion of female representation on the board of directors, following the approach of Cardillo et al. (2021). We posit a positive relationship exists between the proportion of female representation and profitability.

[16] The link (Wharton Research Data Services (upelnn.edu)) will take you to the website of the WRDS platform.

3.3.4 Measurements of Independent Variables

3.3.4.1 Post Bailout Time: It is a variable that presents the Year 2010-2019 dummy for these years

3.3.4.2 Bailed Dummy Variable: It is 0 before and 1 after the bailout.

3.3.4.3 Women Categories

We follow critical mass theory, proposed by Kanter (1977a, 1977b), and posits that the nature of group interactions is contingent upon the size of the subgroup. Specifically, critical mass theory proposes that as the size of the subgroup reaches a certain threshold, referred to as a "critical mass", the subgroup's ability to exert influence within the larger group is amplified. (Torchia et al., 2011).

According to Kanter (1977b), the representation of women on corporate boards can be classified into four distinct categories. These categories include uniform groups, where there is an absence of female representation (0% women); skewed groups, where there is a minimal representation of women (up to 20% women); tilted groups, where there is a moderate representation of women (20-40% women); and balanced groups, where there is a substantial representation of women (40-60% women).

Additionally, it's important to note that the "critical mass" of women directors can be measured in different ways, such as through the number of female board members (at least three female board members) (Torchia et al., 2011) or the percentage of women on corporate boards (30% of WOCBs) (Joecks et al., 2013).

We classified the women into four categories as proposed by Kanter (1977b):

3.3.4.3.1 Uniform groups: Where there is an absence of female representation (0% women). It is a dummy variable that is 1 if there are no women on the board, and 0 if there is at least one woman on the board.

3.3.4.3.2 Skewed groups: Where there is minimal representation of women (up to 20% women). A dummy variable is 1 if up to 20% of the board members are women, and 0 otherwise.

3.3.4.3.3 Tilted groups: Where there is a moderate representation of women (20-40% women). A dummy variable is 1 if more than 20% and less or equal to 40% of the board members are women, and 0 otherwise.

3.3.4.3.4 Balanced groups: Where there is a substantial representation of women (40-60% women). A dummy variable is 1 if more than 40% and less or equal to 60% of the board members are women, and 0 otherwise.

3.3.4.4 Capital

The level of capital is a crucial element in determining the health of a bank and in ensuring stability in the financial system. It serves as a vital indicator in the models employed by regulatory bodies and is frequently utilised as the primary metric in numerous academic studies (Berger & Bouwman, 2009). The bank's capability to fulfil its financial obligations can be gauged through its capital level, represented by the ratio of total equity to total gross assets (Capital Ratio) (Berger et al., 2016).

3.3.4.5 Real Estate Loans to Gross Total Assets

Cole and White (2012) contend that commercial real estate plays a significant role in the failure of financial institutions during the global financial crisis. As a result, the analysis incorporates commercial real estate as a determinant, with the variable represented by the ratio of real estate to gross total assets (GTA).

3.3.4.6 Bank Size

Cole and White (2012) posit that bank size, akin to capital, may serve as a source of economic strength for a financial institution, yet both possess diminishing marginal utility. Cole and White (2012) confirm that smaller banks are more susceptible to failure than larger banks; thus, the size of a bank is deemed to have a detrimental effect on the probability of bankruptcy. The logarithm of gross total assets (GTA) is employed as a surrogate measure for bank size.

3.3.4.7 IETL

The ability of a bank to fulfil its current obligations and unanticipated withdrawals by depositors and creditors hinges on its liquidity. Betz et al. (2014) suggest that the interest expense-to-total-liabilities ratio is a conventional metric employed to gauge liquidity.

3.3.4.8 Gross Loan

In the assessment of credit expansion, the application of the natural logarithm of gross loans is utilised. As employed by Tehulu (2022), this measure is a common method for gauging credit expansion.

3.3.4.9 Liquidity

The customer deposits to gross loan ratio is a metric that reflects the proportion of the gross loan portfolio that is financed by customer deposits. A higher ratio signifies a greater dependence on these deposits to fund lending activities, potentially enhancing liquidity. This measure has been employed by Cucinelli (2015). Furthermore, Wang and Wang (2015) have established an association between high levels of customer deposits and an increased capacity to issue loans and investments. The availability of greater deposits affords financial institutions greater flexibility in their decision-making processes and reduces exposure to the risk of insolvency.

3.3.4.10 Number of Directors

To account for the size of the board, we utilise the number of executive directors, supervisory directors, or all of the directors, as chosen on the Annual Report Date. Measuring board size by taking into account the number of directors is a standard method used by Belkhir (2008).

3.3.4.11 Average Age

We follow Owen and Temesvary (2018) to capture the average demographic characteristics of a board. The Average Age of Board Members is incorporated, wherein the natural logarithm of the average age of board members is computed. This measure serves as a reliable representation of the overall age composition of the board.

3.3.4.12 Experience Measures

To evaluate the level and dispersion of expertise among board members of banks, we apply three measures proposed by Owen and Temesvary (2018).

3.3.4.12.1 Average experience

The natural logarithm of the mean number of corporate board tenures (private, quoted, or other) served by board members over their careers defines the concept of Average Board Experience.

3.3.4.12.2 Average bank board tenure

We adopt the Average Bank Board Tenure measure, which involves computing the natural logarithm of the average number of years that board members have served on bank boards. This measure provides a robust representation of the collective board experience and proficiency.

3.4.12.3 Average Listed Board Tenure

The average listed board tenure is defined as the natural logarithm of the mean number of years that board members have served on the board of a publicly listed company.

To mitigate the effect of extreme values on our statistical estimations, we winsorise all variables at a 1% level, as per the recommendations in the relevant literature.

Table 3.1 defines all covariates in detail.

Table 3.1: Description of the Variables

Variable	Description	Data source
Dependent Variables		
ROE	Earning quality: return on equity = net Income / total Equity.	Federal Reserve Bank (FRB) of Chicago
ROA	Return on Assets = Net Income / Gross Total Assets.	Federal Reserve Bank (FRB) of Chicago
Independent Variables		
Post bailout time	The year 2010-2019 dummy for these years	The US Treasury Department
Bailed	Dummy variable: It is 0 before and 1 after the bailout.	The US Treasury Department
Women Ratio	The proportion of women directors on the firm's boards.	BoardEx
Uniform groups	Dummy variable: 1 if there is no woman on the board and 0 otherwise.	BoardEx
Skewed groups	Dummy variable: It is 1 if there is up to 20% of the board are women, and 0 otherwise.	BoardEx
Tilted groups	Dummy variable: 1 if there is more than 20% and less or equal to 40% of the board are women, and 0 otherwise.	BoardEx
Balanced groups	Dummy variable: 1 if there is more than 40% and less or equal 60% of the board are women, and 0 otherwise.	BoardEx
Interaction dummy	The result of multiplying post-bailout time with bailed and the categories of women ratio.	
Control Variables		
Capital	Total Equity divided by GTA.	Federal Reserve Bank (FRB) of Chicago
RELGTA	Real-estate loans: Real-estate loans / (GTA).	Federal Reserve Bank (FRB) of Chicago
LGTA	Bank size: natural logarithm of (GTA).	Federal Reserve Bank (FRB) of Chicago
IETL	Liquidity: IETL = total Interest expenses / total Liabilities.	Federal Reserve Bank (FRB) of Chicago
LnGrossLoan	Natural logarithm of gross loans.	Federal Reserve Bank (FRB) of Chicago
Liquidity	Liquidity = customer deposit / gross loan.	Federal Reserve Bank (FRB) of Chicago
NumberDirectors	the number of executives, supervisory, or all directors, as chosen on the annual report date to account for the board size.	BoardEx
LnAveAge	The natural logarithm of the average age of board members.	BoardEx
LnAveExp	Natural logarithm of the average number of company boards (private, quoted, or other) that board members have served on over their careers.	BoardEx
LnAveBankBrdTenure	Natural logarithm of the average number of years that board members have spent on bank boards.	BoardEx
LnAveListedBrdTenure	The average number of years board members have sat on a board of a publicly listed company.	BoardEx

Notes: The present study utilises a set of dependent and independent variables and control variables to construct the empirical analysis. A comprehensive overview of these variables is provided in this Table, where the first column lists the names of the variables, the second column provides their definitions, and the third column specifies the data sources utilised.

3.4 Empirical Model and Method

In this section, we present a summary of the statistics for our variables, along with crucial information regarding their intercorrelation. Subsequently, we evaluate each variable's economic and statistical significance through multivariate fixed effect regression analysis to estimate the model for all BHC samples incorporating accounting-based covariates. The major findings are thoroughly explained.

3.4.1 Descriptive Statistics and Correlation

Table 3.2 provides a comprehensive overview of the summary statistics for our variables. It is observed that there are significant differences between the bailed-out and non-bailed-out banks. The bailed-out banks have lower mean values of return on equity (ROE) and return on assets (ROA), higher women ratio, lower levels of capital, a lower proportion of real estate loans, larger bank size, higher liquidity, and higher level of experience compared to the non-bailed-out banks.

Given the increased volatility associated with these institutions, the lower mean values of ROE and ROA in bailed-out banks are expected. A lower ROE and ROA are indicative of poor performance. The mean value of (Capital) for bailed-out banks is lower than for non-bailed-out banks, indicating less stability in the bailed-out banks. The mean value of real estate loans (REALGTA) for bailed-out banks, at around 0.47, is lower than that of the non-bailed-out banks, indicating a lower level of risk. Additionally, the mean value of bank size (LGTA) is higher in bailed-out banks, implying that bank size is crucial. The mean values of the total Interest expenses to total Liabilities (IETL) and customer deposits to gross loans (Liquidity) in the bailed-out have higher liquidity.

Drawing on data from bailed-out banks, it is evident that the (LnAveExp), which captures the average board experience of board members across all boards they have served on, exhibits considerable variation. The average number of boards on which board members have served is 5, with some banks showing values as high as 13. Additionally, the (LnAveBankBrdTenure), representing the average length of board membership across all banks, ranges from 2 to 13 years, with a mean of approximately 9 years. The (LnAveListedBrdTenure), measuring the average duration of board membership for listed companies, is estimated to be around 6 years, although some bank boards have values as high as 14 years. Notably, non-bailed-out banks show lower mean values of all experience measures by nearly a year.

Table 3.2: Summary Statistics Without Categories

Variable	Banks that have been bailed out					Banks that have not been bailed out				
	Mean	Sd	Min	Median	Max	Mean	Sd	Min	Median	Max
ROE	0.1696	0.2888	-1.5111	0.2212	0.6122	0.1860	0.2585	-1.5111	0.2168	0.6122
ROA	0.0177	0.0224	-0.0909	.02218	0.0683	0.0199	0.0199	-0.0909	0.0220	0.0683
Women Ratio	0.1253	0.0965	0	0.111	0.5	0.1087	0.0891	0	0.1	0.5
Capital	0.0989	0.0227	0.0433	0.0974	0.1756	0.1040	0.0317	0.0433	0.0987	0.2135
RELGTA	0.4771	0.1543	0.0014	0.4945	0.8106	0.5075	0.1712	0.0014	0.5273	0.8106
LGTA	15.4705	1.7064	12.1898	15.0192	20.6308	14.7828	1.4204	12.6276	14.5225	20.6308
IETL	0.0358	0.0249	0.0032	0.0297	0.1007	0.0349	0.0245	0.0032	0.0280	0.1007
LnGrossLoan	15.0417	1.6647	12.2619	14.6463	19.6790	14.3200	1.3376	12.1079	14.1009	19.6790
Liquidity	0.1620	0.1434	0.0001	0.1136	0.7962	0.1478	0.1293	0.0001	0.1137	0.7962
NumberDirectors	11.7941	2.8200	6	12	20	11.0654	3.1553	6	11	20
LnAveAge	4.1228	0.0577	3.9659	4.1239	4.2789	4.1202	0.0630	3.9659	4.1219	4.2789
LnAveExp	1.6195	0.4088	0.7621	1.5841	2.5925	1.4946	0.3770	0.7621	1.4469	2.5925
LnAveBankBrdTenure	2.1892	0.4254	0.3364	2.2532	2.9444	2.0610	0.5802	0.3364	2.1984	2.9444
LnAveListedBrdTenure	1.7881	0.5827	0	1.9328	2.6112	1.6414	0.6364	0	1.7676	2.6112
Bailed	1	0	1	1	1	0	0	0	0	0

Notes: This Table provides descriptive data for all variables in consideration, covering the period between 2003 and 2019 for both bailout banks and non-bailout bank holding companies (BHCs).

The results of the pairwise correlation analysis are represented in Table 3.3. The Table demonstrates that the correlation among all the accounting measures is restricted between low to moderate, at a significance level of 1%, whereas bailed variable at a significance level of 5%. There are two exceptions, the average age and the average listed tenure, which are insignificant with one of the performance measures. Furthermore, Table 3.3 reveals that the performance measures exhibit a low correlation with all the accounting variables.

Table 3.3: Pairwise Correlations Without Categories

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) ROE	1.0000														
(2) ROA	0.9259 ***	1.0000													
(3) Women Ratio	0.0486***	0.0849***	1.0000												
(4) Capital	0.1155 ***	0.2895***	0.1282***	1.0000											
(5) RELGTA	-0.1567***	-0.1944***	-0.1902***	-0.1111***	1.0000										
(6) LGTA	0.1191***	0.1778***	0.3574***	0.1805***	-0.5035	1.0000									
(7) IETL	-0.0926***	-0.1594***	-0.2002***	-0.3127***	0.1728***	-0.2062***	1.0000								
(8) LnGrossLoan	0.1086***	0.1625***	0.3486***	0.1670***	-0.3778***	0.9751***	-0.1871***	1.0000							
(9) Liquidity	0.1274***	0.1730***	0.0930***	0.1296***	-0.2908***	0.1540***	-0.4320***	0.0801***	1.0000						
(10) NumberDirectors	0.0749***	0.0819***	0.1558***	0.0279**	-0.1589***	0.3697***	-0.0127***	0.3722***	0.0195	1.0000					
(11) LnAveAge	0.0064	0.0489***	0.0296**	0.1633***	-0.0570***	0.1753***	-0.2847***	0.1605***	0.1660***	0.0377***	1.0000				
(12) LnAveExp	0.0218***	0.0753***	0.2259***	0.1852***	-0.4125***	0.6202***	-0.1917***	0.5976***	0.0935***	0.1981***	0.1069***	1.0000			
(13) LnAveBankBrdTenure	0.0700***	0.0657***	-0.0665***	-0.1435***	-0.0631***	-0.0087***	0.0150***	0.0168***	0.0874***	0.0045***	0.2191***	-0.1760***	1.0000		
((14) LnAveListedBrdTenure	-0.0691***	0.0098	0.2637***	0.2729***	-0.1649***	0.4505***	-0.4467***	0.4522***	0.2218***	0.0661***	0.3734***	0.3437***	0.3105***	1.0000	
(15) Bailed	-0.0299**	-0.0517***	0.0890***	-0.0916***	-0.0921***	0.2125***	0.0180	0.2337***	0.0517***	0.1198***	0.0217	0.1568***	0.1234***	0.1185***	1.0000

Note: This Table presents the correlations among the variables.

3.4.2 The Multivariate Fixed Effect Regression Analysis

This study looks at both gender diversity and diversity of experience to better understand the impact of different perspectives and backgrounds on the outcomes that we are analysing. We utilise the multivariate fixed effect regression technique to estimate a multivariate model for all BHC samples with accounting-based covariates. The following is the model's specification:

$$Performance\ measure_{b,t} = \beta_0 + \beta_1 post\ bailout\ time_{b,t} + \beta_2 bailed_{b,t} + \beta_3 gender\ ratio_{b,t} + \beta_4 post\ bailout\ time_{b,t} * bailed_{b,t} * gender\ ratio_{b,t} + \beta_5 Capital_{b,t} + \beta_6 RELGTA_{b,t} + \beta_7 LGTA_{b,t} + \beta_8 IETL_{b,t} + \beta_9 LnGrossLoan_{b,t} + \beta_{10} Liquidity_{b,t} + \beta_{11} NumberDirectors_{b,t} + \beta_{12} LnAveAge_{b,t} + \beta_{13} LnAveExp_{b,t} + \beta_{14} LnAveBankBrdTenure_{b,t} + \beta_{15} LnAveListedBrdTenure_{b,t} + \delta_{\mathrm{b}} + \varepsilon_{\mathrm{b,t}}$$
(1)

Where $performance\ measures$ are ROE and ROA, the ROE is net income divided by total equity, and ROA is net income divided by gross total assets. The $Post\ bailout\ time_i$ is a dummy variable that takes 1 for the period from 2010 to 2019 and zeroes otherwise, representing the treatment period, which is a period proceeding the bailout and global financial crisis. The $bailed_i$ is a dummy variable that represents the banks that got a bailout. The $gender\ ratio$ includes four categories. The first one is the uniform groups, a dummy variable that takes 1 if there is no woman on the board, and 0 otherwise. The second category is the skewed groups, a dummy variable that takes 1 if up to 20% of the board are women, and 0 otherwise. The third category is the tilted groups, a dummy variable that takes 1 if there is more than 20% and up to 40% of the board are women, and 0 otherwise. The fourth category is the balanced groups, a dummy variable that takes 1 if there is more than 40% and less or equal to 60% of the board are women, and 0 otherwise. The $post\ bailout\ time_i * bailed_i * gender\ ratio_i$ is an interaction dummy resulting from multiplying post-bailout time with bailed and the categories of women ratio. δ_b is BHC fixed effects, and $\varepsilon_{\mathrm{b,t}}$ is an error term. The fixed effects approach accounts for unobserved, time-invariant differences between banks and mitigates serial correlation issues.[17]

By the classification proposed by Kanter (1977b), we have divided the ratio of women into four distinct categories. This categorisation allowed us to identify an optimal range of the female ratio of bank board directors, which is believed to improve the performance of the banks. The first category, referred to as the "uniform groups", is presented in Table 3.4. Our findings indicate that when the women ratio is zero in the board of directors (uniform groups), the interaction dummy has no statistically significant impact on bank performance. These results are consistent with Joecks et al. (2013), who find insignificant results under the uniform groups.

[17] In the panel data, we employ the Hausman test to determine whether to use the fixed effects or random effects model. The outcome recommends the use of the fixed effects model.

Table 3.4: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Uniform Groups

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.055***	-0.002**	0.026	0.001
	(-3.77)	(-2.01)	(1.01)	(0.97)
Bailed	0.020	0.003**	0.0004	0.001
	(1.00)	(2.17)	(0.02)	(0.83)
Uniform groups	0.007	0.0004	0.006	0.0007
	(0.34)	(0.27)	(0.31)	(0.51)
Interaction dummy	-0.019	-0.003	0.027	0.0006
	(-0.68)	(-1.45)	(0.85)	(0.30)
Capital			4.002***	0.357***
			(6.46)	(8.78)
RELGTA			-0.293	-0.024*
			(-1.59)	(-1.82)
LGTA			-0.361**	-0.030***
			(-2.45)	(-2.82)
IETL			0.139	-0.002
			(0.46)	(-0.09)
LnGrossLoan			0.325**	0.029***
			(2.33)	(2.86)
Liquidity			0.256***	0.022***
			(4.37)	(5.20)
NumberDirectors			0.007**	0.0005**
			(2.20)	(2.04)
LnAveAge			-0.056	-0.002
			(-0.28)	(-0.20)
LnAveExp			-0.055	-0.003
			(-1.47)	(-1.45)
LnAveBankBrdTenure			0.122***	0.009***
			(4.43)	(4.74)
LnAveListedBrdTenure			-0.171***	-0.012***
			(-10.71)	(-11.12)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,083	5,083	4,893	4,893
Number of groups	613	613	592	592
R-squared	0.0071	0.0020	0.1454	0.1766

Notes: This Table displays the results of a fixed-effects regression model when we apply the uniform groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

The second category, presented in Table 3.5, is referred to as the "skewed groups", in which the ratio of women on the board of directors is up to 20%. Based on the results of the skewed groups, the interaction dummy has a significant and negative effect on performance, leading to a decrease of 5.9% in ROE and 0.4% in ROA, which contrasts with the finding of Joecks et al. (2013).

Our findings suggest that, under the skewed groups, banks with a higher level of capital are more likely to be more profitable. This finding aligns with the conclusions of Berger (1995), wherein a positive correlation is established between capital and return on equity (ROE).

Additionally, the control variables, such as real estate loans and bank size, have significant negative coefficients, implying that banks with larger real estate loans and greater bank size are more likely to reduce overall performance. The present study finds agreement with the research conducted by Onchomba et al. (2018), demonstrating that real estate loans exhibit an inverse correlation with the return on assets (ROA). In addition, our study's findings align with the research conducted by Pasiouras and Kosmidou (2007), indicating that bank size exerts a detrimental impact on bank performance, regardless of whether domestic or foreign banks are tested.

The liquidity measure, the customer deposits to gross loan ratio, significantly and positively affects performance measures. Our study's findings align with the research conducted by Trujillo-Ponce (2013), which establishes that customer deposits positively impact both returns on equity (ROE) and returns on assets (ROA).

Based on the natural logarithm of gross loan measure, an increase in credit expansion has a significant and positive effect on ROE and ROA. Our study's findings align with the research conducted by Tehulu (2022), which establishes a positive and significant correlation between gross loans and financial sustainability. Furthermore, Martins et al. (2019) demonstrate that banks with greater loan intensity tend to generate higher profits.

Regarding the board size, our findings show that an increase in board size enhances bank performance. This is consistent with Belkhir (2008), who identifies a positive relationship between board size and bank performance, challenging the idea that smaller boards are more efficient. In addition, we do not find significant evidence that the natural logarithm of the average age of board members affects bank performance.

We do not find significant evidence of the effect of the average number of corporate boards tenures on bank performance.

We do not find significant evidence of the effect of the average number of company boards served by board members over their careers on bank performance. The average number of years that board members have served on the board of a publicly listed company has a negative and significant effect on bank performance. These results imply that the type of experience that improves bank performance is the average board tenure in banks, not necessarily more years of experience with publicly listed companies or the average number of boards served on during their careers.

Table 3.5: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Skewed Groups

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.058***	-0.002**	0.027	0.001
	(-4.01)	(-2.18)	(1.06)	(1.03)
Bailed	0.050**	0.005***	0.042	0.004**
	(2.09)	(2.87)	(1.49)	(2.16)
Skewed groups	0.028	0.001	0.027	0.001
	(1.47)	(1.16)	(1.54)	(1.32)
Interaction dummy	-0.054**	-0.004**	-0.059**	-0.004**
	(-2.36)	(-2.42)	(-2.42)	(-2.51)
Capital			3.976***	0.356***
			(6.48)	(8.81)
RELGTA			-0.283	-0.023*
			(-1.56)	(-1.78)
LGTA			-0.364**	-0.030***
			(-2.53)	(-2.90)
IETL			0.163	-0.00007
			(0.54)	(-0.00)
LnGrossLoan			0.325**	.029***
			(2.39)	(2.92)
Liquidity			0.248***	0.022***
			(4.22)	(5.11)
NumberDirectors			0.006*	0.0004*
			(1.95)	(1.86)
LnAveAge			-0.039	-0.001
			(-0.19)	(-0.13)
LnAveExp			-0.050	-0.003
			(-1.39)	(-1.38)
LnAveBankBrdTenure			0.126***	0.009***
			(4.60)	(4.96)
LnAveListedBrdTenure			-0.173***	-.012***
			(-10.71)	(-11.19)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,083	5,083	4,893	4,893
Number of groups	613	613	592	592
R-squared	0.0089	0.0032	0.1470	0.1787

Notes: This Table displays the results of a fixed-effects regression model when we apply the skewed groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

The third category, presented in Table 3.6, is referred to as the "tilted groups", in which the ratio of women on the board of directors ranges from more than 20% to a maximum of 40%. Our findings based on this group indicate that the interaction dummy has a significant and positive effect on performance, resulting in an increase of 8.2% in ROE and 0.7% in ROA. Our findings under tilted groups align with the empirical evidence presented by Joecks et al. (2013), who specify that a critical mass of female representation on boards is achieved when the proportion of women falls within the range of 20% to 40%.

The control variables show consistent results, as discussed previously.

Table 3.6: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Tilted Groups

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.052***	-0.001*	0.028	0.002
	(-3.50)	(-1.78)	(1.09)	(1.07)
Bailed	0.004	0.0005	-0.008	0.0002
	(-0.24)	(0.34)	(-0.32)	(0.16)
Tilted groups	-0.079**	-0.005**	-0.068**	-0.004**
	(-2.20)	(-2.03)	(-2.03)	(-2.14)
Interaction dummy	0.114***	0.009***	0.082**	0.007***
	(3.08)	(3.71)	(2.21)	(2.73)
Capital			3.961***	0.354***
			(6.50)	(8.84)
RELGTA			-0.295	-0.024*
			(-1.59)	(-1.77)
LGTA			-0.361**	-0.030***
			(-2.47)	(-2.84)
IETL			0.145	-0.001
			(0.48)	(-0.06)
LnGrossLoan			0.325**	0.029***
			(2.34)	(2.85)
Liquidity			0.249***	0.022***
			(4.15)	(4.95)
NumberDirectors			0.007**	0.0004*
			(2.05)	(1.94)
LnAveAge			-0.056	-0.002
			(-0.27)	(-0.17)
LnAveExp			-0.054	-0.003
			(-1.47)	(-1.42)
LnAveBankBrdTenure			0.122***	0.009***
			(4.40)	(4.78)
LnAveListedBrdTenure			-0.168***	-0.012***
			(-10.58)	(-10.99)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,083	5,083	4,893	4,893
Number of groups	613	613	592	592
R-squared	0.0122	0.0076	0.1480	0.1801

Notes: This Table displays the results of a fixed-effects regression model when we apply the tilted groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

The fourth category, presented in Table 3.7, is referred to as the "balanced groups", in which the ratio of women on the board of directors ranges from more than 40% to a maximum of 60%. Our analysis of this group suggests that the interaction dummy variable does not statistically affect the return on equity (ROE). These results are consistent with Joecks et al. (2013), who find positive and insignificant results under the balanced groups. However, we observe a statistically significant coefficient on the return on assets (ROA). It should be noted that the significance level of this coefficient is only 10%, and the coefficient is 1.2%, which may not be economically meaningful.

