BANKING INSTABILITY: CAUSES AND REMEDIES

A thesis submitted for the Degree of Doctor of Philosophy

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ABSTRACT

The recent U.S. subprime mortgage crisis rapidly spread throughout the world and put the global financial system under extraordinary pressure. The main implication of the recent crisis is that complex banking regulations failed to adequately identify and limit riskiness of banking systems at both domestic and international levels. In spite of a large empirical literature on the causes and remedies of the recent crisis, there remains substantial uncertainty on (*i*) how risk measuring models performed during crisis, (*ii*) how systematic factors such as house prices affected the financial system, and (*iii*) how effectively government policy responses resolved the financial crisis. This thesis seeks to narrow this gap in the literature by offering three empirical essays.

The first essay investigates the performance of alternative parametric VaR models in forecasting riskiness of international equity portfolios. Notably, alternative univariate VaR models are compared to multivariate conditional volatility models with special focus given to conditional correlation models. Conditional correlation models include the constant conditional correlation (CCC), dynamic conditional correlation (DCC), and asymmetric DCC (ADCC) models. Various criteria are then applied for backtesting VaR models and to evaluate their one-day-ahead forecasting ability in a wide range of countries and during different global financial conditions. It is found that most VaR models have satisfactory performance with small number of violations during pre-crisis period. However, the number of violations, mean deviation of violations, and maximum deviation of violations dramatically increase during crisis period. Furthermore, portfolio models incur lower number of violations compared to univariate models while DCC and ADCC models perform better than CCC models during crisis period. From risk management perspective, most single index models fail to pass Basel criteria for internal VaR models during crisis period, whereas empirical evidence on the choice between CCC, DCC, and ADCC models is mixed.

The recent crisis also raised serious concerns about factors that can systematically destabilise the whole banking system. In particular, the collapse of

house prices in the United States triggered the recent subprime mortgage crisis, which was associated with a sharp increase in the number of nonperforming loans and bank failures. This in turn demonstrates the key role that house prices play in systematically undermining the whole banking system.

The second essay investigates the determinants of nonperforming loans (NPL) with a special focus on house price fluctuations as a key systematic factor. Using a panel of U.S. banking institutions from 1999 to 2012, the analysis is carried out across different loan categories, different types of banks, and different bank size. It is found that house price fluctuations have a significant impact on the evolution of nonperforming loans, while the magnitude of their impact varies across loan categories, institution types, and between large and small banks. Also, the impact of house price fluctuations on nonperforming loans is more pronounced during crisis period.

The last essay of this thesis investigates the effectiveness of the U.S. government strategy to combat the crisis. As a comprehensive response to the recent financial crisis, the US government created the Troubled Asset Relief Program (TARP). The Capital Purchase Program (CPP) was launched as an initial program under the TARP. The CPP was designed to purchase preferred stocks or equity warrants from viable financial institutions. Using a large panel of the U.S. commercial banks over the period 2007Q1 to 2012Q4, survival analysis is used to investigate the impact of TARP funds on the likelihood of survival in the recipient banks. It is found that larger recipient banks are more likely to avoid regulatory closure, while receiving capital assistance does not effectively help banks to avoid technical failure. This implies that governmental capital assistance serves larger banks much better than their smaller counterparts. In addition, TARP recipients are more likely to be acquired, regardless of their size and financial health. In summary, the empirical findings reveal that capital infusions do not enhance the survival likelihood of the recipient banking institutions.

Dedicated to My Family

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DECLARATION

“I certify that this work has not been accepted in substance for any degree, and is not concurrently being submitted for any degree or award, other than that of the PhD, being studied at Brunel University. I declare that this work is entirely the result of my own investigations except where otherwise identified by references and that I have not plagiarised another’s work. In this regard, this thesis has been evaluated for originality checking by the University Library through Turnitin plagiarism detection software prior to the formal submission. I also grant powers of discretion to the University Librarian to allow this thesis to be copied in whole or in part without the necessity to contact me for permission. This permission covers only single copies made for study purposes subject to the normal conditions of acknowledgment.”

Table *of* Contents

List *of* Tables

List *of* Figures

CHAPTER ONE

INTRODUCTION

Banking crises, as a distinct subset of financial crises, are often associated with bank runs, banking panics, and systemic banking crises. Many countries around the world have experienced various episodes of banking crises throughout the history. In particular, the last two decades of the 20th century witnessed an unprecedented increase in the number of systemic banking crises including the U.S. savings and loan crisis of the 1980s, the Asian currency and banking crisis of 1997, and a number of crises in the Nordic countries in the early 1990s.[1] A systemic banking crisis features with a sharp increase in the number of defaults and bank failures, which in turn can generate a large disruption of the economic activities and lead an economy into deep recession. One particularity of the systemic banking crises is that they often begin with an initial failure which triggers further failures in a banking system through externalities and spillover effects. In addition, due to globalisation of financial markets, some systemic banking crises have quickly spread to other countries through contagion (see Mendoza and Quadrini, 2010; Kaminsky and Reinhart, 2000; Calvo and Mendoza, 2000).

In response to these distressing events, researchers and financial regulators paid increasing attention to understand the causes of systemic banking crises and provide better supervisory practices in order to enhance banking stability. Accordingly, banking stability literature expanded in two broad directions. One line of research focused on factors that undermine stability of individual banks. In particular, various frameworks were proposed to assess the stability and predict bank failures by accounting for both systematic and idiosyncratic factors (see, e.g., Wheelock and Wilson, 2000; Tam and Kiang, 1992; DeYoung, 2003, among others). Another line of banking stability literature focused on measuring the state of the economy to design an early warning

[1] For an overview of major systemic banking crises in the past, see Caprio and Klingebiel (2003), Laeven and Valencia (2008), and Reinhart and Rogoff (2009).

system to predict systemic banking crisis and provide better macro-prudential regulations (see, e.g., Demirgüc-Kunt and Detragiache, 2005; Kaminsky and Reinhart, 1999; Davis and Karim, 2008, among others).

Parallel to the banking stability literature, banking regulations evolved enormously to avoid likewise crises. Indeed, the regulatory framework within each banking sector gradually developed as a set of accumulated responses to a long history of distressing events, including crises and scandals in that sector. However, in line with globalisation of financial markets, many large banks gradually spread their activities to other countries around the world. This in turn prompted calls for international coordination of banking regulations to ensure the safety and stability of international banks which pose significant risks to other banking sectors (Kapstein, 1989). Eventually, the Basel Committee on Banking Supervision (BCBS) established the most comprehensive international regulatory framework by announcing the Basel Capital Accord, known as Basel I Accord in 1988.

In general, the main function behind most depository institutions is to accept deposits from individuals and efficiently allocate the deposited money to prosperous and high-yielding investment projects. In this context, banks often direct depositors' savings to two broad types of investment: (*i*) making loan and benefit from interest rate spread and (*ii*) trading activities. Accordingly, depository institutions are exposed to two primary sources of financial risks, namely credit risk and market risk. The BCBS (1988) set minimum capital requirement as a central tool to address credit risk as the main risk faced by banking institutions. In 1996, the BCBS amended the original capital accord of 1988 and introduced a parallel capital requirement framework to calculate market risk, thereby taking both major banking risks into account (see BCBS, 1996a).

Despite all these advances in the literature and banking regulations, in late 2000s, the U.S. economy witnessed a severe banking crisis which is considered as the worst banking crises since the Great Depression of the 1930s. The recent crisis, also known as the global financial crisis, originated with the U.S. subprime mortgage crisis, which rapidly spread throughout the world and put the global financial system under extraordinary pressure (Longstaff, 2010; Eichengreen *et al.*, 2012; Bekaert *et al.*, 2011). One implication of the recent crisis is that all these complex banking regulations failed to adequately identify and limit riskiness of the banking systems at both the domestic and international levels.

The global financial crisis triggered a spike of banking and corporate failures, large declines in asset prices, and adverse movements of key economic indicators in many countries around the world. These distressing episodes have provided renewed impetus for understanding the key drivers of the recent banking crisis in order to determine how banking stability can be achieved. It is, therefore, not surprising that a tremendous number of studies have focused on reinvestigating the regulatory and risk management practices over the last few years (see, e.g., Dell'Ariccia *et al.*, 2012; Brunnermeier, 2009; Ivashina and Scharfstein, 2010, among others). It is argued that although market innovations played a key role in the run-up to the subprime crisis, the drivers of this crisis, in many respects, were similar to those of previous banking crises, (see Reinhart and Rogoff, 2008). In particular, just like many previous banking crises, the recent crisis was associated with a boom-bust cycle in asset prices (Borio and Lowe, 2002; Hartmann *et al.*, 2004), procyclical lending behaviour and credit rating in the banking system (Borio *et al.*, 2001; Amato and Furfine, 2004; Alp, 2013), and excessive risk taking incentives by bank managers (Demirgüc-Kunt and Detragiache, 1998; Acharya and Naqvi, 2012).

Furthermore, following the global financial crisis, many governments around the world established a broad range of immediate policy actions to combat crisis and restore economic growth. Specifically, in a quick response, the Federal Reserve lowered the federal funds target in the United States to resolve the financial crisis (see Afonso *et al.*, 2011; Cecchetti, 2009). Over the course of time, however, the financial turbulence intensified while the room for monetary policy tools was limited. Therefore, the U.S. government went beyond monetary policy measures and enacted large fiscal stimulus packages to support aggregate demand and restore confidence (see Freedman *et al.*, 2010; Cwik and Wieland, 2011; Spilimbergo, 2009).

In addition, the U.S. government deployed a number of alternative policy measures against liquidity crisis in financial institutions and financial markets. The Federal Reserve, on one hand, implemented a broad range of programs to support the liquidity of credit markets. One set of these tools was designed to lend short-term liquidity to financial institutions, which was associated with the traditional role of the Federal Reserve as the lender of last resort (see Wu, 2011; Fleming *et al.*, 2010).[2] A second set of these tools involved providing liquidity directly to key non-bank credit markets which play critical roles in liquidity provision in the United States (see Duygan-Bump *et al.*, 2013; Covitz *et al.*, 2013; Campbell *et al.*, 2011).[3] Finally, the third set of tools was designed to purchase longer-term securities to support stability and functioning of the U.S. credit markets.

Parallel to the Federal Reserve, the Department of the Treasury was authorised to establish the Troubled Asset Relief Program, known as TARP, to either purchase or insure up to $700 billion of troubled mortgage-related assets of financial institutions in order to clean up their balance sheets, enhance market liquidity and stabilise housing and financial markets. As an initial program under TARP, the Treasury launched Capital Purchase Program (CPP) was designed to purchase up to $250 billion of preferred stocks and equity warrants from viable banking institutions. TARP is considered as the largest ever government intervention in the banking sector. Although TARP may appear as successful plan, the effectiveness of TARP and CPP has been challenged by a number of studies. In particular, selection bias in choosing qualifying institutions, lack of efficient monitoring and supervision on reinvestment strategy of recipient institutions, and increased riskiness of supported banks have been suggested as the main drawbacks of TARP and CPP (see, e.g., Veronesi and Zingales, 2010; Duchin and Sosyura, 2012; Farruggio *et al.*, 2013, among others).

Looking beyond the immediate challenges, the recent financial crisis has underlined the essential need for reinvestigations and reforms in at least three areas. These include the adequacy and reliability of current risk measurement approaches; the assessment of the key drivers of systemic risk in the financial industry; and designing

[2] This set of programs includes Term Auction Facility (TAF), Term Securities Lending Facility (TSLF), Primary Dealer Credit Facility (PDCF) as well as the traditional discount window.

[3]This set of tools includes Commercial Paper Funding Facility (CPFF), Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF), Term Asset-Backed Securities Loan Facility (TALF), and Money Market Investor Funding Facility (MMIFF).

better instruments of intervention for governments to restore stability during periods of financial crises.

This thesis follows this line of research and includes three empirical chapters. Specifically, the first essay investigates the performance of alternative parametric Value at Risk (VaR) models in forecasting VaR thresholds of international equity portfolios based on two approaches: the univariate approach and multivariate approach. The second essay focuses on the role of house price fluctuations as a key macroeconomic driver of systemic risk in the banking sector. Notably, the impact of house price fluctuations on the evolution of nonperforming loans in banking institutions is investigated by using dynamic panel models. Finally, survival analysis is employed in the third essay to examine the effectiveness of capital infusion programs as reliable instruments to restore banking stability during periods of financial crisis. Below an outline of the thesis is given.

Chapter 2 examines the performance of alternative parametric models in forecasting one-day-ahead VaR thresholds of international equity portfolios during pre-crisis and crisis period. Over the last two decades, many large banking institutions have become substantially involved in market-based activities (Laeven *et al.* , 2014). Due to deregulations, technological advances, and globalisations of financial markets, many large banks have expanded their portfolios across the world to benefit from portfolio diversifications and potentially higher rates of return. Such banks have received substantial attention from international regulatory bodies including the BCBS because of posing significant systemic risk to financial sectors of countries they operate in.

One of the main risks addressed by the BCBS is market risk, which is the risk of adverse movements in the value of a market portfolio. In 1996, the BCBS proposed adoption of VaR as a measure of the market risk of a portfolio (see BCBS, 1996a). VaR is defined as a maximum expected loss for a portfolio over a given time horizon and at a certain confidence level.[4] To measure daily VaR of market portfolios, banks can either use the standardized approach proposed by the BCBS (1996a) or develop their internal VaR models. Since required capital of the standardized model is relatively high, banks often prefer to use their internal VaR models. In this case, the amount of capital

[4] For a detailed discussion of VaR models, see Jorion (2007), Alexander (2009), and Dowd (2005).

requirement for market risk depends upon the backtesting results of internal models in forecasting VaR thresholds. If an internal model performs poorly, it either imposes high capital charges or fails the backtesting test, which questions reliability of risk modelling in a bank. Therefore, developing a well-performing VaR model is an essential need for banks.

Following the increasing demand for a superior VaR framework, many VaR models have been proposed.[5] Alternative VaR models widely vary in terms of parsimony, accuracy, and their imposing regulatory capital charges. The most popular category of VaR models include parametric models that have been substantially extended after the introduction of autoregressive conditional heteroskedasticity (ARCH) model by Engle (1982) and the generalized ARCH (GARCH) model by Bollerslev (1986). Specifically, parametric models have been developed in both univariate and multivariate directions. The GJR-GARCH model of Glosten *et al.* (1993), EGARCH model of Nelson (1991), and APARCH model of Ding *et al.* (1993) in the univariate framework and Constant Conditional Correlation (CCC) model of Bollerslev (1990), Dynamic Conditional Correlation (DCC) model of Engle (2002), and asymmetric dynamic conditional correlation (ADCC) model of Cappiello *et al.* (2006) in the multivariate framework can be considered as the most significant contributions to this line of literature.

This chapter empirically investigates the performance of alternative univariate and multivariate models in forecasting VaR thresholds of international equity portfolios. An international equity portfolio is exposed to two main risk factors: equity risk and foreign exchange rate risk. Accordingly, a risk manager can apply two broad approaches to calculate aggregate portfolio VaR using parametric models. The first approach is to consider the whole portfolio as a single asset and apply univariate parametric models on portfolio returns, while the second approach is to apply multivariate models on

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[5] In general VaR models can be divided into three main categories: (*i*) parametric methods that estimate portfolio VaR by making assumption about the distribution of portfolio returns, (*ii*) nonparametric methods that estimate portfolio VaR based on portfolio's historical returns but without making any assumption about the distribution of returns, and (*iii*) semi-parametric methods that combine nonparametric methods with parametric methods in order to avoid some shortcomings of parametric and nonparametric methods.

historical return series of portfolio assets or risk components. In Chapter 2 various criteria for backtesting VaR models are considered and their one-day-ahead forecasting ability is compared for several countries and under different global financial conditions.

Chapter 2 makes several contributions to the existing literature. First, most previous studies, including Kuester *et al.* (2006) and Mancini and Trojani (2011), have focused on investigating the performance of alternative univariate VaR models, while much less is known about forecasting ability of multivariate VaR models. Furthermore, few studies that compare forecasting performance of univariate and multivariate VaR models have produced conflicting empirical results (see, e.g., Brooks and Persand, 2003; Santos *et al.,* 2012; McAleer and Da Viega, 2008, among others). Second, most previous studies have focused on investigating performance of VaR models in similar assets such as stock indices of developed countries (see, for instance, Sener *et al.,* 2013; Taylor, 2008). However, stock markets around the world widely vary in terms of volume of transactions, number of investors, the level of government intervention, and interrelation with other stock markets. This chapter aims to investigate if VaR models have consistent performance in a wide range of countries. In particular, this chapter is among the first studies that investigates the performance of alternative VaR models in forecasting aggregate VaR of international equity portfolios. Finally, performance of alternative VaR models may vary along time and financial conditions, which has been less investigated in previous studies. This chapter aims to narrow this gap by examining forecasting ability of VaR models over crisis period and non-crisis period in accordance with the recent global financial crisis.

The empirical results of Chapter 2 reveal that most VaR models have satisfactory performance with small number of violations during pre-crisis period, while the number of violations, mean deviation of violations, and maximum deviation of violations dramatically increase during crisis period. Furthermore, portfolio models incur lower number of violations compared to univariate models, while DCC and ADCC models perform better than CCC models during crisis period. From risk management perspective, most univariate models fail to pass Basel criteria for internal VaR models during crisis period, whereas empirical evidence on the choice between CCC, DCC, and ADCC models is mixed.