Moreover, the significance level is not consistent when we introduce control variables. This suggests that other factors may influence the relationship between the interaction dummy and ROA. It is important to account for these factors in future analyses to obtain a more accurate understanding of the relationship.

Additionally, the ROE measure has a stronger coefficient across all categories of women's ratios. This suggests that gender diversity may have a stronger impact on ROE than on ROA. Future research could investigate this relationship further and explore potential mechanisms for this difference.

Overall, our findings of the control variables are consistent with the results observed in all groups.

Table 3.7: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Balanced Groups

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.056***	-0.002**	0.025	0.001
	(-3.90)	(-2.08)	(1.00)	(0.96)
Bailed	0.016	0.002*	0.005	0.001
	(0.83)	(1.77)	(0.22)	(0.94)
Balanced groups	-0.056	-0.0049	0.013	0.001
	(-0.74)	(0.438)	(0.15)	(0.15)
Interaction dummy	0.135	0.012*	0.068	0.006
	(1.49)	(1.83)	(0.60)	(0.73)
Capital			3.988***	0.357***
			(6.46)	(8.81)
RELGTA			-0.285	-0.024*
			(-1.56)	(-1.80)
LGTA			-0.359**	-0.030***
			(-2.46)	(-2.84)
IETL			0.127	-0.002
			(0.42)	(-0.11)
LnGrossLoan			0.321**	0.029***
			(2.32)	(2.87)
Liquidity			0.252***	0.022***
			(4.30)	(5.18)
NumberDirectors			0.007**	0.0004**
			(2.08)	(1.96)
LnAveAge			-0.052	-0.002
			(-0.26)	(-0.19)
LnAveExp			-0.050	-0.003
			(-1.39)	(-1.38)
LnAveBankBrdTenure			0.124***	0.009***
			(4.46)	(4.81)
LnAveListedBrdTenure			-0.171***	-0.012***
			(-10.65)	(-11.10)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	5,083	5,083	4,893	4,893
Number of groups	613	613	592	592
R-squared	0.0072	0.0016	0.1451	0.1768

Notes: This Table displays the results of a fixed-effects regression model when we apply the balanced groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Most of the literature concurs that there is a linear relationship between gender diversity and performance. However, our findings confirm that there is a U-shaped link between the women ratio on the board and bank performance, which aligns with the empirical evidence presented by Joecks et al. (2013), who have conducted a study on German companies and determined a critical mass of female representation on boards which is achieved when the proportion of women falls within the range of 20% to 40%. Our results provide a clear image and establish an optimal proportion of the interaction dummy for the tilted groups that enhances the performance of banks. These findings support our primary hypothesis that post-bailout, the performance of banks with a specified percentage of women on their boards is superior to that of banks without female representation or with a lower percentage of women.

3.5 Robustness Checks

3.5.1 Bank Size

In our primary findings, we incorporate the logarithm of GTA to account for the size of the banks. Nevertheless, it is essential to recognise that this may not completely resolve the intertemporal disparities in certain institutions. In addition, it is necessary to determine whether the variables exhibit distinct significance or have different economic interpretations across different samples and investigate the consistency of variable behaviour across different samples. To address these concerns, we implement the methodology of Berger and Bouwman (2013) and divide our sample into small banks (GTA less than $1 billion), medium banks (GTA of more than $1 billion but less than $3 billion), and large banks (GTA more than $3 billion). Based on these measurement categories, we perform regression analyses for each group. We refrain from reporting the results for the balanced group due to the insufficient number of observations that resulted from dividing the sample by bank size category. Therefore, it is worth investigating the impact of board members if the majority are women, considering the possibility of such an influence.

Tables 3.8, 3.9, and 3.10 show the results for small, 3.11, 3.12, and 3.13 illustrate the results for medium banks, and Tables 3.14, 3.15, and 3.16 present the results for the large banks.

Our main results are consistent in the medium and large banks presented in Tables 3.13 and 3.16. Noticeably, the interaction dummy for the "tilted groups" indicates a significant and positive effect on medium and large bank performance, resulting in an increase of 14.1% and 8.9% in ROE and 1.2% and 0.6% in ROA, respectively. However, our results are contrary to the main results in the small banks category. Specifically, Table 3.10 shows that the interaction dummy for the "tilted groups" has a significant and negative effect on small bank performance, resulting in a decrease of 43.6% in ROE at a 1% significance level. The ROA decreases by 3%, but this is insignificant.

Our analysis of the control variables, including capital, real estate loans, and bank size, shows that their effects are consistent with those found in the main regression, except for the small banks sample, which shows insignificant results for real estate loans and bank size. In terms of the liquidity and natural logarithm of the gross loan measures, we find that they have a significant and positive effect on bank performance in all bank sizes, consistent with the results observed in the primary regression. Furthermore, our analysis of the experience measures yields the same results as those presented in previous groups. Specifically, we find that the average number of years board members have served on bank boards positively and significantly affects medium and large banks performance. However, it has insignificant effects on small bank performance; this highlights the importance of board member experience in driving positive bank performance outcomes in medium and large banks.

Finally, it is notable that medium-sized banks tend to exhibit the largest coefficients, with large banks closely following. This observation suggests that bank performance measures applied to banks of medium size are frequently more effective.

Table 3.8: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Uniform Groups For Small Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.095***	-0.005**	-0.042	-0.002
	(-2.85)	(-2.39)	(-0.97)	(-0.94)
Bailed	0.116*	0.008	0.129*	0.009*
	(1.66)	(1.59)	(1.76)	(1.82)
Uniform groups	-0.030	-0.002	0.038	0.002
	(-0.89)	(-1.01)	(1.07)	(0.87)
Interaction dummy	0.019	0.001	-0.008	-0.0004
	(0.17)	(0.17)	(-0.09)	(-0.05)
Capital			5.321***	0.442***
			(4.68)	(5.77)
RELGTA			0.020	0.002
			(0.06)	(0.11)
LGTA			-0.392*	-0.030*
			(-1.68)	(-1.81)
IETL			0.464	0.024
			(0.64)	(0.47)
LnGrossLoan			0.434**	0.035**
			(1.94)	(2.24)
Liquidity			0.690***	0.055***
			(4.18)	(4.94)
NumberDirectors			0.015	-0.042
			(1.59)	(-1.23)
LnAveAge			-0.480	-0.002
			(-0.99)	(-0.20)
LnAveExp			-0.162*	-0.008
			(-1.70)	(-1.09)
LnAveBankBrdTenure			0.077	0.007*
			(1.25)	(1.72)
LnAveListedBrdTenure			-0.095***	-0.007***
			(-3.15)	(-3.82)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,070	1,070	1,055	1,055
Number of groups	248	248	245	245
R-squared	0.0199	0.0148	0.2205	0.2418

Notes: This Table displays the results of a fixed-effects regression model when we apply the uniform groups for small banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.9: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Skewed Groups For Small Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.093***	-0.005**	-0.042	-0.002
	(-2.79)	(-2.29)	(-0.97)	(-0.91)
Bailed	0.117	0.009	0.078	0.005
	(1.32)	(1.25)	(1.06)	(0.96)
Skewed groups	0.018	0.001	-0.001	0.0007
	(0.70)	(0.93)	(-0.06)	(0.30)
Interaction dummy	0.010	-0.0006	0.081	0.005
	(0.10)	(-0.08)	(0.85)	(0.73)
Capital			5.388***	0.447***
			(4.71)	(5.83)
RELGTA			0.025	0.002
			(0.08)	(0.13)
LGTA			-0.380*	-0.029*
			(-1.68)	(-1.81)
IETL			0.484	0.025
			(0.68)	(0.51)
LnGrossLoan			0.424*	0.034**
			(1.93)	(2.25)
Liquidity			0.685***	0.055***
			(4.09)	(4.85)
NumberDirectors			0.012	0.0007
			(1.29)	(0.99)
LnAveAge			-0.428	-0.039
			(-0.91)	(-1.18)
LnAveExp			-0.145	-0.007
			(-1.53)	(-0.95)
LnAveBankBrdTenure			0.068	0.007
			(1.11)	(1.57)
LnAveListedBrdTenure			-0.096***	-0.007***
			(-3.19)	(-3.88)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,070	1,070	1,055	1,055
Number of groups	248	248	245	245
R-squared	0.0196	0.0145	0.2208	0.2425

Notes: This Table displays the results of a fixed-effects regression model when we apply the skewed groups for small banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.10: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Tilted Groups For Small Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.097***	-0.005**	-0.042	-0.002
	(-2.87)	(-1.78)	(-0.96)	(-0.90)
Bailed	0.132**	0.009*	0.140**	0.010**
	(2.03)	(1.79)	(2.36)	(2.29)
Tilted groups	0.023	0.0005	-0.042	-0.004
	(0.80)	(0.22)	(-1.10)	(-1.31)
Interaction dummy	-0.137**	-0.004	-0.436***	-0.030**
	(-2.50)	(-0.96)	(-2.67)	(-2.42)
Capital			5.692***	0.469***
			(4.98)	(-2.42)
RELGTA			0.209	0.015
			(0.66)	(0.74)
LGTA			-0.281	-0.022
			(-1.24)	(-1.37)
IETL			0.205	0.006
			(0.29)	(0.12)
LnGrossLoan			0.374*	0.031**
			(1.72)	(2.03)
Liquidity			0.725***	0.058***
			(4.35)	(4.95)
NumberDirectors			0.010	0.0005
			(1.05)	(0.85)
LnAveAge			-0.641	-0.054*
			(-1.37)	(-1.68)
LnAveExp			-0.095	-0.004
			(-0.96)	(-0.50)
LnAveBankBrdTenure			0.037	0.004
			(0.61)	(1.11)
LnAveListedBrdTenure			-0.098***	-0.008***
			(-3.23)	(-3.92)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,070	5,083	1,055	1,055
Number of groups	248	248	245	245
R-squared	0.0201	0.0138	0.2297	0.2511

Notes: This Table displays the results of a fixed-effects regression model when we apply the tilted groups for small banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.11: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Uniform Groups For Medium Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.048	-0.0008	0.049	0.004
	(-1.47)	(-0.39)	(0.99)	(1.35)
Bailed	0.010	0.0005	0.069	0.004
	(0.21)	(0.15)	(1.18)	(1.16)
Uniform groups	0.054	0.004	0.038	0.002
	(1.10)	(1.27)	(0.78)	(0.86)
Interaction dummy	-0.057	-0.005	-0.027	-0.003
	(-1.08)	(-1.20)	(-0.42)	(-0.72)
Capital			7.241***	0.530***
			(6.26)	(-1.89)
RELGTA			-0.709**	-0.047*
			(-2.02)	(-1.89)
LGTA			-0.713***	-0.057***
			(-3.11)	(-2.82)
IETL			1.249*	0.063
			(1.89)	(1.35)
LnGrossLoan			0.656***	0.052***
			(3.12)	(3.32)
Liquidity			0.565***	0.044***
			(3.61)	(4.17)
NumberDirectors			0.007	0.0003
			(0.85)	(0.51)
LnAveAge			0.090	-0.003
			(0.20)	(-0.11)
LnAveExp			-0.128	-0.004
			(-1.43)	(-0.89)
LnAveBankBrdTenure			0.175**	0.0124***
			(2.35)	(2.60)
LnAveListedBrdTenure			-0.227***	-0.015***
			(-6.46)	(-6.64)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,705	1,705	1,689	1,689
Number of groups	314	314	309	309
R-squared	0.0082	0.0040	0.2398	0.2521

Notes: This Table displays the results of a fixed-effects regression model when we apply the uniform groups for medium banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.12: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Skewed Groups For Medium Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.050	-0.001	0.053	0.005
	(-1.55)	(-0.45)	(1.07)	(1.43)
Bailed	0.009	0.0004	0.078	0.004
	(0.21)	(0.12)	(1.36)	(1.32)
Skewed groups	0.053	0.003	0.034	0.002
	(1.05)	(1.16)	(0.77)	(0.85)
Interaction dummy	-0.040	-0.003	-0.045	-0.003
	(-0.80)	(-0.90)	(-0.85)	(-0.97)
Capital			7.195***	0.527***
			(6.28)	(6.86)
RELGTA			-0.658*	-0.044*
			(-1.87)	(-1.75)
LGTA			-0.713***	-0.057***
			(-2.53)	(-3.49)
IETL			1.295**	0.067
			(2.01)	(1.46)
LnGrossLoan			0.649***	0.051***
			(3.12)	(3.32)
Liquidity			0.572***	0.044***
			(3.56)	(4.09)
NumberDirectors			0.005	0.0002
			(0.62)	(0.35)
LnAveAge			0.116	-0.002
			(0.25)	(-0.08)
LnAveExp			-0.133	-0.005
			(-1.47)	(-0.98)
LnAveBankBrdTenure			0.183**	0.013***
			(2.47)	(2.77)
LnAveListedBrdTenure			-0.230***	-0.015***
			(-6.44)	(-6.70)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,705	1,705	1,689	1,689
Number of groups	314	314	309	309
R-squared	0.0088	0.0040	0.2402	0.2524

Notes: This Table displays the results of a fixed-effects regression model when we apply the skewed groups for medium banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.13: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Tilted Groups For Medium Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.031	0.0003	0.059	0.005
	(-0.88)	(0.14)	(1.19)	(1.56)
Bailed	-0.045	-0.004	0.030	0.0009
	(-0.95)	(-1.29)	(0.51)	(0.24)
Tilted groups	-0.215**	-0.015***	-0.136*	-0.009**
	(-2.40)	(-2.95)	(-1.89)	(-2.19)
Interaction dummy	0.188**	0.015***	0.141**	0.012***
	(2.37)	(2.86)	(2.13)	(2.59)
Capital			7.149***	0.524***
			(6.43)	(7.00)
RELGTA			-0.733**	-0.050**
			(-2.10)	(-2.02)
LGTA			-0.720***	-0.058***
			(-3.19)	(-3.53)
IETL			1.333**	0.071
			(2.06)	(1.54)
LnGrossLoan			0.664***	0 .052***
			(3.20)	(3.43)
Liquidity			0.578***	0.044***
			(3.68)	(4.21)
NumberDirectors			0.006	0.0002
			(0.65)	(0.35)
LnAveAge			0.080	-0.004
			(0.18)	(-0.15)
LnAveExp			-0.147*	-0.006
			(-1.66)	(-1.16)
LnAveBankBrdTenure			0.170**	0.012***
			(2.31)	(2.60)
LnAveListedBrdTenure			-0.218***	-0.014***
			(-6.06)	(-6.40)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,705	1,705	1,689	1,689
Number of groups	314	314	309	309
R-squared	0.0246	0.0213	0.2465	0.2596

Notes: This Table displays the results of a fixed-effects regression model when we apply the tilted groups for medium banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.14: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Uniform Groups For Large Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.019	0.0008	0.084*	0.006*
	(-0.76)	(0.45)	(1.88)	(1.89)
Bailed	-0.010	0.001	-0.034	-0.0008
	(-0.32)	(0.50)	(-0.84)	(-0.26)
Uniform groups	0.011	0.0004	-0.009	-0.001
	(0.32)	(0.17)	(-0.30)	(-0.51)
Interaction dummy	-0.034	0.004	0.005	-0.00002
	(-0.77)	(-1.41)	(0.11)	(-0.01)
Capital			2.652***	0.284***
			(3.04)	(4.85)
RELGTA			-0.531**	-0.045***
			(-2.51)	(-2.67)
LGTA			-0.203	-0.021*
			(-1.37)	(-1.86)
IETL			0.326	0.032
			(0.74)	(0.93)
LnGrossLoan			0.256*	0.026**
			(1.84)	(2.43)
Liquidity			0.115*	0.022**
			(1.82)	(2.42)
NumberDirectors			0.004	0.0003
			(1.04)	(1.08)
LnAveAge			-0.228	-0.005
			(-0.71)	(-0.24)
LnAveExp			-0.003	-0.0007
			(-0.05)	(-0.17)
LnAveBankBrdTenure			0.133***	0.008***
			(3.03)	(2.74)
LnAveListedBrdTenure			-0.287***	-6.79***
			(-6.88)	(-11.12)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,308	2,308	2,149	2,149
Number of groups	282	282	264	264
R-squared	0.0033	0.0023	0.1116	0.1416

Notes: This Table displays the results of a fixed-effects regression model when we apply the uniform groups for large banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.15: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Skewed Groups For Large Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.024	0.0006	0.081*	0.006*
	(-0.96)	(0.34)	(1.84)	(1.85)
Bailed	0.025	0.003	0.018	0.003
	(0.59)	(1.08)	(0.35)	(0.82)
Skewed groups	0.021	0.0008	0.038	0.002
	(0.77)	(0.41)	(1.43)	(1.39)
Interaction dummy	-0.054	-0.004	-0.070*	-0.005**
	(-1.57)	(-1.55)	(-1.88)	(-1.99)
Capital			2.674***	0.286***
			(3.08)	(4.90)
RELGTA			-0.503**	-0.042**
			(-2.36)	(-2.47)
LGTA			-0.202	-0.021*
			(-1.39)	(-2.90)
IETL			0.329	0.032
			(0.75)	(0.91)
LnGrossLoan			0.256*	0.026**
			(1.87)	(2.42)
Liquidity			0.109*	0.012**
			(1.76)	(2.37)
NumberDirectors			0.004	0.0003
			(0.97)	(1.10)
LnAveAge			-0.215	-0.004
			(-0.68)	(-0.21)
LnAveExp			0.001	-0.0005
			(0.02)	(-0.12)
LnAveBankBrdTenure			0 .139***	0.009***
			(3.20)	(2.93)
LnAveListedBrdTenure			-0.292***	-0.022***
			(-6.89)	(-6.81)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,308	2,308	2,149	2,149
Number of groups	282	282	264	264
R-squared	0.0052	0.0039	0.1153	0.1454

Notes: This Table displays the results of a fixed-effects regression model when we apply the skewed groups for large banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.16: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Tilted Groups For Large Banks

Variable	(ROE)	(ROA)	(ROE)	(ROA)
Post bailout time	-0.019	0.0007	0.085*	0.007*
	(-0.79)	(0.45)	(1.88)	(1.91)
Bailed	-0.032	-0.001	-0.052	-0.002
	(-1.00)	(-0.44)	(-1.28)	(-0.75)
Tilted groups	-0.048	-0.001	-0.060	-0.003
	(-1.14)	(-2.03)	(-1.39)	(-1.21)
Interaction dummy	0.087*	0.006*	0.089*	0.006*
	(1.85)	(1.81)	(1.80)	(1.85)
Capital			2.654***	0.284***
			(3.07)	(4.88)
RELGTA			-0.497**	-0.041**
			(-1.32)	(-2.39)
LGTA			-0.198	-0.020*
			(-1.32)	(-1.77)
IETL			0.327	0.031
			(0.74)	(0.89)
LnGrossLoan			0.252*	0.026**
			(1.78)	(2.31)
Liquidity			0.101	0.011**
			(1.59)	(4.95)
NumberDirectors			0.004	0.0004
			(1.07)	(1.20)
LnAveAge			-0.224	-0.004
			(-0.70)	(-0.22)
LnAveExp			-0.001	-0.0006
			(-0.03)	(-0.15)
LnAveBankBrdTenure			0.134***	0.008***
			(3.10)	(2.82)
LnAveListedBrdTenure			-0.283***	-0.021***
			(-6.91)	(-6.76)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,308	2,308	2,149	2,149
Number of groups	282	282	264	264
R-squared	0.0071	0.0061	0.1159	0.1456

Notes: This Table displays the results of a fixed-effects regression model when we apply the tilted groups for large banks, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Column (1) presents the measure of ROE, column (2) presents the measure of ROA, while columns (3) and (4) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

3.5.2 Instrumental Variable Approach

The assignment of women to corporate boards is not a random process, which must be acknowledged in the context of board composition. Therefore, when formulating our empirical framework, it becomes essential to address potential endogeneity concerns. To overcome the inherent self-selection bias that could result from female board members choosing banks that align with their personal preferences or other missing variables that might affect the women ratio, we adopt the methodology outlined by Huang and Kisgen (2013) and employ instrumental variables to mitigate the endogeneity issue. The instrument they utilise to identify firms with female executives is based on a prior study conducted by Sugarman and Straus (1988), which quantifies a state's level of gender status equality. Huang and Kisgen (2013) suggest that states with higher levels of gender equality would be more conducive to enhancing female executives. In our analysis, we use the state's gender status equality value, a function of the instrumental variable, in relation to each bank's headquarters location. This continuous metric ranges from 0 to 100, allowing for a detailed evaluation of gender-related parity within the organisation.

However, due to the age of the study by Sugarman and Straus (1988), we have chosen to use a more updated version of this research conducted by Di Noia (2002).

We divide the IV, the predicted ratio of women, into four distinct categories. Each instrumental variable category is determined based on the corresponding ratio of women. This categorisation allows us to identify an optimal range of bank board directors, which is believed to improve the performance of the banks, thereby confirming our key findings. Due to the high correlation between the Instrumental variable (IV) and both the logarithm of gross total assets (LGTA) and the average listed board tenure (LnAveListedBrdTenure), we have dropped (LGTA) and (LnAveListedBrdTenure).

We estimate a two-stage least squares (2SLS) instrumental variable as follows:

Step 1:

$$gender\ ratio_{b,t} = \beta_0 + \beta_1 post\ bailout\ time_{b,t} + \beta_2 bailed_{b,t} + \beta_3 gender\ equality_{b,t} + \beta_4 Capital_{b,t} + \beta_5 RELGTA_{b,t} + \beta_6 IETL_{b,t} + \beta_7 LnGrossLoan_{b,t} + \beta_8 Liquidity_{b,t} + \beta_9 NumberDirectors_{b,t} + \beta_{10} LnAveAge_{b,t} + \beta_{11} LnAveExp_{b,t} + \beta_{12} LnAveBankBrdTenure_{b,t} + \delta_{\mathrm{b}} + \varepsilon_{\mathrm{b,t}}$$

(2)

Step 2:

$$Performance\ measure_{b,t+1} = \beta_0 + \beta_1 post\ bailout\ time_{b,t} + \beta_2 bailed_{b,t} + \beta_3 IV + \beta_4 post\ bailout\ time_{b,t} * bailed_{b,t} * IV + \beta_5 Capital_{b,t} + \beta_6 RELGTA_{b,t} + \beta_7 IETL_{b,t} + \beta_8 LnGrossLoan_{b,t} + \beta_9 Liquidity_{b,t} + \beta_{10} NumberDirectors_{b,t} + \beta_{11} LnAveAge_{b,t} + \beta_{12} LnAveExp_{b,t} + \beta_{13} LnAveBankBrdTenure_{b,t} + \delta_{\mathrm{b}} + \varepsilon_{\mathrm{b,t}}$$

(3)

Tables 3.17, 3.18, 3.19, and 3.20 show the results of the Instrumental variable approach. The instrumental variable regression results are generally consistent with the main results we obtained previously using the woman ratio. In Table 3.17, the "uniform groups" become significant and has a negative effect on bank performance, meaning that banks without women on the board decrease the ROE and ROA by 36.7% and 3.2%, respectively. The second category, presented in Table 3.18, the "skewed groups", has an insignificant effect on performance, which does not support our main results. The third category, presented in Table 3.19, the "tilted groups", has a significant and positive effect on bank performance, increasing ROE by 10.02% and ROA by 0.8%, respectively. The fourth category, presented in Table 3.20, the "balanced groups", suggests a statistically significant negative effect on bank performance, resulting in a decrease of 8.2% in ROE and 0.6% in ROA, respectively.

Based on the instrumental variable results, our main findings are supported, identifying the optimal proportion of the interaction dummy for the tilted group, which enhances institutional performance. These results align with the critical mass theory and support our primary hypothesis.

Table 3.17: The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Uniform Groups

Variable	(ROE)	(ROA)
Post bailout time	-0.083***	-0.007***
	(-3.92)	(-4.98)
Bailed	0.042*	0.005***
	(1.84)	(3.01)
Uniform groups	0.091***	0.007***
	(3.89)	(4.37)
Interaction dummy	-0.367***	-0.032***
	(-19.24)	(-23.49)
Capital	-0.213	0.039
	(-0.41)	(1.14)
RELGTA	-0.063	-0.007
	(-0.54)	(-0.84)
IETL	-4.405***	-0.362***
	(-11.87)	(-13.43)
LnGrossLoan	-0.117***	-0.006***
	(-5.03)	(-3.76)
Liquidity	0.126**	0.010**
	(2.09)	(2.29)
NumberDirectors	0.012***	0.0008***
	(3.32)	(3.06)
LnAveAge	-0.639***	-0.043***
	(-3.25)	(-3.02)
LnAveExp	0.023	0.001
	(0.56)	(0.66)
LnAveBankBrdTenure	0.012	0.0004
	(0.49)	(0.25)
Bank Fixed Effects	Yes	Yes
Observations	4,266	4,266
Number of groups	548	548
R-squared	0.1198	0.1414

Notes: This Table displays the results of a fixed-effects regression model when we apply the uniform groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.18: The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Skewed Groups

Variable	(ROE)	(ROA)
Post bailout time	-0.099***	-0.008***
	(-4.87)	(-5.95)
Bailed	0.039	0.005***
	(1.58)	(2.80)
Skewed groups	0.002	0.0005
	(0.13)	(0.40)
Interaction dummy	0.009	-0.0007
	(0.22)	(-0.26)
Capital	-0.141	0.044
	(-0.27)	(1.29)
RELGTA	-0.067	-0.007
	(-0.56)	(-0.82)
IETL	-4.458***	-0.367***
	(-12.00)	(-13.51)
LnGrossLoan	-0.124***	-0.006***
	(-5.30)	(-4.06)
Liquidity	0.148**	0.012***
	(2.43)	(2.62)
NumberDirectors	0.011***	0.0007***
	(3.03)	(2.74)
LnAveAge	-0.596***	-0.038***
	(-2.95)	(-2.62)
LnAveExp	0.017	0.001
	(0.41)	(0.52)
LnAveBankBrdTenure	0.012	0.0004
	(0.47)	(0.23)
Bank Fixed Effects	Yes	Yes
Observations	4,266	4,266
Number of groups	548	548
R-squared	0.1138	0.1343

Notes: This Table displays the results of a fixed-effects regression model when we apply the skewed groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.19: The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Tilted Groups

Variable	(ROE)	(ROA)
Post bailout time	-0.074***	-0.006***
	(-3.51)	(-4.33)
Bailed	-0.017	-0.0001
	(-0.54)	(-0.06)
Tilted groups	-0.076***	-0.006***
	(-3.40)	(-3.83)
Interaction dummy	0.100***	0.008***
	(2.90)	(3.51)
Capital	-0.078	0.050
	(-0.15)	(1.45)
RELGTA	-0.064	-0.007
	(-0.57)	(-0.89)
IETL	-4.456***	-0.366***
	(-12.00)	(-13.52)
LnGrossLoan	-0.118***	-0.006***
	(-5.05)	(-3.77)
Liquidity	0.142**	0.012***
	(2.34)	(2.55)
NumberDirectors	0.013***	0.0008***
	(3.41)	(3.19)
LnAveAge	-0.609***	-0.040***
	(-3.06)	(-2.85)
LnAveExp	0.016	0.001
	(0.40)	(0.45)
LnAveBankBrdTenure	0.006	-0.00002
	(0.26)	(-0.01)
Bank Fixed Effects	Yes	Yes
Observations	4,266	4,266
Number of groups	548	548
R-squared	0.1200	0.1427

Notes: This Table displays the results of a fixed-effects regression model when we apply the tilted groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.20: The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Balanced Groups

Variable	(ROE)	(ROA)
Post bailout time	-0.102***	-0.008***
	(-4.96)	(-6.14)
Bailed	0.050**	0.005***
	(2.07)	(3.16)
Balanced groups	0.081**	0.006**
	(2.33)	(2.35)
Interaction dummy	-0.082**	-0.006**
	(-2.36)	(-2.15)
Capital	-0.162	0.043
	(-0.31)	(1.24)
RELGTA	-0.061	-0.007
	(-0.54)	(-0.81)
IETL	-4.427***	-0.364***
	(-11.91)	(-13.42)
LnGrossLoan	-0.128***	-0.007***
	(-5.47)	(-4.38)
Liquidity	0.157***	0.013***
	(2.62)	(2.82)
NumberDirectors	0.011***	0.0007**
	(2.96)	(2.67)
LnAveAge	-0.572***	-0.037***
	(-2.85)	(-2.56)
LnAveExp	0.015	0.001
	(0.37)	(0.46)
LnAveBankBrdTenure	0.011	0.0003
	(0.44)	(0.20)
Bank Fixed Effects	Yes	Yes
Observations	4,266	4,266
Number of groups	548	548
R-squared	0.1153	0.1360

Notes: This Table displays the results of a fixed-effects regression model when we apply the balanced groups, which utilises a sample of bank bailouts and board directors from 2003 to 2019. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

3.5.3 Five-Year Post-Bailout Window Analysis

We conducted additional analyses by restricting the sample period to a five-year post-bailout window to assess the robustness of our findings regarding the optimal women ratio that enhances bank performance. Using the fixed-effects regression model, we examined the impact of women's ratio categories representing uniform, skewed, tilted, and balanced groups.

The results for the five-year window align with our main findings, supporting that the interaction dummy for the tilted group, as presented in Table 3.23, consistently yields the most significant positive effect on post-bailout performance. Specifically, this interaction dummy demonstrates a significant and positive impact on performance, resulting in an increase of 8.9% in ROE and 0.8% in ROA. These findings are consistent with the empirical evidence presented by Joecks et al. (2013).

Other women categories provide further insights. For instance, the uniform group, as shown in Table 3.21, and the balanced group, presented in Table 3.24, exhibit insignificant coefficients. In contrast, the skewed group, detailed in Table 3.22, significantly decreases performance, leading to a reduction of 5.8% in ROE and 0.4% in ROA. This pattern is consistent with our main findings and reinforces the conclusion that the interaction dummy for the tilted group positively enhances bank performance after the bailout period.

Table 3.21: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Uniform Groups, Applying a 5-Year Post-Bailout Window

Variable	(ROE)	(ROA)
Post bailout time	0.066**	0.005***
	(2.44)	(2.70)
Bailed	-0.022	-0.0003
	(-0.81)	(-0.20)
Uniform groups	0.037	0.003*
	(1.56)	(1.91)
Interaction dummy	0.040	0.001
	(1.08)	(0.71)
Capital	5.406***	0.428***
	(7.34)	(8.87)
RELGTA	-0.249	-0.022
	(-1.25)	(-1.54)
LGTA	-0.396***	-0.034***
	(-3.03)	(-3.79)
IETL	0.837**	0.045*
	(2.53)	(1.95)
LnGrossLoan	0.293**	0.027***
	(2.31)	(3.02)
Liquidity	0.297***	0.025***
	(4.22)	(4.97)
NumberDirectors	0.014***	0.001***
	(3.06)	(3.31)
LnAveAge	-0.356	-0.030
	(-1.33)	(-1.58)
LnAveExp	-0.117**	-0.007**
	(-2.15)	(-2.01)
LnAveBankBrdTenure	0.129***	0.009***
	(3.41)	(3.77)
LnAveListedBrdTenure	-0.174***	-0.012***
	(-9.93)	(-10.01)
Bank Fixed Effects	Yes	Yes
Observations	3,721	3,721
Number of groups	540	540
R-squared	0.1970	0.2133

Notes: This Table displays the results of a fixed-effects regression model when we apply the uniform groups, which utilises a sample of bank bailouts and board directors from 2003 to 2014. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.22: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Skewed Groups, Applying a 5-Year Post-Bailout Window

Variable	(ROE)	(ROA)
Post bailout time	0.065**	0.005***
	(2.43)	(2.72)
Bailed	0.023	0.002
	(0.74)	(1.29)
Skewed groups	0.023	0.001
	(1.05)	(0.81)
Interaction dummy	-0.058*	-0.004**
	(-1.85)	(-1.96)
Capital	5.355***	0.424
	(7.33)	(8.83)
RELGTA	-0.247	-0.021
	(-1.25)	(-1.56)
LGTA	-0.406***	-0.035***
	(-3.20)	(-3.98)
IETL	0.860***	0.048**
	(2.60)	(2.04)
LnGrossLoan	0.303**	0.028***
	(2.45)	(3.19)
Liquidity	0.290***	0.024***
	(4.06)	(4.85)
NumberDirectors	0.012***	0.0009***
	(2.60)	(2.88)
LnAveAge	-0.320	-0.027
	(-1.21)	(-1.47)
LnAveExp	-0.113**	-0.007**
	(-2.10)	(-1.96)***
LnAveBankBrdTenure	0.131***	0.009***
	(3.41)	(3.81)
LnAveListedBrdTenure	-0.177***	-0.012***
	(-10.09)	(-10.16)
Bank Fixed Effects	Yes	Yes
Observations	3,721	3,721
Number of groups	540	540
R-squared	0.1965	0.2129

Notes: This Table displays the results of a fixed-effects regression model when we apply the skewed groups, which utilises a sample of bank bailouts and board directors from 2003 to 2014. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.23: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Tilted Groups, Applying a 5-Year Post-Bailout Window

Variable	(ROE)	(ROA)
Post bailout time	0.065**	0.005***
	(2.40)	(2.68)
Bailed	-0.022	-0.0009
	(-0.79)	(-0.50)
Tilted groups	-0.109**	-0.007***
	(-2.52)	(-2.79)
Interaction dummy	0.089*	0.008**
	(1.85)	(2.35)
Capital	5.350***	0.423***
	(7.42)	(8.95)
RELGTA	-0.272	-0.023*
	(-1.35)	(-1.66)
LGTA	-0.404***	-0.035***
	(-3.15)	(-3.97)
IETL	0.841***	0.046**
	(2.54)	(1.98)
LnGrossLoan	0.300**	0.027***
	(2.40)	(3.16)
Liquidity	0.294***	0.024***
	(4.02)	(4.73)
NumberDirectors	0.012***	0.0009***
	(2.66)	(2.91)
LnAveAge	-0.344	-0.028
	(-1.29)	(-1.53)
LnAveExp	-0.121**	-0.007**
	(-2.26)	(-2.14)
LnAveBankBrdTenure	0.123***	0.009***
	(3.19)	(3.59)
LnAveListedBrdTenure	-0.168***	-0.012***
	(-9.80)	(-9.77)
Bank Fixed Effects	Yes	Yes
Observations	3,721	3,721
Number of groups	540	540
R-squared	0.2000	0.2166

Notes: This Table displays the results of a fixed-effects regression model when we apply the tilted groups, which utilises a sample of bank bailouts and board directors from 2003 to 2014. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 3.24: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Balanced Groups, Applying a 5-Year Post-Bailout Window

Variable	(ROE)	(ROA)
Post bailout time	0.063**	0.004***
	(2.37)	(2.63)
Bailed	-0.011	0.0001
	(-0.45)	(0.07)
Balanced groups	0.130*	0.009*
	(1.77)	(1.72)
Interaction dummy	-0.083	-0.0008
	(-1.03)	(-0.14)
Capital	5.389***	0.426***
	(7.32)	(8.85)
RELGTA	-0.235	-0.020
	(-1.19)	(-1.49)
LGTA	-0.392***	-0.034***
	(-3.09)	(-3.89)
IETL	0.842***	0.046**
	(2.54)	(1.98)
LnGrossLoan	0.290**	0.027***
	(2.34)	(3.09)
Liquidity	0.294***	0.024***
	(4.13)	(4.91)
NumberDirectors	0.012***	0.0009***
	(2.72)	(2.99)
LnAveAge	-0.310	-0.026
	(-1.16)	(-1.41)
LnAveExp	-0.113**	-0.007*
	(-2.11)	(-1.94)
LnAveBankBrdTenure	0.127***	0.009***
	(3.26)	(3.67)
LnAveListedBrdTenure	-0.176***	-0.012***
	(-10.10)	(-10.15)
Bank Fixed Effects	Yes	Yes
Observations	3,721	3,721
Number of groups	540	540
R-squared	0.1952	0.2116

Notes: This Table displays the results of a fixed-effects regression model when we apply the balanced groups, which utilises a sample of bank bailouts and board directors from 2003 to 2014. The return on Equity (ROE) and return on assets (ROA) serve as dependent variables. Columns (1) and (2) present the measures of ROE and ROA, respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. The last three rows of the Table indicate the total yearly observations for each bank, the number of groups, and the R-squared. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

3.6 Conclusion

In conclusion, the present study has made significant contributions to the existing literature on board diversity by addressing three fundamental questions related to the impact of gender diversity on the performance of banks in the United States. Firstly, this study has provided comprehensive empirical evidence that the relationship between board gender diversity and bank performance is contingent on a specific level of gender diversity. The findings of this study support the hypothesis that post-bailout, banks with a particular percentage of women on their boards outperform those without female representation or with a lower rate of women. Secondly, the study has identified the optimal ratio of women on the board that positively affects performance. The research findings suggest that a U-shaped correlation exists between the proportion of women on the board and bank performance, consistent with the empirical results reported by Joecks et al. (2013). Thirdly, this study supports the applicability of critical mass theory in corporate governance and demonstrates that an optimal proportion of women on boards enhances bank performance.

Furthermore, the study reconciles the mixed findings from previous research. This empirical investigation addresses a notable gap in the literature by examining the support for the critical mass theory in corporate governance. The study provides a comprehensive account of the methodology, including descriptive statistics, correlation, and multivariate fixed effect regression analysis, which increases the validity and reliability of the study.

In conclusion, this study has provided a lucid picture of the impact of gender diversity on bank performance, and its results are likely to spur further research in this area. The study motivates us to examine the sources of gender diversity's effects to enrich the literature further. Ultimately, our investigation has prompted us to consider the implications of gender diversity for bank performance after the bailout and to identify those entities that have successfully absorbed the lessons and learned from these events. Therefore, the results of this study provide a valuable contribution to the literature and have practical implications for policymakers, regulators, and practitioners in the banking industry.

Chapter Four: Do Females Manage Risk Better During Crises: An Analysis of Bank Risk After Bailouts

4.1 Introduction

The famous statement made by IMF member Christine Lagarde in 2010 was, "If Lehman Brothers had been Lehman Sisters, today's economic crisis clearly would look quite different" (Lagarde, 2010; Palvia et al., 2014). The failure of boards of directors to assess risks, evaluate the sensitivity of banks to economic disruptions, and act prudently contributed to the failure of numerous banks (Abou-El-Sood, 2021; Group of Thirty, 2012). Harriet Harman, the deputy leader of the United Kingdom Labour Party, attributes the financial crisis to male dominance in banks (Adams & Funk, 2012; Morris, 2009). However, a board of directors that makes less risky decisions helps the firm to meet the best interest of its shareholders (Jane Lenard et al., 2014; C. J. Wang, 2012). Therefore, studies have attempted to determine the relationship between board characteristics and firm risk (Sila et al., 2016). Specifically, clarifying the importance of providing women on boards can be one of the solutions to mitigate risks.

The primary motivation for our study is the absence of similar studies in the field. Multiple studies indicate a lack of evidence about the impact of having female board members on reducing excessive risk-taking in banks, as shown by Abou-El-Sood (2021), Arango and Gaitan (2021), Manello et al. (2023), Sila et al. (2016), Tran et al. (2020), and Valls Martínez and Soriano Román (2022). Therefore, we extend our analysis to investigate how women influence bank risk, providing a more complete picture of their contribution to the banking sector. Specifically, it examines the influence of gender diversity on the credit, market, and operational risk of banks in the United States after the government's rescue efforts to determine whether such diversity has a meaningful impact. Thus, our study aims to determine the optimal gender diversity ratio that leads to more conservative or balanced risk-taking behaviors.

The current study examines three key questions: Firstly, does gender diversity, particularly the inclusion of women on a bank's board of directors, decrease credit, market, and operational risk during post-financial crisis periods? Secondly, what is the ideal proportion of female representation on the board that negatively affects these forms of risk? Thirdly, does critical mass theory effectively describe the impact of board gender diversity on banks' credit, market, and operational risk?

This research provides valuable insights into the relationship between board gender diversity and bank risk, addressing a crucial knowledge gap in the existing literature. It offers substantial contributions to understanding the influence of women directors on bank risk. It presents an extensive empirical evidence about the association between the range of genders on a board and the degree of credit, market, and operational risk in a bank depending on a certain level of gender diversity on the board. Furthermore, this research fills an essential gap in the literature by assessing the support for the critical mass theory in corporate governance. Finally, our analysis is based on a robust dataset comprising 2,317 bank-year observations of 179 bailout BHCs and 2,766 bank-year observations of 434 BHCs that have not received bailouts, providing a longer period of coverage than previous studies.

Utilising critical mass theory, as used by Kanter (1977a, 1977b), we propose that the actions and impact of a subgroup are determined by its size. More specifically, the proposal suggests that when the subgroup hits a certain threshold, referred to as the "critical mass", it has the capacity to have a more substantial impact on the wider group (Torchia et al., 2011). Following Kante's (1977b) approach, the representation of women on corporate boards can be classified into four separate groups. These groups can be categorised into four types based on the level of female representation: uniform groups (0% women), skewed groups (up to 20% women), tilted groups (20-40% women), and balanced groups (40-60% women).

Our study's outcomes align with the findings documented by Joecks et al. (2013), who investigated German companies. A critical mass of female involvement on boards is achieved when the proportion of women ranges from 20% to 40%. Our analysis presents a straightforward and accurate picture and determines the ideal ratio of women on boards within the tilted groups that mitigate bank risk.

Furthermore, we use bank size as a robustness check, following the methods outlined by Berger an Bouwman (2013). Our findings indicate that medium and large banks align with the primary results, confirming that the "tilted groups" significantly and negatively affect bank risk. Additionally, we follow the methods described by Huang and Kisgen (2013) to apply the instrumental variable approach and address the endogeneity problem. The instrumental variable regression findings align with the prior results obtained using the woman ratio. The findings of our study confirm the primary hypothesis that, in the following years of the bailout, banks with a certain percentage of women on their boards reduce risk more effectively than banks without female representation or with a lower percentage of women.

The structure of this chapter is as follows. Firstly, we summarise the current literature on the impact of gender diversity on bank risk. Subsequently, we outline our methodology, including collecting research data, building the sample, and reviewing both dependent and independent variables. Next, we thoroughly explain our empirical model and method, which covers descriptive statistics, correlation analysis, and multivariate fixed effect regression analysis. We then apply robustness checks to reinforce our main findings. Lastly, the chapter concludes with the study's key outcomes.

4.2 Literature Review

Women's wider perspectives

Increasing the number of female top managers is one way to diversify the cognitive perspectives available to a firm to identify strategic opportunities, discover alternatives, and deal with environmental changes (Perryman et al., 2016; Wiersema & Bantel, 1992). Gender diversity may therefore enable top managers to accomplish common goals and decisions effectively, regardless of whether they share the same meanings or perspectives (Perryman et al., 2016); play an essential part in framing the board's opinions and making consensual decisions (Gulamhussen & Santa, 2015; Kinateder et al., 2021); and supports ethical thinking (Adams & Ferreira, 2004; Kinateder et al., 2021; Lewellyn & Muller-Kahle, 2020; Moreno-Gómez & Calleja-Blanco, 2018).

Women's supervision characteristics

Greater gender diversity in managerial positions has improved monitoring processes and can be an effective alternative for better corporate governance control (Gul et al., 2011; Melero, 2011; Perryman et al., 2016). The inclusion of gender-diverse members on boards has the potential to enhance board oversight and accountability, as women are more inclined to exhibit independent thinking compared to their male counterparts (Chen et al., 2019); assists in reducing the bias towards groupthink (Chen et al., 2019; Larcker & Tayan, 2013); and hence enhancing its effectiveness in providing advice and counsel to the organisation (Adams & Ferreira, 2004; S. Chen et al., 2016; Daily et al., 1999). Additionally, such a board is more likely to raise enquiries and engage in critical analysis as a result of its varied composition, which draws upon individuals from various backgrounds (Mohsni et al., 2021; Yi, 2011).

It is important to note that firms with boards that have a diverse representation of genders have a lower occurrence of financial reporting errors and participate in less fraudulent activities (Wahid, 2019). Additionally, such firms are known to enhance their organisational processes; promote transparency; and encourage high-quality decision-making (Jain & Jamali, 2016; Kinateder et al., 2021; Sila et al., 2016).

Highlighting women's sense of responsibility

In their study of a sample of US corporations, Adams and Ferreira (2009) find that female directors, when appointed to boards of directors, show a greater feeling of duty and responsibility in performing their roles than their male counterparts (Manello et al., 2023). The inclusion of female members on boards has been found to have several positive effects. Firstly, it leads to higher overall meeting attendance rates. Additionally, discussions become more inclusive, considering a wider range of alternatives. Discussions also become curious and less influenced by political factors. Moreover, directors tend to receive more equity-based pay, indicating a stronger alignment of interests. Furthermore, the quality of earnings improves and becomes more conservative. Lastly, including female members strengthens management oversight (Chen et al., 2019). Research has shown that female board directors exhibit a higher level of preparedness for meetings and are more likely to engage in questioning. This behaviour contributes to the inclusion of fresh perspectives and enhances the overall quality of board discussions (Farrell & Hersch, 2005; Jizi & Nehme, 2017; Konrad et al., 2008). According to the survey-based research conducted by Adams and Funk (2012) on Swedish directors, observed that female directors show a greater tendency towards empathy, universalism, and stimulation while appearing to have a comparatively lower emphasis on power, security, conformity, and tradition (Reddy & Jadhav, 2019). According to Adams and Funk (2012), women who earned their positions in the boardroom via competitive means tend to exhibit higher levels of power and accomplishment orientation than female worker representatives. Huang and Kisgen (2013) illustrate the presence of caution in relation to debt financing through their empirical study of publicly traded companies in the United States. Their findings indicate that organisations led by female executives exhibit a reduced tendency to use debt for the purpose of making acquisitions, thus resulting in a comparatively slower growth path (Manello et al., 2023).

Risks

In January 2001, the Basle Committee proposed a framework that categorises the assessment of bank risks into three primary components: credit risk, market risk, and operational risk. Credit risk refers to the potential for financial loss resulting from a borrower's failure to fulfil their obligation to repay a loan or meet other credit obligations (Sun & Chang, 2011). According to Loh (2018), a bank's credit risk may indeed be influenced by macroeconomic factors, like the growth rate of GDP, unemployment rate, and inflation rate. Hence, the bank faces not just credit risk but also market risk and operational risk. Consequently, banks must be able to alleviate these risks to prevent any negative effect on their intended outcomes (Sondakh et al., 2021). Market risk refers to the potential for a decline in an investment's value due to fluctuations in market variables such as equity risk, interest rate risk, and currency risk. Operational risk, as defined by Basel II, includes the potential for loss arising from inadequacies or failures in internal processes, personnel, and systems, as well as from external events (Sun & Chang, 2011). Operational losses may arise through the actions of many staff, including boards of directors, regardless of their seek, as noted by De Jongh et al. (2013). According to Chernobai et al. (2021), it has been seen that the growth of banks into nonbanking activities has resulted in increasing complexity, which in turn has led to a drop in banks' operational risk management. The significance of operational risk is potentially escalating due to the rising number of banks engaging in partnerships with FinTech businesses and the continuing growth of cyber risks (Berger et al., 2022; Santucci, 2018). According to Berger et al. (2022), James Bullard, the President of the Federal Reserve Bank of St. Louis, has observed that operational risk can potentially exceed credit risk in significance for several community banks in the future.

Women and risk

An increasing amount of scholarly research has provided insight into the significant influence women, in their capacity as primary decision-makers, have on affecting risk perceptions, behaviours, and outcomes across different social settings. Emotions, motivations, and perceptions may shape individuals' preferences for various options. These factors vary among individuals and the same individual over time. Despite these variations, prior research has yielded significant insights about demographic characteristics, such as gender, which permanently influence risk choices (Comeig et al., 2022). Several studies have provided evidence suggesting that there are gender differences in personality characteristics, specifically in terms of women displaying higher levels of risk aversion and ethical sensitivity (Chen et al., 2019; Cumming et al., 2015; Kinateder et al., 2021; Manello et al., 2023; Sila et al., 2016).

Previous studies have indicated that women exhibit lower levels of self-confidence compared to men, particularly in the context of financial and investment choices (Barber & Odean, 2001; Byrnes et al., 1999; Croson & Gneezy, 2009; Manello et al., 2023). Additionally, it has been observed that these women tend to make ethical decisions more frequently, although not necessarily displaying greater risk aversion compared to their male counterparts (Doan & Iskandar-Datta, 2020; Manello et al., 2023). The differences may be caused by biological reasons, namely genetic variations between males and females (Buss, 1989; Loukil & Yousfi, 2016; Saad & Gill, 2000), as well as psychological and social influences (Loukil & Yousfi, 2016; Meier-Pesti & Penz, 2008). According to Miller and Ubeda (2012), there is a suggestion that women display a higher level of sensitivity towards the environment when decision-making occurs. A different view is that women tend to stick to a budget, leading them to monitor their financial situation more closely than males (Abou-El-Sood, 2019).

Characteristics of women during crisis

Based on Van Staveren (2014), it has been observed that female portfolio managers mitigate risk by employing a strategy involving a higher degree of investment diversification. This approach enables them to outperform their male counterparts in various market conditions, including stable periods and times characterised by crisis and price volatility. Notably, female portfolio managers exhibit greater patience and self-control by maintaining their investment roles and engaging in less frequent trading activities during challenging market circumstances (Valls Martínez & Soriano Román, 2022). Valls Martínez and Soriano Román (2022) confirm that if the gender gap in the United States continues to expand, it is likely that a greater number of women will be restricted to supervisory roles, thereby having more influence on risk. According to Kirk and Gwin (2009), it may be argued that these characteristics have significant value, especially during challenging economic periods (Adams & Funk, 2012).

Women on the board and risk

A significant portion of the literature relevant to corporate decision-making in finance has mostly concentrated on the influence exerted by firm-specific characteristics rather than the individual characteristics of the managers (Hurley & Choudhary, 2020). Female directors have the potential to boost board effectiveness and improve risk management by taking the roles of monitor and adviser. Including risk management within corporate governance is the highest priority for the survival of a corporation. Risk ignorance by the board of directors has been identified as the primary factor contributing to the occurrence of previous financial crises and corporate failures (OECD, 2009). Hence, it is essential to evaluate the involvement of women directors in risk management (Chen et al., 2016).