Chapter 3 investigates the determinants of nonperforming loans (NPL) with a special focus on house price fluctuations. The collapse of real estate bubble in the United States triggered the recent financial crisis, which had widespread economic and financial ramifications. In particular, the U.S. banking institutions suffered from a sharp increase in their nonperforming loans, while they had a marked contribution to the creation of house price bubble through their lending behaviour in the pre-crisis period. This demonstrates the key role that house prices play in systemically destabilising the entire banking system. It is argued that house prices largely affect the performance of loan portfolios as (*i*) real estate loans usually form a large portion of a bank's aggregate loan portfolio, (*ii*) real estate assets are widely used as collateral for other loan categories to secure the loan repayments (see e.g. Goodhart and Hofmann, 2008; Davis and Zhu, 2009). Using a large panel of the insured U.S. banks, Chapter 3 employs dynamic panel data models to empirically investigate the impact of house price fluctuations on the evolution of nonperforming loans over three periods; the pre-crisis period of 1999-2005, the crisis period of 2006-2012, and full sample period of 1999-2012. The analysis is further developed by examining how this relationship varies across different loan categories, different types of banking institutions, and different bank size.

Chapter 3 complements the existing literature in several ways. First, this chapter is among few studies that empirically examines the impact of house prices on the quality of loan portfolios at bank-level. Most previous studies have focused on the role of house prices in undermining the banking system as a whole, and far less is known about the impact of house price fluctuations on individual banks (see, e.g., Reinhart and Rogoff, 2008; Reinhart and Rogoff, 2009; Barrell *et al.*, 2010). Second, this chapter constitutes a first attempt to investigate how different loan categories are affected by house price developments. This is of crucial importance as the composition of loan portfolios widely varies across banks (see, e.g., Louzis *et al.*, 2012). Third, differences in the mission and institutional structure of different types of banks may lead to potential differences in the dynamics of nonperforming loans of these banks (see, e.g., Salas and Saurina, 2002). This chapter is an attempt to narrow this gap by examining the linkage between house prices and quality of loan portfolios in different types of banks. Fourth, risk taking incentives and lending strategies of banks depend upon their size and complexity (see, e.g., Tabak *et al.*, 2011; De Haan and Poghosyan, 2012). This study is among the first studies that examines if larger banks are more vulnerable to swings in house prices, compared to smaller banks. Finally, while dynamics of house prices widely vary both over time and across geographical regions (see Holly *et al.*, 2010), the impact of time and regional variations in house prices on the evolution of credit risk has been largely neglected by the literature. Chapter 3 aims to narrow this gap.

The empirical findings of Chapter 3 suggest that nonperforming loans across US banks can be explained by a mixture of idiosyncratic and systematic factors used in this study. Notably, a strong negative linkage between house price fluctuations and NPL is detected, i.e., falling house prices are tightly linked to rising NPL levels. Also, the impact of house price fluctuations on nonperforming loans is more pronounced during crisis period, indicating that the linkage between house prices and credit risk is asymmetric. Regarding the loan categories, it is found that the impact of house price fluctuations widely vary across different loan categories, with real estate loans being the most responsive loan category. Furthermore, it is found that commercial banks are more affected by adverse house price fluctuations, compared to savings institutions. Finally, the empirical findings suggest that falling house prices have greater impact on the evolution of NPL in large banks during crisis period.

Chapter 4 investigates the impact of TARP funds on the likelihood of survival in recipient banking institutions. The recent subprime mortgage crisis triggered a severe liquidity crisis in the U.S. financial system, which eventually culminated in a series of unprecedented events in September 2008. As a comprehensive response, the U.S. government created TARP to bailout the US financial system and restart the economy. The CPP was launched as an initial program under TARP to purchase preferred stock and equity warrants from qualified banking institutions to help them survive and stimulate lending activities. Over the course of the CPP, 707 financial institutions, in 48 states, received approximately $205 billion as CPP investments. This largest ever government intervention in the banking sector has raised questions regarding the effectiveness of emergency capital injections as reliable instruments to restore banking stability during periods of financial crisis. Accordingly, government bailout literature has been substantially expanded, while there is no consensus in the literature on how efficiently bank recapitalisation works (see, e.g., Diamond and Rajan, 2005; Bayazitova and Shivdasani, 2012; Mehran and Thakor, 2011; Hoshi and Kashyap, 2010, among others). Using a panel of the US commercial banks over the period 2007Q1 to 2012Q4, the Cox (1972) proportional hazard model is applied in this chapter to investigate the impact of receiving capital assistance on two different types of bank exits; exit due to regulatory closure and exit due to acquisition. This analysis is further developed by examining how this relationship varies across large and small recipient banks.

The main contributions of Chapter 4 to the existing literature are as follows: First, this study is among the first studies that examines the impact of governmental capital assistance on failure and acquisition of recipient banks. Previous TARP studies mainly focus on financial health of TARP banks throughout the program (see, e.g., Duchin and Sosyura, 2012; Bayazitova and Shivdasani, 2012, Wilson and Wu, 2012, among others) or the stock price performance of CPP recipients in response to various TARP events (see, e.g., Veronesi and Zingales, 2010; Kim and Stock, 2012; Liu *et al.*, 2013; Farruggio *et al.*, 2013). Second, this study focuses on the performance of TARP recipients at bank-level, while most previous TARP studies analyse the at bank holding level. Finally, most recent studies on banking stability, including Cole and White (2012) and Berger and Bouwman (2013), focus only on bank failure, while factors affecting probability and timing of bank acquisition have been widely neglected. This study aims to narrow this gap.

The empirical results in Chapter 4 reveal that larger recipient banks are more likely to avoid regulatory closure, while receiving capital assistance does not effectively help recipient banks to avoid technical insolvency. These findings suggest that governmental capital assistance serves larger banks much better than their smaller counterparts. Also, TARP recipients are more likely to be acquired, regardless of their size and financial health. Overall, the empirical findings of Chapter 4 suggest that receiving governmental capital assistance do not enhance the survival likelihood of recipient banks.

Chapter 5 summarises the main findings of this thesis and offers some suggestions regarding policy implications. It also identifies and discusses the main limitations of this thesis while making suggestions for future research in ways beyond the current scope of this thesis.

CHAPTER TWO

EVALUATING MARKET RISK OF INTERNATIONAL EQUITY PORTFOLIOS

2.1. INTRODUCTION

The main function behind most depository institutions is to borrow funds from external sources and reinvest those funds. While lending activities have been the most traditional reinvestment strategy, many large banks have become substantially involved in market-based activities as an alternative strategy (see Berkowitz and O'Brien, 2002; Laeven *et al.,* 2014). This indicates that in addition to credit risk, many large banks have become highly exposed to market risk.

Furthermore, due to deregulations, technological advances, and globalisations of financial markets, many large banks have expanded their portfolios across the world to benefit from portfolio diversification and potentially higher rates of return. Indeed, these large banks pose significant systematic threat to the stability of financial markets they operate in. In response to growing calls for supervisory treatment of risks in large international banks, the Basel committee on banking supervision (BCBS) established the most comprehensive international regulatory framework by publishing Basel I Accord in 1988 (see BCBS, 1988). This framework has been amended several times to set minimum capital requirements for major sources of risks in banking institutions (see BCBS, 1995; BCBS, 1996a; BCBS, 2009).

One of the main risk categories addressed by the Basel Accords is market risk, which is the risk of adverse movements in the value of a portfolio due to market risk factors, including equity risk, commodity risk, foreign exchange rate risk, and interest rate risk. To calculate the market risk exposure, the 1995 amendment to the Basel

Accord proposed adoption of Value-at-Risk (VaR) as a measure of the market risk. VaR is defined as a maximum expected loss for a portfolio over a given period of time and at a certain confidence level (see Jorion, 2007; Alexander, 2009, for a comprehensive discussion of VaR).

Although the concept of VaR is easy and attractive, the estimation of VaR threshold can be a very complex task. According to the Basel II Accord, banks can either use the BCBS standardised approach or use their internal VaR models to measure riskiness of their portfolios. The standardized approach, however, is very conservative and imposes excessive capital charges as it does not take into account the diversification between different risk factors in a portfolio. For this reason, banks prefer to use their internal VaR models to measure market risk. Furthermore, to encourage banks to accurately forecast the riskiness of their market portfolios, the BCBS (1996b) provides a framework to backtest internal VaR models. Accordingly, higher capital charges are imposed on banks with poorly performing internal models. Also, if a bank experiences more than 9 violations in a year, it may be asked to either revise its VaR model or use the standardized model, which may dramatically damage the bank's reputation. This in turn has motivated some banks to disclose overestimated VaR figures (see Pérignon *et al.*, 2008).

A desirable VaR model needs to concurrently satisfy both regulators and risk managers, which is a complex burden. While regulators are primarily interested in the number and magnitude of violations, risk managers are more interested in optimising and reducing regulatory capital for market risk. It is, therefore, not surprisingly that VaR forecasting has held the attention of many researchers and practitioners over the last few decades. In particular, a wide variety of alternative methods have been proposed to estimate VaR thresholds, indicating that choosing the best model is an essential task for financial institutions.[1]

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[1] Manganelli and Engle (2001) divide the existent VaR methods into three main categories: (*i*) parametric methods that estimate portfolio VaR by making assumption about the distribution of portfolio returns, (*ii*) nonparametric methods that estimate portfolio VaR based on portfolio's historical returns but without making any assumption about the distribution of returns (The most popular nonparametric approaches are historical simulation and Monte Carlo simulation), and (*iii*) semi-parametric methods that combine nonparametric methods with parametric methods in order to avoid some shortcomings of parametric and

Following the introduction of the autoregressive conditional heteroskedasticity (ARCH) model by Engle (1982) and the generalized ARCH (GARCH) model by Bollerslev (1986), many studies, including Glosten *et al.* (1993) and Nelson (1991), have focused on designing various GARCH specifications to forecast volatility in a univariate framework. Additionally, some studies have concentrated on modelling conditional correlations among risk components in a portfolio to measure portfolio riskiness in a multivariate framework.[2] In a seminal work Bollerslev (1990) proposed the Constant Conditional Correlation (CCC) method to measure the conditional correlation among portfolio components. This approach was later developed by Dynamic Conditional Correlation (DCC) model of Engle (2002) and Tse and Tsui (2002), and Asymmetric DCC model of Cappiello *et al.* (2006).

Compared to other VaR models, parametric GARCH models have become incredibly popular in risk measurement for two key reasons. First, GARCH models are able to capture several empirical features of financial return series, such as time-dependent volatility, clustering and persistence of volatility, and asymmetric response to negative and positive shocks of the same magnitude. Second, multivariate GARCH models can capture marginal contribution of each asset or risk component to riskiness of a portfolio, which is of crucial importance for risk managers.

An international equity portfolio is composed of two main risk factors: equity risk and foreign exchange rate risk. During the recent financial crisis, on the one hand, the U.S. dollar was depreciated vis-à-vis most currencies due to the U.S. subprime mortgage crisis and potential collapse of the U.S. financial system. On the other hand, stock prices in many countries declined dramatically due to the global financial crisis.

nonparametric methods. The most popular semi-parametric methods include filtered historical simulation (FHS) proposed by Barone-Adesi *et al.* (1998), volatility-weight historical simulation proposed by Hull and White (1998), CaViaR model proposed by Engle and Manganelli (2004), and Extreme Value Theory (EVT). Furthermore, recent studies have proposed VaR models based on a combination of models either across (see Kuester *et al.,* 2006) or within these categories (see Fuertes and Olmo, 2013). In particular, Fuertes and Olmo (2013) propose an optimal combination of two parametric methods, GARCH and ARFIMA models, and show that additionally exploiting intra-day information improves the accuracy of one-day-ahead VaR forecasts.

[2] Interested readers can refer to Bauwens *et al.* (2006) and Silvennoinen and Terasvirta (2009) for a comprehensive review of multivariate GARCH models.

Therefore, many large U.S. banks suffered from significant losses in their international equity portfolios. This in turn offers a unique laboratory to assess the forecasting ability of quantitative models in measuring riskiness of these portfolios.

The study at hand investigates the performance of alternative parametric models in forecasting VaR thresholds of international equity portfolios. Two main approaches are used in this chapter to estimate VaR thresholds. The first approach is to use alternative univariate models on a time series of portfolio returns, while the second approach is to apply multivariate time series models on historical return series of portfolio risk components to estimate aggregate VaR of the portfolio. The analysis is carried out on a sample of eight countries and over two subsample periods. Subsequently, nine different criteria are employed to evaluate the performance of VaR models from both regulatory and risk management perspectives.

This chapter complements the existing VaR literature in several ways. First, most previous studies, including Kuester *et al.* (2006) and Mancini and Trojani (2011), have investigated the performance of univariate VaR models, while much less is known about forecasting ability of multivariate VaR models. Also, few studies that compare forecasting performance of univariate and multivariate VaR models have produced mixed empirical results. Notably, Brooks and Persand (2003) show that additional information used in multivariate models do not improve forecasting ability of VaR models, while Santos *et al.* (2012) find that multivariate models are superior to their univariate counterparts in VaR forecasting. Furthermore, McAleer and Da Viega (2008) show that, compared to multivariate models, univariate models lead to more violations and lower regulatory capital requirements. This study attempts to shed more light on the forecasting performance of univariate and multivariate VaR models.

Second, most previous empirical works have examined performance of alternative models in estimating VaR thresholds in a specific country or in a group of similar countries (see, for instance, Sener *et al.*, 2013; Taylor, 2008). However, stock markets around the world widely vary in terms of volume of transactions, number of investors, the level of government intervention, and interrelation with other stock markets. Thus, it is of paramount importance to investigate the performance of alternative VaR models over a broader range of countries before making a general conclusion about forecasting ability of alternative VaR models. With this target in mind, four different groups of countries are considered in this study: developed countries, industrialized emerging countries, emerging countries, and developing countries.

Third, large international banks and hedge funds have spread their trading activities to stock markets in emerging and less developed countries over the last few years. This can be mainly due to higher rate of stock market returns in those countries, compared to advanced countries. Therefore, it is of crucial importance to investigate the performance of VaR models in forecasting aggregate portfolio risk in emerging and developing countries. Although some prior studies, including Gençay and Selçuk (2004) and Rossignolo *et al.* (2012), have investigated equity VaR in emerging markets, the author is not aware of any study that considers investment risk of international equity portfolios, particularly in a multivariate framework. This chapter aims to fill this gap. Finally, performance of alternative VaR models may vary along time and financial conditions, which has been less investigated in previous studies. To examine this important feature, this chapter examines forecasting ability of VaR models over crisis period and non-crisis period in accordance with the recent global financial crisis.

In a nutshell, the empirical results reveal that most VaR models have satisfactory performance with small number of violations during pre-crisis period, while the number of violations, mean deviation of violations, and maximum deviation of violations dramatically increase during crisis period. Furthermore, one of the major drawbacks of most VaR models, univariate models in particular, is that they produce more than 9 violations in 250 days during crisis period. Compared to univariate models, however, portfolio models exhibit better performance with lower number of violations during crisis period. Nonetheless, portfolio models produce slightly higher regulatory capital requirements and weaker goodness of fit. In Addition, the empirical results on the choice between alternative multivariate models are mixed.

The remainder of this chapter is structured as follows. Section 2.2 describes the methodology and econometric framework used in this study. Section 2.3 presents the data and empirical results and forecasting performance of alternative VaR models are discussed in Section 2.4. Finally, Section 2.5 presents the main conclusions of this chapter.

2.2. METHODOLOGY

The information set needed to estimate one-day-ahead VaR thresholds is one of the most critical decisions that risk managers have to make. Obviously the simplest choice in this respect is to use historical daily returns based on closing prices. Although using daily returns has been a common practice in the forecasting literature, some recent studies, including Fuertes *et al.* (2009), Fuertes and Olmo (2013), and Louzis *et al.* (2014), advocate the use of additional high-frequency intraday information to forecast one-day-ahead VaR more accurately. Also, Fuertes *et al.* (2014) advocate the use of daily trading volume, intraday returns and overnight returns to obtain better VaR estimates. In this chapter, however, only returns based on daily closing prices are used due to data constraints.

This study investigates the performance of alternative parametric VaR models in measuring the riskiness of international equity portfolios. There are two possible approaches for risk managers to estimate VaR threshold of such portfolios. The first approach is to measure portfolio VaR by estimating univariate parametric models based on historical portfolio returns. However, financial portfolios are usually exposed to different risk factors such as equity risk, exchange rate risk, interest rate risk, commodity risk and credit spread risk. Therefore, the aggregate VaR figure for large and complex portfolios is not very informative, and risk managers tend to map their portfolios into the risk factors. Accordingly, the aggregate VaR of a portfolio is disaggregated into risk components and the contribution of each risk factor to the aggregate VaR figure is estimated. Disaggregating the aggregate VaR of a portfolio into risk factor VaR provides an essential tool for portfolio managers to decide whether to hedge or change their positions on different risk factors in order to achieve the optimal capital allocation.