Although several studies confirm that there is a lack of evidence on whether having female board members mitigates bank excessive risk-taking such as Abou-El-Sood (2021), Arango and Gaitan (2021), Manello et al. (2023), Sila et al. (2016), Tran et al. (2020), and Valls Martínez and Soriano

Román (2022), numerous studies have been conducted to examine the effects of board gender diversity on key factors that contribute to protecting organisations from financial difficulties. Illustratively, the presence of gender diversity on corporate boards has negative associations with the practice of tax avoidance (Chen et al., 2019); the dependence on debt (Faccio et al., 2016; Tran et al., 2020); the number of lawsuits (Adhikari et al., 2019); earnings management practices (Kyaw et al., 2015); the likelihood of financial statement manipulation or tax fraud (Wahid, 2019); and the ambiguity in disclosing financial risk (Bufarwa et al., 2020; Valls Martínez & Soriano Román, 2022). Furthermore, the presence of women on boards has been found to enhance corporate governance and risk management (Chen et al., 2016), as well as lead to more cautious choices regarding acquisitions and financing (Huang & Kisgen, 2013; Hurley & Choudhary, 2020).

Numerous studies have shown a negative association between gender diversity and firms' and banks' various risk types, specifically, firm risk (Perryman et al., 2016); credit default (Manello et al., 2023); stock return volatility (Jane Lenard et al., 2014; Adams & Ferreira, 2004; Jizi & Nehme, 2017; Valls Martínez & Soriano Román, 2022); the likelihood to experience failures (Faccio et al., 2016; Palvia et al., 2014); downside risk and systemic risk (Tran et al., 2020); the likelihood for risk-taking during mergers and acquisitions (Levi et al., 2014); the volatility in return on average assets among banks (Mateos de Cabo et al., 2012); and the volatility of return on assets (Faccio et al., 2016).

Mixed impacts of women on board toward risks

Some studies find an insignificant impact of gender diversity on the risk. For example, Sila et al. (2016) find no empirical evidence supporting the idea that the presence of women on corporate boards significantly impacts equity risk. In addition, there is no apparent distinction between firms with at least one female director and those without female directors (Ali et al., 2022). Furthermore, Matsa et al. (2013) confirm that there is no observed change in the level of company leverage after applying a required female boardroom participation quota in Norway (Sila et al., 2016).

Other studies have confirmed that women on boards are negatively associated with risk, as demonstrated by Abou-El-Sood (2021), Adams and Ragunathan (2017), Adhikari et al. (2019), Arango and Gaitan (2021), Bernile et al. (2018), Charness and Gneezy (2012), Jizi and Nehme (2017), Kinateder et al. (2021), Manello et al. (2023), Martin et al. (2009), Mateos de Cabo et al. (2009), Palvia et al. (2020), Perryman et al. (2016), and Safiullah et al. (2022).

In contrast, several studies have shown a positive relationship between gender diversity in banks and firm risks. For instance, female directors employed at well-capitalised banks have a greater tendency to take higher-risk positions (Abou-El-Sood, 2021). The findings indicate that firms with a more excellent representation of female directors tend to increase risk-taking, operational and insolvency risks (Safiullah et al., 2022); portfolio risk (Berger et al., 2014); frequency of trading and risk taking (Switzer & Huang, 2007); bad corporate governance (Al-Yahyaee et al., 2017); and the level of security concern (Adams & Funk, 2012).

However, risk-aversion characteristics have disappeared as women overcome obstacles to advancement, such as the glass ceiling, and have adapted to male-dominated environments (Adams & Funk, 2012). In addition, the level of risk tendency among female directors may differ depending on their particular roles, whether they hold non-executive or executive positions. Therefore, it is worth noting that female and male executive directors may exhibit similar tendencies toward risk-taking (Farag & Mallin, 2017). Furthermore, it is essential to acknowledge the potential influence of the self-selection process on the representation of females in managerial roles. According to the proposition by Croson and Gneezy (2009), women who choose management roles are often risk-takers and are expected to show risk preferences equivalent to those of their male counterparts (Hurley & Choudhary, 2020). In general, the available information presents a mixed and unclear image. The level of risk aversion shown by women may vary based on several factors such as current circumstances, cultural influences, the specific measure used, and the chosen sample population (Adamus, 2018; Maxfield et al., 2010; Valls Martínez & Soriano Román, 2022).

To the best of our knowledge, this research is the first empirical investigation into the influence of women on credit, market, and operational risk. It covers an essential period after the financial crisis in the United States, offering a broader timeframe than previous studies. Our final dataset from 2003 to 2019 consists of 179 bailout BHCs and 434 BHCs that have not received bailouts. Our hypothesis proposes that banks with a certain percentage of women on their boards reduce risk more effectively than banks without female representation or with a lower percentage of women in the following years of the bailout. We use the multivariate fixed effect regression method to test our hypothesis and to generate a comprehensive model for all BHC samples. This model incorporates both accounting-based and market-based variables. The fixed effects method helps address the serial correlation issue by considering unobservable, time-invariant variations across banks.

4.3 Methodology

In this section, we provide an overview of the sources of our dataset. We then go on to describe the methodology used to create the sample that is being studied. Lastly, we outline the essential independent and dependent variables for the regression estimate.

4.3.1 Research Data

This empirical study gathers data from various sources to conduct our analysis. Specifically, accounting data from 2003 to 2019 are obtained from the Federal Reserve Bank (FRB) of Chicago, which served as the primary source of accounting information for US Bank Holding Companies (BHCs). Second, the Center for Research in Security Prices (CRSP) is the primary source for market-related information concerning publicly traded Bank Holding Companies (BHCs), comprising a range of data points such as daily stock returns, stock prices, and the volume of outstanding shares. Third, we use the CRSP-FRB link (provided by the Federal

Reserve Bank of New York) to obtain PERMCO IDs. We obtain bailout data from the US Treasury Department. The US bank board data from 2003 to 2019 are sourced from BoardEx. Finally, we use the BoardEx-CRSP Compustat Link to merge CRSP with BoardEX. These sources are selected to provide a comprehensive examination of the data.

4.3.2 Sample Construction

Our sample selection is limited to US-based bank holding companies (BHCs) due to the specific focus of our research. First, we gather accounting data from the Federal Reserve Bank (FRB) of Chicago and link it with the bailout data obtained from the US Treasury Department. Then, we use the CRSP-FRB link (provided by the Federal Reserve Bank of New York) [18] to connect entity IDs (RSSD9001) in the FR Y-9C to PERMCO IDs in CRSP to merge the data, which is an effective method utilised by previous papers (Gandhi et al., 2019; Goetz et al., 2016). After that, we use the BoardEx-CRSP Compustat Link to match the FRB dataset with BoardEx using PERMCOs.[19]

Our sample starts in 2003 because BoardEx data coverage before 2003 is limited, and it ends in 2019 to avoid the effect of the COVID-19 pandemic. We exclude companies that have missing data points or missing reporting periods between their first and last years in the sample. The final dataset includes 2,317 bank-year observations of 179 bailout BHCs and 2,766 bank-year observations of 434 BHCs that have not been bailed out.

[18] The link (https://www.newyorkfed.org/research/banking_research/datasets.html) will take you to the website of the Federal Reserve Bank (FRB) of New York.
[19] The link (Wharton Research Data Services (upelnn.edu)) will take you to the website of the WRDS platform.

4.3.3 Measurement of Dependent Variables

In empirical research, various measures have been employed to assess credit, market, and operational risks.

4.3.3.1 Credit Risk Measures

4.3.3.1.1 Credit Risk (CR)

Credit risk is assessed by comparing the current year's net loan losses - calculated by deducting loan recoveries from loan charge-offs - to the previous year's total allowance for loan and lease losses. Imbierowicz and Rauch (2014) develop this measure, which is used to evaluate credit risk. The proposed measure aims to assess the unexpected occurrences of loan defaults and their effect on the risk aspects of the loan portfolio, which may be significantly changed by the decisions made by the bank's management within a short period of time (Imbierowicz & Rauch, 2014). Using this metric, we can assess how accurately banks predict short-term loan losses that could affect their long-term stability.

4.3.3.1.2 Loan Loss Reserve Ratio (LLRR)

We follow Sun and Chang (2011) to account for credit risk by applying a bank's loan loss reserve ratio (LLRR), the percentage of gross loans that have been put aside as reserves to protect against probable losses. The ratio is standardised as the ratio of loan loss reserves to gross loans. A higher (LLRR) indicates a greater level of expectation for non-performing loans within a bank's loan portfolio, which signifies a more careful and risk-averse approach. In contrast, a lower LLRR may signal a stronger level of trust in the ability of borrowers to repay their loans.

4.3.3.2 Market Risk Measures

In this chapter, we examine Value at Risk (VaR) and Expected Shortfall (ES) as dependent variables to assess the impact of women on the board on bank risk. The foundational methodologies for calculating these metrics are consistent with those detailed in Chapter Two (see Section 2.2.4.1: Downside Risk Measures).

4.3.3.2.1 Value at Risk (VaR)

VaR represents the maximum potential loss over a specific time period at a given confidence level. Our calculations employ the historical method, which does not assume a specific distribution for returns. Instead, we use historical return data to compute VaR by identifying the 1st percentile of returns, corresponding to a 99% confidence level.

4.3.3.2.2 Expected Shortfall (ES)

ES estimates the expected loss in cases where the VaR threshold is exceeded. We use the historical returns that exceeded the VaR threshold, providing an estimate of the expected loss in extreme scenarios.

To align with the annual frequency of other variables, we annualise the risk measures by averaging the quarterly VaR and ES values for each bank within each year. This approach smooths out short-term fluctuations and ensures consistency with other annual variables in our analysis.

4.3.3.3 Operational Risk Measures

4.3.3.3.1 Return on Assets Volatility (ROA_V)

We follow Sun and Chang (2011) to account for operational risk by utilising Return on Assets volatility (ROA_V). ROA_V is an accounting-based indicator calculated as the logged 5-year standard deviation of ROA.

4.3.3.3.2 Stock Return Volatility (Ret_V)

We follow Sun and Chang (2011) to account for operational risk by employing stock return volatility (Ret_V). Ret_V is a market-based indicator computed as the annualised standard deviation of the monthly log return.

4.3.4 Measurements of Independent Variables

We have used the same independent variables as in the previous chapter. Therefore, we prefer to mention them briefly here instead of providing detailed descriptions, as follows:

Post Bailout Time, Bailed Dummy Variable, Women Categories (Uniform groups, Skewed groups, Tilted groups, Balanced groups), Capital, Real Estate Loans to Gross Total Assets, Bank Size, IETL, Gross Loan, Liquidity, Number of Directors, Average Age, and Experience Measures (Average experience, Average bank board tenure, Average Listed Board Tenure).

To address the potential impact of outliers on our statistical estimates, we have used the technique of winsorisation on all variables at a significance level of 1%, in accordance with the guidance provided in the relevant academic literature.

Table 4.1 provides a comprehensive description of all variables.

Table 4.1: Description of the Variables

Variable	Description	Data source
Dependent Variables		
CR	Credit risk = the net loan charge-offs / the loan loss allowance in the previous year.	Federal Reserve Bank (FRB) of Chicago
LLRR	Loan loss reserve ratio = loan loss reserves/gross loans	Federal Reserve Bank (FRB) of Chicago
VaR	Value-at-Risk determined using daily returns over the previous 12 months at 1% significance level.	CRSP
ES	Expected Shortfall determined using daily returns over the previous 12 months at 1% significance level.	CRSP
ROA_V	Return on assets volatility is computed by a logged 5-year standard deviation of ROA.	Federal Reserve Bank (FRB) of Chicago
Ret_V	Stock return volatility is calculated by the annualized standard deviation from the monthly log return.	CRSP
Independent Variables		
Post bailout time	The year 2010-2019 dummy for these years	The US Treasury Department
Bailed	Dummy variable: It is 0 before and 1 after the bailout	The US Treasury Department
Women Ratio	The proportion of women directors on the firm's boards.	BoardEx
Uniform groups	Dummy variable: 1 if there is no woman on the board and 0 otherwise.	BoardEx
Skewed groups	Dummy variable: It is 1 if there is up to 20% of the board are women, and 0 otherwise.	BoardEx
Tilted groups	Dummy variable: 1 if there is more than 20% and less or equal to 40% of the board are women, and 0 otherwise.	BoardEx
Balanced groups	Dummy variable: 1 if there is more than 40% and less or equal 60% of the board are women, and 0 otherwise.	BoardEx
Interaction dummy	The result of multiplying post-bailout time with bailed and the categories of women ratio.	BoardEx
Control Variables		
Capital	Total Equity divided by GTA.	Federal Reserve Bank (FRB) of Chicago
RELGTA	Real-estate loans: Real-estate loans / (GTA)	Federal Reserve Bank (FRB) of Chicago
LGTA	Bank size: natural logarithm of (GTA).	Federal Reserve Bank (FRB) of Chicago
IETL	Liquidity: IETL = total Interest expenses / total Liabilities	Federal Reserve Bank (FRB) of Chicago
LnGrossLoan	Natural logarithm of gross loans.	Federal Reserve Bank (FRB) of Chicago
Liquidity	Liquidity = customer deposit / gross loan	Federal Reserve Bank (FRB) of Chicago
NumberDirectors	The number of executives, supervisory, or all directors, as chosen on the annual report date to account for the board size.	BoardEx
LnAveAge	The natural logarithm of the average age of board members.	BoardEx
LnAveExp	Natural logarithm of the average number of company boards (private, quoted, or other) that board members have served on over their careers.	BoardEx
LnAveBankBrdTenure	Natural logarithm of the average number of years that board members have spent on bank boards.	BoardEx
LnAveListedBrdTenure	The average number of years board members have sat on a board of a publicly listed company.	BoardEx

Notes: The present study utilises a set of dependent, independent, and control variables to construct the empirical analysis. A comprehensive overview of these variables is provided in this Table, where the first column lists the names of the variables, the second column provides their definitions, and the third column specifies the data sources utilised.

4.4 Empirical Model and Method

Here, we provide a summary of our variables' statistics and essential details about how they are correlated. Following this, we assess each variable's statistical significance by using multivariate fixed-effect regression analysis. This allows us to estimate the model for all samples of bank holding companies (BHC) incorporating accounting-based and market-based variables. The primary findings are comprehensively discussed.

4.4.1 Descriptive Statistics and Correlation

The summary statistics for our variables are shown in detail in Table 4.2. Significant differences exist between banks that have received bailouts and those that have not. Bailed-out banks have higher mean values of credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), stock return volatility (Ret_V), women ratio, liquidity, level of experience, and larger bank size compared to the non-bailed-out banks.

Non-bailed-out banks have the mean priority of capital levels and proportion of real estate loans. Given the increased volatility associated with these institutions, the higher mean values of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V) in bailed-out banks are expected. A higher number of these risk measures is indicative of higher risk.

The average value of (Capital) among banks that had bailouts is less than that of banks that did not get bailouts, suggesting a lower stability level in the first group. The average value of real estate loans (REALGTA) for banks that had bailouts, around 0.47, is comparatively lower than that of banks that did not get bailouts. This difference suggests a reduced risk and a more cautious approach regarding real estate loans. Furthermore, bailed-out banks have a larger mean value in terms of bank size (LGTA), suggesting that bank size has an important role. The bailed-out banks have better liquidity, as shown by the mean values of the total interest expenses to total Liabilities (IETL) and customer deposits to gross loans (Liquidity).

Although greater customer deposits to gross loan ratios show that bailed-out banks have boosted their liquidity levels after the financial crisis, the higher interest expenses to total liabilities may be a double-edged sword. This suggests a planned shift in focus towards more liquid liabilities. Still, on the other hand, it may imply a high degree of risk since a greater percentage of interest expenses to total liabilities has been linked to a higher probability of bank failure.

Based on the analysis of data obtained from banks that received bailouts, it becomes apparent that the variable (LnAveExp), representing the average board experience of the board members across all boards they have been served on, displays considerable variability. The average number of boards on which board members have served is typically 5, while some banks have (LnAveExp) values as high as 13. Furthermore, the variable labelled as (LnAveBankBrdTenure), which indicates an average length of board membership in various banks, exhibits a range of 2 to 13 years, with an estimated mean value of 9 years. The (LnAveListedBrdTenure) measure assesses the mean length of time individuals serve as board members in listed companies. It has been approximated that the average (LnAveListedBrdTenure) is around six years; however, some banking institutions exhibit much longer durations, with values reaching up to 14 years. It is worth noting that banks that did not get bailouts have lower average values across all experience metrics, with a difference of about one year.

Table 4.2: Summary Statistics Without Categories

Variable	Banks that have been bailed out					Banks that have not been bailed out				
	Mean	Sd	Min	Median	Max	Mean	Sd	Min	Median	Max
CR	0.6538	0.6540	-0.1698	0.4604	3.1378	0.5462	0.6331	-0.1698	0.3511	3.1378
LLRR	0.0195	0.0138	0.0021	0.0139	0.0735	0.0150	0.0106	0.0021	0.01221	0.0735
VaR	0.0623	0.0395	0.0164	0.0478	0.2796	0.0544	0.0330	0.0149	0.0448	0.3335
ES	0.0748	0.0489	0.0178	0.0570	0.4055	0.0651	0.0409	0.0192	0.0531	0.4369
ROA_V	-5.0894	1.1323	-8.5417	-5.1837	-2.9071	-5.4541	1.1127	-8.5417	-5.4834	-2.9071
Ret_V	0.2997	0.2012	0.0729	0.2354	1.1583	0.2518	0.1646	0.0729	0.2116	1.1583
Women Ratio	0.1253	0.0965	0	0.111	0.5	0.1087	0.0891	0	0.1	0.5
Capital	0.0989	0.0227	0.0433	0.0974	0.1756	0.1040	0.0317	0.0433	0.0987	0.2135
RELGTA	0.4771	0.1543	0.0014	0.4945	0.8106	0.5075	0.1712	0.0014	0.5273	0.8106
LGTA	15.4705	1.7064	12.1898	15.0192	20.6308	14.7828	1.4204	12.6276	14.5225	20.6308
IETL	0.0358	0.0249	0.0032	0.0297	0.1007	0.0349	0.0245	0.0032	0.0280	0.1007
LnGrossLoan	15.0417	1.6647	12.2619	14.6463	19.6790	14.3200	1.3376	12.1079	14.1009	19.6790
Liquidity	0.1620	0.1434	0.0001	0.1136	0.7962	0.1478	0.1293	0.0001	0.1137	0.7962
NumberDirectors	11.7941	2.8200	6	12	20	11.0654	3.1553	6	11	20
LnAveAge	4.1228	0.0577	3.9659	4.1239	4.2789	4.1202	0.0630	3.9659	4.1219	4.2789
LnAveExp	1.6195	0.4088	0.7621	1.5841	2.5925	1.4946	0.3770	0.7621	1.4469	2.5925
LnAveBankBrdTenure	2.1892	0.4254	0.3364	2.2532	2.9444	2.0610	0.5802	0.3364	2.1984	2.9444
LnAveListedBrdTenure	1.7881	0.5827	0	1.9328	2.6112	1.6414	0.6364	0	1.7676	2.6112
Bailed	1	0	1	1	1	0	0	0	0	0

Notes: This Table provides descriptive data for all variables in consideration, covering the period between 2003 and 2019 for both bailout banks and non-bailout bank holding companies (BHCs).

Table 4.3 presents the results of the pairwise correlation analysis. Table 4.3 demonstrates that the correlation among most accounting measures exhibits low to moderate levels and is significant at 1%.

Several exceptions show an insignificant correlation among some control variables with risk measures, such as the natural logarithm of average age (LnAveAge) with credit risk (CR). In addition, the loan loss reserve ratio (LLRR) shows an insignificant relation with the following variables: the bank size (LGTA), the total Interest expenses to total Liabilities (IETL), the natural logarithm of gross loans (LnGrossLoan), the natural logarithm of average age (LnAveAge).

Also, these risk metrics, value at risk (VaR) and expected shortfall (ES), show insignificant relation with the following variables: the average length of board membership across all banks (LnAveBankBrdTenure) and the average duration of board membership for listed companies (LnAveListedBrdTenure). The return on assets volatility (ROA_V) has an insignificant correlation with the (women ratio), the (capital), the real estate loans (REALGTA), the bank size (LGTA), and the natural logarithm of gross loans (LnGrossLoan). Finally, the stock return volatility (Ret_V) has insignificant relation with the bank size (LGTA), the natural logarithm of gross loans (LnGrossLoan), the natural logarithm of average age (LnAveAge), the average board experience of board members across all boards they have served (LnAveExp), and the average length of board membership across all banks (LnAveBankBrdTenure).

Even though we use some variables with insignificant correlations with specific risk measures in the model, their inclusion is motivated by existing literature. Additionally, in a comprehensive investigation, it is common to include factors that have significance within the larger field context, even if they do not exhibit significant correlations in every case. This methodology has the potential to provide an in-depth understanding of the topic at hand.

Furthermore, Table 4.3 reveals the results of the pairwise correlation analysis.

Table 4.3: Pairwise Correlations Without Categories

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) CR	1.0000																		
(2) LLRR	0.3195***	1.0000																	
(3) VaR	0.4886***	0.4927***	1.0000																
(4) ES	0.4851***	0.4854***	0.9780***	1.0000															
(5) ROA_V	0.3831***	0.4955***	0.4840***	0.4837***	1.0000														
(6) Ret_V	0.4655***	0.4728***	0.7913***	0.7727***	0.4785***	1.0000													
(7) Women Ratio	-0.0247*	-0.0488***	-0.0965***	-0.0942***	-0.0140	-0.0490***	1.0000												
(8) Capital	-0.0409***	-0.0993***	-0.2141***	-0.2074***	0.0194	-0.1843***	0.1282***	1.0000											
(9) RELGTA	-0.1163***	-0.0794***	0.0632***	0.0524***	0.0003	0.0460***	-0.1902***	-0.1111***	1.0000										
(10) LGTA	0.1036***	-0.0113	-0.1282***	-0.1233***	0.0156	-0.0124	0.3574***	0.1805***	-0.5035***	1.0000									
(11) IETL	0.1278***	0.0018	0.1700***	0.1676***	-0.0465***	0.1674***	-0.2002***	-0.3127***	0.1728***	-0.2062***	1.0000								
12) LnGrossLoan	0.1063***	-0.0035	-0.1327***	-0.1300***	0.0153	-0.0081	0.3486***	0.1670***	-0.3778***	0.9751***	-0.1871***	1.0000							
(13) Liquidity	-0.1678***	-0.1014***	-0.1630***	-0.1535***	-0.0783***	-0.1413***	0.0930***	0.1296***	-0.2908***	0.1540***	-0.4320***	0.0801***	1.0000						
(14) Number of Directors	-0.0261*	-0.0856***	-0.0789***	-0.0834***	-0.0864***	-0.0634***	0.1558***	0.0279**	-0.1589***	0.3697***	-0.0127	0.3722***	0.0195	1.0000					
(15) LnAveAge	-0.0452***	-0.0228	-0.0580***	-0.0546***	0.0266*	-0.0035	0.0296**	0.1633***	-0.0570***	0.1753***	-0.2847***	0.1605***	0.1660***	0.0377***	1.0000				
(16) LnAveExp	0.0906***	0.0391***	-0.0395***	-0.0316**	0.1211***	0.0199	0.2259***	0.1852***	-0.4125***	0.6202***	-0.1917***	0.5976***	0.0935***	0.1981***	0.1069***	1.0000			
(17) LnAveBank BrdTenure	0.0145	0.0395***	-0.0008	-0.0056	-0.0533***	0.0020	-0.0665***	-0.1435***	-0.0631***	-0.0087	0.0150	-0.0168	0.0874***	0.0045	0.2191***	-0.1760***	1.0000		
(18) LnAveListed BrdTenure	0.0949***	0.0499***	0.0097	0.0121	0.2210***	0.0805***	0.2637***	0.2729****	-0.1649***	0.4505***	-0.4467***	0.4522***	0.2218***	0.0661***	0.3734***	0.3437***	0.3105***	1.0000	
(19) Bailed	0.0831***	0.1782***	0.1083***	0.1074***	0.1603***	0.1297***	0.0890***	-0.0916***	-0.0921***	0.2125***	0.0180	0.2337***	0.0517***	0.1198***	0.0217	0.1568***	0.1234***	0.1185***	1.0000

Note: This Table presents the correlations among the variables.