To disaggregate the portfolio VaR, this study assumes that the portfolio under consideration is static over the risk horizon, meaning that portfolio holdings in each risk component are held constant. Given that the portfolio is composed of m risk components, the portfolio value at time t is given by

$$P_t = \sum_{i=1}^{m} n_i p_{it}, \tag{2.1}$$

where p_{it} is the price of the i^{th} risk component at time *t* and n_i is the number of units of the i^{th} risk factor in the portfolio. Accordingly, risk factor sensitivity of the i^{th} risk factor at time *t* can be defined as

$$\theta_{it} = \frac{n_i p_{it}}{P_t}. \tag{2.2}$$

This indicates that risk factor sensitivities vary with time and when the price of each risk factor changes. Therefore, total systemic return of a portfolio over the holding time is given by

$$r_{pt} = \sum_{i=1}^{m} \theta_{it} r_{it} = \boldsymbol{\theta}'_t \boldsymbol{r_t}, \tag{2.3}$$

where r_{it} is the return of i^{th} risk factor over the holding period and θ_{it} is portfolio sensitivity to the i^{th} risk factor. Thus, the expected portfolio return at time *t* is

$$E(r_{pt}|I_{t-1}) = \boldsymbol{\theta}'_t \boldsymbol{\mu_t}, \tag{2.4}$$

where I_{t-1} is the information set up to time $t-1$ and $\boldsymbol{\mu_t} = [E(r_{1,t}), \ldots, E(r_{m,t})]$ is the vector of conditional expected returns for each risk factor over the risk horizon. Similarly, the variance of portfolio return at time *t* is

$$Var(r_{pt}|I_{t-1}) = \boldsymbol{\theta'_t \Omega_t \theta_t}, \tag{2.5}$$

where $\boldsymbol{\Omega_t}$ is the time varying conditional covariance matrix of portfolio risk factor returns, which is defined as

$$\boldsymbol{\Omega_t} = E(\boldsymbol{r_t r'_t}) = \begin{pmatrix} \mathrm{Var}(\mathrm{r}_1) & \ldots & \mathrm{Cov}(\mathrm{r}_1, \mathrm{r}_\mathrm{m}) \\ \vdots & \ddots & \vdots \\ \mathrm{Cov}(\mathrm{r}_1, \mathrm{r}_\mathrm{m}) & \ldots & \mathrm{Var}(\mathrm{r}_\mathrm{m}) \end{pmatrix}. \tag{2.6}$$

This covariance matrix can be decomposed into separate variance and correlation matrices as follows

$$\boldsymbol{\Omega_t} = \boldsymbol{D_t R_t D_t}, \tag{2.7}$$

where $\mathbf{D}_{\boldsymbol{t}}$ is a diagonal matrix of conditional variances defined as

$$\mathbf{D}_{\boldsymbol{t}} = \text{diag}\{\sqrt{\sigma_{i,t}}\} = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{m,t} \end{bmatrix}, \tag{2.8}$$

and $\mathbf{R}_{\boldsymbol{t}}$ is a symmetric $m \times m$ conditional correlation matrix specified as

$$\mathbf{R}_{\boldsymbol{t}} = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1m,t} \\ \rho_{21,t} & 1 & \cdots & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{m1,t} & \rho_{m2,t} & \cdots & 1 \end{bmatrix}, \tag{2.9}$$

where $\sigma_{i,t}$ is the conditional volatility of the i^{th} risk factor and $\rho_{ij,t}$ is the conditional pair-wise correlation of the ij^{th} risk factors. In this context, various parameterizations for multivariate time series models have been developed to measure the conditional mean and conditional covariance matrix of a portfolio.[3] The rest of this section presents various parameterizations used in this study for estimation of portfolio VaR based on conditional mean, conditional volatility, and conditional correlations of portfolio components.

2.2.1. Conditional mean models

The conditional mean of a given return time series can be modelled by an $ARMA(p,q)$ process given by

[3] There are two approaches to model conditional covariance matrix $\boldsymbol{\Omega_t}$: The first approach is to model $\boldsymbol{\Omega_t}$ directly through BEKK model proposed by Engle and Kroner (1995), while the second approach is to model $\boldsymbol{\Omega_t}$ indirectly via modelling $\boldsymbol{R_t}$ by using alternative conditional correlation models. Using the first approach, however, may be less appealing in risk management due to the archetypal "curse of dimensionality" highlighted by Caporin and McAleer (2012). Therefore, only the second approach is considered in this study.

$$\Psi(L)r_t = c + \Pi(L)\varepsilon_t, \tag{2.10}$$

where L is the lag operator; $\Psi(L) = 1 - \Psi_1 L - \cdots - \Psi_p L^p$ and $\Pi(L) = 1 - \Pi_1 L - \cdots - \Pi_q L^q$ are polynomials in L; and ε_t is the disturbance process representing the market shocks that are distributed with mean 0 and σ_t standard deviation. One main challenge in fitting an $ARMA(p,q)$ process is to find appropriate values for p and q so to remove the serial autocorrelation. In this context, however, it's a common practice to model daily financial return series by a stationary *AR(p)* process (see, e.g., Giot and Laurent, 2004; Bos *et al.*, 2000; McAleer and Da Viega, 2008).

2.2.2. Conditional volatility models

In combination with conditional mean equation, the conditional variance equation can be estimated using alternative parameterizations. The resulting standardized residuals that are identically and independently distributed with zero mean and one standard deviation, that is

$$\eta_t = \frac{\varepsilon_t}{\sigma_t} \sim iid(0,1). \tag{2.11}$$

In what follows, alternative conditional variance models used in this study are presented in ascending order of complexity.

I. Exponentially weighted moving average:

The exponentially weighted moving average (EWMA) model is the simplest parametric approach considered in this study. It assigns more weight on more recent observations i.e. the weighting of older observations decreases exponentially. In the EWMA framework, the conditional variance of each return series at time *t* is estimated as

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)\varepsilon_{t-1}^2, \tag{2.12}$$

where σ_{t-1}^2 is the conditional variance of the disturbance term at time $t-1$, and λ is the decay factor. RiskMetrics (1996) subjectively sets decay factor at 0.94 for analyzing daily data. RiskMetrics model has been very popular due to its good performance during different financial conditions and ease of implementation, as there is no need for parameter estimation. However, the main drawback of this methodology is that it assigns the same decay factor to all daily series. Also, the EWMA model assumes that disturbance term is identically and independently distributed, which is a restrictive assumption in financial applications.

II. GARCH:

Financial daily return series often exhibit volatility persistence, meaning that large (small) volatilities tend to be followed by other large (small) volatilities. To capture time varying volatility and volatility clustering features of financial return series, Engle (1982) proposed the autoregressive conditional heteroskedasticity (ARCH) models. An ARCH model of order *q*, *ARCH(q)*, is defined as

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2. \tag{2.13}$$

Sufficient conditions for the positivity of the conditional variance are $\omega > 0$ and $\alpha_j \geq 0$, for $j = 1, .., q$. Bollerslev (1986) extended ARCH models by including the lagged conditional variance as autoregressive terms. The generalized ARCH (GARCH) model is defined as

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2. \tag{2.14}$$

In this case, sufficient conditions to ensure strictly positive conditional variance are $\omega > 0$, $\alpha_j \geq 0$ for $j = 1, .., q$, and $\beta \geq 0$ for $i = 1, ..., p$. While ARCH captures the short-run persistence of shocks, GARCH effect presents contribution of shocks to the long-run persistence. Since ARCH and GARCH models are nonlinear models, their parameters can no longer be estimated by OLS methodology. Instead, the maximum likelihood estimation (MLE) method is used. The error term, ε_t, can be written as

$$\varepsilon_t = \sigma_t z_t, \tag{2.15}$$

where z_t is a random variable representing market shocks. It is usually assumed that it is an independently and identically distributed random variable following a Gaussian distribution i.e. $z_t \sim N(0,1)$. However, Bollerslev (1987) suggests using symmetric Student-*t* distribution as conditional distribution of market shocks. In that case, the degree of freedom of the underlying distribution is an additional parameter to be estimated. In this chapter, both Gaussian distribution and Student-*t* distribution are considered.

III. GJR-GARCH:

In financial time series data a negative shock increases debt to equity ratio and is likely to increases volatility more than a positive shock of the same magnitude. One of the main shortcomings of GARCH model is its equal sensitivity to positive and negative shocks in the market, which makes it incapable of taking leverage effect into account. To resolve this issue, researchers have moved towards asymmetric GARCH models. To capture asymmetric effect of positive and negative shocks, Glosten *et al.* (1993) suggest GJR-GARCH as an alternative to symmetric GARCH model. This model simply adds an extra parameter to the symmetric GARCH to capture the leverage effect. The model takes the form

$$\sigma_t^2 = \omega + \sum_{j=1}^{q} (\alpha_j + \gamma d_{t-j}) \varepsilon_{t-j}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^2, \tag{2.16}$$

where d_t is a dummy variable taking value 1 when$\varepsilon_t < 0$, and 0 otherwise. Thus, when news impact is asymmetric, $\gamma \neq 0$, a positive shock impact, α, is distinguished from the impact of a negative shock, $(\alpha + \gamma)$. In this case, sufficient conditions for the positivity of conditional variance are $\omega > 0$, $\alpha_j + \gamma \geq 0$ for $j = 1, .., q$, and $\beta_i \geq 0$ for $i = 1, ..., p$.

IV. EGARCH:

As seen before, to construct a GARCH model, different constraints have to be imposed to ensure a strictly positive conditional variance. The Exponential GARCH (EGARCH) introduced by Nelson (1991) handles these constraints by simply using the log of variance in the conditional variance formula. The specification of conditional variance equation for an EGARCH (p, q) model is given by

$$l\,n(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{k=1}^{q} \gamma_k \left[\frac{|\varepsilon_{t-k}|}{\sigma_{t-k}} - E\left\{\frac{|\varepsilon_{t-k}|}{\sigma_{t-k}}\right\}\right] + \sum_{j=1}^{p} \beta_j \ln\left(\sigma_{t-j}^2\right). \tag{2.17}$$

As this equation gives us the results for the log of conditional variance, it is guaranteed that the conditional variance is always positive and consequently there is no need to impose any parametric restrictions. EGARCH model is an alternative model to capture asymmetric effect of large positive and negative shocks. Furthermore, in financial return series, small positive shocks increase volatility more than small negative shocks with the same magnitude. The specification of EGARCH model has made advantageous to previous models reviewed in this chapter to capture such features of financial data.

V. APARCH:

The asymmetric power ARCH (APARCH) model proposed by Ding *et al.* (1993) was an extension to Taylor-Schwert GARCH (TS-GARCH) model of Taylor (1986) and Schwert (1990). The APARCH model is specified as

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \alpha_j (\left|\varepsilon_{t-j}\right| - \gamma_j \varepsilon_{t-j})^{\delta} + \sum_{i=1}^{p} \beta_i \sigma_{t-1}^{\delta}, \tag{2.18}$$

where δ is the power parameter while γ captures potential asymmetric effects of market shocks. In this case, $\omega > 0$, $\alpha_j \geq 0$, with at least one $\alpha_j > 0$, $\beta_i \geq 0$, $\delta \geq 0$, and $|\gamma| < 1$ are necessary and sufficient conditions for the existence of moments for APARCH (see Ling and McAleer, 2002). In addition to some basic features including volatility clustering, excess kurtosis (fat tails), and asymmetry in volatility, APARCH models capture long-memory property of financial return series. Long-memory property refers to a stylized fact of most financial return series, particularly high-frequency data, where correlation between absolute returns is substantially higher than that between squared returns.

2.2.3. Conditional correlation models

While $\sigma_{i,t}$ can be estimated by univariate volatility models, estimating $\rho_{ij,t}$ has been one of the main challenges for researchers and risk managers. In this context, various parameterizations for multivariate time series models have been developed to measure the conditional covariance matrix of a portfolio. Perhaps, the simplest specification to calculate $\rho_{ij,t}$ is the rolling correlation estimator defined as

$$\rho_{ij,t} = \frac{\sum_{s=1}^{t-1} \varepsilon_{i,t-s}\varepsilon_{j,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1} \varepsilon_{i,t-s}^2\right)\left(\sum_{s=1}^{t-1} \varepsilon_{j,t-s}^2\right)}}. \tag{2.19}$$

However, using this specification for estimating $\rho_{ij,t}$ may be too strict in empirical applications as it does not account for various features of financial time series data. Therefore, in a seminal work in this area, Bollerslev (1990) proposed the Constant Conditional Correlation (CCC) multivariate GARCH (MGARCH) model to estimate the conditional correlation. In his model, the conditional covariance matrix is given by

$$\boldsymbol{\Omega_t} = \boldsymbol{D_t R D_t}, \tag{2.20}$$

where $\boldsymbol{D_t}$ is a time varying diagonal matrix of conditional standard deviations from univariate GARCH processes and $\boldsymbol{R}$ is a time invariant matrix of unconditional correlations of the standardized residuals. The standardized residuals are given by

$$\boldsymbol{\eta_t} = \boldsymbol{D_t^{-1}\varepsilon_t}. \tag{2.21}$$

Accordingly, each element of $\boldsymbol{R}$ is defined as

$$\rho_{ij} = \frac{\sum_{s=1}^{t-1} \eta_{i,t-s}\eta_{j,t-s}}{\sqrt{\left(\sum_{s=1}^{t-1} \eta_{i,t-s}^2\right)\left(\sum_{s=1}^{t-1} \eta_{j,t-s}^2\right)}}. \tag{2.22}$$

Despite the parsimony of CCC models, the assumption of constant conditional correlations may be too restrictive in empirical applications. Engle (2002) extended the CCC model and proposed Dynamic Conditional Correlation (DCC) model by relaxing the assumption of constant conditional correlation and allowing $\boldsymbol{R}$ to be time varying. Accordingly, $\boldsymbol{R_t}$ is defined as

$$\boldsymbol{R_t} = \boldsymbol{Q_t^{*-1}} \boldsymbol{Q_t} \boldsymbol{Q_t^{*-1}}, \tag{2.23}$$

where

$$\boldsymbol{Q_t} = (1-\alpha-\beta)\overline{\boldsymbol{Q}} + \alpha \boldsymbol{\varepsilon_{t-1}} \boldsymbol{\varepsilon'_{t-1}} + \beta \boldsymbol{Q_{t-1}}, \tag{2.24}$$

where $\boldsymbol{Q_t} \equiv [q_{ij,t}]$, $\overline{\boldsymbol{Q}}$ is the unconditional covariance matrix of the standardized residuals, and $\boldsymbol{Q_t^*}$ is a diagonal matrix that contains the square roots of the diagonal element of $\boldsymbol{Q_t}$. This model is covariance stationary if $\alpha + \beta < 1$. Thus, the conditional correlation between the ij^{th} risk factors at time *t* is given by

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}. \tag{2.25}$$

One of the main drawbacks of the DCC model is that it does not account for potential asymmetric effects of market shocks on the conditional correlations between financial return series. Therefore, Cappiello *et al.* (2006) incorporate leverage effect into the conditional correlation and propose the asymmetric dynamic conditional correlation (ADCC) model, which takes the following form

$$\boldsymbol{Q_t} = (1-\alpha-\beta)\overline{\boldsymbol{Q}} - \delta\overline{\Gamma} + \alpha \boldsymbol{\varepsilon_{t-1}} \boldsymbol{\varepsilon'_{t-1}} + \beta \boldsymbol{Q_{t-1}} + \delta \xi_{t-1} \xi'_{t-1}, \tag{2.26}$$

where $\overline{\Gamma} = [\xi_t \xi'_t]$ and $\xi_t = I(\varepsilon_t < 0) \circ \varepsilon_t$; the I(.) is an indicator function taking on value 1 if the argument is true, and 0 otherwise, whereas 'o' represents the Hadamard product.

In this case, necessary and sufficient conditions for Q_t to be positive definite include $(1-\alpha-\beta)\bar{Q}-\delta\bar{\Gamma}$ and Q_0 to be positive definite.

2.2.4. VaR estimation

In general, VaR of a specific portfolio is a function of two fundamental parameters set by regulators: (*i*) confidence level representing the expected probability that portfolio return falls below VaR figure, and (*ii*) risk horizon representing the time period over which the potential loss is estimated. Accordingly, VaR is defined as the maximum potential loss in the value of the portfolio over a certain risk horizon and with certain confidence level. Mathematically, a portfolio VaR over a specific holding period is given by

$$\Pr(r_h < -VaR_h | I_{t-1}) = \alpha, \tag{2.27}$$

where h is the holding period and r_h is the change in portfolio value over the holding period, and $(1-\alpha)$ is the VaR confidence level. Making an assumption about portfolio return distribution, parametric VaR models is given by

$$VaR_h^{1-\propto} = \Phi^{-1}(1-\alpha)\hat{\sigma}_h - \hat{\mu}_h, \tag{2.28}$$

where $\Phi^{-1}(1-\alpha)$ is the standardized α-quantile of the assumed distribution while $\hat{\mu}_h$ and $\hat{\sigma}_h$ denote the expected mean and standard deviation of portfolio's return distribution over the holding period, respectively. Another approach is to derive the aggregate portfolio VaR from univariate conditional mean and covariance of portfolio risk components. Once $\sigma_{i,t}$ and $\rho_{ij,t}$ for all risk factors are estimated, the aggregate portfolio VaR can be estimated as follows

$$VaR\left(r_{pt} \middle| I_{t-1}\right) = \Phi^{-1}(1-\alpha)\boldsymbol{\theta}_t'\boldsymbol{\Omega}_t\boldsymbol{\theta}_t. \tag{2.29}$$

Furthermore, the contribution of each risk factor to aggregate VaR can be determined by estimating stand-alone VaR and marginal VaR of each risk factor. As its name indicates, the stand-alone VaR of a specific risk factor is its VaR when it is isolated from the rest of portfolio, i.e., its correlation with other risk factors is not taken into account.

$$Stand - alone\ VaR_{X_i} = \Phi^{-1}(1-\alpha)\sqrt{\boldsymbol{\theta}'_{X_i}\boldsymbol{\Omega_t}\boldsymbol{\theta}_{X_i}}\,, \tag{2.30}$$

where θ_{X_i} is the sensitivity vector when all risk factor sensitivities except sensitivity to $X_i$is set to zero. Stand-alone VaRs are not additive, meaning that sum of all stand-alone components is greater than the portfolio VaR, unless all risk factors are perfectly correlated.

Marginal VaR, on the other hand, is a measure of each risk factor's contribution to the aggregate VaR of a portfolio. In other words, marginal VaR of a risk factor is a measure of how total portfolio VaR changes given a (small) change in the position of that risk factor. Let $f(\boldsymbol{\theta})$ be the aggregate VaR of a portfolio as defined in Equation (2.30). Taking the first partial derivative of $f(\boldsymbol{\theta})$ with respect to each risk component, θ_i, produces the following gradient vector

$$\boldsymbol{g}(\boldsymbol{\theta}) = \left(f_1(\boldsymbol{\theta}), \dots, f_m(\boldsymbol{\theta})\right)' = \frac{\Phi^{-1}(1-\alpha)\boldsymbol{\Omega_t}\,\boldsymbol{\theta_t}}{\sqrt{\boldsymbol{\theta}'_t\boldsymbol{\Omega_t}\boldsymbol{\theta_t}}}, \tag{2.31}$$

where

$$f_i(\boldsymbol{\theta}) = \frac{\partial f(\boldsymbol{\theta})}{\partial \theta_i}, \qquad\qquad i = 1, \dots, m; \tag{2.32}$$

Accordingly, the marginal VaR of the i^{th} risk factor is defined as

$$Marginal - VaR_{X_i} = \theta_i f_i(\boldsymbol{\theta}) = \boldsymbol{\theta}'_{X_i}\boldsymbol{g}(\boldsymbol{\theta}). \tag{2.33}$$

Using the first order of Taylor expansion, sum of marginal VaR is given by

$$f(\theta) \approx \theta' g(\theta) = \sum_{i=1}^{m} \theta_i f_i(\theta). \tag{2.34}$$

Thus, it is proven that sum of marginal VaR of all risk factors in a portfolio is approximately equal to portfolio VaR figure, which is one of the main advantageous of parametric VaR models over their counterparts.

2.3. DATA

To investigate the performance of alternative models in forecasting one-step ahead VaR of international equity portfolios, historical daily equity indices and foreign exchange rates data of eight countries are used in this chapter. The countries that are included in this study can be divided into four groups based on their level of economic developments. The main reason for inclusion of a wide range of countries is that characteristics and nature of stock markets vary widely across countries with different level of economic developments. The sample countries include Japan and the United Kingdom as developed countries, India, Brazil, Chile and Philippines as emerging counties while Tunisia and Egypt represent developing countries. In addition, due to their large and fast-growing economies, Brazil and India are distinguished from Chile and Philippines. Brazil and India can be classified as advanced emerging countries, while Philippines and Chile are considered as emerging countries.

Equity indices and exchange rate data were obtained from Datastream. Equity indices include FTSE 100 index (UK), NIKKEI225 index (Japan), BOVESPA index (Brazil), CNX 500 index (India), IPSA index (Chile), PSEI index (Philippines), TUNINDEX index (Tunisia), and EGX 30 index (Egypt). Furthermore, the US dollar is employed as the benchmark currency in this study since the focus of this thesis is on the US banks and US dollar is the most widely used currency in the world.[4]

The sample period under consideration is from January 1999 to December 2010. In this study, the one-day ahead conditional variances, conditional correlations, and

[4] Among sample countries, UK, and Chile have free float exchange rate systems; Japan has free float exchange rate system, while its central bank monitors various indicators in conducting monetary policy; India has floating exchange rate system, while its central monitors various indicators in conducting monetary policy; Philippines and Brazil have floating exchange rate system under inflation-targeting framework; Tunisia has crawl-like exchange rate arrangement; Egypt has stabilized exchange rate arrangement.

VaR thresholds are estimated based on a rolling window of 1,000 observations. Accordingly, the forecasting period starts from January 1, 2003, and ends in December 31, 2010, while observations before January 2003 are used for estimation purposes only. This forecasting period enables the author to evaluate the performance of alternative VaR models in different global economic conditions. More specifically, the forecasting period includes two sub-periods: the pre-crisis period from January 1, 2003, to December 31, 2006, and the crisis period from January 1, 2007, to December 31, 2010. Daily return series for each time series is obtained from the following formula

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right), \tag{2.35}$$

where P_t is daily value of equity indices or exchange rates at time t. Graphical illustrations of synchronous daily foreign exchange rates and equity returns across sample countries are given in Figure 2.1. All return series exhibit volatility clustering at different time periods, indicating the presence of ARCH effects, which need to be modelled by an appropriate time series model. Also, all stock markets exhibit high volatility during global financial crisis, which originated by the US subprime mortgage crisis.

Furthermore, exchange rates exhibit sharp drops during the global financial crisis, indicating that the US banks that spread their trading portfolios across the world suffered severely from depreciation of both equity prices and exchange rates.

Table 2.1 presents the descriptive statistics for equity returns in local currency, exchange rates, and equity returns in the US dollar over the period January 1, 2003, and December 31, 2010. For each return series, basic descriptive statistics, Jarque-Bera test of normality, and Augmented Dickey-Fuller (ADF) test of stationarity are presented. It appears that mean and median values observed for all series are close to zero while the range of daily returns is very similar for most series. In all sample countries, standard deviation of equity returns are higher than that of exchange rates, indicating that equity markets are more volatile than foreign exchange markets. Estimated skewness is slightly different from zero while all series have positive kurtosis. Not surprisingly, the Jarque-Bera test statistics reject the null hypothesis of normality for all return series

Figure 2.1. Daily stock price returns (blue line) and corresponding exchange rates (red line) over the period January 1, 2002-December 30, 2010.

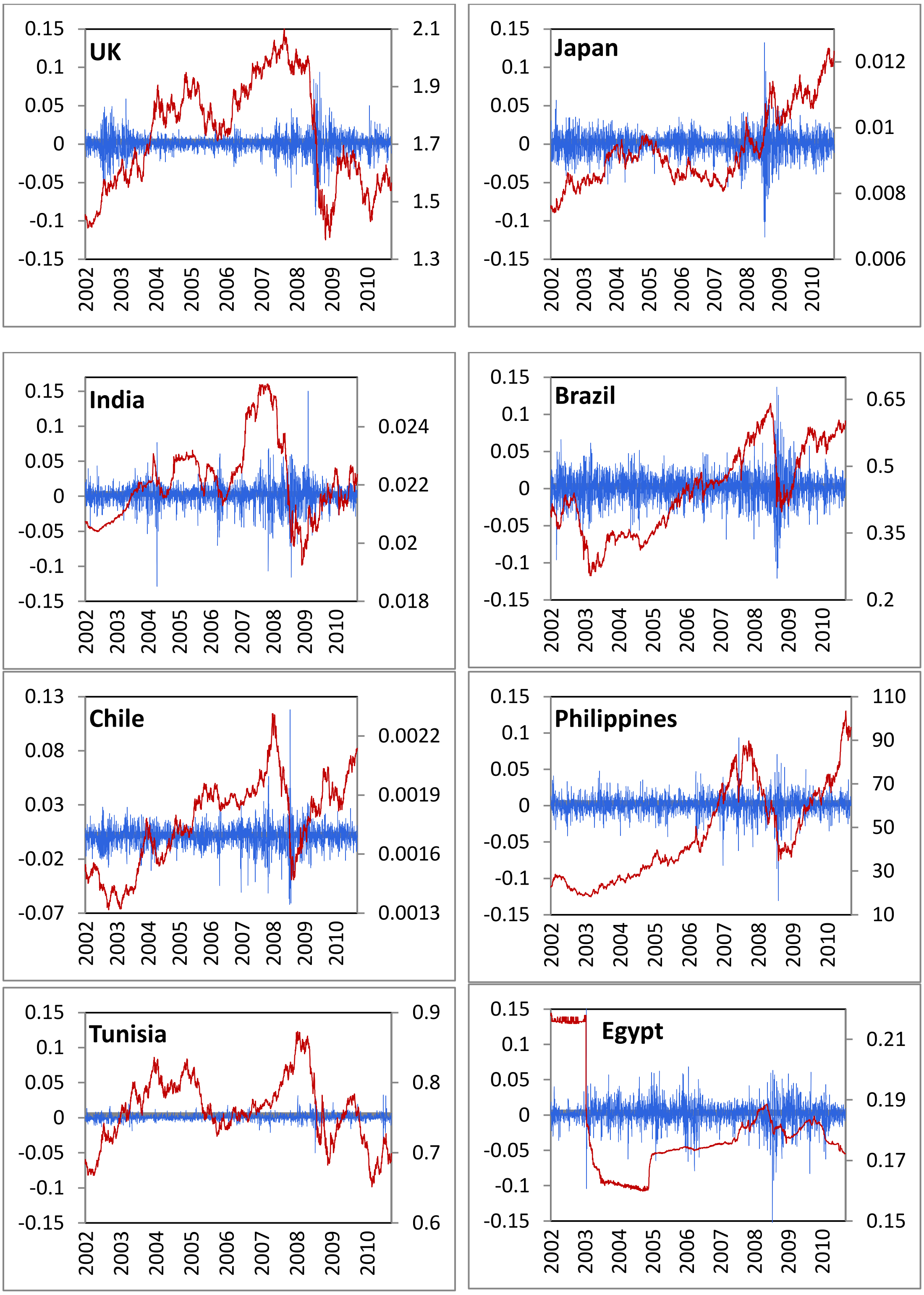

Table 2.1. Descriptive statistics for equity returns in local currency, exchange rate returns, and equity returns in US dollars.

	Statistics	UK	Japan	India	Brazil	Chile	Philippines	Tunisia	Egypt
Equity returns (LC)	Mean	0.0002	0.0001	0.0009	0.0010	0.0008	0.0007	0.0007	0.0013
	Median	0.0002	0.0000	0.0015	0.0016	0.0007	0.0000	0.0002	0.0011
	Maximum	0.0938	0.1323	0.1503	0.1368	0.1180	0.0937	0.0325	0.1837
	Minimum	-0.0927	-0.1211	-0.1288	-0.1210	-0.0621	-0.1309	-0.0500	-0.1799
	SD	0.0126	0.0155	0.0167	0.0195	0.0104	0.0136	0.0051	0.0184
	Skewness	-0.0909	-0.4650	-0.5501	-0.0727	0.0716	-0.6147	-0.3816	-0.4096
	Kurtosis	12.031	11.854	11.791	7.698	14.605	11.099	14.968	14.340
	CoV	65.062	184.109	18.810	20.154	13.631	20.053	7.047	14.432
	Jarque-Bera	**7098.5**	**6895.6**	**6828.7**	**1923.4**	**11718.7**	**5838.4**	**12512.8**	**11245.9**
	ADF test	**-22.643**	**-34.633**	**-41.821**	**-45.836**	**-39.839**	**-39.776**	**-37.488**	**-39.592**
Foreign exchange rate returns	Mean	0.0000	0.0002	0.0000	0.0003	0.0002	0.0001	0.0000	0.0000
	Median	0.0001	0.0000	0.0000	0.0008	0.0002	0.0000	0.0000	0.0000
	Maximum	0.0447	0.0461	0.0307	0.1194	0.0393	0.0127	0.0353	0.0147
	Minimum	-0.0392	-0.0308	-0.0246	-0.0846	-0.0546	-0.0131	-0.0270	-0.0155
	SD	0.0066	0.0068	0.0039	0.0116	0.0072	0.0035	0.0046	0.0019
	Skewness	-0.0885	0.4760	-0.0761	-0.0919	-0.5171	-0.0974	0.1883	-0.6037
	Kurtosis	7.3754	6.9930	9.3286	14.9188	8.6652	4.0039	6.4036	16.1031
	CoV	-493.61	37.11	115.63	40.52	34.77	37.36	-138.20	-51.56
	Jarque-Bera	**1668.3**	**1466.0**	**3486.5**	**12367.8**	**2885.3**	**91.0**	**1020.2**	**15064.1**
	ADF test	**-42.861**	**-47.056**	**-43.504**	**-46.321**	**-45.021**	**-44.372**	**-45.110**	**-17.307**
Equity returns (USD)	Mean	0.0002	0.0003	0.0009	0.0013	0.0010	0.0008	0.0007	0.0012
	Median	0.0006	0.0004	0.0020	0.0022	0.0000	0.0004	0.0007	0.0012
	Maximum	0.1222	0.1164	0.1811	0.1893	0.1455	0.0933	0.0384	0.1874
	Minimum	-0.1054	-0.1119	-0.1282	-0.1655	-0.1167	-0.1391	-0.0636	-0.1829
	SD	0.0153	0.0156	0.0186	0.0265	0.0140	0.0151	0.0069	0.0189
	Skewness	-0.0667	-0.2764	-0.3612	-0.3095	-0.3309	-0.6472	-0.1719	-0.5536
	Kurtosis	13.514	8.430	11.666	8.342	14.973	9.813	9.431	14.878
	CoV	84.933	58.262	20.218	21.143	14.406	19.568	9.916	16.161
	Jarque-Bera	**9618.2**	**2592.2**	**6579.4**	**2517.3**	**12509.8**	**4184.1**	**3608.2**	**12381.1**
	ADF test	**-21.924**	**-36.735**	**-41.393**	**-43.307**	**-41.666**	**-39.537**	**-28.682**	**-40.343**

Note: Entries in bold are significant at 1% level.

considered in this study. Finally, in order to test the stationarity of the return series, the ADF test is calculated. The ADF test statistics indicate that all return series are stationary.

Table 2.2. Pairwise correlation between equity returns and exchange rate returns.

Country	Correlation	Country	Correlation
UK	0.2000***	Chile	0.2382***
Japan	-0.0995***	Philippines	0.3205***
India	0.4099***	Tunisia	-0.0028
Brazil	0.4128***	Egypt	0.0134

Note: ***, **, and * entries are statistically significant at 1%, 5%, and 10%, respectively.

Table 2.2 presents pairwise correlation coefficients of equity returns and exchange rate returns. It appears that, apart from developing countries, estimated correlation coefficients are statistically significant at 1% significance level. Furthermore, with the exception of Japan, the correlation coefficient between equity returns and exchange rate returns are positive across all developed and emerging countries. This is not surprising as higher equity return in a country may indicate that the economy is growing and therefore the exchange rate will be appreciated.

2.4. EMPIRICAL RESULTS

In this Section, forecasting ability of alternative parametric VaR models described in Section 2.2 is investigated. Following Basel Accords, VaR thresholds are calculated for one day horizon and with 99% confidence level. As a fundamental assumption in parametric VaR models, it is first assumed that market shocks follow normal distribution. However, the normality assumption is often too restrictive for financial return series (see Bollerslev, 1987; Sajjad *et al*., 2008). In fact, many studies, including Bollerslev (1987) and McAleer *et al*. (2013), suggest that market shocks follow a Student-*t* distribution as they can be approximately modelled by a unimodal symmetric distribution that has fatter tails than the normal distribution.[5] Therefore, following McAleer *et al*. (2008), Şener *et al*. (2012), and McAleer *et al*. (2013), this

[5] There are also other distributional assumptions for market shocks in forecasting literature. In particular, Giot and Laurent (2003, 2004) take into account the leverage effects in market shocks, and advocate using the skewed Student-*t* distribution as an alternative assumption for the distribution of market shocks. They show that the assumption that market shocks follow a skewed Student distribution leads to superior forecasting performance in APARCH models.

study considers both normal and Student-t distributions as underlying assumption for market shocks.

2.4.1. General review of violations

The first step in comparing forecasting ability of alternative VaR models is to review the number of violations. A violation occurs if the realized return on a portfolio in a day is lower than the forecasted VaR for that day. Given that the number of violations is obtained, it is possible to evaluate the probability of a violation occurring when a specific VaR model is used. Although the number of violations is the primary focus of regulators when evaluating a VaR model, regulators are also interested in the pattern and distribution of violations, such as average deviation from estimated VaR thresholds and maximum potential deviation from VaR estimates when a given model is employed (see BCBS, 1996a,; BCBS, 1996b). This enables regulators to estimate the magnitude of losses when a violation occurs.

Table 2.3 reports number of violations, average size of the violations beyond VaR estimates, and maximum size of violations beyond VaR estimates for all sample countries during pre-crisis period. Each table contains four blocks corresponding to four different methods employed to model the correlation between equity returns and foreign exchange rate returns. The first block presents the results for univariate VaR models, the second block corresponds to the CCC model, the third block relates to the DCC VaR models, and the last block corresponds to ADCC VaR models.

In general, it appears from Table 2.3 that the number of violations remains relatively low during pre-crisis period, regardless of the model under consideration. This finding is robust across all countries and all models. Choosing 1% significance level for VaR estimation, a well performing model should produce ten violations in each sample period, i.e., one violation per 100 estimations. Number of violations range from 5 to 25 in the sample countries, which indicates that all VaR models have satisfactory performance from regulators' point of view. Among univariate models, RiskMetrics, GJR-*t*, EGARCH-*t*, and APARCH-*t* produce lower number of violations, compared to other VaR models.

Table 2.3. General overview of violations during the period 2003-2006.