4.4.2 The Multivariate Fixed Effect Regression Analysis

The multivariate fixed effect regression approach is used to estimate a multivariate model for all BHC samples, including accounting-based and market-based variables. The following section presents the specifications of the model:

$$Risk\ measure_{b,t} = \beta_0 + \beta_1 post\ bailout\ time_{b,t} + \beta_2 bailed_{b,t} + \beta_3 gender\ ratio_{b,t} + \beta_4 post\ bailout\ time_{b,t} * bailed_{b,t} * gender\ ratio_{b,t} + \beta_5 Capital_{b,t} + \beta_6 RELGTA_{b,t} + \beta_7 LGTA_{b,t} + \beta_8 IETL_{b,t} + \beta_9 LnGrossLoan_{b,t} + \beta_{10} Liquidity_{b,t} + \beta_{11} NumberDirectors_{b,t} + \beta_{12} LnAveAge_{b,t} + \beta_{13} LnAveExp_{b,t} + \beta_{14} LnAveBankBrdTenure_{b,t} + \beta_{15} LnAveListedBrdTenure_{b,t} + \delta_b + \varepsilon_{b,t} \quad (1)$$

Where $risk\ measures$ are credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), stock return volatility (Ret_V). The variable $Post\ bailout\ time_i$ is a binary variable that is assigned a value of 1 during the period from 2010 to 2019, and a value of 0 otherwise. This variable represents the treatment period, which refers to the period following the bailout and global financial crisis. The variable $bailed_i$ is a binary indicator that reflects the banks that received a bailout. The $gender\ ratio$ includes four distinct categories. The first variable is the uniform groups, a binary variable that assumes a value of 1 when there is an absence of women on the board, and 0 otherwise. The second category refers to skewed groups, represented by a binary variable that takes the value of 1 if the proportion of women on the board is up to 20%, and 0 otherwise. The third category belongs to tilted groups, a binary variable that assumes a value of 1 when the proportion of women on the board ranges from more than 20% to less than or equal to 40%, and 0 otherwise. The fourth category relates to balanced groups, represented by a binary variable that takes on a value of 1 if the proportion of women on the board falls between more than 40% and less or equal to 60%, and a value of 0 otherwise. The $post\ bailout\ time_i * bailed_i * gender\ ratio_i$ is an interaction dummy resulting from multiplying post-bailout time with bailed and the categories of women ratio. δ_b if BHC fixed effects, and $\varepsilon_{b,t}$ is an error term. By considering unobserved, time-invariant variations between banks, the fixed effects method reduces the consequences of serial correlation.[20]

According to Kante's (1977b) categorisation, the ratio of women has been categorised into four main groups. The classification technique enabled us to find an appropriate range for the proportion of female bank board members. This range is believed to effectively mitigate banks' risks, including credit, market, and operational risks. Based on all groups, the post-bailout period variable significantly increases (LLRR) and (ROA_V), while decreasing market risk measures and (Ret_V). Other measures are not significant.

The first classification, known as the "uniform groups", is shown in Table 4.4. The bailed variable decreases all risk measures, but only (Ret_V) shows a significant result. The uniform group itself increases (LLRR) significantly at the 10% level. The results of our study suggest that in cases when no women serving on the board of directors (uniform groups), the interaction dummy variable has a statistically significant impact on credit risk, market risk, and operational risk, leading to an increase of 27.2% in (CR), 0.5% in (LLRR), 0.9% in (VaR), 1.2% in (ES), 31.1% in (ROA_V), and 6.3% in (Ret_V). Only (CR) remains significant at the 1% level when the control variables are included. The findings presented in this research are in line with the findings of Joecks et al. (2013), in terms of studying the critical mass theory based on women groups, who also saw non-significant results when examining the effects of uniform groups.

[20] In the panel data, we employed the Hausman test to determine whether to use the fixed effects or random effects model. The outcome recommended the use of the fixed effects model.

Table 4.4: The Fixed-Effects Regression Model when the Women Ratio Category Is the Uniform Groups

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.0008	0.004***	-0.009***	-0.010***	0.520***	-0.016*	0.054	0.008***	-0.031***	-.035***	0.047	-0.110***
	(-0.03)	(4.53)	(-4.98)	(-4.52)	(7.76)	(-1.84)	(1.07)	(6.30)	(-9.78)	(-8.93)	(0.50)	(-7.13)
Bailed	-0.059	-0.0001	-.00008	-0.0001	0.109	-0.022*	-0.053	0.0003	0.001	0.001	0.198*	-0.006
	(-1.30)	(-0.14)	(-0.04)	(-0.06)	(1.14)	(-1.92)	(-1.06)	(0.27)	(0.55)	(0.42)	(1.94)	(-0.49)
Uniform groups	0.003	0.001*	0.001	0.0004	0.031	-0.012	-0.021	0.00005	0.001	0.001	0.044	-0.006
	(0.08)	(1.86)	(0.40)	(0.14)	(0.30)	(-0.85)	(-0.51)	(0.05)	(0.56)	(0.39)	(0.48)	(-0.46)
Interaction dummy	0.272***	0.005***	0.009**	0.012**	0.311**	0.063***	0.182***	0.002	-0.0009	-0.00002	0.001	0.024
	(3.96)	(2.67)	(2.34)	(2.35)	(2.01)	(2.87)	(2.73)	(1.44)	(-0.22)	(-0.00)	(0.01)	(1.14)
Capital							-3.156***	-0.081***	-0.332***	-0.395***	-2.277	-2.106***
							(-3.70)	(-3.71)	(-5.63)	(-5.39)	(-1.51)	(-6.74)
RELGTA							0.889***	0.0006	0.060**	0.073***	0.248	0.328***
							(2.77)	(-0.05)	(2.56)	(2.64)	(0.31)	(3.65)
LGTA							1.227***	0.011	0.082***	0.104***	1.237**	0.383***
							(4.89)	(0.93)	(4.34)	(4.72)	(2.28)	(6.03)
IETL							2.064***	0.012	-0.308***	-0.341***	1.512	-0.567***
							(2.96)	(0.94)	(-7.45)	(-6.71)	(1.29)	-2.82
LnGrossLoan							-1.169***	-0.018	-0.084***	-0.105***	-1.673***	-0.341***
							(-4.94)	(-1.61)	(-4.63)	(-5.03)	(-3.26)	(-5.69)
Liquidity							-1.218***	-0.024***	-0.075***	-0.089***	-1.966***	-0.323***
							(-7.51)	(-8.00)	(-8.56)	(-8.12)	(-8.02)	(-8.24)
Number of Directors							-0.026***	-0.0002	-0.001***	-0.001***	-0.0128	-0.008***
							(-3.66)	(-1.62)	(-3.21)	(-3.07)	(-0.88)	(-3.73)
LnAveAge							-0.262	-0.004	-0.005	-0.007	-1.744*	0.146
							(-0.62)	(0.39)	(-0.19)	(-0.24)	(-1.70)	(1.15)
LnAveExp							0.061	0.003*	0.005	0.006	0.413**	-0.017
							(0.73)	(1.87)	(1.01)	(1.19)	(2.39)	(-0.77)
LnAveBank BrdTenure							-0.032	-0.0007	-0.014***	-0.017***	-0.383***	-0.079***
							(-0.63)	(0.59)	(-4.56)	(-4.76)	(-2.91)	(-4.81)
LnAveListed BrdTenure							0.174***	0.002***	0.029***	0.035***	1.415***	0.135***
							(4.92)	(-0.59)	(13.67)	(12.99)	(12.93)	(12.67)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,083	5,083	5,083	5,083	4,455	5,083	4,893	4,893	4,893	4,893	4,304	4,893
Number of groups	613	613	613	613	566	613	592	592	592	592	550	592
R-squared	0.0060	0.0555	0.0142	0.0118	0.0951	0.0062	0.0983	0.2222	0.1814	0.1711	0.2670	0.1698

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the uniform groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

The second category, labelled as "skewed groups" in Table 4.5, exhibits a proportion of women on the board of directors that ranges up to 20%. The bailed variable shows the same result as the uniform group. The skewed group itself decreases all risk measures, but none of these decreases are significant.

The findings from the skewed groups indicate that the interaction dummy significantly increases credit risk, market risk, and operational risk. Specifically, it leads to increases of 13.3% in (CR), 0.4% in (LLRR), 0.7% in (VaR), 0.7% in (ES), and 31.6% in (ROA_V). The only exception is (Ret_V) which shows an insignificant coefficient. Notably, the coefficients of risk measures are lower than those of uniform groups, which clarifies that women may play a good role in decreasing risk in the bank. The results are consistent and significant after the inclusion of the control variables. They align with the findings made by Joecks et al. (2013) in terms of studying the critical mass theory based on women groups, demonstrating a positive association between skewed groups and the examined risk measures.

Moreover, our results indicate that, within skewed groups, banks exhibiting a greater degree of capital tend to have a lower risk tendency. This finding is consistent with the findings of Berger and Bouwman (2013), wherein there is a positive relation between capital and bank survival.

Furthermore, it is worth noting that the control variable, namely real estate loans, has a statistically significant positive coefficient. This suggests that banks with higher levels of real estate loans are more likely to increase their level of risk. This finding aligns with the research conducted by Berger et al. (2012), who confirm that an increase in real estate loans indicates a greater potential for distress faced by the bank. Also, the coefficient associated with bank size has a statistically significant positive relationship, suggesting that an increase in bank size is associated with a higher likelihood of risk. This is consistent with the finding of Bhagat et al. (2012) that there is a favourable correlation between size and risk-taking measures, which is consistent with the concept of "too-big-to-fail".

Our finding confirms that the interest expenses to total liabilities significantly increase (CR) while decreasing (VaR), (ES), and (Ret_V). Betz et al. (2014) confirm that a higher proportion of interest expenses to total liabilities is anticipated to exhibit a positive association with the occurrence of a bank failure.

The liquidity measure, namely the ratio of customer deposits to gross loans, significantly decreases the risk measurements. The results of our investigation are consistent with the research done by Bologna (2015), which establishes that bank's resilience is enhanced by maintaining a balanced funding position characterised by a higher proportion of deposits and a lower loans-deposits gap.

The empirical findings suggest a statistically significant and negative relationship between credit expansion and risk measures, as shown by the natural logarithm of gross loan measure. The results of our investigation are consistent with the conclusion of Tehulu (2016), who establishes a negative and significant impact of gross loan portfolio on credit risk.

We find that a higher number of directors significantly lowers our risk measures. These results are consistent with Zion and Markarian (2018), who confirm that small board banks are riskier. We find the average age (LnAveAge) of the board of directors only affects the (ROA_V) which is one of the operational risk measures, and its effect is negative and significant at 10%. This result is consistent with Hsu and Wang (2014), who has shown that the structure of a board, particularly the average age of its members, has been found to have an impact on reducing the likelihood of information security events.

The average number of corporate board experiences that board members have accumulated over their careers has a significant and positive influence, meaning it increases (LLRR) and (ROA_V).

The average length of a board member's years of service on bank boards has a negative and statistically significant effect, meaning it decreases market and operational risks. Credit risk, market risk, and operational risk all significantly increase with the average number of years that board members have served on the board of a publicly listed company. Based on these findings, it appears that the average bank board tenure—rather than a higher number of years spent at a different company or listed company—is the type of expertise associated with lowering risk.

Table 4.5: The Fixed-Effects Regression Model when the Women Ratio Category Is the Skewed Groups

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.00006	0.004***	-0.009***	-0.010***	0.521***	-0.013	0.049	0.008***	-0.031***	-.035***	0.035	-0.110***
	(0.00)	(4.40)	(-5.00)	(-4.51)	(7.87)	(-1.62)	(0.98)	(6.25)	(-9.88)	(-9.00)	(0.37)	(-7.15)
Bailed	-0.081	-0.001	-0.002	-0.002	-0.010	-0.026*	-0.095	-0.001	-0.003	-0.004	0.010	-0.019
	(-1.46)	(-1.05)	(-0.80)	(-0.51)	(-0.09)	(-1.68)	(-1.65)	(-0.87)	(-1.12)	(-1.01)	(0.09)	(-1.20)
Skewed groups	-0.024	-0.0005	-0.003	-0.003	-0.083	-0.016	-0.024	-0.0004	-0.004**	-0.004	-0.077	-0.016
	(-0.64)	(-0.71)	(-1.41)	(-1.07)	(-1.13)	(-1.35)	(-0.70)	(-0.57)	(-2.20)	(-2.00)	(-1.17)	(-1.52)
Interaction dummy	0.133**	0.004***	0.007**	0.007*	0.316***	0.024	0.135**	0.004***	0.008***	0.008**	0.330***	0.027*
	(2.18)	(3.45)	(2.47)	(1.94)	(2.90)	(1.63)	(2.32)	(3.37)	(2.83)	(2.44)	(3.43)	(1.79)
Capital							-3.156***	-0.082***	-0.331***	-0.394***	-2.337	-2.104***
							(-3.79)	(-3.80)	(2.58)	(-5.41)	(-1.56)	(-6.75)
RELGTA							0.888***	-0.001	0.060**	0.073***	0.165	0.333***
							(2.76)	(-0.11)	(2.58)	(2.66)	(0.21)	(3.69)
LGTA							1.248***	0.011	0.083***	0.105***	1.232**	0.390***
							(4.99)	(0.95)	(4.43)	(4.82)	(2.30)	(6.20)
IETL							1.964***	0.010	-0.311***	-0.346***	1.444	-0.594***
							(2.83)	(0.83)	(-7.56)	(-6.82)	(1.23)	(-2.96)
LnGrossLoan							-1.192***	-0.018	-0.085***	-0.106***	-1.660***	-0.348***
							(-5.05)	(-1.64)	(-4.73)	(-5.13)	(-3.28)	(-5.87)
Liquidity							-1.219***	-0.023***	-0.075***	-0.089***	-1.933***	-0.323***
							(-7.63)	(-8.38)	(-8.60)	(-8.15)	(-8.01)	(-8.38)
Number of Directors							-0.026***	-0.0003*	-0.001***	-0.001***	-0.014	-0.007***
							(-3.85)	(-1.89)	(-3.12)	(-2.97)	(-1.06)	(-3.59)
LnAveAge							-0.250	-0.003	-0.005	-0.008	-1.734*	0.142
							(-0.58)	(-0.36)	(-0.20)	(-0.26)	(-1.70)	(1.14)
LnAveExp							0.065	0.003*	0.004	0.006	0.402**	-0.017
							(0.79)	(1.92)	(1.01)	(1.19)	(2.39)	(-0.75)
LnAveBank BrdTenure							-0.044	-0.001	-0.014***	-0.017***	-0.413***	-0.081***
							(-0.87)	(-0.87)	(-4.66)	(-4.85)	(-3.16)	(-4.91)
LnAveListed BrdTenure							0.182***	0.002***	0.029***	0.035***	1.425***	0.137***
							(5.15)	(4.53)	(13.82)	(13.17)	(13.07)	(12.83)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,083	5,083	5,083	5,083	4,455	5,083	4,893	4,893	4,893	4,893	4,304	4,893
Number of groups	613	613	613	613	566	613	592	592	592	592	550	592
R-squared	0.0022	0.0517	0.0136	0.0106	0.0963	0.0042	0.0982	0.2280	0.1838	0.1730	0.2721	0.1705

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the skewed groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

The third category, shown in Table 4.6, is known as the "tilted groups", where the percentage of women on the board of directors ranges from above 20% to up to 40%. Based on this group, the bailed variable increases all risk measures significantly, except for (Ret_V). The tilted group itself significantly increases all market and operational risk measures but has an insignificant impact on credit risk measures.

Our findings show that the interaction dummy significantly decreases credit, market, and operational risks. Specifically, it leads to a decrease of 39.9% in (CR), indicating improved loan quality; 0.9% in (LLRR), reflecting better asset management; 1.8% in (VaR), suggesting lower potential loss in worst-case scenarios; 2.1% in (ES), highlighting reduced risk in extreme market conditions; 69.2% in (ROA_V), suggesting improved oversight and operational efficiency; and 10.7% in (Ret_V), showing less fluctuation in stock returns. After using the control variables, the coefficient of all risk measures remains significant at the 1% level, indicating that including control variables does not change the significant impact of the interaction dummy on these risk measures. The results of our study conducted on tilted groups are consistent with the empirical findings reported by Joecks et al. (2013). According to their research, it is seen that a critical mass of female representation on corporate boards is achieved when the percentage of women ranges from 20% to 40%.

The study on all control variables reveals that their effects align with those seen in the skewed groups category. Additionally, the metrics of experience have the same results, which is a negative and statistically significant relationship between the average tenure of board members on bank boards and both market and operational risk.

Table 4.6: The Fixed-Effects Regression Model when the Women Ratio Category Is the Tilted Groups

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.007	0.004***	-0.009***	-0.010***	0.503***	-0.018**	0.042	0.008***	-0.031***	-.036***	0.028	-0.112***
	(-0.23)	(4.39)	(-5.49)	(-4.97)	(7.56)	(-2.16)	(0.84)	(6.20)	(-9.90)	(-9.04)	(0.30)	(-7.24)
Bailed	0.090*	0.003***	0.005**	0.006**	0.335***	0.010	0.062	0.002**	0.003	-0.004	0.309***	0.012
	(1.92)	(2.93)	(2.35)	(2.22)	(3.27)	(0.85)	(1.25)	(2.16)	(1.36)	(1.24)	(2.98)	(0.95)
Tilted groups	0.105	0.00009	0.007**	0.008*	0.228**	0.066***	0.127**	0.001	0.008**	0.009**	0.138	0.052***
	(1.61)	(0.09)	(2.02)	(1.78)	(2.47)	(3.69)	(2.05)	(1.54)	(2.44)	(2.35)	(1.56)	(3.11)
Interaction dummy	-0.399***	-0.009***	-0.018***	-0.021***	-0.692***	-0.107***	-0.359***	-0.008***	-0.012***	-0.015***	-0.466***	-0.077***
	(-5.47)	(-6.69)	(-4.59)	(-4.25)	(-6.33)	(-5.53)	(-4.84)	(-5.98)	(-3.26)	(-3.20)	(-4.30)	(-3.86)
Capital							-3.114***	-0.080***	-0.329***	-0.391***	-2.195	-2.089***
							(-3.70)	(-3.74)	(-5.64)	(-5.39)	(-1.47)	(-6.75)
RELGTA							0.829***	-0.003	0.060**	0.073***	0.085	0.331***
							(2.59)	(-0.24)	(2.51)	(2.59)	(0.11)	(3.64)
LGTA							1.222***	0.010	0.082***	0.104***	1.183**	0.387***
							(5.07)	(0.89)	(4.32)	(4.72)	(2.23)	(6.15)
IETL							2.002***	0.012	-0.308***	-0.342***	1.519	-0.585***
							(2.89)	(0.93)	(-7.45)	(-6.72)	(1.30)	(-2.90)
LnGrossLoan							-1.156***	-0.017	-0.084***	-0.105***	-1.597***	-0.345***
							(-5.07)	(-1.55)	(-4.61)	(-5.02)	(-3.18)	(-5.80)
Liquidity							-1.180***	-0.022***	-0.074***	-0.088***	-1.886***	-0.319***
							(-7.35)	(-8.13)	(-8.36)	(-7.94)	(-7.74)	(-8.10)
Number of Directors							-0.027***	-0.0002*	-0.0016***	-0.001***	-0.015	-0.008***
							(-3.86)	(1.88)	(-3.37)	(-3.22)	(-1.09)	(-3.82)
LnAveAge							-0.286	-0.005	-0.003	-0.006	-1.779*	0.150
							(-0.67)	(-0.49)	(-0.14)	(-0.20)	(-1.74)	(1.19)
LnAveExp							0.051	0.002*	0.005	0.007	0.378**	-0.016
							(0.62)	(1.68)	(1.02)	(1.19)	(2.29)	(-0.71)
LnAveBank BrdTenure							-0.045	-0.001	-0.014***	-0.017***	-0.402***	-0.080***
							(-0.87)	(-0.89)	(-4.53)	(-4.77)	(-3.04)	(-4.87)
LnAveListed BrdTenure							0.175***	0.002***	0.029***	0.034***	1.408***	0.133***
							(5.05)	(4.39)	(13.63)	(12.99)	(12.88)	(12.71)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,083	5,083	5,083	5,083	4,455	5,083	4,893	4,893	4,893	4,893	4,304	4,893
Number of groups	613	613	613	613	566	613	592	592	592	592	550	592
R-squared	0.0131	0.0781	0.0185	0.0153	0.1065	0.0125	0.1054	0.2383	0.1848	0.1742	0.2737	0.1743

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the tilted groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.7 displays the fourth category, "balanced groups". Within these groups, the proportion of women on the board of directors ranges from above 40% to a maximum of 60%. The bailed variable significantly increases only ROA_V, while other measures show insignificant results. The balanced group itself significantly increases all risk measures except for LLRR, which is insignificant.

It can be observed that the interaction dummy variable significantly decreases credit risk, market risk, and operational risk. Specifically, it leads to a decrease of 58.1% in (CR), 1.4% in (LLRR), 3.0% in (VaR), 3.6% in (ES), 102.7% in (ROA_V), and 1.47% in (Ret_V). The significant reduction of 58.1% in (CR) indicates that higher gender diversity in balanced groups is associated with lower credit risk, suggesting enhanced risk management practices. Although (LLRR) shows a decrease of 1.4%, it is not statistically significant, indicating no clear effect. The 3.0% reduction in (VaR) demonstrates that balanced groups contribute to lower market risk through more careful risk management. Similarly, the 3.6% decrease in (ES) signifies a meaningful reduction in market risk. The substantial decline of 102.7% in (ROA_V) shows a strong negative impact, suggesting improved oversight and operational efficiency. Despite a 1.47% reduction in (Ret_V), the result is insignificant, indicating no clear evidence of an effect on this measure. After including control variables, the only coefficients that remain significant are (CR) and (VaR) at 5% and 10%, respectively. This contrasts with Joecks et al. (2013), who found an insignificant effect of balanced groups, suggesting that gender diversity slightly impacts risk measures.

Table 4.7: The Fixed-Effects Regression Model when the Women Ratio Category Is the Balanced Groups

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.002	0.004***	-0.009***	-0.010***	0.517***	-0.014*	0.054	0.008***	-0.031***	-.036***	0.047	-0.110***
	(-0.06)	(4.38)	(-5.21)	(-4.70)	(7.84)	(-1.74)	(1.07)	(6.34)	(-9.79)	(-8.94)	(0.50)	(-7.12)
Bailed	-0.004	0.001	0.001	0.002	0.173*	-0.010	-0.017	0.0009	0.001	0.001	0.201**	-0.001
	(-0.11)	(0.94)	(0.79)	(0.78)	(1.83)	(-0.94)	(-0.36)	(0.70)	(0.54)	(0.46)	(2.00)	(-0.16)
Balanced groups	0.357**	0.007	0.020***	0.027***	0.518*	0.017*	0.224**	0.003	0.008*	0.013**	0.008	-0.020
	(2.07)	(0.80)	(2.94)	(2.95)	(9.48)	(1.69)	(2.29)	(0.50)	(1.75)	(2.19)	(0.10)	(-1.19)
Interaction dummy	-0.581**	-0.014	-0.030***	-0.036***	-1.027***	-0.0147	-0.395**	-0.008	-0.014*	-0.017	-0.301	0.022
	(-2.47)	(-1.52)	(-3.96)	(-2.89)	(-1.79)	(-0.47)	(-2.00)	(-1.02)	(-1.75)	(-1.38)	(-0.50)	(0.53)
Capital							-3.208***	-0.082***	-0.333***	-0.396***	-2.288	-2.113***
							(-3.77)	(-3.77)	(-5.65)	(-5.41)	(-1.52)	(-6.75)
RELGTA							0.918***	-0.0001	0.060**	0.073***	0.245	0.332***
							(2.84)	(-0.01)	(2.55)	(2.64)	(0.31)	(3.68)
LGTA							1.247***	0.011	0.082***	0.104***	1.233**	0.386***
							(4.90)	(0.94)	(4.29)	(4.69)	(2.26)	(6.07)
IETL							2.016***	0.012	-0.306***	-0.3407***	1.565	-0.578***
							(2.90)	(0.90)	(-7.37)	(-6.66)	(1.32)	(-2.87)
LnGrossLoan							-1.195***	-0.018	-0.084***	-0.105***	-1.671***	-0.345***
							(-4.98)	(-1.63)	(-4.60)	(-5.01)	(-3.24)	(-5.75)
Liquidity							-1.234***	-0.024***	-0.075***	-0.090***	-1.966***	-0.3250***
							(-7.66)	(-8.19)	(-8.61)	(-8.16)	(-8.08)	(-8.37)
Number of Directors							-0.026***	-0.0002*	-0.001***	0.001***	-0.014	-0.0083***
							(-3.78)	(-1.77)	(-3.38)	(-3.22)	(-1.04)	(-3.82)
LnAveAge							-0.219	-0.003	-0.0034	-0.006	-1.680	0.146
							(-0.51)	(-0.29)	(-0.13)	(-0.19)	(-1.63)	(1.16)
LnAveExp							0.067	0.0035*	0.004	0.006	0.413**	-0.016
							(0.80)	(1.94)	(1.00)	(1.18)	(2.36)	(-0.72)
LnAveBank BrdTenure							-0.039	-0.0009	-0.014***	-0.017***	-0.390***	-0.079***
							(-0.77)	(-0.69)	(-4.57)	(-4.78)	(-2.99)	(-4.80)
LnAveListed BrdTenure							0.178***	0.002***	0.029***	0.035***	1.411***	0.136***
							(5.04)	(4.27)	(13.73)	(13.08)	(12.76)	(12.81)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,083	5,083	5,083	5,083	4,455	5,083	4,893	4,893	4,893	4,893	4,304	4,893
Number of groups	613	613	613	613	566	613	592	592	592	592	550	592
R-squared	0.0006	0.0430	0.0124	0.0099	0.0924	0.0032	0.0963	0.2207	0.1814	0.1712	0.2671	0.1694

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the balanced groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

The interaction dummy of the tilted group results significantly decreases all six risk measures—credit, market, and operational risks—indicating that this range of women's representation is most effective in lowering risk. The balanced group has a limited influence on risk measures, which are significant only for (CR) and (VaR), suggesting that the protective effect is still there but less so than in the tilted group.

Noticeably, the significance level changes when control variables are included. Although the results of tilted groups significantly lower credit risk, market risk, and operational risk with or without the control variables, it is necessary to include these control variables in future research.

The results of our analysis are consistent with the empirical findings reported by Joecks et al. (2013), who conducted a research investigation on German companies. They find a critical mass of female participation on boards, which occurs when the percentage of women falls within the range of 20% to 40%. The findings of our study provide a comprehensive understanding and indicate an optimal percentage within tilted groups, effectively mitigating the banks' risk. These results support our primary hypothesis that banks with a certain percentage of women on their boards reduce risk more effectively than banks without female representation or with a lower percentage of women in the following years of the bailout.

4.5 Robustness Checks

4.5.1 Bank Size

It is necessary to determine if the variables have obvious importance or have different economic meanings across various samples and examine the consistency of variable behaviour across different samples. To address these issues, we use the technique employed by Berger and Bouwman (2013) and categorise our sample into three distinct groups: small banks (GTA of less than $1 billion), medium banks (GTA of more than $1 billion but less than $3 billion), and large banks (GTA more than $3 billion). Regression analyses are conducted for each group based on the measurement categories provided. The release of findings for the balanced group has been omitted due to the insufficient number of observations resulting from the division of the sample by bank size category. Hence, it seems necessary to examine the potential influence that may arise from having a majority of female board members.

Tables 4.8, 4.9, and 4.10 display the findings regarding small banks, while Tables 4.11, 4.12, and 4.13 show the outcomes for medium banks. Furthermore, Tables 4.14, 4.15, and 4.16 exhibit the analysis results conducted on large banks.

We find that our primary findings align with the medium and large banks shown in Tables 4.13 and 4.16, where the interaction dummy under the "tilted groups" significantly decreases all types of risk in medium and large banks. Specifically, it results in a decrease of 53.7% and 35.4% in (CR), 0.7% and 0.8% in (LLRR), 1.8% and 1.6% in (VaR), 2.1% and 1.8% in (ES), 54.8% and 77.7% in (ROA_V), and 13.1% and 9.5% in (Ret_V) respectively. In addition, the coefficient of all risk measures remains significant with the inclusion of control variables. The results of our study conducted on tilted groups are consistent with the empirical findings reported by Joecks et al. (2013). According to their research, it is concluded that a critical mass of female representation on corporate boards is achieved when the percentage of women ranges from 20% to 40%.

However, in the small bank sample, the interaction dummy shows that the only variables remaining significant after including the control variables are (LLRR) and (VaR), which decrease by 1.4% and 4.0%, respectively. Nevertheless, the interaction dummy for the “tilted groups” significantly increases (CR), resulting in an increase of 111% at a 5% significance level.

The control variables, including capital, bank size, liquidity, and the natural logarithm of gross loans, align with those seen in the primary regression analysis conducted on small, medium, and large banks.

Furthermore, for medium and large banks, real estate loans has a statistically significant positive coefficient, supporting our main results. In contrast, for small banks, real estate loans decrease

(LLRR) and (ROA_V). This suggests that small banks with higher levels of real estate loans are more likely to reduce their level of risk.

Based on a sample of large banks, the effect of the number of directors on risk measures is consistent with the primary results. For the medium bank, the effect is negative but insignificant, while for small banks, (CR) and (ROA_V) are negatively and significantly affected by the number of directors at the 5% significance level.

Furthermore, regardless of the banks' size categories, we find that the average number of years board members have served on bank boards negatively and significantly affects market and operational risk.

Overall, it is worth noting that most coefficients for medium-sized banks are the largest, followed closely by those for large banks. These results suggest that bank size should be considered when studying bank risk.

Table 4.8: The Fixed-Effects Regression Model when the Women Ratio Category Is the Uniform Groups For Small Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.152***	0.007***	0.001	0.002	0.475***	0.023	0.304***	0.007***	-0.026***	-0.030***	-0.036	-0.026
	(2.68)	(3.44)	(0.43)	(0.48)	(3.15)	(1.15)	(3.09)	(4.28)	(-3.87)	(-3.60)	(-0.21)	(-0.96)
Bailed	0.126	0.002	0.001	0.0007	0.192	-0.029	0.032	0.002	-0.002	-0.006	0.084	-0.037
	(0.98)	(0.49)	(0.21)	(0.07)	(0.72)	(-0.72)	(0.30)	(0.73)	(-0.38)	(-0.69)	(0.36)	(-0.88)
Uniform groups	0.118	-0.001	0.005	0.007	0.245	0.018	-0.037	-0.003*	0.0002	-0.0002	-0.053	-0.013
	(1.42)	(-0.99)	(0.94)	(0.93)	(1.34)	(0.60)	(-0.41)	(-1.83)	(0.03)	(-0.03)	(-0.33)	(-0.40)
Interaction dummy	0.138	0.005	-0.003	-0.004	0.775**	0.006	0.222	0.002	0.001	0.002	0.873***	0.031
	(0.75)	(0.87)	(-0.28)	(-0.28)	(2.36)	(0.12)	(1.29)	(0.44)	(0.12)	(0.14)	(2.79)	(0.45)
Capital							-2.458	-0.120***	-0.518***	-0.578***	-11.387***	-2.729***
							(-1.16)	(-2.96)	(-4.08)	(-3.80)	(-4.36)	(-3.99)
RELGTA							1.320*	-0.036*	0.049	0.052***	-4.060***	0.278
							(1.94)	(-1.90)	(1.12)	(0.90)	(-3.28)	(1.32)
LGTA							1.554***	0.004	0.077**	0.096**	-0.812	0.211*
							(3.23)	(0.53)	(2.46)	(2.37)	(-0.93)	(1.84)
IETL							1.449	0.028	-0.505***	-0.628***	-1.879	-0.670*
							(0.84)	(1.09)	(-4.85)	(-5.01)	(-0.67)	(-1.70)
LnGrossLoan							-1.326***	-0.015*	-0.090***	-0.107**	0.547	-0.260**
							(-3.21)	(-1.71)	(-2.87)	(-2.57)	(0.72)	(-2.40)
Liquidity							-1.822***	-0.021***	-0.122***	-0.152***	-2.396***	-0.478***
							(-4.42)	(-3.10)	(-6.01)	(-5.89)	(-4.51)	(-5.08)
Number of Directors							-0.055***	-0.0006	-0.0002	-0.0005	-0.095**	-0.004
							(-2.59)	(-1.23)	(-0.12)	(-0.25)	(-2.28)	(-0.75)
LnAveAge							0.3901	0.032	0.063	0.077	-0.463	0.450
							(0.32)	(1.21)	(0.72)	(0.70)	(-0.18)	(1.44)
LnAveExp							0 .231	0.002*	0.036**	0.050**	0.157	0.071
							(0.73)	(0.60)	(2.19)	(2.41)	(0.42)	(1.13)
LnAveBank BrdTenure							-0.066	-0.002	-0.013	-0.017*	-1.056***	-0.044
							(-0.45)	(-0.65)	(-1.58)	(-1.67)	(-3.09)	(-1.28)
LnAveListed BrdTenure							-0.065	0.002**	0.022***	0.027***	1.328***	0.068***
							(-0.88)	(2.48)	(4.24)	(4.02)	(6.44)	(3.44)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,070	1,070	1,070	1,070	829	1,070	1,055	1,055	1,055	1,055	818	1,055
Number of groups	248	248	248	248	205	248	245	245	245	245	203	245
R-squared	0.0243	0.1673	0.0017	0.0016	0.1235	0.0030	0.0926	0.3276	0.1744	0.1631	0.3528	0.1526

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the uniform groups for small banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.9: The Fixed-Effects Regression Model when the women Ratio Category Is the Skewed Groups For Small Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.147**	0.007***	0.001	0.002	0.483***	0.023	0.307***	0.007***	-0.026***	-0.031***	-0.012	-0.026
	(2.52)	(3.46)	(0.37)	(0.41)	(3.15)	(1.12)	(3.06)	(4.24)	(-3.88)	(-3.61)	(-0.07)	(-0.95)
Bailed	0.374**	0.004	-0.002	-0.003	0.839***	-0.037	0.338**	0.003	-0.004	-0.007	0.841***	0.012
	(2.25)	(0.72)	(-0.26)	(-0.25)	(2.89)	(-0.81)	(2.35)	(0.66)	(-0.32)	(-0.51)	(2.75)	(-0.22)
Skewed groups	-0.066	0.002	-0.003	-0.004	0.069	-0.001	-0.005	0.002	-0.003	-0.003	0.201	0.003
	(-0.66)	(1.53)	(-0.70)	(-0.72)	(0.40)	(-0.05)	(-0.06)	(1.58)	(-0.68)	(-0.59)	(1.54)	(0.15)
Interaction dummy	-0.352**	-0.00008	0.005	0.003	-0.654*	0.018	-0.383**	-0.0002	0.003	0.003	-0.757**	0.022
	(-1.97)	(-0.01)	(0.46)	(0.27)	(-1.95)	(0.32)	(-2.31)	(-0.05)	(0.26)	(0.20)	(-2.26)	(-0.33)
Capital							-2.792	-0.117***	-0.515***	-0.575***	-11.915***	-2.735***
							(-1.32)	(-2.98)	(-3.99)	(-3.73)	(-4.46)	(-3.94)
RELGTA							1.222*	-0.036*	0.047	0.050	-4.420***	0.268
							(1.93)	(-1.92)	(1.12)	(0.89)	(-3.49)	(1.30)
LGTA							1.482***	0.004	0.076**	0.095**	-0.977	0.206*
							(3.24)	(0.53)	(2.47)	(2.38)	(-1.09)	(1.83)
IETL							1.556	0.028	-0.504***	-0.628***	-1.345	-0.659*
							(0.91)	(1.04)	(-4.82)	(-5.01)	(-0.48)	(-1.66)
LnGrossLoan							-1.276***	-0.015*	-0.091***	-0.108**	0.691	-0.257**
							(-3.19)	(-1.64)	(-2.87)	(-2.57)	(0.92)	(-2.39)
Liquidity							-1.838***	-0.019***	-0.122***	-0.153***	-2.364***	-0.475***
							(-4.36)	(-2.95)	(-6.08)	(-6.04)	(-4.43)	(-5.20)
Number of Directors							-0.049***	-0.0006	0.0000029	-0.0002	-0.100**	-0.003
							(-2.45)	(-1.13)	(0.00)	(-0.13)	(-2.51)	(-0.67)
LnAveAge							0.380	0.029	0.068	0.082	-0.287	0.451
							(0.32)	(1.09)	(0.79)	(0.76)	(-0.11)	(1.49)
LnAveExp							0.162	0.002*	0.037**	0.051**	-0.016	0.066
							(0.52)	(0.46)	(2.19)	(2.40)	(-0.04)	(1.03)
LnAveBank BrdTenure							-0.032	-0.002	-0.013	-0.017	-1.001***	-0.042
							(-0.24)	(-0.65)	(-1.55)	(-1.63)	(-2.90)	(-1.20)
LnAveListed BrdTenure							-0.064	0.002**	0.023***	0.027***	1.327***	0.069***
							(-0.86)	(2.54)	(4.27)	(4.05)	(6.49)	(3.46)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,070	1,070	1,070	1,070	829	1,070	1,055	1,055	1,055	1,055	818	1,055
Number of groups	248	248	248	248	205	248	245	245	245	245	203	245
R-squared	0.0275	0.1663	0.0012	0.0011	0.1152	0.0025	0.0960	0.3247	0.1750	0.1635	0.3516	0.1521

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the skewed groups for small banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.10: The Fixed-Effects Regression Model when the women Ratio Category Is the Tilted Groups For Small Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.164***	0.007***	0.002	0.003	0.541***	0.025	0.314***	0.007***	-0.027***	-0.032***	-0.031	-0.029
	(2.62)	(3.45)	(0.50)	(0.55)	(3.49)	(1.22)	(3.07)	(4.07)	(-3.99)	(-3.73)	(-0.18)	(-1.06)
Bailed	0.116	0.005	0.0005	-0.001	0.445*	-0.022	0.077	0.004	-0.0004	-0.004	0.429*	-0.021
	(1.13)	(1.48)	(0.07)	(-0.15)	(1.77)	(-0.63)	(0.78)	(1.17)	(-0.06)	(-0.43)	(1.74)	(-0.58)
Tilted groups	-0.145	-0.002	-0.004	-0.005	-0.669***	-0.022	-0.023	0.0007	0.010**	0.012*	-0.402*	0.024
	(-0.71)	(-1.09)	(-1.00)	(0.254)	(-3.39)	(-0.72)	(-0.13)	(0.50)	(2.07)	(1.88)	(-1.69)	(0.72)
Interaction dummy	1.045***	-0.020***	-0.006	0.005	0.198	-0.090**	1.115**	-0.014**	-0.040*	-0.040	-0.359	-0.063
	(4.87)	(-6.41)	(-0.91)	(0.69)	(0.79)	(-2.30)	(2.42)	(-2.17)	(-1.68)	(-1.39)	(-0.52)	(-0.72)
Capital							-3.216	-0.107***	-0.500***	-0.561***	-10.233***	-2.69***
							(-1.53)	(-2.60)	(-3.80)	(-3.54)	(-3.57)	(-3.76)
RELGTA							0.807	-0.031*	0.060	0.063	-4.076***	0.286
							(1.33)	(-1.66)	(1.27)	(1.03)	(-2.99)	(1.37)
LGTA							1.280***	0.007	0.083**	0.102**	-0.770	0.216*
							(2.83)	(0.87)	(2.42)	(2.32)	(-0.81)	(1.85)
IETL							2.224	0.019	-0.524***	-0.647***	-2.099	-0.688*
							(1.28)	(0.68)	(-4.80)	(-4.93)	(-0.77)	(-1.68)
LnGrossLoan							-1.158***	-0.017**	-0.097***	-0.114***	0.578	-0.270**
							(-3.00)	(-1.97)	(-2.88)	(-2.61)	(0.72)	(-2.46)
Liquidity							-1.870***	-0.020***	-0.124***	-0.155***	-2.126***	-0.482***
							(-4.44)	(-2.92)	(-6.08)	(-5.99)	(-3.73)	(-4.97)
Number of Directors							-0.045**	-0.0005	-0.0004	-0.0008	-0.094**	-0.003
							(-2.21)	(-1.11)	(-0.31)	(-0.40)	(-2.28)	(-0.75)
LnAveAge							0.859	0.027	0.061	0.077	-0.432	0.464
							(0.72)	(0.95)	(0.70)	(0.69)	(-0.15)	(1.47)
LnAveExp							0.020	0.005	0.047**	0.061***	0.140	0.090
							(0.06)	(1.07)	(2.51)	(2.61)	(0.32)	(1.29)
LnAveBank BrdTenure							0.016	-0.002	-0.014*	-0.018*	-1.158***	-0.045
							(0.12)	(-0.84)	(-1.74)	(-1.77)	(-3.17)	(-1.29)
LnAveListed BrdTenure							-0.057	0.002**	0.022***	0.027***	1.349***	0.068***
							(-0.76)	(2.53)	(4.26)	(4.05)	(6.64)	(3.46)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,070	1,070	1,070	1,070	829	1,070	1,055	1,055	1,055	1,055	818	1,055
Number of groups	248	248	248	248	205	248	245	245	245	245	203	245
R-squared	0.0302	0.1849	0.0011	0.0009	0.1209	0.0046	0.0977	0.3247	0.1776	0.1654	0.3454	0.1525

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the tilted groups for small banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.11: The Fixed-Effects Regression Model when the women Ratio Category Is the Uniform Groups For Medium Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.076 (-1.04)	0.006*** (4.84)	-0.012*** (-4.06)	-0.013*** (-3.89)	0.603*** (4.75)	-0.039 (-2.34)	-0.059 (-0.62)	0.009*** (5.22)	-0.033*** (-6.40)	-0.034*** (-5.58)	-0.084 (-0.52)	-0.117*** (-3.98)
Bailed	0.106 (1.06)	0.003 (1.52)	0.008 (1.60)	0.009 (1.49)	0.342* (1.84)	0.038 (1.29)	0.023 (0.23)	0.0004 (0.22)	-0.001 (-0.20)	-0.001 (-0.22)	0.185 (1.01)	-0.002 (-0.07)
Uniform groups	-0.064 (-0.72)	-0.0001 (-0.08)	-0.004 (-0.93)	-0.004 (-0.87)	-0.137 (-0.75)	-0.012 (-0.41)	-0.049 (-0.56)	-0.00004 (-0.03)	-0.003 (-0.60)	-0.002 (-0.47)	0.023 (0.14)	0.001 (0.04)
Interaction dummy	0.190 (1.61)	0.004 (1.57)	0.009 (1.28)	0.013 (1.43)	0.080 (0.36)	0.069 (1.56)	0.171 (1.42)	0.004* (1.76)	0.005 (0.76)	0.008 (0.96)	-0.041 (-0.24)	0.056 (1.40)
Capital							-6.355*** (-3.83)	-0.152*** (-4.35)	-0.611*** (-6.02)	-0.764*** (-6.03)	-5.702** (-2.47)	-3.720*** (-6.41)
RELGTA							1.164* (1.72)	0.041*** (2.99)	0.143*** (2.90)	0.165*** (2.77)	2.010 (1.24)	0.687*** (3.10)
LGTA							2.021*** (4.94)	0.042*** (5.09)	0.153*** (5.09)	0.188*** (5.10)	2.556*** (2.68)	0.655*** (4.54)
IETL							2.220* (1.67)	0.030 (1.16)	-0.325*** (-4.36)	-0.322*** (-3.50)	1.380 (0.60)	-0.758* (-1.78)
LnGrossLoan							-1.922*** (-5.02)	-0.052*** (-6.32)	-0.160*** (-5.37)	-0.196*** (-5.41)	-3.339*** (-3.83)	-0.626*** (-4.54)
Liquidity							-2.223*** (-7.56)	-0.033*** (-5.83)	-0.134*** (-7.24)	-0.155*** (-6.92)	-2.531*** (-4.67)	-0.602*** (-6.73)
Number of Directors							-0.020 (-1.31)	-0.00008 (-0.29)	-0.001 (-1.59)	-0.001 (-1.45)	0.026 (0.98)	-0.004 (-0.83)
LnAveAge							0.668 (0.70)	-0.011 (-0.62)	0.018 (0.34)	0.015 (0.24)	-1.806 (-1.01)	0.297 (1.07)
LnAveExp							-0.145 (-0.84)	0.001 (0.48)	0.007 (0.65)	0.005 (0.46)	0.685** (2.17)	-0.014 (-0.29)
LnAveBank BrdTenure							-0.113 (-0.97)	-0.003 (-1.37)	-0.021*** (-3.20)	-0.026*** (-3.38)	-0.620*** (-2.79)	-0.124*** (-3.02)
LnAveListed BrdTenure							0.240*** (3.40)	0.004*** (3.51)	0.033*** (7.51)	0.038*** (7.19)	1.851*** (8.55)	0.168*** (7.11)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,705	1,705	1,705	1,705	1,497	1,705	1,689	1,689	1,689	1,689	1,485	1,689
Number of groups	314	314	314	314	273	314	309	309	309	309	271	309
R-squared	0.0060	0.1545	0.0101	0.0092	0.1381	0.0078	0.1551	0.3636	0.2874	0.2801	0.3797	0.2621

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the uniform groups for medium banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.12: The Fixed-Effects Regression Model when the Women Ratio Category Is the Skewed Groups For Medium Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.073	0.006***	-0.011***	-0.013***	0.605***	-0.040**	-0.068	0.009***	-0.033***	-0.035***	-0.104	-0.119***
	(-1.02)	(4.81)	(-4.08)	(-3.92)	(4.87)	(-2.50)	(-0.70)	(5.15)	(-6.42)	(-5.58)	(-0.66)	(-4.05)
Bailed	0.106	0.004**	0.010*	0.013**	0.281	0.058*	0.036	0.002	-0.0001	0.001	0.064	0.014
	(1.05)	(2.04)	(1.87)	(1.98)	(1.32)	(1.86)	(0.36)	(1.00)	(-0.03)	(0.22)	(0.33)	(0.46)
Skewed groups	-0.038	-0.001	-0.004	-0.005	-0.107	-0.038	-0.008	-0.001	-0.002	-0.003	-0.092	-0.023
	(-0.52)	(-1.25)	(-0.91)	(-1.02)	(-0.81)	(-1.55)	(-0.12)	(-1.16)	(-0.51)	(-0.66)	(-0.82)	(-1.05)
Interaction dummy	0.132	0.0003	0.001	-0.0004	0.200	0.008	0.092	-0.0001	0.002	0.0002	0.235*	0.006
	(1.19)	(0.12)	(0.30)	(-0.06)	(1.16)	(0.25)	(0.89)	(-0.07)	(0.39)	(0.03)	(1.69)	(0.19)
Capital							-6.367***	-0.151***	-0.609***	-0.760***	-5.640**	-3.702***
							(-3.81)	(-4.32)	(-5.99)	(-6.01)	(-2.44)	(-6.40)
RELGTA							1.097	0.039***	0.138***	0.159***	2.010	0.661***
							(1.60)	(2.73)	(2.82)	(2.68)	(1.24)	(2.98)
LGTA							2.032***	0.042***	0.153***	0.187***	2.576***	0.654***
							(4.97)	(5.02)	(5.18)	(5.17)	(2.74)	(4.61)
IETL							2.11	0.030	-0.328***	-0.324***	1.165	-0.768*
							(1.59)	(1.18)	(-4.48)	(-3.57)	(0.51)	(-1.85)
LnGrossLoan							-1.913***	-0.051***	-0.160***	-0.195***	-3.353***	-0.620***
							(-4.99)	(-6.14)	(-5.42)	(-5.44)	(-3.89)	(-4.57)
Liquidity							-2.205***	-0.033***	-0.134***	-0.156***	-2.519***	-0.606***
							(-7.43)	(-5.85)	(-7.12)	(-6.81)	(-4.67)	(-6.73)
Number of Directors							-0.022	-0.0001	-0.001	-0.001	0.027	-0.004
							(-1.57)	(-0.47)	(-1.55)	(-1.46)	(1.06)	(-1.01)
LnAveAge							0.767	-0.009	0.017	0.015	-1.745	0.321
							(0.79)	(-0.54)	(0.34)	(0.25)	(-1.00)	(1.15)
LnAveExp							-0.125	0.001	0.007	0.007	0.705**	-0.004
							(-0.70)	(0.71)	(0.71)	(0.55)	(2.21)	(-0.09)
LnAveBank BrdTenure							-0.137	-0.003	-0.022***	-0.027***	-0.633***	-0.129***
							(-1.18)	(-1.51)	(-3.37)	(-3.57)	(-2.90)	(-3.21)
LnAveListed BrdTenure							0.238***	0.004***	0.033***	0.038***	1.852***	0.165***
							(3.24)	(3.35)	(7.51)	(7.18)	(8.72)	(6.94)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,705	1,705	1,705	1,705	1,497	1,705	1,689	1,689	1,689	1,689	1,485	1,689
Number of groups	314	314	314	314	273	314	309	309	309	309	271	309
R-squared	0.0050	0.1514	0.0094	0.0086	0.1388	0.0080	0.1539	0.3605	0.2869	0.2795	0.3817	0.2608

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the skewed groups for medium banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.13: The Fixed-Effects Regression Model when the Women Ratio Category Is the Tilted Groups For Medium Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.092	0.006***	-0.013***	-0.015***	0.563***	-0.050***	-0.083	0.008***	-0.034***	-0.035***	-0.107	-0.124***
	(-1.23)	(4.57)	(-4.64)	(-4.47)	(4.32)	(-2.96)	(-0.87)	(4.98)	(-6.61)	(-5.78)	(-0.67)	(-4.26)
Bailed	0.272***	0.006***	0.014***	0.017***	0.481**	0.087***	0.162*	0.003*	0.003	0.004	0.247	0.035
	(2.93)	(3.03)	(3.26)	(3.17)	(2.41)	(3.04)	(1.72)	(1.67)	(0.65)	(0.67)	(1.35)	(1.19)
Tilted groups	0.205*	0.004**	0.018**	0.022***	0.470***	0.115***	0.108	0.004*	0.009*	0.012*	0.175	0.060*
	(1.84)	(2.04)	(2.47)	(2.59)	(2.78)	(3.32)	(1.11)	(1.93)	(1.70)	(1.82)	(1.21)	(1.90)
Interaction dummy	-0.537***	-0.007***	-0.018**	-0.021**	-0.548***	-0.131***	-0.419***	-0.006**	-0.013*	-0.014*	-0.394*	-0.097**
	(-4.47)	(-2.94)	(-2.32)	(-2.08)	(-2.58)	(-3.07)	(-4.07)	(-2.40)	(-1.81)	(-1.65)	(-1.69)	(-2.42)
Capital							-6.329***	-0.151***	-0.606***	-0.757***	-5.620**	-3.700***
							(-3.81)	(-4.40)	(-6.06)	(-6.07)	(-2.46)	(-6.45)
RELGTA							1.239*	0.042***	0.145***	0.167***	2.174	0.713***
							(1.87)	(3.06)	(3.03)	(2.89)	(1.37)	(3.38)
LGTA							2.064***	0.043***	0.154***	0.188***	2.577***	0.663***
							(5.21)	(5.16)	(5.26)	(5.27)	(2.73)	(4.74)
IETL							1.904	0.026	-0.334***	-0.332***	1.113	-0.824*
							(1.44)	(1.02)	(-4.57)	(-3.66)	(0.49)	(-1.96)
LnGrossLoan							-1.960***	-0.052***	-0.161***	-0.197***	-3.379***	-0.634***
							(-5.30)	(-6.43)	(-5.56)	(-5.59)	(-3.95)	(-4.80)
Liquidity							-2.184***	-0.032***	-0.134***	-0.155***	-2.505***	-0.598***
							(-7.57)	(-5.86)	(-7.18)	(-6.87)	(-4.66)	(-6.85)
Number of Directors							-0.018	-0.0001	-0.001	-0.001	0.029	-0.005
							(-1.20)	(-0.59)	(-1.56)	(-1.58)	(1.13)	(-1.11)
LnAveAge							0.721	-0.007	0.020	0.020	-1.792	0.348
							(0.76)	(-0.44)	(0.40)	(0.34)	(-1.04)	(1.28)
LnAveExp							-0.137	0.002	0.008	0.008	0.683**	-0.001
							(-0.78)	(0.83)	(0.78)	(0.63)	(2.19)	(-0.03)
LnAveBank BrdTenure							-0.122	-0.003	-0.021***	-0.026***	-.601***	-0.124***
							(-1.08)	(-1.43)	(-3.31)	(-3.57)	(-2.75)	(-3.17)
LnAveListed BrdTenure							0.240***	0.004***	0.032***	0.036***	1.845***	0.161***
							(3.27)	(3.28)	(7.47)	(7.08)	(8.64)	(6.82)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,705	1,705	1,705	1,705	1,497	1,705	1,689	1,689	1,689	1,689	1,485	1,689
Number of groups	314	314	314	314	273	314	309	309	309	309	271	309
R-squared	0.0168	0.1601	0.0186	0.0171	0.1463	0.0189	0.1612	0.3662	0.2902	0.2823	0.3827	0.2649