	Models	UK			Japan			Brazil			India		
			AD of violations			AD of violations			AD of violations			AD of violations	
		NV	Mean	Max	NV	Mean	Max	NV	Mean	Max	NV	Mean	Max
Univariate models	RiskMetrics	8	0.337	0.693	10	0.935	2.629	11	0.725	2.442	18	1.392	4.848
	GARCH	21	0.413	0.903	14	0.922	3.362	14	0.619	2.765	20	1.258	5.09
	GARCH-*t*	16	0.386	0.768	13	0.958	3.244	11	0.744	2.671	19	1.373	4.999
	GJR	18	0.42	1.088	14	0.807	3.272	9	0.878	3.049	24	1.189	5.069
	GJR-*t*	13	0.392	0.834	9	0.901	2.332	7	0.978	2.976	19	1.23	4.444
	EGARCH	21	0.41	0.992	13	0.891	3.38	9	1.045	3.241	25	1.139	5.428
	EGARCH-*t*	15	0.38	0.778	10	0.886	2.998	10	0.805	3.017	19	1.223	4.884
	APARCH	22	0.431	1.074	16	0.793	3.406	10	0.953	3.253	23	1.238	5.076
	APARCH-*t*	15	0.389	0.954	15	0.743	3.222	9	0.913	3.006	19	1.192	4.517
CCC models	GARCH	17	0.343	0.846	10	1.068	3.113	13	0.639	2.92	18	1.315	4.804
	GARCH-*t*	10	0.375	0.685	10	1.012	3.074	12	0.63	2.623	19	1.299	4.707
	GJR	13	0.361	0.976	9	1.067	3.001	9	0.76	2.875	22	1.211	4.815
	GJR-*t*	8	0.373	0.902	10	0.964	2.982	7	0.848	2.804	19	1.142	4.137
	EGARCH	16	0.391	1.142	10	0.913	3.069	9	0.805	3.178	23	1.194	5.247
	EGARCH-*t*	12	0.355	0.98	11	0.744	2.954	9	0.719	3.014	17	1.279	4.674
	APARCH	16	0.429	1.154	10	0.927	3.115	10	0.707	3.203	23	1.178	4.973
	APARCH-*t*	12	0.39	1.033	9	0.836	3	8	0.76	3	17	1.257	4.31
DCC models	RiskMetrics	9	0.301	0.65	11	0.924	2.674	9	0.941	2.313	18	1.384	4.895
	GARCH	13	0.38	0.878	12	0.894	2.792	12	0.765	2.445	17	1.308	4.446
	GARCH-*t*	10	0.292	0.777	12	0.851	2.751	11	0.776	2.473	18	1.288	4.33
	GJR	11	0.356	1.085	10	0.952	2.683	9	0.848	2.873	22	1.164	4.466
	GJR-*t*	7	0.339	1.018	9	1.014	2.574	7	0.967	2.802	19	1.083	3.716
	EGARCH	16	0.345	1.237	9	1	2.76	9	0.824	3.177	23	1.14	4.976
	EGARCH-*t*	12	0.292	1.086	9	0.921	2.626	9	0.747	3.012	17	1.211	4.354
	APARCH	16	0.373	1.248	9	1.008	2.806	9	0.837	3.201	23	1.123	4.699
	APARCH-*t*	13	0.297	1.14	8	0.926	2.673	9	0.702	2.998	17	1.188	3.985
ADCC models	GARCH	13	0.349	1.008	12	0.915	2.69	11	0.844	2.54	23	1.198	4.821
	GARCH-*t*	9	0.281	0.917	12	0.872	2.648	10	0.868	2.568	18	1.244	4.245
	GJR	11	0.33	1.196	11	0.891	2.582	10	0.779	2.968	21	1.191	4.386
	GJR-*t*	7	0.298	1.135	10	0.943	2.467	9	0.766	2.9	19	1.053	3.62
	EGARCH	16	0.322	1.333	9	1.031	2.661	10	0.76	3.272	23	1.118	4.914
	EGARCH-*t*	12	0.265	1.192	11	0.781	2.521	10	0.693	3.11	19	1.046	4.28
	APARCH	15	0.372	1.343	9	1.039	2.708	10	0.768	3.298	24	1.052	4.636
	APARCH-*t*	11	0.318	1.248	9	0.841	2.569	10	0.646	3.097	16	1.218	3.911

Note: Entries in this table include Number of violations (NV), mean and maximum of absolute deviation (AD) of violations for each model. This table includes four blocks. First block includes univariate models, while other blocks include different multivariate models.

Table 2.3. (Continued)

	Models	Chile			Philippines			Tunisia			Egypt		
			AD of violations			AD of violations			AD of violations			AD of violations	
		NV	Mean	Max	NV	Mean	Max	NV	Mean	Max	NV	Mean	Max
Univariate models	RiskMetrics	17	0.509	2.483	14	0.869	5.705	5	0.15	0.252	14	1.299	3.253
	GARCH	22	0.63	3.199	16	1.025	5.811	11	0.179	0.455	13	1.212	3.447
	GARCH-*t*	19	0.594	3.008	13	1.179	5.759	9	0.144	0.385	11	1.27	3.664
	GJR	21	0.575	3.019	14	0.994	5.611	11	0.178	0.468	13	1.185	3.314
	GJR-*t*	17	0.555	2.813	13	0.956	5.546	10	0.143	0.405	12	1.232	3.825
	EGARCH	21	0.589	2.921	14	1.073	5.442	17	0.154	0.49	14	1.073	5.442
	EGARCH-*t*	18	0.54	2.712	13	1.075	5.373	11	0.162	0.409	13	1.121	3.394
	APARCH	22	0.578	2.919	13	1.192	5.495	19	0.153	0.549	12	1.114	3.542
	APARCH-*t*	17	0.593	2.717	13	1.102	5.402	11	0.166	0.457	13	1.149	3.654
CCC models	GARCH	12	0.677	2.891	14	1.008	5.692	7	0.081	0.182	10	1.387	3.829
	GARCH-*t*	8	0.774	2.671	13	0.987	5.633	10	0.141	0.397	10	1.316	3.971
	GJR	12	0.636	2.832	15	0.89	5.697	6	0.103	0.179	11	1.424	4.012
	GJR-*t*	8	0.678	2.557	13	0.974	5.643	7	0.11	0.319	11	1.309	3.953
	EGARCH	12	0.599	2.831	14	1.012	5.62	6	0.082	0.129	12	1.3	3.609
	EGARCH-*t*	7	0.752	2.575	14	0.981	5.565	5	0.093	0.146	11	1.121	2.65
	APARCH	12	0.624	2.755	13	1.092	5.634	5	0.105	0.188	13	1.189	3.642
	APARCH-*t*	8	0.773	2.515	14	0.983	5.573	5	0.095	0.172	10	1.265	2.78
DCC models	RiskMetrics	17	0.51	2.359	13	0.912	5.722	5	0.143	0.275	13	1.227	3.113
	GARCH	13	0.586	2.581	14	0.996	5.676	8	0.073	0.182	10	1.391	3.834
	GARCH-*t*	9	0.605	2.333	13	0.973	5.616	5	0.089	0.152	10	1.319	3.974
	GJR	14	0.518	2.516	14	0.942	5.68	7	0.096	0.179	11	1.426	4.015
	GJR-*t*	9	0.539	2.202	12	1.041	5.626	8	0.096	0.202	11	1.311	3.955
	EGARCH	13	0.516	2.515	12	1.169	5.602	7	0.074	0.112	12	1.304	3.614
	EGARCH-*t*	8	0.577	2.224	14	0.969	5.547	6	0.079	0.146	11	1.129	2.658
	APARCH	13	0.559	2.441	13	1.083	5.616	6	0.083	0.15	13	1.193	3.647
	APARCH-*t*	9	0.609	2.167	13	1.046	5.554	6	0.074	0.118	10	1.273	2.788
ADCC models	GARCH	16	0.531	2.56	12	1.036	5.626	7	0.12	0.29	10	1.305	3.618
	GARCH-*t*	11	0.52	2.31	12	0.954	5.564	6	0.075	0.152	10	1.274	3.839
	GJR	15	0.545	2.495	12	1.003	5.631	7	0.132	0.293	11	1.387	3.893
	GJR-*t*	12	0.44	2.178	12	0.938	5.574	8	0.12	0.284	11	1.271	3.83
	EGARCH	16	0.476	2.493	14	0.913	5.548	8	0.079	0.196	14	0.913	5.548
	EGARCH-*t*	11	0.453	2.2	13	0.929	5.49	6	0.097	0.166	8	1.372	2.27
	APARCH	15	0.549	2.42	13	0.987	5.562	7	0.089	0.217	14	1.049	3.418
	APARCH-*t*	13	0.453	2.144	13	0.94	5.497	6	0.094	0.195	10	1.134	2.411

Note: Entries in this table include Number of violations (NV), mean and maximum of absolute deviation (AD) of violations for each model. This table includes four blocks. First block includes univariate models, while other blocks include different multivariate models.

Among multivariate models, however, there is no clear pattern on which models perform better to forecast VaR during pre-crisis period across all countries. Nonetheless, the number of violations slightly reduces in most countries when multivariate models are used. Furthermore, empirical results show that using Student-*t* distribution as an assumption for the distribution of market shocks leads to lower number of violations across all models and countries.

In addition, there is no significant variation in mean deviation and maximum deviation of violations across alternative VaR models. However, mean deviation and maximum deviation of violations largely vary across different countries, which may reflect the dissimilarities in the pattern of fluctuations in international equity portfolios. For instance, mean and maximum deviations of violations in Tunisia are much smaller than those in other countries. However, when Japan and Philippines are compared, mean deviations of violations are very similar, while maximum deviation of violations is much higher in Philippines.

Although most VaR models have satisfactory performance during pre-crisis period, the story changes during crisis period. Table 2.4 presents the general overview of violations during crisis period. It appears that the number of violations dramatically increases during crisis period for all VaR models and across all countries, while a large variation is observed across countries. For instance, the number of violations is much higher in the UK compared to those in Japan.

Just like pre-crisis period, it is observed that multivariate models produce lower number of violations compared to univariate models, indicating that incorporating more information in VaR models leads to more accurate VaR estimation. Among multivariate models, however, no superior model can be selected due to inconsistent performance of alternative VaR models across different countries. For instance, CCC models perform reasonably well in Japan while DCC models and ADCC models have better performance for most other countries.

Table 2.4. General overview of violations during the period 2007-2010.

	Models	UK			Japan			Brazil			India		
			AD of violations			AD of violations			AD of violations			AD of violations	
		NV	Mean	Max	NV	Mean	Max	NV	Mean	Max	NV	Mean	Max
Univariate models	RiskMetrics	25	0.927	3.533	16	1.36	3.27	24	1.222	4.439	21	1.165	6.452
	GARCH	48	0.954	4.143	14	1.053	2.634	26	1.341	4.294	30	1.296	5.076
	GARCH-*t*	37	0.931	3.481	14	1.028	2.787	24	1.355	4.234	31	1.235	5.257
	GJR	46	1.017	4.217	15	0.642	1.609	30	1.16	4.171	38	1.178	4.073
	GJR-*t*	41	0.885	3.641	20	0.817	2.54	27	1.138	4.074	30	1.095	3.671
	EGARCH	51	1.057	4.926	18	0.717	1.92	32	1.338	4.84	41	1.11	3.661
	EGARCH-*t*	41	0.917	4.321	14	0.566	1.642	31	1.28	4.748	27	1.187	3.362
	APARCH	50	1.014	4.722	18	0.66	2.098	33	1.338	4.833	38	1.174	3.728
	APARCH-*t*	37	0.968	4.244	14	0.94	2.138	33	1.172	4.605	30	1.093	3.202
CCC models	GARCH	30	0.948	3.761	14	0.765	2.244	28	1.242	4.46	24	1.153	5.031
	GARCH-*t*	23	0.9	3.271	12	0.802	2.354	25	1.287	4.408	22	1.248	5.539
	GJR	30	0.926	3.972	11	0.599	1.109	25	1.235	4.415	27	1.185	3.634
	GJR-*t*	22	0.939	3.491	10	0.666	1.262	20	1.398	4.331	21	1.199	3.336
	EGARCH	31	0.97	4.521	17	0.692	1.825	29	1.368	5.132	32	1.119	3.633
	EGARCH-*t*	23	0.989	4.088	11	0.663	1.327	29	1.278	4.977	18	1.377	3.717
	APARCH	32	0.939	4.655	16	0.756	2.287	30	1.387	5.134	31	1.15	3.435
	APARCH-*t*	25	0.864	4.182	14	0.603	1.553	29	1.285	4.871	20	1.276	3.618
DCC models	RiskMetrics	22	1.021	3.506	18	1.198	3.231	22	1.329	4.344	21	1.152	6.404
	GARCH	27	0.85	3.286	17	1.033	2.889	24	1.356	4.325	22	1.187	5.022
	GARCH-*t*	18	0.885	3.047	17	0.945	3.042	23	1.322	4.268	21	1.226	5.531
	GJR	23	0.932	3.503	19	0.649	1.906	23	1.245	4.28	26	1.166	3.568
	GJR-*t*	16	1.029	2.984	14	0.758	2.032	20	1.293	4.19	20	1.188	3.328
	EGARCH	24	0.943	4.058	22	0.952	2.883	26	1.365	4.796	31	1.066	3.626
	EGARCH-*t*	19	0.871	3.585	18	0.847	2.062	25	1.324	4.635	17	1.354	3.71
	APARCH	25	0.925	4.198	21	0.975	3.349	29	1.294	4.805	30	1.094	3.407
	APARCH-*t*	18	0.84	3.685	19	0.841	2.307	25	1.33	4.534	19	1.235	3.611
ADCC models	GARCH	26	0.854	3.301	18	0.999	2.928	24	1.354	4.31	30	1.152	5.535
	GARCH-*t*	18	0.856	3.072	17	0.971	3.084	23	1.32	4.252	21	1.181	5.519
	GJR	21	0.991	3.398	19	0.659	2.007	23	1.241	4.265	24	1.225	3.563
	GJR-*t*	16	1.003	2.871	14	0.773	2.148	20	1.288	4.174	17	1.357	3.316
	EGARCH	24	0.899	3.956	23	0.923	2.872	25	1.426	4.772	29	1.104	3.616
	EGARCH-*t*	18	0.872	3.474	19	0.814	2.052	25	1.331	4.611	16	1.389	3.7
	APARCH	24	0.923	4.096	21	0.988	3.338	29	1.299	4.781	28	1.132	3.397
	APARCH-*t*	16	0.913	3.575	21	0.774	2.353	25	1.338	4.51	18	1.255	3.6

Note: Entries in this table include Number of violations (NV), mean and maximum of absolute deviation (AD) of violations for each model. This table includes four blocks. First block includes univariate models, while other blocks include different multivariate models.

Table 2.4. (Continued)

	Models	Chile			Philippines			Tunisia			Egypt		
			AD of violations			AD of violations			AD of violations			AD of violations	
		NV	Mean	Max	NV	Mean	Max	NV	Mean	Max	NV	Mean	Max
Univariate models	RiskMetrics	14	1.208	4.175	24	1.115	5.915	14	0.543	3.558	22	1.463	12.91
	GARCH	48	0.828	5.435	36	1.033	6.453	30	0.464	3.727	21	1.616	13.4
	GARCH-*t*	34	0.892	5.219	33	1.032	6.451	29	0.43	3.667	20	1.616	13.64
	GJR	39	0.925	5.543	24	1.023	5.738	31	0.45	3.747	21	1.486	13.49
	GJR-*t*	29	0.994	5.349	22	1.052	5.6	29	0.445	3.686	20	1.611	15.46
	EGARCH	41	0.965	5.492	27	1.025	6.367	41	0.413	4.224	27	1.025	6.367
	EGARCH-*t*	33	0.972	5.192	25	1.05	6.333	37	0.424	4.192	16	1.812	15.31
	APARCH	43	0.944	5.486	28	1.002	6.31	43	0.39	4.252	19	1.606	14.51
	APARCH-*t*	33	1	5.202	25	1.073	6.39	37	0.42	4.22	17	1.715	15.18
CCC models	GARCH	16	1.103	4.202	25	1.068	6.025	13	0.556	3.172	20	1.677	13.32
	GARCH-*t*	13	1.094	3.871	23	1.08	6.183	29	0.443	3.693	20	1.632	13.57
	GJR	16	1.095	4.432	26	1.008	6.073	18	0.501	3.422	21	1.534	14.35
	GJR-*t*	14	0.984	4.06	25	0.951	5.893	21	0.511	3.502	19	1.587	14.23
	EGARCH	22	1.001	4.584	26	1.079	6.569	11	0.727	3.795	18	1.792	14.3
	EGARCH-*t*	16	1.014	4.123	24	1.064	6.474	10	0.623	2.695	18	1.618	15.11
	APARCH	19	1.099	4.556	27	1.047	6.451	14	0.608	3.82	18	1.737	14.27
	APARCH-*t*	13	1.171	3.932	26	1.001	6.64	13	0.53	2.743	17	1.721	15.03
DCC models	RiskMetrics	14	1.19	4.05	22	1.211	5.916	14	0.516	3.182	21	1.54	12.92
	GARCH	14	1.046	3.476	25	0.996	5.85	13	0.549	3.107	20	1.68	13.32
	GARCH-*t*	12	0.942	3.087	21	1.094	6.003	9	0.734	2.65	20	1.635	13.57
	GJR	17	0.829	3.757	23	1.044	5.903	19	0.469	3.359	21	1.536	14.35
	GJR-*t*	12	0.857	3.318	21	1.033	5.715	12	0.567	2.751	19	1.588	14.23
	EGARCH	18	0.972	3.942	24	1.092	6.405	13	0.609	3.741	18	1.795	14.3
	EGARCH-*t*	14	0.861	3.394	21	1.125	6.283	10	0.601	2.626	18	1.616	15.11
	APARCH	18	0.973	3.847	23	1.154	6.287	14	0.583	3.767	18	1.738	14.27
	APARCH-*t*	12	0.989	3.186	22	1.104	6.468	12	0.531	2.679	17	1.718	15.03
ADCC models	GARCH	14	1.037	3.472	23	1.075	5.818	14	0.512	3.084	20	1.66	13.31
	GARCH-*t*	10	1.123	3.083	20	1.143	5.97	9	0.68	2.58	20	1.61	13.56
	GJR	17	0.822	3.753	23	1.037	5.872	19	0.462	3.337	21	1.513	14.35
	GJR-*t*	12	0.847	3.314	21	1.025	5.683	12	0.545	2.729	18	1.654	14.23
	EGARCH	18	0.971	3.939	23	1.134	6.375	13	0.607	3.721	23	1.134	6.375
	EGARCH-*t*	13	0.931	3.39	21	1.119	6.249	11	0.542	2.601	18	1.589	15.11
	APARCH	18	0.972	3.843	23	1.147	6.257	15	0.544	3.748	18	1.725	14.27
	APARCH-*t*	11	1.074	3.181	20	1.207	6.437	10	0.614	2.656	17	1.694	15.03

Note: Entries in this table include Number of violations (NV), mean and maximum of absolute deviation (AD) of violations for each model. This table includes four blocks. First block includes univariate models, while other blocks include different multivariate models.

In addition to the number of violations, there is a sharp increase in mean deviation and maximum deviation of violations for most VaR models and across majority of sample countries during the crisis period. In particular, mean deviation of violations increases between 2 to 4 times in countries like UK and Tunisia, while maximum deviation of violations is between 3 to 20 times higher in Tunisia and Egypt. Among the sample countries, Japan is the only country that has lower mean deviation and maximum deviation of violations during crisis period for most VaR models. This may be related to the consequences of the collapse of asset price bubble until the mid-2000s in Japan. In other words, Japanese economy faced distressing experiences during the first sub-sample period.

In summary, general overview of violation patterns across VaR models and different countries indicate that (*i*) the number of violations, mean deviation of violations, and maximum deviation of violations dramatically increase during crisis period, (*ii*) multivariate models produce less violations compared to univariate models while DCC and ADCC models perform better than CCC models during crisis period, and (*iii*) the assumption that market shocks follow Student-*t* distribution leads to more accurate and conservative VaR estimations.

2.4.2. Christoffersen tests

It is also possible to assess out-of-sample forecasting performance of VaR models statistically. Christoffersen (1998) introduced three likelihood ratio (LR) tests of unconditional coverage, independence, and conditional coverage to evaluate the frequency of violations when using a specific VaR models. Accordingly, the frequency of violations in a well performing VaR model remains statistically close enough to the expected frequency of violations while violations are serially uncorrelated. This approach is based on the hit function of a VaR model which is defined as follows

$$I_{t+1} = \begin{cases} 1, & if\ r_{t+1} < VaR_{t+1} \\ 0, & if\ r_{t+1} \geq VaR_{t+1}, \end{cases} \tag{2.36}$$

where r_{t+1} is the return of the portfolio in day $t+1$ and VaR_{t+1} is the VaR estimate for day $t+1$. The first LR statistic in Christoffersen's approach is related to the test of unconditional coverage which was originally introduced by Kupiec (1995). The LR_{UC} test statistic is defined as follows

$$LR_{UC} = -2\left[log(\alpha^x(1-\alpha)^{N-x}) - \log\left((0.01^x)(0.99^{N-x})\right)\right] \sim \chi^2(1), \quad (2.37)$$

where $x = \sum I_{t+1}$ is the total number of violations, N is the number of forecasts, and $\alpha = x/N$ is the average number of violations. Under the null hypothesis of correct unconditional coverage, the LR_{UC} statistic is asymptotically distributed as a $\chi^2(1)$. In other words, when null hypothesis is accepted, it indicates that average number of violations, $E(x/N)$, is equal to the expected number of violations, p.

The second LR test statistic in Christoffersen's (1998) approach corresponds to the test of serial independence of violations based on a first-order Markov stochastic process. Accordingly, this test examines if the probability of a violation occurring at time t depends on the existence of a violation at time $t-1$. Denoting violation state with 1 and non-violation state with 0, the number of states in a Markov chain process is denoted as n_{00}, n_{10}, n_{01}, and n_{11}. Accordingly, the transition matrix of violations and non-violations is defined as

$$\Pi = \begin{pmatrix} \pi_{00} & \pi_{01} \\ \pi_{10} & \pi_{11} \end{pmatrix}, \quad (2.38)$$

where

$$\pi_{00} = \frac{n_{00}}{n_{00}+n_{01}}, \ \pi_{01} = \frac{n_{01}}{n_{00}+n_{01}}, \ \pi_{00} = \frac{n_{10}}{n_{10}+n_{11}}, \ \pi_{11} = \frac{n_{11}}{n_{10}+n_{11}}. \quad (2.39)$$

Thus, the LR_{SI} test of serial independence is defined as

$$LR_{SI} = -2\,log\left[\frac{(1-\pi_2)^{(n_{00}+n_{10})}\pi_2{}^{(n_{01}+n_{11})}}{(1-\pi_{01})^{n_{00}}(1-\pi_{11})^{n_{10}}\pi_{01}{}^{n_{01}}\pi_{11}{}^{n_{11}}}\right] \sim \chi^2(1). \quad (2.40)$$

The LR_{SI} test statistic is also asymptotically distributed as a $\chi^2(1)$ under the null hypothesis of serial independence against the alternative of first-order Markov dependence. Finally, Christoffersen (1998) combined the first two tests and introduced a joint test of coverage and independence called conditional coverage test which is defined as

$$LR_{CC} = LR_{UC} + LR_{SI}. \tag{2.41}$$

The LR_{CC} test statistic of conditional coverage is asymptotically distributed as a $\chi^2(2)$ under the joint null hypothesis.

Table 2.5 presents the results of Christoffersen's (1998) backtesting tests for alternative VaR models during the period January 1, 2003, to December 31, 2006. In particular, for each VaR model, three LR tests are presented: test of unconditional coverage (UC), test of serial independence (SI), and test of conditional coverage (CC). Lower LR_{UC} statistic indicates that the VaR model provides better coverage, while a LR_{UC} statistic of zero indicates that the model provides full coverage, i.e., the number of realized violations is consistent with the confidence level of the VaR model. In general, the empirical evidence by the LR_{UC} test statistics indicates that almost all VaR models provide statistically satisfactory coverage at 1% significance level across all countries and during the pre-crisis period. However, when the significance level increases to 10% some VaR models fail to provide satisfactory coverage. This is consistent with the results obtained by general overview of violations as the LR_{UC} statistic is based on the number of violations.

Furthermore, compared to univariate models, multivariate models provide better coverage across most countries. Among univariate models, RiskMetrics, GJR-*t*, EGARCH-*t*, and APARCH-*t* produce lower number of violations, compared to other VaR models.

Among multivariate models, however, there is no consistent evidence on which model produces lower LR_{UC} statistic during pre-crisis period and across all countries. Nonetheless, most multivariate VaR models pass the UC test at 1 % and 5% significance levels. Furthermore, compared to univariate models, multivariate models provide better coverage across most countries. Among univariate models, RiskMetrics, GJR-*t*, EGARCH-*t*, and APARCH-*t* produce lower number of violations, compared to other VaR models. Among multivariate models, however, there is no consistent evidence on which model produces lower LR_{UC} statistic during pre-crisis period and across all countries. Nonetheless, most multivariate VaR models pass the UC test at 1 % and 5% significance levels. Furthermore, empirical results of UC test provide conflicting evidence on the choice of distributional assumption for market shocks.

Table 2.5. LR tests of unconditional coverage, serial independence and conditional coverage during the period 2003-2006

	Models	UK			Japan			Brazil			India		
		UC	SI	CC	UC	SI	CC	UC	SI	CC	UC	SI	CC
Univariate models	RiskMetrics	0.19	1.67	1.86	0.00	0.09	0.09	0.04	0.11	0.15	2.27	1.68	3.95
	GARCH	4.03	3.07	7.10	0.62	0.76	1.38	0.62	0.17	0.80	3.40	1.12	4.52
	GARCH-*t*	1.34	3.31	4.64	0.36	0.11	0.47	0.04	0.07	0.11	2.81	1.24	4.06
	GJR	2.27	3.85	6.12	0.62	0.76	1.38	0.05	0.07	0.12	6.18	0.51	6.69
	GJR-*t*	0.36	4.48	4.84	0.05	0.06	0.10	0.44	0.04	0.48	2.81	0.39	3.20
	EGARCH	4.03	3.07	7.10	0.36	0.87	1.23	0.05	0.07	0.12	**6.97**	0.09	7.05
	EGARCH-*t*	0.95	3.57	4.52	0.00	0.87	0.87	0.00	0.06	0.06	2.81	0.19	3.00
	APARCH	4.71	2.84	7.54	1.34	0.57	1.90	0.00	0.09	0.09	5.42	0.15	5.58
	APARCH-*t*	0.95	3.31	4.26	0.95	0.66	1.61	0.05	0.07	0.12	2.81	0.19	3.00
CCC models	GARCH	1.78	2.03	3.81	0.00	0.09	0.09	0.36	0.87	1.23	2.27	1.12	3.39
	GARCH-*t*	0.00	1.00	1.00	0.00	0.09	0.09	0.16	0.09	0.25	2.81	1.38	4.19
	GJR	0.36	2.94	3.30	0.05	0.07	0.12	0.05	0.07	0.12	4.71	0.43	5.14
	GJR-*t*	0.19	1.29	1.48	0.00	0.06	0.06	0.44	0.04	0.48	2.81	0.35	3.17
	EGARCH	1.34	2.23	3.57	0.00	0.09	0.09	0.05	0.07	0.12	5.42	0.15	5.58
	EGARCH-*t*	0.16	0.87	1.04	0.04	0.07	0.11	0.05	0.07	0.12	1.78	0.19	1.97
	APARCH	1.34	2.23	3.57	0.00	0.09	0.09	0.00	0.09	0.09	5.42	0.15	5.58
	APARCH-*t*	0.16	2.45	2.61	0.05	0.06	0.10	0.19	0.06	0.24	1.78	0.24	2.02
DCC models	RiskMetrics	0.05	1.47	1.52	0.04	0.11	0.15	0.05	0.07	0.12	2.27	1.68	3.95
	GARCH	0.36	0.87	1.23	0.16	0.13	0.29	0.16	1.00	1.16	1.78	1.12	2.90
	GARCH-*t*	0.00	0.66	0.66	0.16	0.13	0.29	0.04	0.09	0.13	2.27	1.38	3.65
	GJR	0.04	1.13	1.18	0.00	0.09	0.09	0.05	0.07	0.12	4.71	0.43	5.14
	GJR-*t*	0.44	0.09	0.53	0.05	0.06	0.10	0.44	0.04	0.48	2.81	0.35	3.17
	EGARCH	1.34	2.23	3.57	0.05	0.07	0.12	0.05	0.07	0.12	5.42	0.15	5.58
	EGARCH-*t*	0.16	1.00	1.16	0.05	0.07	0.12	0.05	0.06	0.10	1.78	0.39	2.17
	APARCH	1.34	2.23	3.57	0.05	0.07	0.12	0.05	0.07	0.12	5.42	0.15	5.58
	APARCH-*t*	0.36	2.23	2.59	0.19	0.04	0.23	0.05	0.07	0.12	1.78	0.15	1.93
ADCC models	GARCH	0.36	0.87	1.23	0.16	0.13	0.29	0.04	0.11	0.15	5.42	0.15	5.58
	GARCH-*t*	0.05	0.49	0.53	0.16	0.13	0.29	0.00	0.09	0.09	2.27	1.38	3.65
	GJR	0.04	0.11	0.15	0.04	0.11	0.15	0.00	0.09	0.09	4.03	0.39	4.42
	GJR-*t*	0.44	0.09	0.53	0.00	0.09	0.09	0.05	0.07	0.12	2.81	0.35	3.17
	EGARCH	1.34	2.23	3.57	0.05	0.07	0.12	0.00	0.09	0.09	5.42	0.47	5.89
	EGARCH-*t*	0.16	1.13	1.30	0.04	0.09	0.13	0.00	0.09	0.09	2.81	0.43	3.24
	APARCH	0.95	2.45	3.40	0.05	0.07	0.12	0.00	0.09	0.09	6.18	0.12	6.29
	APARCH-*t*	0.04	2.03	2.08	0.05	0.06	0.10	0.00	0.09	0.09	1.34	0.15	1.49

Note: This table presents the results of three likelihood ratio (LR) tests proposed by Christoffersen (1998) for all sample countries. The LR tests include unconditional coverage (UC), serial independence (SI), and conditional coverage (CC). Critical values for UC and SI tests are 2.706, 3.841, and 6.635 for 10%, 5% and 1% significance level, respectively. Critical values for CC test are 4.605, 5.991, and 9.210 for 10%, 5% and 1% significance level, respectively. Entries in bold denote significance at 1% level.

Table 2.5. (Continued)

	Models	Chile			Philippines			Tunisia			Egypt		
		UC	SI	CC	UC	SI	CC	UC	SI	CC	UC	SI	CC
Univariate models	RiskMetrics	1.78	0.49	2.26	0.62	0.17	0.80	1.34	0.02	1.37	0.62	0.76	1.38
	GARCH	4.71	1.24	5.95	1.34	0.23	1.56	0.04	0.11	0.15	0.36	0.15	0.51
	GARCH-*t*	2.81	1.12	3.93	0.36	0.15	0.51	0.05	0.07	0.12	0.04	0.11	0.15
	GJR	4.03	1.38	5.41	0.62	0.17	0.80	0.04	0.11	0.15	0.36	0.15	0.51
	GJR-*t*	1.78	1.52	3.30	0.36	0.15	0.51	0.00	0.07	0.07	0.16	1.00	1.16
	EGARCH	4.03	1.38	5.41	0.62	0.17	0.80	1.78	0.49	2.26	0.62	0.87	1.49
	EGARCH-*t*	2.27	1.38	3.65	0.36	0.15	0.51	0.04	0.07	0.11	0.36	0.87	1.23
	APARCH	4.71	1.24	5.95	0.36	0.15	0.51	2.81	0.35	3.16	0.16	0.13	0.29
	APARCH-*t*	1.78	1.24	3.02	0.36	0.15	0.51	0.04	0.11	0.15	0.36	0.87	1.23
CCC models	GARCH	0.16	1.00	1.16	0.62	0.17	0.80	0.44	0.04	0.48	0.00	0.09	0.09
	GARCH-*t*	0.19	0.11	0.29	0.36	0.15	0.51	0.00	0.01	0.01	0.00	0.09	0.09
	GJR	0.16	0.13	0.29	0.95	0.20	1.15	0.82	0.03	0.85	0.04	1.13	1.18
	GJR-*t*	0.19	0.11	0.29	0.36	0.15	0.51	0.44	0.04	0.48	0.04	1.13	1.18
	EGARCH	0.16	0.13	0.29	0.62	0.17	0.80	0.82	0.03	0.85	0.16	1.00	1.16
	EGARCH-*t*	0.44	0.06	0.50	0.62	0.17	0.80	1.34	0.02	1.37	0.04	1.13	1.18
	APARCH	0.16	0.13	0.29	0.36	0.15	0.51	1.34	0.02	1.37	0.36	0.87	1.23
	APARCH-*t*	0.19	0.09	0.28	0.62	0.17	0.80	1.34	0.02	1.37	0.00	1.29	1.29
DCC models	RiskMetrics	1.78	0.49	2.26	0.36	0.15	0.51	1.34	0.02	1.37	0.36	0.87	1.23
	GARCH	0.36	0.15	0.51	0.62	0.17	0.80	0.19	0.06	0.24	0.00	0.09	0.09
	GARCH-*t*	0.05	0.15	0.19	0.36	0.15	0.51	1.34	0.03	1.38	0.00	0.09	0.09
	GJR	0.62	0.17	0.80	0.62	0.17	0.80	0.44	0.04	0.48	0.04	1.13	1.18
	GJR-*t*	0.05	0.13	0.17	0.16	0.13	0.29	0.19	0.04	0.23	0.04	1.13	1.18
	EGARCH	0.36	0.15	0.51	0.16	0.13	0.29	0.44	0.04	0.48	0.16	1.00	1.16
	EGARCH-*t*	0.19	0.09	0.28	0.62	0.17	0.80	0.82	0.03	0.85	0.04	1.13	1.18
	APARCH	0.36	0.15	0.51	0.36	0.15	0.51	0.82	0.03	0.85	0.36	0.87	1.23
	APARCH-*t*	0.05	0.15	0.19	0.36	0.15	0.51	0.82	0.03	0.85	0.00	1.29	1.29
ADCC models	GARCH	1.34	0.57	1.90	0.16	0.13	0.29	0.44	0.04	0.48	0.00	0.09	0.09
	GARCH-*t*	0.04	0.20	0.24	0.16	0.13	0.29	0.82	0.02	0.84	0.00	0.09	0.09
	GJR	0.95	0.20	1.15	0.16	0.13	0.29	0.44	0.04	0.48	0.04	1.13	1.18
	GJR-*t*	0.16	0.17	0.34	0.16	0.13	0.29	0.19	0.04	0.23	0.04	1.13	1.18
	EGARCH	1.34	0.57	1.90	0.62	0.17	0.80	0.19	0.06	0.24	0.62	1.00	1.62
	EGARCH-*t*	0.04	0.17	0.22	0.36	0.15	0.51	0.82	0.03	0.85	0.19	1.67	1.86
	APARCH	0.95	0.66	1.61	0.36	0.15	0.51	0.44	0.04	0.48	0.62	0.76	1.38
	APARCH-*t*	0.36	0.20	0.56	0.36	0.15	0.51	0.82	0.03	0.85	0.00	1.29	1.29

Note: This table presents the results of three likelihood ratio (LR) tests proposed by Christoffersen (1998) for all sample countries. The LR tests include unconditional coverage (UC), serial independence (SI), and conditional coverage (CC). Critical values for UC and SI tests are 2.706, 3.841, and 6.635 for 10%, 5% and 1% significance level, respectively. Critical values for CC test are 4.605, 5.991, and 9.210 for 10%, 5% and 1% significance level, respectively. Entries in bold denote significance at 1% level.

More specifically, in most VaR models assuming that market shocks follow Student-*t* distribution leads to lower LR_{UC} statistics while, in some cases, normality assumption produces equal or lower LR_{UC} statistic.

The second column of backtesting results for each country presents the serial independence test statistics. It appears that violation patterns of none of the VaR models exhibit serial dependence at 1% significance level. However, the null hypothesis of no serial dependence is rejected for some VaR models at higher significance levels. Furthermore, compared to univariate models, multivariate models provide lower SI test statistics across most countries. For instance, most univariate VaR models in the UK fail to pass serial independence test while most multivariate models produce statistically satisfactory LR_{SI} statistics.

Finally, the last column of backtesting results for each country presents conditional coverage test statistics. In general, the empirical findings of the LR_{CC} test statistics are very similar to the findings of UC and SI tests as the CC test statistics are the sum of LR_{UC} and LR_{SI} test statistics. For instance, the empirical evidence by the LR_{CC} test statistics indicates that all VaR models provide statistically satisfactory coverage at 1% significance level across all countries and during the pre-crisis period. Also, multivariate models provide lower LR_{CC} statistics for most VaR models and across most countries. In addition, assuming that market shocks follow Student-*t* distribution leads to lower LR_{CC} test statistics across most VaR models and across most sample countries.