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the tilted groups for medium banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.14: The Fixed-Effects Regression Model when the Women Ratio Category Is the Uniform Groups For Large Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.107*	0.002	-0.016***	-0.020***	0.395***	-0.055***	-0.120	0.007***	-0.046***	-0.055***	-0.011	-0.211***
	(-1.70)	(1.28)	(-4.71)	(-4.55)	(3.78)	(-3.52)	(-1.39)	(2.61)	(-8.68)	(-8.20)	(-0.07)	(-8.09)
Bailed	-0.070	-0.0007	0.001	0.003	0.058	-0.025	-0.087	-0.001	0.001	0.001	0.152	-0.007
	(-0.94)	(-0.33)	(0.49)	(0.59)	(0.41)	(-1.45)	(-1.08)	(-0.54)	(0.23)	(0.34)	(0.94)	(-0.30)
Uniform groups	-0.011	0.002	-0.002	-0.004	0.026	-0.043*	0.020	0.0007	0.003	0.003	0.083	-0.006
	(-0.15)	(1.11)	(-0.79)	(-1.02)	(0.15)	(-1.78)	(0.27)	(0.36)	(0.88)	(0.79)	(0.50)	(-0.30)
Interaction dummy	0.237**	0.008***	0.006	0.006	0.501**	0.039	0.117	0.003	-0.004	-0.008	0.019	0.003
	(2.12)	(2.72)	(1.59)	(1.18)	(2.23)	(1.22)	(1.03)	(0.90)	(-0.94)	(-1.18)	(0.09)	(0.10)
Capital							-2.393*	-0.048	-0.173**	-0.173*	0.202	-1.206***
							(-1.96)	(-1.47)	(-2.14)	(-1.78)	(0.09)	(-3.03)
RELGTA							1.046**	0.007	0.073**	0.096***	0.821	0.280**
							(2.45)	(0.52)	(2.47)	(2.72)	(0.80)	(2.15)
LGTA							1.008***	0.002	0.073***	0.093***	0.975	0.357***
							(3.58)	(0.18)	(3.63)	(4.03)	(1.64)	(4.87)
IETL							0.360	-0.040**	-0.415***	-0.473***	0.482	-1.059***
							(0.33)	(-2.00)	(-6.29)	(-5.75)	(0.29)	(-3.20)
LnGrossLoan							-1.040***	-0.011	-0.076***	-0.098***	-1.628***	-0.332***
							(-4.02)	(-0.91)	(-3.98)	(-4.44)	(-2.95)	(-4.92)
Liquidity							-0.806***	-0.019***	-0.053***	-0.062***	-1.833***	-0.243***
							(-3.51)	(-4.66)	(-5.02)	(-4.48)	(-5.81)	(-4.97)
Number of Directors							-0.018*	-0.0002	-0.001**	-0.001**	-0.021	-0.008**
							(-1.86)	(-1.13)	(-2.36)	(-2.15)	(-1.07)	(-2.56)
LnAveAge							-0.677	-0.009	-0.013	-0.018	-1.610	0.009
							(-1.24)	(-0.54)	(-0.40)	(-0.46)	(-1.16)	(0.05)
LnAveExp							0.035	0.005*	-0.002	-0.002	0.151	-0.062*
							(0.30)	(1.80)	(-0.42)	(-0.33)	(0.66)	(-1.85)
LnAveBank BrdTenure							0.005	0.001	-0.012**	-0.014**	-0.212	-0.075***
							(0.08)	(0.55)	(-2.28)	(-2.22)	(-1.12)	(-3.20)
LnAveListed BrdTenure							0.375***	0.004**	0.048***	0.057***	1.713***	0.253***
							(4.35)	(2.39)	(8.01)	(7.78)	(8.19)	(8.30)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,308	2,308	2,308	2,308	2,129	2,308	2,149	2,149	2,149	2,149	2,001	2,149
Number of groups	282	282	282	282	269	282	264	264	264	264	254	264
R-squared	0.0167	0.0295	0.0371	0.0339	0.0525	0.0314	0.0987	0.1713	0.1912	0.1821	0.2146	0.1819

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the uniform groups for large banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.15: The Fixed-Effects Regression Model when the Women Ratio Category Is the Skewed Groups For Large Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.097 (-1.55)	0.002*** (1.18)	-0.016*** (-4.31)	-0.0193*** (-4.12)	0.420*** (4.05)	-0.045*** (-2.83)	-0.108 (-1.24)	0.007*** (2.69)	-0.046*** (-8.67)	-0.054*** (-8.21)	0.001 (0.01)	-0.208*** (-7.94)
Bailed	-0.196** (-1.98)	-0.003** (-1.22)	-0.004 (-0.70)	-0.004 (-0.54)	-0.240 (-1.43)	-0.054* (-1.90)	-0.286*** (-2.74)	-0.005 (-1.57)	-0.010 (-1.65)	-0.011* (-1.68)	-0.206 (-1.12)	-0.051 (-1.65)
Skewed groups	-0.052 (-0.87)	-0.0005 (-0.38)	-0.002 (-0.67)	-0.001 (-0.38)	-0.187* (-1.75)	-0.014 (-0.75)	-0.108** (-2.00)	-0.001 (-0.91)	-0.008** (-2.33)	-0.009** (-2.18)	-0.195* (-1.88)	-0.029* (-1.71)
Interaction dummy	0.223** (2.57)	0.006*** (3.14)	0.009** (2.35)	0.011** (2.17)	0.487*** (3.35)	0.040* (1.87)	0.294*** (3.37)	0.006*** (3.48)	0.015*** (3.51)	0.018*** (3.58)	0.519*** (4.07)	0.059*** (2.62)
Capital							-2.554** (-2.12)	-0.053 (-1.63)	-0.176** (-2.21)	-0.177* (-1.84)	-0.190 (-0.08)	-1.22*** (-3.08)
RELGTA							0.882** (2.09)	0.002 (0.17)	0.067** (2.25)	0.087** (2.49)	0.494 (0.49)	0.257*** (1.99)
LGTA							0.985*** (3.75)	0.001 (0.10)	0.073*** (3.70)	0.093*** (4.12)	0.926 (1.63)	0.358*** (5.11)
IETL							0.434 (0.40)	-0.036* (-1.80)	-0.415*** (-6.38)	-0.472*** (-5.81)	0.612 (0.37)	-1.066*** (-3.25)
LnGrossLoan							-1.024*** (-4.25)	-0.010 (-0.84)	-0.076*** (-4.06)	-0.097*** (-4.53)	-1.578*** (-2.98)	-0.333*** (-5.13)
Liquidity							-0.780*** (-3.49)	-0.018*** (-4.91)	-0.052*** (-4.98)	-0.059*** (-4.42)	-1.763*** (-5.87)	-0.237*** (-5.08)
Number of Directors							-0.019** (-1.98)	-0.0003 (-1.40)	-0.001** (-2.40)	-0.001** (-2.18)	-0.023 (-1.21)	-0.007** (-2.53)
LnAveAge							-0.716 (-1.31)	-0.010 (-0.57)	-0.015 (-0.47)	-0.022 (-0.55)	-1.666 (-1.22)	-0.007 (-0.04)
LnAveExp							0.023 (0.20)	0.004* (1.79)	-0.003 (-0.57)	-0.003 (-0.52)	0.122 (0.56)	-0.067** (-2.05)
LnAveBank BrdTenure							-0.025 (-0.36)	0.0005 (0.22)	-0.013** (-2.49)	-0.015** (-2.46)	-0.276 (-1.48)	-0.081*** (-3.42)
LnAveListed BrdTenure							0.396*** (4.74)	0.004** (2.57)	0.048*** (8.08)	0.057*** (7.89)	1.740*** (8.38)	0.259*** (8.52)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,308	2,308	2,308	2,308	2,129	2,308	2,149	2,149	2,149	2,149	2,001	2,149
Number of groups	282	282	282	282	269	282	264	264	264	264	254	264
R-squared	0.0215	0.0302	0.0404	0.0377	0.0581	0.0308	0.1101	0.1889	0.1994	0.1903	0.2279	0.1866

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the skewed groups for large banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.16: The Fixed-Effects Regression Model when the Women Ratio Category Is the Tilted Groups For Large Banks

	Credit risk		Market risk		Operational risk		Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.107*	0.002	-0.016***	-0.019***	0.385***	-0.049***	-0.125	0.007***	-0.047***	-0.055***	-0.029	-0.211***
	(-1.76)	(1.22)	(-4.80)	(-4.61)	(3.92)	(-3.26)	(-1.45)	(2.61)	(-8.68)	(-8.25)	(-0.19)	(-8.08)
Bailed	0.051	0.003	0.006	0.008*	0.309**	-0.006	0.023	0.001	0.004	0.006	0.323**	0.010
	(0.66)	(1.50)	(1.63)	(1.68)	(2.03)	(-0.38)	(0.29)	(0.56)	(0.93)	(1.07)	(1.97)	(0.45)
Tilted groups	0.1077	-0.001	0.007	0.0074	0.316***	0.067***	0.178**	0.001	0.011*	0.012*	0.262**	0.059**
	(1.23)	(-0.72)	(1.20)	(0.94)	(2.67)	(2.61)	(2.14)	(0.93)	(1.91)	(1.78)	(1.99)	(2.18)
Interaction dummy	-0.354***	-0.008***	-0.016***	-0.018**	-0.777***	-0.095***	-0.413***	-0.008***	-0.017***	-0.021***	-0.633***	-0.090***
	(-3.60)	(-4.68)	(-2.74)	(-2.50)	(-5.21)	(-3.68)	(-4.06)	(-4.64)	(-2.97)	(-2.96)	(-4.04)	(-3.10)
Capital							-2.472**	-0.051	-0.172**	-0.172*	-0.027	-1.207***
							(-2.06)	(-1.57)	(-2.18)	(-1.80)	(-0.01)	(-3.09)
RELGTA							0.814*	0.001	0.065***	0.086**	0.407	0.247*
							(1.92)	(0.07)	(2.14)	(2.39)	(0.40)	(1.88)
LGTA							0.967***	0.001	0.072**	0.092***	0.892	0.355***
							(3.66)	(0.08)	(3.51)	(3.94)	(1.54)	(4.99)
IETL							0.445	-0.036*	-0.414***	-0.472***	0.616	-1.068***
							(0.41)	(-1.79)	(-6.31)	(-5.78)	(0.37)	(-3.24)
LnGrossLoan							-0.997***	-0.010	-0.075***	-0.096***	-1.527***	-0.330***
							(-4.12)	(-0.77)	(-3.84)	(-4.33)	(-2.81)	(-5.00)
Liquidity							-0.735***	-0.017	-0.050***	-0.058***	-1.700***	-0.229***
							(-3.30)	(-4.75)	(-4.75)	(-4.23)	(-5.65)	(-4.81)
Number of Directors							-0.020**	-0.0003***	-0.001***	-0.001**	-0.024	-0.008***
							(-2.17)	(-1.42)	(-2.60)	(-2.36)	(-1.30)	(-2.66)
LnAveAge							-0.745	-0.011	-0.0142	-0.020	-1.722	-0.002
							(-1.41)	(-0.68)	(-0.42)	(-0.51)	(-1.27)	(-0.02)
LnAveExp							0.021	0.004*	-0.003	-0.003	0.126	-0.065*
							(0.19)	(1.74)	(-0.48)	(-0.43)	(0.59)	(-1.93)
LnAveBank BrdTenure							-0.010	0.0008	-0.012**	-0.014**	-0.241	-0.077***
							(-0.15)	(0.36)	(-2.32)	(-2.29)	(-1.27)	(-3.29)
LnAveListed BrdTenure							0.373***	0.0041**	0.047***	0.056***	1.695***	0.252***
							(4.68)	(2.50)	(8.06)	(7.90)	(8.08)	(8.52)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,308	2,308	2,308	2,308	2,129	2,308	2,149	2,149	2,149	2,149	2,001	0.1900
Number of groups	282	282	282	282	269	282	264	264	264	264	254	264
R-squared	0.0293	0.0584	0.0437	0.0404	0.0707	0.0383	0.1162	0.1976	0.1992	0.1897	0.2300	2,149

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the tilted groups for large banks, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Column (1) presents (CR), column (2) presents (LLRR), column (3) presents (VaR), column (4) presents (ES), column (5) presents (ROA_V), column (6) presents (Ret_V), while columns (7), (8), (9) , (10), (11), and (12) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

4.5.2 Instrumental Variable Approach

The selection of women to corporate boards is a non-random procedure that requires recognition within the framework of board structure. Hence, it is essential to consider and mitigate any endogeneity issues while constructing our empirical framework. To address the potential self-selection bias that may arise from female board members selecting banks that align with their personal preferences or other unobserved factors that could influence the gender ratio, we utilise the approach proposed by Huang and Kisgen (2013) and employ instrumental variables to mitigate the endogeneity concern. According to the assumption put out by Huang and Kisgen (2013), it is suggested that states characterised by greater levels of gender equality will provide a more favourable environment for the advancement of female executives. In our study, we use the gender status equality value of the state as a determinant, which is a function of the instrumental variable concerning the geographical location of each bank's headquarters. The measure used in this context is a continuous scale that spans from 0 to 100, enabling a comprehensive assessment of gender equality within the institution.

To support our primary findings, we have split the instrumental variable, namely the predicted proportion of women, into four classifications. The categorisation of each instrumental variable is established by considering the relevant ratio of women. This classification enables us to identify an ideal range of bank board members, which is believed to reduce the banks' risk, corroborating our principal findings. Because there is a strong correlation between the Instrumental Variable (IV) and both (LGTA) and (LnAveListedBrdTenure), we have excluded (LGTA) and (LnAveListedBrdTenure) from the analysis.

We use two-stage least squares (2SLS) to estimate an instrumental variable in the manner described below:

Step 1:

$$gender\ ratio_{b,t} = \beta_0 + \beta_1 post\ bailout\ time_{b,t} + \beta_2 bailed_{b,t} + \beta_3 gender\ equality_{b,t} + +\beta_4 Capital_{b,t} + \beta_5 RELGTA_{b,t} + \beta_6 IETL_{b,t} + \beta_7 LnGrossLoan_{b,t} + \beta_8 Liquidity_{b,t} + \beta_9 NumberDirectors_{b,t} + \beta_{10} LnAveAge_{b,t} + \beta_{11} LnAveExp_{b,t} + \beta_{12} LnAveBankBrdTenure_{b,t} + \delta_{\mathrm{b}} + \varepsilon_{\mathrm{b,t}}$$

(2)

Step 2:

$$Risk\ measure_{b,t+1} = \beta_0 + \beta_1 post\ bailout\ time_{b,t} + \beta_2 bailed_{b,t} + \beta_3 IV + \beta_4 post\ bailout\ time_{b,t} * bailed_{b,t} * IV + \beta_5 Capital_{b,t} + \beta_6 RELGTA_{b,t} + \beta_7 IETL_{b,t} + \beta_8 LnGrossLoan_{b,t} + \beta_9 Liquidity_{b,t} + \beta_{10} NumberDirectors_{b,t} + \beta_{11} LnAveAge_{b,t} + \beta_{12} LnAveExp_{b,t} + \beta_{13} LnAveBankBrdTenure_{b,t} + \delta_{\mathrm{b}} + \varepsilon_{\mathrm{b,t}}$$

(3)

The findings of the Instrumental variable method are shown in Tables 4.17, 4.18, 4.19, and 4.20.

Overall, the instrumental variable regression analysis findings support our conclusions regarding the optimal ratio, aligning with the earlier results obtained using the woman ratio.

The "uniform groups" findings in Table 4.17 indicate that the interaction dummy significantly increases bank risk, meaning banks without women on the board experience higher credit, market, and operational risks. Specifically, the lack of women's presence has led to an increase of 50.67% in (CR), 1.68% in (LLRR), 0.8% in (VaR), 2.49% in (ES), and 55.01% in (ROA_V). The only exception is (Ret_V), which leads to a decrease of 4.47 %.

The second category, presented in Table 4.18, is called the "skewed groups". The interaction dummy significantly increases only credit and operational risks, increasing 21.9% in (CR) and 4.6% in (Ret_V). Notably, the coefficients of risk measures are lower than those of uniform groups, which indicates that women might play a good role in bank risk.

The third category, presented in Table 4.19, is referred to as the "tilted groups", where the interaction dummy significantly lowers credit, market, and operational risks. Specifically, it leads to a decrease of 22.02% (CR), 2.75% in (LLRR), 0.8% in (VaR), 0.8% in (ES), 24.73% in (ROA_V), and 6.98% in (Ret_V). These results are observed with the inclusion of control variables.

The fourth category, presented in Table 4.20, is called the "balanced groups". Our analysis of this group suggests that the interaction dummy variable has an insignificant and negative effect on credit, market, and operational risks.

Table 4.17 The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Uniform Groups

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.116*** (2.57)	0.006*** (6.95)	0.004** (2.04)	0.007*** (2.63)	0.740*** (9.25)	0.043*** (3.62)
Bailed	-0.059 (-1.28)	-0.001 (-1.15)	-0.002 (-0.96)	-0.002 (-0.81)	0.069 (0.73)	-0.020* (-1.70)
Uniform groups	-0.251*** (-5.47)	-0.003*** (-3.70)	-0.010*** (-3.32)	-0.011*** (-2.72)	-0.607*** (-5.41)	-0.067*** (-5.30)
Interaction dummy	0.506*** (14.24)	0.016*** (22.47)	0.008*** (4.00)	0.024*** (9.49)	0.550*** (7.77)	-0.044*** (-4.49)
Capital	0.265 (0.29)	-0.073*** (-2.95)	-0.216*** (-3.26)	-0.292*** (-3.53)	2.369 (1.38)	-1.217*** (-3.72)
RELGTA	0.148 (0.61)	-0.005 (-0.95)	0.012 (0.89)	0.015 (0.86)	-0.295 (-0.55)	0.121* (1.76)
IETL	10.947*** (13.75)	0.089*** (6.22)	0.770*** (21.08)	0.945*** (20.72)	16.053*** (12.27)	4.269*** (19.32)
LnGrossLoan	0.223*** (6.22)	-0.002*** (-2.96)	0.013*** (6.68)	0.017*** (6.63)	0.105 (1.26)	0.109*** (10.17)
Liquidity	-0.796*** (-5.45)	-0.025*** (-7.45)	-0.035*** (-4.46)	-0.040*** (-4.01)	-1.515*** (-5.74)	-0.090** (-2.37)
Number of Directors	-0.022*** (-4.94)	-0.0004** (-2.44)	-0.002*** (-4.68)	-0.002*** (-4.27)	-0.055*** (-3.70)	-0.008*** (-4.26)
LnAveAge	0.573 (1.46)	0.016 (1.47)	0.089*** (3.38)	0.103*** (3.22)	1.057 (1.00)	0.594*** (4.70)
LnAveExp	0.102 (1.15)	0.002 (1.52)	0.011** (2.36)	0.014** (2.42)	0.732*** (4.23)	-0.002 (-0.11)
LnAveBank BrdTenure	0.064 (1.26)	0.001 (0.84)	-0.002 (-0.89)	-0.005 (-1.36)	0.164 (1.36)	-0.020 (-1.37)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,266	4,266	4,266	4,266	4,265	4,266
Number of groups	548	548	548	548	547	548
R-squared	0.1842	0.1146	0.2439	0.2333	0.1796	0.2697

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the uniform groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.18: The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Skewed Groups

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.154***	0.006***	0.006***	0.009***	0.838***	0.052***
	(3.40)	(7.38)	(2.70)	(3.15)	(10.90)	(4.36)
Bailed	-0.095*	-0.001*	-0.002	-0.002	0.059	-0.029**
	(-1.94)	(-1.72)	(-0.99)	(-0.74)	(0.61)	(-2.30)
Skewed groups	-0.023	-0.001**	-0.001	-0.002	-0.031	-0.010
	(-0.68)	(-2.00)	(-0.61)	(-0.82)	(-0.46)	(-0.99)
Interaction dummy	0.219***	0.002	0.0002	-0.001	0.058	0.046**
	(3.11)	(1.51)	(0.05)	(-0.31)	(0.36)	(1.97)
Capital	0.228	-0.076***	-0.226***	-0.307***	1.931	-1.250****
	(0.25)	(-3.08)	(-3.42)	(-3.72)	(1.10)	(-3.83)
RELGTA	0.107	-0.005	0.013	0.016	-0.288	0.114
	(0.43)	(-1.02)	(0.90)	(0.90)	(-0.53)	(1.60)
IETL	11.117***	0.092***	0.778***	0.953***	16.427***	4.318***
	(13.85)	(6.43)	(21.12)	(20.82)	(12.66)	(19.48)
LnGrossLoan	0.257***	-0.002***	0.014***	0.018***	0.160*	0.117***
	(6.83)	(-2.62)	(7.07)	(6.92)	(1.88)	(10.85)
Liquidity	-0.852***	-0.026***	-0.037***	-0.043***	-1.651***	-0.104***
	(-5.17)	(-7.59)	(-4.72)	(-4.28)	(-6.23)	(-2.65)
Number of Directors	-0.024***	-0.0004**	-0.001***	-0.002***	-0.047***	-0.007***
	(-3.31)	(-2.25)	(-4.33)	(-3.99)	(-3.13)	(-3.79)
LnAveAge	0.284	0.013	0.083***	0.099***	0.666	0.524***
	(0.69)	(1.18)	(3.11)	(3.04)	(0.63)	(4.08)
LnAveExp	0.093	0.002	0.012	0.015***	0.764***	-0.002
	(1.04)	(1.56)	(2.53)	(2.64)	(4.51)	(-0.12)
LnAveBank BrdTenure	0.060	0.001	-0.002	-0.004	0.164	-0.021
	(1.18)	(0.89)	(-0.84)	(-1.27)	(1.37)	(-1.39)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,266	4,266	4,266	4,266	4,265	4,266
Number of groups	548	548	548	548	547	548
R-squared	0.1786	0.1109	0.2401	0.2306	0.1625	0.2648

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the skewed groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.19: The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Tilted Groups

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.098**	0.006***	0.004*	0.006**	0.728***	0.037***
	(2.06)	(6.29)	(1.77)	(2.33)	(9.07)	(3.06)
Bailed	0.071	0.0005	0.002	0.002	0.216*	0.020
	(1.20)	(0.39)	(0.81)	(0.54)	(1.66)	(1.17)
Tilted groups	0.185***	0.003***	0.007***	0.008***	0.347***	0.052***
	(4.47)	(4.02)	(3.14)	(2.87)	(4.24)	(4.50)
Interaction dummy	-0.220***	-0.002*	-0.008**	-0.008*	-0.247*	-0.069***
	(-3.35)	(-1.80)	(-2.41)	(-1.75)	(-1.81)	(-3.90)
Capital	-0.096	-0.079***	-0.230***	-0.309***	1.516	-1.316***
	(-0.11)	(-3.28)	(-3.50)	(-3.76)	(0.90)	(-4.02)
RELGTA	0.148	-0.005	0.012	0.015	-0.326	0.123*
	(0.63)	(-1.04)	(0.89)	(0.84)	(-0.63)	(1.80)
IETL	11.095***	0.091***	0.776***	0.952***	16.469***	4.306***
	(14.00)	(6.40)	(21.06)	(20.74)	(13.05)	(19.64)
LnGrossLoan	0.230***	-0.002***	0.014***	0.018***	0.139*	0.110***
	(6.42)	(-2.95)	(6.84)	(6.82)	(1.73)	(10.27)
Liquidity	-0.836***	-0.025***	-0.036***	-0.042***	-1.594***	-0.100***
	(-5.24)	(-7.56)	(-4.67)	(-4.17)	(-6.08)	(-2.61)
Number of Directors	-0.028***	-0.0004***	-0.002***	-0.002***	-0.055***	-0.009***
	(-3.98)	(-2.71)	(-4.61)	(-4.24)	(-3.68)	(-4.40)
LnAveAge	0.471	0.014	0.084***	0.098***	0.751	0.566***
	(1.17)	(1.35)	(3.11)	(2.98)	(0.71)	(4.42)
LnAveExp	0.119	0.002	0 .012**	0.015***	0.764***	0.002
	(1.36)	(1.62)	(2.54)	(2.57)	(4.48)	(0.11)
LnAveBank BrdTenure	0.078	0.001	-0.002	-0.004	0.188	-0.016
	(1.49)	(1.03)	(-0.70)	(-1.18)	(1.57)	(-1.09)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,266	4,266	4,266	4,266	4,265	4,266
Number of groups	548	548	548	548	547	548
R-squared	0.1835	0.1173	0.2429	0.2328	0.1731	0.2701

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the tilted groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.20: The Fixed-Effects Regression Model when the Instrumental Variables Category Represents the Balanced Groups

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	0.161*** (3.66)	0.007*** (7.72)	0.006*** (2.79)	0.009*** (3.25)	0.840*** (11.05)	0.054*** (4.56)
Bailed	-0.028 (-0.58)	-0.0002 (-0.27)	-0.002 (-0.89)	-0.001 (-0.62)	0.137 (1.38)	-0.018 (-1.37)
Balanced groups	-0.094 (-1.27)	0.0004 (0.23)	0.006 (1.46)	0.009 (1.60)	0.079 (0.46)	-0.002 (-0.13)
Interaction dummy	-0.064 (-0.82)	-0.003 (-1.55)	-0.003 (-0.71)	-0.006 (-1.02)	-0.300 (-1.61)	-0.008 (-0.38)
Capital	0.171 (0.19)	-0.074*** (-2.99)	-0.225*** (-3.37)	-0.301*** (-3.63)	2.047 (1.17)	-1.258*** (-3.83)
RELGTA	0.078 (0.31)	-0.006 (-1.15)	0.014 (0.99)	0.017 (0.95)	-0.377 (-0.69)	0.118* (1.66)
IETL	11.118*** (13.97)	0.092*** (6.46)	0.777*** (21.22)	0.953*** (20.90)	16.510*** (12.94)	4.310*** (19.66)
LnGrossLoan	0.268*** (7.20)	-0.001** (-2.29)	0.014*** (6.71)	0.017*** (6.74)	0.181** (2.22)	0.116*** (10.50)
Liquidity	-0.839*** (-5.17)	-0.025*** (-7.47)	-0.037*** (-4.69)	-0.042*** (-4.13)	-1.608*** (-5.95)	-0.103*** (-2.63)
Number of Directors	-0.024*** (-3.42)	-0.0003** (-2.18)	-0.001*** (-4.34)	-0.002*** (-3.96)	-0.047*** (-3.10)	-0.008*** (-3.82)
LnAveAge	0.267 (0.65)	0.011 (1.06)	0.086*** (3.26)	0.101*** (3.13)	0.515 (0.49)	0.542*** (4.20)
LnAveExp	0.091 (1.01)	0.002 (1.32)	0.012** (2.52)	0.015** (2.54)	0.726*** (4.17)	-0.0006 (-0.03)
LnAveBank BrdTenure	0.060 (1.17)	0.001 (0.78)	-0.002 (-0.88)	-0.005 (-1.35)	0.154 (1.29)	-0.021 (-1.38)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,266	4,266	4,266	4,266	4,265	4,266
Number of groups	548	548	548	548	547	548
R-squared	0.1780	0.1113	0.2404	0.2308	0.1642	0.2637

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the balanced groups, using a sample of bank bailouts and board directors ranging from 2003 to 2019. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

The conclusions of our analysis align with the empirical data presented by Joecks et al. (2013), who performed a research study focusing on German companies. A critical mass of female involvement on boards has been detected by a proportion of women ranging from 20% to 40%.