Although most VaR models produce statistically satisfactory results during pre-crisis periods, it is also crucial to investigate the performance of VaR models during crisis periods. With this target in mind, Table 2.6 presents Christoffersen's (1998) backtesting results of VaR models during the crisis period. In general, the empirical evidence by the LR_{UC} test statistics indicates that most univariate VaR models fail to provide statistically satisfactory coverage at 1% significance level across most sample countries. This reflects the high number of violations across univariate VaR models during crisis period. However, these results improve when multivariate models are employed, which indicates that incorporating more information in VaR modelling enhances the performance of VaR models. Among multivariate models, it appears that
employed, which indicates that incorporating more information in VaR modelling

Table 2.6. LR tests of unconditional coverage, serial independence and conditional coverage during the period 2007-2010.

	Models	UK			Japan			Brazil			India		
		UC	SI	CC	UC	SI	CC	UC	SI	CC	UC	SI	CC
Univariate models	RiskMetrics	**6.97**	0.56	7.52	1.34	0.57	1.90	6.18	0.51	6.69	4.03	0.15	4.18
	GARCH	**33.03**	0.02	**33.05**	0.62	0.17	0.80	**7.79**	0.60	8.40	**11.43**	0.05	**11.48**
	GARCH-*t*	**18.92**	0.34	**19.26**	0.62	0.17	0.80	6.18	0.47	6.65	**12.42**	0.01	**12.43**
	GJR	**30.28**	0.34	**30.62**	0.95	0.20	1.15	**11.43**	0.81	**12.24**	**20.09**	0.09	**20.18**
	GJR-*t*	**23.75**	1.84	**25.59**	3.40	0.32	3.72	**8.66**	0.65	**9.31**	**11.43**	0.12	**11.55**
	EGARCH	**37.31**	0.07	**37.38**	2.27	0.29	2.56	**13.43**	0.92	**14.35**	**23.75**	0.03	**23.78**
	EGARCH-*t*	**23.75**	0.03	**23.78**	0.62	0.23	0.85	**12.42**	0.86	**13.28**	**8.66**	0.15	8.81
	APARCH	**35.86**	0.05	**35.92**	2.27	0.29	2.56	**14.48**	0.98	**15.46**	**20.09**	0.07	**20.16**
	APARCH-*t*	**18.92**	0.01	**18.92**	0.62	0.17	0.80	**14.48**	0.98	**15.46**	**11.43**	0.19	**11.63**
CCC models	GARCH	**11.43**	0.81	**12.24**	0.62	0.17	0.80	**9.55**	0.70	**10.25**	6.18	0.00	6.18
	GARCH-*t*	5.42	0.65	6.07	0.16	0.11	0.27	**6.97**	0.51	7.48	4.71	0.01	4.72
	GJR	**11.43**	0.81	**12.24**	0.04	0.11	0.15	**6.97**	0.56	7.52	**8.66**	0.70	**9.36**
	GJR-*t*	4.71	0.70	5.41	0.00	0.09	0.09	3.40	0.35	3.75	4.03	0.80	4.83
	EGARCH	**12.42**	0.86	**13.28**	1.78	0.26	2.03	**10.48**	0.75	**11.23**	**13.43**	0.34	**13.78**
	EGARCH-*t*	5.42	0.60	6.03	0.04	0.11	0.15	**10.48**	0.75	**11.23**	2.27	0.70	2.97
	APARCH	**13.43**	0.00	**13.43**	1.34	0.23	1.56	**11.43**	0.81	**12.24**	**12.42**	0.40	**12.82**
	APARCH-*t*	**6.97**	0.65	7.62	0.62	0.15	0.77	**10.48**	0.75	**11.23**	3.40	0.62	4.02
DCC models	RiskMetrics	4.71	0.43	5.14	2.27	0.41	2.68	4.71	0.43	5.14	4.03	0.15	4.18
	GARCH	**8.66**	0.65	**9.31**	1.78	0.26	2.03	6.18	0.51	6.69	4.71	0.00	4.71
	GARCH-*t*	2.27	0.47	2.74	1.78	0.23	2.00	5.42	0.47	5.89	4.03	0.03	4.06
	GJR	5.42	0.47	5.89	2.81	0.32	3.13	5.42	0.47	5.89	**7.79**	0.80	8.59
	GJR-*t*	1.34	0.35	1.69	0.62	0.15	0.77	3.40	0.35	3.75	3.40	1.12	4.52
	EGARCH	6.18	0.51	6.69	4.71	0.43	5.14	**7.79**	0.60	8.40	**12.42**	0.40	**12.82**
	EGARCH-*t*	2.81	0.51	3.32	2.27	0.29	2.56	**6.97**	0.56	7.52	1.78	1.12	2.90
	APARCH	**6.97**	0.56	7.52	4.03	0.39	4.42	**10.48**	0.75	**11.23**	**11.43**	0.47	**11.90**
	APARCH-*t*	2.27	0.43	2.70	2.81	0.29	3.10	**6.97**	0.56	7.52	2.81	0.90	3.71
ADCC models	GARCH	**7.79**	0.60	8.40	2.27	0.29	2.56	6.18	0.51	6.69	**11.43**	0.00	**11.44**
	GARCH-*t*	2.27	0.39	2.66	1.78	0.26	2.03	5.42	0.47	5.89	4.03	0.04	4.07
	GJR	4.03	0.39	4.42	2.81	0.32	3.13	5.42	0.47	5.89	6.18	0.12	6.29
	GJR-*t*	1.34	0.32	1.66	0.62	0.15	0.77	3.40	0.35	3.75	1.78	0.19	1.97
	EGARCH	6.18	0.51	6.69	5.42	0.47	5.89	**6.97**	0.56	7.52	**10.48**	0.01	**10.49**
	EGARCH-*t*	2.27	0.47	2.74	2.81	0.29	3.10	**6.97**	0.56	7.52	1.34	0.19	1.53
	APARCH	6.18	0.51	6.69	4.03	0.39	4.42	**10.48**	0.75	**11.23**	**9.55**	0.62	**10.17**
	APARCH-*t*	1.34	0.43	1.77	4.03	0.29	4.32	**6.97**	0.56	7.52	2.27	0.15	2.42

Note: This table presents the results of three likelihood ratio (LR) tests proposed by Christoffersen (1998) for all sample countries. The LR tests include unconditional coverage (UC), serial independence (SI), and conditional coverage (CC). Critical values for UC and SI tests are 2.706, 3.841, and 6.635 for 10%, 5% and 1% significance level, respectively. Critical values for CC test are 4.605, 5.991, and 9.210 for 10%, 5% and 1% significance level, respectively. Entries in bold denote significance at 1% level.

Table 2.6. (Continued)

	Models	Chile			Philippines			Tunisia			Egypt		
		UC	SI	CC	UC	SI	CC	UC	SI	CC	UC	SI	CC
Univariate models	RiskMetrics	0.62	0.76	1.38	6.18	2.42	8.60	0.62	5.21	5.83	4.71	2.84	7.54
	GARCH	**33.03**	2.05	**35.09**	**17.77**	0.78	**18.55**	**11.43**	2.79	**14.22**	4.03	1.38	5.41
	GARCH-*t*	**15.55**	0.34	**15.89**	**14.48**	0.29	**14.77**	**10.48**	3.00	**13.47**	3.40	1.52	4.92
	GJR	**21.29**	0.09	**21.38**	6.18	0.51	6.69	**12.42**	2.60	**15.01**	4.03	0.24	4.27
	GJR-*t*	**10.48**	0.03	**10.51**	4.71	0.19	4.90	**10.48**	3.22	**13.69**	3.40	0.29	3.69
	EGARCH	**23.75**	0.40	**24.15**	**8.66**	0.04	8.70	**23.75**	2.11	**25.85**	**8.66**	0.49	9.14
	EGARCH-*t*	**14.48**	0.47	**14.95**	**6.97**	0.09	7.05	**18.92**	1.76	**20.68**	1.34	0.23	1.56
	APARCH	**26.30**	0.29	**26.59**	**9.55**	0.03	**9.57**	**26.30**	0.91	**27.21**	2.81	0.35	3.16
	APARCH-*t*	**14.48**	0.40	**14.88**	**6.97**	0.09	7.05	**18.92**	2.07	**20.98**	1.78	0.49	2.26
CCC models	GARCH	1.34	0.57	1.90	**6.97**	0.90	7.86	0.36	2.94	3.30	3.40	1.52	4.92
	GARCH-*t*	0.36	0.17	0.53	5.42	1.12	6.54	**10.48**	1.67	**12.15**	3.40	1.52	4.92
	GJR	1.34	0.23	1.56	**7.79**	0.80	8.59	2.27	3.85	6.12	4.03	0.24	4.27
	GJR-*t*	0.62	0.23	0.85	**6.97**	0.90	7.86	4.03	3.22	7.25	2.81	0.35	3.16
	EGARCH	4.71	0.43	5.14	**7.79**	0.80	8.59	0.04	3.54	3.58	2.27	0.41	2.68
	EGARCH-*t*	1.34	0.39	1.73	6.18	1.00	7.18	0.00	4.29	4.29	2.27	0.41	2.68
	APARCH	2.81	0.32	3.13	**8.66**	0.70	**9.36**	0.62	2.68	3.31	2.27	0.41	2.68
	APARCH-*t*	0.36	0.32	0.68	**7.79**	0.80	8.59	0.36	1.00	1.36	1.78	0.49	2.26
DCC models	RiskMetrics	0.62	0.76	1.38	4.71	2.84	7.54	0.62	2.68	3.31	4.03	3.07	7.10
	GARCH	0.62	0.76	1.38	**6.97**	2.23	9.20	0.36	2.94	3.30	3.40	1.52	4.92
	GARCH-*t*	0.16	0.13	0.29	4.03	1.38	5.41	0.05	1.67	1.72	3.40	1.52	4.92
	GJR	1.78	0.26	2.03	5.42	1.12	6.54	2.81	3.57	6.38	4.03	0.24	4.27
	GJR-*t*	0.16	0.20	0.36	4.03	1.38	5.41	0.16	3.22	3.38	2.81	0.35	3.16
	EGARCH	2.27	0.29	2.56	6.18	1.00	7.18	0.36	2.94	3.30	2.27	0.41	2.68
	EGARCH-*t*	0.62	0.23	0.85	4.03	1.38	5.41	0.00	3.89	3.89	2.27	0.41	2.68
	APARCH	2.27	0.29	2.56	5.42	1.12	6.54	0.62	2.68	3.31	2.27	0.41	2.68
	APARCH-*t*	0.16	0.23	0.39	4.71	1.24	5.95	0.16	1.13	1.30	1.78	0.49	2.26
ADCC models	GARCH	0.62	0.76	1.38	5.42	1.12	6.54	0.62	2.68	3.31	3.40	1.52	4.92
	GARCH-*t*	0.00	0.15	0.15	3.40	1.52	4.92	0.05	1.47	1.52	3.40	1.52	4.92
	GJR	1.78	0.26	2.03	5.42	1.12	6.54	2.81	3.57	6.38	4.03	0.24	4.27
	GJR-*t*	0.16	0.20	0.36	4.03	1.38	5.41	0.16	3.22	3.38	2.27	0.41	2.68
	EGARCH	2.27	0.29	2.56	5.42	1.12	6.54	0.36	2.94	3.30	5.42	0.41	5.84
	EGARCH-*t*	0.36	0.23	0.59	4.03	1.38	5.41	0.04	3.89	3.94	2.27	0.41	2.68
	APARCH	2.27	0.29	2.56	5.42	1.12	6.54	0.95	0.66	1.61	2.27	0.41	2.68
	APARCH-*t*	0.04	0.23	0.27	3.40	1.52	4.92	0.00	1.47	1.47	1.78	0.49	2.26

Note: This table presents the results of three likelihood ratio (LR) tests proposed by Christoffersen (1998) for all sample countries. The LR tests include unconditional coverage (UC), serial independence (SI), and conditional coverage (CC). Critical values for UC and SI tests are 2.706, 3.841, and 6.635 for 10%, 5% and 1% significance level, respectively. Critical values for CC test are 4.605, 5.991, and 9.210 for 10%, 5% and 1% significance level, respectively. Entries in bold denote significance at 1% level.

enhances the performance of VaR models. Among multivariate models, it appears that DCC models and ADCC models have better performance and produce lower LR_{UC} test statistics. Nonetheless, the null hypothesis of correct unconditional coverage is rejected for some DCC and ADCC VaR models at 5% and 10% significance levels. Furthermore, empirical results show that, in most VaR models, normality assumption for market shocks results in high LR_{UC} statistics, thereby weaker conditional coverage. This finding lends support to the results obtained by McAleer and da Viega (2008).

The second column of backtesting results for each country in Table 2.6 presents the serial independence test statistics. Although most VaR models failed to provide correct conditional coverage during crisis period, all VaR models pass the test of serial independence at 1% significance level. In other word, the null hypothesis of no serial dependence is accepted for all VaR models at 1% significance level. This finding is robust across all countries and for most VaR models even when the significance level is increased to 5% or 10%. One of the main shortcomings of Christoffersen's LR_{SI} test is that it only considers first order dependence, i.e., violations are only considered to be serially dependent if they occur in consecutive days. This is perhaps the main reason why most VaR models pass the serial independence test. Finally, the last column of backtesting results for each country in Table 2.6 presents conditional coverage test statistics. In general, it appears that the estimated LR_{CC} statistics are very similar to the LR_{UC} statistics. This is not surprising as LR_{CC} test statistics are the sum of LR_{UC} and LR_{SI} test statistics, while estimated SI statistics are much lower than LR_{UC} statistics in most VaR models. Therefore, the empirical evidence by the LR_{CC} test statistics indicates that most VaR models fail to provide statistically satisfactory coverage at 1% significance level during crisis period. However, portfolio models provide lower LR_{CC} statistics for most VaR models and across most countries. Furthermore, the Student-t distributional assumption for market shocks results in lower LR_{CC} test statistics across most VaR models and across most sample countries.

2.4.3. Regulatory capital charges

According to Basel accords, banks are required to set aside regulatory capital to buffer market risk exposure. The amount of market risk capital charges (MRCC) is to be based on the VaR estimates generated by internal VaR models. In particular, banks are required to compute VaR threshold on a daily basis and with 99% confidence level. The daily VaR figure is then scaled up by a reasonable approach to calculate VaR for a 10-day holding period.[6] Accordingly, capital requirements is set as the higher of the previous day VaR figure and the average of VaR figures over the last 60 business days, multiplied by a scaling factor, $(3+k)$. More specifically, the MRCC is calculated based on the following formula[7]

$$MRCC_t = max\left\{VaR_{t-1}; \frac{(3+k)}{60}\sum_{i=1}^{60} VaR_{t-i}\right\}. \tag{2.42}$$

The scaling factor is set by individual supervisory authority and must not be lower than 3. Indeed, the scaling factor equals 3 plus a varying factor, *k*, which acts as a penalty for poorly performing internal models. The varying factor ranges from 0 to 1 according to the backtesting results of the internal model over the last 250 business days. To determine *k*, the BCBS (1996b) provides a framework which defines three zones distinguished by three colours: green, yellow, and red. The Basel Accord penalty zones are summarized in Table 2.7. Internal models that fall in the green zone are favourable models from regulatory point of view, while the yellow zone corresponds to internal models with dubious performance. Furthermore, an internal model with more than 9 violations in 250 business days falls into the red zone, where the bank is required to either revise its internal VaR model or adopt the standardized method.

6 One of the interesting features of GARCH family models is that 10-day ahead VaR can be easily derived from 1-day-ahead VaR threshold.

7 The 2009 amendment to Basel II market risk framework adds an additional term called stressed VaR to the MRCC. However, stressed VaR is not considered in this study as the model used for stressed VaR can be different and the stress period can be chosen arbitrarily.

Table 2.7. Basel Accord penalty zones for 250 business days

Zone	Number of violations	Increase in scaling factor
Green	0-4	0.00
Yellow	5	0.40
	6	0.50
	7	0.65
	8	0.75
	9	0.85
Red	10+	1.00

Risk managers are not only concerned with the accuracy of risk models, but also favour models that impose lower regulatory capital charges (McAleer *et al.*, 2010). In this chapter, the mean daily capital charges (MDCC) of alternative VaR models are compared to determine favourable VaR models from risk management perspective. Furthermore, this chapter determines VaR models that fall into the red zone to avoid promoting poorly performing VaR models that lead to lower MDCC. This approach has been widely used in the recent VaR studies (see, e.g., McAleer *et al.*, 2013; Louzis *et al.*, 2014; McAleer, 2009, among others)

Another approach to assess the efficiency of alternative VaR models is to measure their goodness of fit to the realized portfolio losses. Accordingly, goodness of fit of a VaR model is calculated through the root mean squared error (RMSE) which is defined as follows

$$RMSE = \sqrt{E[(VaR_t - L_t)^2]} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(VaR_t - L_t)^2}\,, \qquad (2.43)$$

where L_t is the actual loss on a portfolio at date t and T is the total number of out-of-sample observations. In this context, a desirable VaR model, from risk management perspective, should produce low RMSE and impose low capital requirement.

To evaluate alternative VaR models from risk management standpoint, Table 2.8 presents the RMSE and MDCC for all sample countries during pre-crisis period. In addition, bold MDCC denotes VaR models that fall into red zone by producing more than 9 violations in 250 business days during the pre-crisis period. From Table 2.8, it appears that the magnitude of RMSE widely varies across sample countries. For instance, RMSE figures in Brazil and Egypt are much higher than those in the UK, Tunisia, and Chile. One possible explanation for this finding is that return series in Brazil and Egypt are not as clustered as those in the UK or Chile (see Figure 2.1). In such cases, large losses largely increase VaR figures while they are followed by small losses. Furthermore, there is no clear and consistent evidence on which VaR model produces lower RMSE during pre-crisis period and across all countries. Nonetheless, most multivariate VaR models produce higher RMSE figures compared to univariate models. The empirical results also reveal that assuming that market shocks follow Student-*t* distribution leads to higher RMSE. This indicates that Student-*t* distribution assumption may lead to lower number of violations mainly because it creates larger VaR figures.