The results of our instrumental variable approach provide a comprehensive understanding and highlight an optimal level of the interaction dummy for the tilted groups, effectively reducing the risk faced by banks. The findings of this section provide empirical evidence in favour of our primary hypothesis, which suggests that banks exhibiting a certain proportion of women on their boards are more successful in mitigating risk compared to banks without female representation or having a lower proportion of women throughout the years that followed after the bailout.

4.5.3 Five-Year Post-Bailout Window Analysis

To further validate our findings regarding the optimal women ratio that mitigates credit, market, and operational risks, we performed additional analyses by limiting the sample period to a five-year post-bailout window. This approach allowed us to test the consistency and reliability of our results under a focused timeframe.

The results support our main conclusions regarding the optimal ratio, aligning with earlier findings. Specifically, the interaction dummy for the tilted group, as shown in Table 4.23, significantly reduces credit, market, and operational risks. It leads to a reduction of 40.1% in (CR), 0.6% in (LLRR), 1.2% in (VaR), 1.3% in (ES), and 9.3% in (Ret_V). The only exception is (ROA_V), which shows an insignificant result.

Other women categories corroborate the main findings. For example, Table 4.21 demonstrates that the interaction dummy for the uniform group significantly increases (CR) by 13.4%. Similarly, Table 4.22 indicates that the interaction dummy for the skewed group significantly increases (LLRR) by 0.3% and VaR by 0.8%. In contrast, Table 4.24 shows that the interaction dummy for the balanced group significantly decreases (CR) by 40.1%, (VaR) by 1.2%, and (ES) by 1.3%, while significantly increasing (ROA_V) by 92.6%.

These results confirm that the interaction dummy for the tilted group is the most effective in lowering credit, market, and operational risks for bank holding companies (BHCs) after the bailout period.

Table 4.21: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Uniform Groups, Applying a 5-Year Post-Bailout Window

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.073	0.006***	-0.041***	-0.047***	-0.262***	-0.149***
	(-1.39)	(4.89)	(-12.94)	(-11.81)	(-2.94)	(-8.88)
Bailed	0.010	0.002**	0.004	0.004	0.409***	0.003
	(0.18)	(2.05)	(1.46)	(1.22)	(3.82)	(0.21)
Uniform groups	-0.083*	-0.001	-0.001	-0.002	-0.002	-0.028
	(-1.66)	(-0.90)	(-0.49)	(-0.60)	(-0.02)	(-1.55)
Interaction dummy	0.134*	0.0007	-0.003	-0.002	-0.222	0.025
	(1.68)	(0.35)	(-0.81)	(-0.41)	(-1.45)	(0.96)
Capital	-4.231***	-0.104***	-0.407***	-0.483***	-5.207***	-2.546***
	(-4.34)	(-4.44)	(-5.97)	(-5.73)	(-3.31)	(-6.60)
RELGTA	0.948**	-0.008	0.090***	0.102***	-0.499	0.480***
	(2.50)	(-0.66)	(3.41)	(3.22)	(-0.59)	(4.22)
LGTA	1.505***	0.012	0.108***	0.132***	0.982**	0.495***
	(6.08)	(1.29)	(6.31)	(6.50)	(2.23)	(7.99)
IETL	-0.689	-0.030**	-0.540***	-0.612***	-3.024***	-1.421***
	(-0.95)	(-2.44)	(-12.97)	(-11.89)	(-2.58)	(-6.54)
LnGrossLoan	-1.240***	-0.019**	-0.105***	-0.128***	-1.173***	-0.442***
	(-5.25)	(-2.02)	(-6.04)	(-6.23)	(-2.85)	(-7.44)
Liquidity	-1.283***	-0.023***	-0.090***	-0.106***	-1.630***	-0.420***
	(-6.91)	(-7.95)	(-9.13)	(-8.32)	(-6.48)	(-9.08)
Number of Directors	-0.040***	-0.0004**	-0.002***	-0.002***	-0.026	-0.013***
	(-4.79)	(-2.52)	(-3.97)	(-3.75)	(-1.45)	(-4.09)
LnAveAge	-0.103	0.011	0.042	0.044	-0.687	0.319*
	(-0.19)	(0.86)	(1.22)	(1.08)	(-0.54)	(1.80)
LnAveExp	0.036	0.005**	0.014**	0.019**	0.450**	0.024
	(0.33)	(2.25)	(2.16)	(2.50)	(2.20)	(0.66)
LnAveBank BrdTenure	0.0007	-0.003*	-0.017***	-0.021***	-0.731***	-0.088***
	(0.01)	(-1.94)	(-4.02)	(-4.13)	(-4.23)	(-3.72)
LnAveListedBrdTenure	0.200***	0.004***	0.034***	0.040***	1.786***	0.152***
	5.12	(5.98)	(13.80)	(13.06)	(15.42)	(11.77)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,721	3,721	3,721	3,721	3,180	3,721
Number of groups	540	540	540	540	501	540
R-squared	0.1226	0.2966	0.2298	0.2159	0.4211	0.2068

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the uniform groups, using a sample of bank bailouts and board directors ranging from 2003 to 2014. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.22: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Skewed Groups, Applying a 5-Year Post-Bailout Window

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.078	0.006***	-0.042***	-0.047***	-0.265***	-0.149***
	(-1.48)	(4.82)	(-12.98)	(-11.80)	(-2.97)	(-8.92)
Bailed	-0.023	0.001	-0.001	-0.0006	0.259**	-0.005
	(-0.35)	(0.75)	(-0.40)	(-0.15)	(2.10)	(-0.29)
Skewed groups	-0.0009	0.0001	-0.003	-0.003	-0.016	-0.004
	(-0.02)	(0.17)	(-1.24)	(-1.08)	(-0.21)	(-0.31)
Interaction dummy	0.108	0.003**	0.008**	0.007	.0169	0.023
	(1.48)	(2.01)	(2.17)	(1.62)	(1.45)	(1.15)
Capital	-4.184***	-0.103***	-0.402***	-0.478***	-5.120***	-2.528***
	(-4.29)	(-4.40)	(-5.88)	(-5.65)	(-3.25)	(-6.55)
RELGTA	0.969***	-0.007	0.091***	.0103***	-0.500	0.482***
	(2.58)	(-0.63)	(3.46)	(3.26)	(-0.60)	(4.27)
LGTA	1.544***	0.012	0.110***	0.133***	0.992**	0.504***
	(6.31)	(1.36)	(6.45)	(6.63)	(2.26)	(8.20)
IETL	-0.777	-0.031***	-0.542***	-0.615***	-3.052***	-1.443***
	(-1.07)	(-2.58)	(-13.10)	(-11.98)	(-2.61)	(-6.67)
LnGrossLoan	-1.280***	-0.019**	-0.107***	-0.130***	-1.179***	-0.451***
	(-5.50)	(-2.09)	(-6.17)	(-6.35)	(-2.87)	(-7.67)
Liquidity	-1.270***	-0.023***	-0.089***	-0.105***	-1.602***	-0.417***
	(-7.01)	(-8.06)	(-9.08)	(-8.27)	(-6.39)	(-9.11)
Number of Directors	-0.038***	-0.0004**	-0.002***	-0.002***	-0.024	-0.012***
	(-4.71)	(-2.49)	(-3.73)	(-3.52)	(-1.40)	(-3.86)
LnAveAge	-0.105	0.011	0.040	0.042	-0.725	0.309*
	(-0.20)	(0.87)	(1.17)	(1.03)	(-0.58)	(1.76)
LnAveExp	0.033	0.005**	0.014**	0.019**	0.443**	0.022
	(0.31)	(2.26)	(2.13)	(2.47)	(2.20)	(0.61)
LnAveBank BrdTenure	-0.010	-0.003**	-0.017***	-0.021***	-0.732***	-0.090***
	(-0.16)	(-2.09)	(-4.06)	(-4.17)	(-4.20)	(-3.84)
LnAveListedBrdTenure	0.211***	0.004***	0.034***	0.040***	1.785***	0.155***
	(5.36)	(6.18)	(13.98)	(13.32)	(15.26)	(12.08)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,721	3,721	3,721	3,721	3,180	3,721
Number of groups	540	540	540	540	501	540
R-squared	0.1222	0.2994	0.2310	0.2167	0.4208	0.2060

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the skewed groups, using a sample of bank bailouts and board directors ranging from 2003 to 2014. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.23: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Tilted Groups, Applying a 5-Year Post-Bailout Window

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.081	0.006***	-0.041***	-0.047***	-0.258***	-0.150***
	(-1.53)	(4.83)	(-12.90)	(-11.74)	(-2.87)	(-8.94)
Bailed	0.104*	0.004***	0.005*	0.005	0.366***	0.022
	(1.94)	(2.78)	(1.71)	(1.54)	(3.39)	(1.44)
Tilted groups	0.167***	0.001	0.009**	0.011**	-0.001	0.060***
	(2.30)	(1.26)	(2.16)	(2.06)	(-0.02)	(2.59)
Interaction dummy	-0.401***	-0.006***	-0.012**	-0.013**	-0.036	-.093***
	(-3.90)	(-3.70)	(-2.41)	(-2.18)	(-0.30)	(-3.41)
Capital	-4.055***	-0.101***	-0.401***	-0.476***	-5.165***	-2.500***
	(-4.20)	(-4.36)	(-5.91)	(-5.66)	(-3.28)	(-6.54)
RELGTA	1.014***	-0.007	0.093***	0.105***	-0.531	0.499***
	(2.67)	(-0.61)	(3.47)	(3.29)	(-0.63)	(4.36)
LGTA	1.562***	0.012	0.109***	0.133***	0.963**	0.509***
	(6.64)	(1.37)	(6.41)	(6.63)	(2.22)	(8.35)
IETL	-0.765	-0.031**	-0.540***	-0.613***	-3.004**	-1.439***
	(-1.05)	(-2.54)	(-12.97)	(-11.86)	(-2.56)	(-6.63)
LnGrossLoan	-1.291***	-0.019**	-0.106***	-0.129***	-1.149***	-0.454***
	(-5.74)	(-2.08)	(-6.11)	(-6.34)	(-2.84)	(-7.82)
Liquidity	-1.238***	-0.022***	-0.089***	-0.105***	-1.619***	-0.411***
	(-6.75)	(-7.82)	(-8.82)	(-8.05)	(-6.40)	(-8.81)
Number of Directors	-0.037***	-0.0004**	-0.002***	-0.002***	-0.024	-0.012***
	(-4.57)	(-2.35)	(-3.85)	(-3.66)	(-1.37)	(-3.85)
LnAveAge	-0.109	0.010	0.042	0.044	-0.765	0.317*
	(-0.20)	(0.82)	(1.22)	(1.08)	(-0.60)	(1.80)
LnAveExp	0.044	0.005**	0.015**	0.020**	0.437**	0.027
	(0.41)	(2.25)	(2.19)	(2.53)	(2.18)	(0.72)
LnAveBank BrdTenure	-0.002	-0.003**	-0.017***	-0.020***	-0.720***	-0.087***
	(-0.03)	(-1.97)	(-3.87)	(-4.03)	(-4.13)	(-3.69)
LnAveListedBrdTenure	0.197***	0.004***	0.033***	0.039***	1.780***	0.150***
	(5.08)	(6.07)	(13.74)	13.07	(15.17)	(11.75)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,721	3,721	3,721	3,721	3,180	3,721
Number of groups	540	540	540	540	501	540
R-squared	0.1284	0.3022	0.2320	0.2179	0.4197	0.2102

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the tilted groups, using a sample of bank bailouts and board directors ranging from 2003 to 2014. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

Table 4.24: The Fixed-Effects Regression Model when the Women Ratio Category Represents the Balanced Groups, Applying a 5-Year Post-Bailout Window

	Credit risk		Market risk		Operational risk	
Variable	(CR)	(LLRR)	(VaR)	(ES)	(ROA_V)	(Ret_V)
Post bailout time	-0.073	0.006***	-0.041***	-0.047***	-0.257***	-0.148***
	(-1.39)	(4.95)	(-12.94)	(-11.79)	(-2.87)	(-8.88)
Bailed	0.040	0.003**	0.003	0.004	0.356***	0.008
	(0.77)	(2.18)	(1.28)	(1.17)	(3.45)	(0.57)
Balanced groups	0.059	-0.002	0.017	0.025	-0.125*	-0.016
	(0.62)	(-0.46)	(1.13)	(1.16)	(-1.70)	(-0.42)
Interaction dummy	-0.254**	-0.009	-0.038**	-0.047**	0.926***	0.024
	(-2.19)	(-1.60)	(-2.44)	(-2.11)	(7.77)	(0.59)
Capital	-4.206***	-0.103***	-0.404***	-0.479***	-5.201***	-2.538***
	(-4.30)	(-4.42)	(-5.89)	(-5.66)	(-3.31)	(-6.56)
RELGTA	0.948**	-0.008	0.089***	0.101***	-0.525	0.477***
	(2.52)	(-0.68)	(3.39)	(3.22)	(-0.62)	(4.23)
LGTA	1.523***	0.012	0.108***	0.131***	0.960**	0.499***
	(6.20)	(1.31)	(6.35)	(6.56)	(2.22)	(8.19)
IETL	-0.744	-0.030**	-0.539***	-0.611***	-2.989***	-1.435***
	(-1.03)	(-2.49)	(-12.93)	(-11.85)	(-2.55)	(-6.62)
LnGrossLoan	-1.260***	-0.019**	-0.105***	-0.128***	-1.145***	-0.446***
	(-5.40)	(-2.05)	(-6.08)	(-6.29)	(-2.84)	(-7.68)
Liquidity	-1.286***	-0.023***	-0.090***	-0.106***	-1.622***	-0.420***
	(-6.97)	(-7.99)	(-9.11)	(-8.30)	(-6.45)	(-9.11)
Number of Directors	-0.038***	-0.0004**	-0.002***	-0.002***	-0.024	-0.012***
	(-4.63)	(-2.43)	(-3.91)	(-3.72)	(-1.36)	(-3.92)
LnAveAge	-0.122	0.010	0.041	0.043	-0.760	0.305*
	(-0.23)	(0.81)	(1.19)	(1.06)	(-0.60)	(1.73)
LnAveExp	0.029	0.005**	0.013**	0.019**	0.446**	0.022
	(0.27)	(2.19)	(2.05)	(2.40)	(2.22)	(0.60)
LnAveBank BrdTenure	-0.006***	-0.003**	-0.017***	-0.021***	-0.714***	-0.089***
	(-0.09)	(-1.97)	(-4.01)	(-4.16)	(-4.09)	(-3.76)
LnAveListedBrdTenure	0.209	0.004***	0.034***	0.040***	1.778***	0.154***
	(5.35)	(6.11)	(14.00)	(13.31)	(15.17)	(12.12)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,721	3,721	3,721	3,721	3,180	3,721
Number of groups	540	540	540	540	501	540
R-squared	0.1210	0.2969	0.2297	0.2160	0.4201	0.2056

Notes: The presented Table illustrates the outcomes of a fixed-effects regression model when we apply the balanced groups, using a sample of bank bailouts and board directors ranging from 2003 to 2014. The credit risk (CR), loan loss reserve ratio (LLRR), value at risk (VaR), expected shortfall (ES), return on assets volatility (ROA_V), and stock return volatility (Ret_V) serve as dependent variables. Columns (1), (2), (3) , (4), (5), and (6) present the measures of (CR), (LLRR), (VaR), (ES), (ROA_V), and (Ret_V), respectively, with the inclusion of control variables. A comprehensive explanation of each variable can be found in Table 1. All coefficients are winsorised at the 1 percent level. The symbols (*), (**), and (***) indicate significance levels of 10%, 5%, and 1%, respectively.

4.6 Conclusion

In short, this research has made significant contributions to the current body of knowledge on board diversity by examining critical questions about the influence of gender diversity on the risk of banks in the United States. First, this research has shown extensive empirical evidence that the relationship between board gender diversity and bank risk depends on a particular degree of gender diversity. The results of this investigation confirm our hypothesis that banks with a certain percentage of women on their boards reduce risk more effectively than banks without female representation or with a lower percentage of women in the following years of the bailout. Second, the research has determined the ideal proportion of women on the board. The study findings align with the outcomes that Joecks et al. (2013) documented. Third, the study resolves the contradictory results obtained in prior studies and aims to fill a significant research gap by empirically examining the support for the critical mass theory in corporate governance. The research offers comprehensive analysis by focusing on three risk types and provides essential coverage of the methodology, including descriptive statistics, correlation, and multivariate fixed effect regression analysis.

In conclusion, this study has presented a clear and comprehensive understanding of how gender diversity affects bank risk. The results should encourage more research in this field and motivate the investigation of the impacts of gender diversity on risk, which enhances the existing body of knowledge. Our analysis has led us to examine the effects of gender diversity on bank risk after a bailout and to identify the institutions that have effectively absorbed the knowledge and insights gained from these events. Hence, the findings of this research provide a significant addition to the existing body of literature and have implications for policymakers, regulators, and professionals in the banking sector.

Chapter Five: Conclusion

5.1 Key Outcomes and Implications

This thesis presents an extensive investigation of the banking system, starting with an analysis of the predictability of bank failure. Subsequently, it dives into an examination of the impact of gender diversity on the banking industry, specifically evaluating the association between the presence of women on the board of directors and the performance of banks. Furthermore, the research expands its scope to assess the influence of gender diversity on other risk factors in banks, including credit, market, and operational risks. This provides a comprehensive analysis of the impact of gender balance on risk management methods in the banking industry.

This thesis concentrates on the bailout period since bank bailout events indicate serious issues within individual institutions and highlight broader weaknesses throughout the financial system. These critical phases provide a distinct viewpoint for analysing the processes that lead to a bank's fall into crisis and the potential paths toward resilience and recovery.

In Chapter Two, we define any bank that has been bailed out in any way as a failed bank. By framing bailouts as indicators of financial failure requiring external support, this study highlights their role as a critical measure of bank distress. This simple and straightforward definition of a bank failure differs from the earlier literature. In addition, we differentiate ourselves from prior studies by conducting the first empirical investigation that establishes an association between banks' tail risk indicators and their likelihood of obtaining bailouts. Therefore, we are motivated to study the hypothesis that an increase in the frequency of extremely negative daily equity returns indicates larger tail risks, putting banks at a greater probability of bailouts. We aim to explore the following questions to address the current gap in the existing body of literature: Does an increase in the frequency of extremely negative daily equity returns indicate larger tail risks, putting banks at a greater probability of bailouts? Do our results support the extreme value theory?

We restrict our sample to BHCs in the US due to the nature of our research. The final dataset shows 9,519 bank-quarter observations of 202 bailout BHCs and 13,995 bank-quarter observations of 674 BHCs that have not been bailed out. Our study shows a significant positive association between the VaR, VaRCF, ES estimations, and the bank's bailout. Our research finds that financial regulators and policymakers can enhance their monitoring systems by considering market variables, specifically tail risk indicators and accounting variables. This approach can help make more informed decisions regarding bank bailouts and potentially intervene earlier to prevent bank failures.

To achieve effective outcomes, we have dedicated Chapters Three and Four to explore the period during and after the global financial crisis. We use this phase as a source of motivation to investigate and focus on distinctive opportunities for analysis.

The objective of Chapter Three is to examine the following questions to address the existing gap in the literature: Does gender diversity, specifically the presence of females on a bank's board of directors, enhance bank performance after the financial crisis, and what is the optimal ratio of women on the board that leads to positive effects on performance? Does critical mass theory effectively describe the impact of board gender diversity on bank performance? Our analysis is based on a robust dataset comprising 2,317 bank-year observations of 179 bailout BHCs and 2,766 bank-year observations of 434 BHCs that have not received bailouts, providing more extended coverage than prior studies. Our study confirms the existence of a U-shaped association between the percentage of women serving on a board and a bank's performance. The critical mass occurs when there is a significant representation of women on boards, specifically within the range of 20% to 40%. Our research findings provide a clear picture and determine the optimal proportion of the interaction dummy for the tilted groups, which enhances the performance of banks. This chapter's findings suggest that encouraging gender diversity, mainly by providing a critical mass of women on boards, can improve banks' stability and performance during recovery times. This highlights the need for gender diversity programmes within financial organisations.

Chapter Four expands our study to examine the impact of women on bank risk, offering a comprehensive understanding of their role in the banking industry. As far as we know, this research is the first empirical investigation focusing on the three specific categories of bank risk: credit, market, and operational risk, during and after the bailout event. Chapter Four addresses the following questions to address the existing gap in the literature: Firstly, does gender diversity, particularly the inclusion of women on a bank's board of directors, decrease credit, market, and operational risk post-financial crisis periods? Secondly, what is the ideal proportion of female representation on the board that negatively affects these forms of risk? Thirdly, does critical mass theory effectively describe the impact of board gender diversity on banks' credit, market, and operational risk?

By using women categorisation, we were able to identify an ideal range for the proportion of female members on bank boards, namely a tilted group ranging from 20% to 40%. The findings show that the interaction dummy for the tilted group reduces all six risk indicators related to credit, market, and operational risk. This suggests that having a diverse range of women's representation is particularly beneficial in reducing risk. The findings of this chapter provide a comprehensive understanding and determine an optimal ratio among tilted groups, leading to mitigating the risk banks face. This highlights the significance of gender diversity, not only in terms of performance but also in terms of risk management. It suggests that banks with diverse boards are more effective in dealing with issues that arise during and after a crisis.

Beyond the policy, regulatory, and practical implications for banks, this thesis also provides significant academic contributions. This study contributes to the field by showing the efficacy of market indicators in forecasting bank failure, hence encouraging more investigation and improvement of these models. Moreover, this study contributes to the expanding literature supporting diversity in corporate governance by emphasising the tangible benefits of gender diversity in the banking industry.

5.2 Limitation and Future Research

The present study is not without limitations. The study focuses exclusively on publicly traded BHCs in the United States. This limitation implies that the findings may not be generalisable to private banks, smaller financial institutions, or banks in other countries with different regulatory and market environments. The study restricts its performance measures to accounting-based indicators such as return on equity (ROE) and return on assets (ROA). Future research may consider incorporating stock prices and their behavior, profit growth, and sales growth to provide a more comprehensive assessment of firm performance.

Moreover, this study focuses on several aspects of board diversity, namely gender diversity, board experience, board size, and board age. Future studies should explore other board characteristics, such as the cultural background and educational qualifications of board members, to gain a more comprehensive understanding of the impact of board diversity on firm performance and risk. In addition, we should study this topic again in the future to understand the new developments, clear up any confusion, and figure out the limits of what we have learned. Finally, the present study relies solely on quantitative research methods and secondary data. Future studies may explore other research methodologies, such as surveys, case studies, and qualitative research, to better understand the optimal ratio of women on boards and its impact on firm performance and risk.

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