The empirical results of the MDCC show that most VaR models do not exceed more than 9 violations in every 250 days during pre-crisis period while there is no clear evidence on which VaR model produces lower MDCC during pre-crisis period. However, it is found that multivariate models and Student-*t* distribution assumption for market shocks impose slightly higher capital charges, which is consistent with McAleer and da Viega's (2008) findings.

Table 2.9 presents RMSE and MDCC results for alternative VaR models during crisis period. It appears that both RMSE and MDCC largely increase for all VaR models during crisis period. More importantly, most univariate VaR models and some multivariate models produce more than 9 violations in a 250 business day period. This indicates that many VaR models fall into the red zone at some point during the crisis, meaning that they have to be either reviewed or replaced by the standardized model which imposes very high capital requirements.

The most striking finding of this chapter is that performance of VaR models is highly sensitive to the underlying portfolio and no VaR model, particularly among multivariate models, is found to be superior to its counterparts across all countries. In addition, there is mixed evidence on which model produces the lowest RMSE across all sample countries, while multivariate models lead to higher RMSE in most cases. Finally, it is found that assuming that market shocks follow Student-*t* distribution lead to lower RMSE and higher MDCC for most VaR models and across most sample countries.

Table 2.8. Capital requirements and goodness of fit during the period 2003-2006.

	Models	UK		Japan		Brazil		India	
		RMSE	MDCC	RMSE	MDCC	RMSE	MDCC	RMSE	MDCC
Univariate models	RiskMetrics	2.580	6.627	5.612	9.546	13.815	15.199	8.495	11.166
	GARCH	1.566	6.008	4.707	9.106	13.720	15.433	7.403	10.550
	GARCH-*t*	1.935	6.204	5.062	9.372	13.999	15.196	7.481	10.411
	GJR	1.645	5.961	4.731	9.203	13.458	14.570	5.769	10.049
	GJR-*t*	2.030	6.264	5.686	9.627	14.157	14.874	7.196	10.434
	EGARCH	1.494	5.916	4.413	8.760	13.304	14.523	5.251	9.874
	EGARCH-*t*	1.872	6.119	5.548	9.566	13.740	14.834	6.463	10.336
	APARCH	1.495	5.986	4.389	8.906	13.324	14.831	5.286	9.842
	APARCH-*t*	1.877	6.130	4.773	9.138	14.024	14.822	6.493	10.328
CCC models	GARCH	1.721	5.998	5.336	9.365	13.772	15.465	7.923	10.720
	GARCH-*t*	2.140	6.201	5.654	9.569	14.206	15.454	7.938	10.681
	GJR	1.728	5.839	5.319	9.364	13.810	14.956	6.095	10.132
	GJR-*t*	2.141	6.165	5.336	9.368	14.563	15.179	7.545	10.719
	EGARCH	1.609	5.808	5.394	9.452	13.636	14.891	5.508	10.037
	EGARCH-*t*	1.926	6.002	5.615	9.640	14.145	15.107	6.814	10.477
	APARCH	1.605	5.781	5.297	9.367	13.601	14.883	5.527	10.085
	APARCH-*t*	1.981	6.152	5.638	9.622	14.475	15.146	6.839	10.460
DCC models	RiskMetrics	2.626	6.644	5.652	9.725	14.144	14.929	8.535	11.181
	GARCH	1.867	5.854	5.574	9.664	13.939	15.194	8.117	10.525
	GARCH-*t*	2.325	6.340	5.906	9.873	14.398	15.035	8.130	10.721
	GJR	1.883	5.964	5.556	9.460	14.023	14.873	6.249	10.188
	GJR-*t*	2.336	6.303	5.865	9.655	14.800	15.196	7.742	10.779
	EGARCH	1.759	5.913	5.632	9.519	13.808	14.821	5.622	10.087
	EGARCH-*t*	2.115	6.138	5.871	9.677	14.332	15.037	6.979	10.530
	APARCH	1.760	5.889	5.529	9.432	13.768	14.813	5.641	10.135
	APARCH-*t*	2.171	6.349	5.891	9.690	14.666	15.180	7.005	10.513
ADCC models	GARCH	1.928	5.982	5.609	9.670	13.849	14.990	6.627	10.321
	GARCH-*t*	2.403	6.375	5.944	9.880	14.311	15.176	8.221	10.745
	GJR	1.950	5.927	5.592	9.668	13.966	14.838	6.325	10.123
	GJR-*t*	2.421	6.337	5.904	9.694	14.745	15.160	7.839	10.805
	EGARCH	1.823	5.935	5.669	9.526	13.730	14.783	5.684	10.079
	EGARCH-*t*	2.200	6.346	5.911	9.891	14.257	14.998	7.069	10.724
	APARCH	1.826	5.902	5.566	9.439	13.695	14.776	5.704	10.218
	APARCH-*t*	2.252	6.351	5.929	9.698	14.595	15.142	7.095	10.314

Note: Root mean squared errors (RMSE) and mean daily capital charges (MDCC) are presented for each country. Entries in bold denote models that incur more than 10 violations in 250 business days during pre-crisis period.

Table 2.8. (Continued)

	Models	Chile		Philippines		Tunisia		Egypt	
		RMSE	MDCC	RMSE	MDCC	RMSE	MDCC	RMSE	MDCC
Univariate models	RiskMetrics	2.605	7.254	4.887	8.667	0.897	3.845	8.467	11.830
	GARCH	**1.947**	7.212	5.032	9.111	0.661	3.450	7.857	11.410
	GARCH-*t*	**2.273**	7.390	5.109	8.895	0.741	3.623	10.000	12.050
	GJR	**2.020**	7.245	4.860	8.842	0.680	3.493	8.222	11.590
	GJR-*t*	**2.391**	7.462	5.334	9.054	0.744	3.635	9.925	12.240
	EGARCH	1.979	7.097	4.997	8.939	0.617	3.630	4.997	8.939
	EGARCH-*t*	2.336	7.306	5.379	9.125	0.690	3.528	10.120	12.400
	APARCH	**1.985**	7.222	4.967	8.763	0.592	3.635	8.287	11.760
	APARCH-*t*	**2.353**	7.268	5.419	9.141	0.676	3.501	9.898	12.240
CCC models	GARCH	2.785	7.373	5.123	9.055	0.923	3.912	8.880	11.450
	GARCH-*t*	3.494	7.857	5.475	9.139	0.723	3.588	9.650	11.710
	GJR	2.767	7.347	5.111	9.139	0.913	3.906	9.320	11.820
	GJR-*t*	3.482	7.836	5.351	9.068	0.885	3.881	10.020	12.170
	EGARCH	2.746	7.349	5.166	9.159	0.955	3.971	8.814	11.750
	EGARCH-*t*	3.480	7.848	5.468	9.355	1.040	4.108	12.590	13.510
	APARCH	2.738	7.341	5.169	8.917	0.945	3.952	8.954	11.830
	APARCH-*t*	3.459	7.829	5.515	9.378	1.023	4.084	12.090	13.320
DCC models	RiskMetrics	2.504	7.145	4.934	8.762	0.870	3.778	8.585	11.800
	GARCH	2.607	7.146	5.097	9.038	0.935	3.943	8.854	11.430
	GARCH-*t*	3.273	7.689	5.445	9.120	1.000	4.056	9.636	11.700
	GJR	2.586	7.121	5.090	8.966	0.925	3.937	9.307	11.800
	GJR-*t*	3.263	7.670	5.326	9.026	0.955	3.993	10.010	12.160
	EGARCH	2.553	7.097	5.137	8.888	0.968	4.004	8.789	11.720
	EGARCH-*t*	3.245	7.681	5.430	9.333	1.053	4.141	12.530	13.470
	APARCH	2.549	7.090	5.139	8.898	0.958	3.985	8.931	11.810
	APARCH-*t*	3.227	7.659	5.476	9.198	1.037	4.117	12.030	13.280
ADCC models	GARCH	2.521	7.222	5.222	8.940	0.925	3.921	9.585	11.820
	GARCH-*t*	3.162	7.618	5.591	9.185	1.014	4.089	10.030	11.920
	GJR	2.504	7.049	5.219	9.020	0.917	3.915	9.687	12.020
	GJR-*t*	3.157	7.602	5.475	9.115	0.943	3.969	10.420	12.380
	EGARCH	2.477	7.202	5.249	9.074	0.956	3.980	5.249	9.074
	EGARCH-*t*	3.146	7.616	5.560	9.266	1.035	4.113	14.440	14.150
	APARCH	2.471	7.154	5.254	8.985	0.948	3.962	9.713	12.310
	APARCH-*t*	3.129	7.599	5.608	9.288	1.019	4.089	13.810	13.990

Note: Root mean squared errors (RMSE) and mean daily capital charges (MDCC) are presented for each country. Entries in bold denote models that incur more than 10 violations in 250 business days during pre-crisis period.

Table 2.9. Capital requirements and goodness of fit during the period 2007-2010.

	Models	UK		Japan		Brazil		India	
		RMSE	MDCC	RMSE	MDCC	RMSE	MDCC	RMSE	MDCC
Univariate models	RiskMetrics	9.384	13.801	7.836	**12.370**	23.615	21.070	15.399	**17.609**
	GARCH	5.730	**12.476**	9.205	12.237	21.660	20.571	11.833	**16.087**
	GARCH-*t*	7.185	**13.256**	9.692	12.474	22.809	20.334	11.964	**16.079**
	GJR	5.478	**12.346**	9.077	12.180	21.459	**20.824**	10.289	**15.298**
	GJR-*t*	6.765	**13.154**	7.497	**12.326**	22.992	20.798	12.460	**15.771**
	EGARCH	4.776	**11.947**	7.893	12.438	18.829	**20.377**	9.030	**15.073**
	EGARCH-*t*	6.159	**12.984**	9.830	13.046	19.606	**20.495**	11.307	**15.399**
	APARCH	4.740	**11.932**	7.931	12.647	18.565	**20.374**	9.504	**15.096**
	APARCH-*t*	6.311	**12.944**	8.215	12.099	19.723	**20.872**	11.399	**15.718**
CCC models	GARCH	7.873	**13.354**	9.982	12.381	21.395	20.565	14.738	**16.897**
	GARCH-*t*	9.676	**13.700**	10.821	12.664	22.681	20.443	15.037	**16.515**
	GJR	7.372	**13.315**	9.532	11.517	19.954	19.764	12.571	**15.913**
	GJR-*t*	9.074	13.319	10.065	11.666	21.594	19.208	15.211	**16.022**
	EGARCH	6.378	**12.880**	8.245	12.463	17.626	**20.162**	11.032	**15.711**
	EGARCH-*t*	8.047	13.204	9.188	12.229	18.324	**20.431**	14.432	**16.121**
	APARCH	6.312	**12.903**	8.198	12.365	17.329	**20.159**	11.329	**15.706**
	APARCH-*t*	8.402	**13.802**	9.221	12.492	18.419	**20.384**	14.495	**16.471**
DCC models	RiskMetrics	9.474	13.577	7.832	**12.691**	23.863	20.757	15.644	**17.745**
	GARCH	9.970	13.947	8.408	12.373	22.632	20.343	15.728	**16.936**
	GARCH-*t*	12.246	13.736	9.124	12.667	23.983	20.519	16.120	**16.643**
	GJR	9.365	13.337	7.975	12.269	21.179	19.773	13.359	**16.053**
	GJR-*t*	11.511	13.139	8.845	12.006	22.929	19.648	16.236	**16.405**
	EGARCH	7.954	**13.234**	7.013	**12.320**	18.660	**19.968**	11.662	**16.091**
	EGARCH-*t*	10.044	13.583	7.803	**12.610**	19.401	**20.047**	15.444	**16.032**
	APARCH	7.923	**13.303**	6.966	**12.271**	18.344	**20.272**	11.964	**16.068**
	APARCH-*t*	10.545	13.601	7.807	**12.610**	19.501	**20.128**	15.501	**16.493**
ADCC models	GARCH	10.222	13.977	8.330	12.420	22.698	20.370	12.815	**16.727**
	GARCH-*t*	12.554	13.879	9.043	12.588	24.050	20.547	16.319	**16.768**
	GJR	9.600	12.972	7.887	12.261	21.261	19.802	13.536	**15.965**
	GJR-*t*	11.799	13.320	8.753	11.999	23.013	19.676	16.458	**16.005**
	EGARCH	8.125	13.257	6.927	**12.361**	18.742	**19.806**	11.834	**16.174**
	EGARCH-*t*	10.256	13.526	7.712	**12.696**	19.485	**20.075**	15.693	**16.041**
	APARCH	8.101	13.208	6.880	**12.254**	18.426	**20.301**	12.136	**16.106**
	APARCH-*t*	10.777	13.202	7.717	**12.696**	19.586	**20.157**	15.748	**16.533**

Note: Root mean squared errors (RMSE) and mean daily capital charges (MDCC) are presented for each country. Entries in bold denote models that incur more than 10 violations in 250 business days during crisis period.

Table 2.9. (Continued)

	Models	Chile		Philippines		Tunisia		Egypt	
		RMSE	MDCC	RMSE	MDCC	RMSE	MDCC	RMSE	MDCC
Univariate models	RiskMetrics	7.556	11.390	8.818	**13.110**	1.690	4.843	10.300	**13.690**
	GARCH	3.919	**10.000**	7.454	**12.560**	0.921	**4.332**	11.010	13.440
	GARCH-*t*	4.704	**10.370**	7.922	**12.780**	0.965	**4.436**	11.400	13.500
	GJR	3.818	**9.689**	9.634	**13.210**	0.927	**4.402**	12.060	13.680
	GJR-*t*	4.601	**10.200**	10.050	**13.360**	0.950	**4.455**	11.680	13.340
	EGARCH	3.555	**9.810**	8.512	**13.110**	0.802	**4.307**	8.512	13.110
	EGARCH-*t*	4.298	**10.090**	9.054	**13.260**	0.816	**4.329**	11.410	13.020
	APARCH	3.606	**9.786**	8.507	**13.150**	0.813	**4.377**	11.150	13.310
	APARCH-*t*	4.291	**10.050**	9.046	**13.260**	0.825	**4.356**	11.380	13.160
CCC models	GARCH	7.297	10.910	8.961	**13.080**	1.571	4.767	11.200	13.390
	GARCH-*t*	8.815	11.300	9.397	**13.310**	0.942	4.437	11.260	13.480
	GJR	6.938	10.630	8.920	**13.170**	1.345	4.444	11.090	13.260
	GJR-*t*	8.353	11.320	9.397	**13.420**	1.120	**4.452**	11.920	13.450
	EGARCH	5.906	**10.890**	7.967	**12.850**	1.304	4.582	10.750	**13.180**
	EGARCH-*t*	7.275	**11.350**	8.488	**13.030**	1.362	4.744	11.770	13.570
	APARCH	5.982	**10.670**	7.977	**12.900**	1.324	4.771	11.080	13.310
	APARCH-*t*	7.424	**11.040**	8.513	**13.240**	1.408	4.907	11.550	13.310
DCC models	RiskMetrics	7.502	11.370	8.852	**12.990**	1.730	4.894	10.290	**13.520**
	GARCH	8.723	10.900	9.335	**13.320**	1.642	4.806	11.180	13.380
	GARCH-*t*	10.530	11.630	9.789	**13.510**	1.583	4.750	11.240	13.470
	GJR	8.211	11.210	9.286	**13.220**	1.408	4.533	11.070	13.250
	GJR-*t*	9.875	11.430	9.785	**13.420**	1.374	**4.822**	11.900	13.430
	EGARCH	6.800	10.810	8.280	**12.780**	1.346	4.788	10.740	**13.170**
	EGARCH-*t*	8.316	11.500	8.819	**13.040**	1.399	4.723	11.750	13.560
	APARCH	6.919	10.890	8.290	**12.740**	1.367	4.839	11.060	13.300
	APARCH-*t*	8.596	11.300	8.848	**13.110**	1.444	4.919	11.520	13.300
ADCC models	GARCH	8.758	10.920	9.407	**13.210**	1.676	4.967	11.360	13.450
	GARCH-*t*	10.570	11.420	9.866	**13.380**	1.637	4.832	11.430	13.540
	GJR	8.246	11.230	9.361	**13.170**	1.415	4.529	11.270	13.330
	GJR-*t*	9.916	11.440	9.865	**13.390**	1.398	**4.899**	12.110	13.400
	EGARCH	6.829	10.870	8.351	**12.760**	1.372	4.798	8.351	**12.760**
	EGARCH-*t*	8.352	11.390	8.895	**13.050**	1.423	4.885	12.250	13.650
	APARCH	6.950	10.910	8.360	**12.770**	1.394	4.911	11.230	13.370
	APARCH-*t*	8.635	11.180	8.924	12.970	1.470	4.885	11.910	13.430

Note: Root mean squared errors (RMSE) and mean daily capital charges (MDCC) are presented for each country. Entries in bold denote models that incur more than 10 violations in 250 business days during crisis period.

2.5. CONCLUSIONS

This chapter examines the performance of alternative parametric VaR models in forecasting one-day-ahead VaR thresholds for international equity portfolios. An international equity portfolio is composed of two major risk components: equity risk and foreign exchange rate risk. During the recent financial crisis, U.S. banks suffered from significant losses in their international equity portfolios as both exchange rates and equity indices dramatically declined in most countries. This in turn provides a unique opportunity for risk managers to assess the performance of alternative risk models in measuring VaR of international equity portfolios. Two main approaches can be used to estimate VaR threshold of international equity portfolios: (*i*) applying univariate VaR models on portfolio returns, and (*ii*) applying multivariate VaR models on portfolio's risk components.

In this chapter, a variety of GARCH type models have been employed to model conditional volatilities in both univariate and multivariate frameworks. Notably, special focus is given to correlations between equity indices and exchange rates by considering three popular conditional correlation models: namely CCC, DCC, and ADCC models. The performance of VaR models is investigated in eight countries and over two sample periods: pre-crisis period, from January 2003 to December 2006, and crisis period, from January 2007 to December 2010. Subsequently, nine backtesting criteria are employed to evaluate the performance of VaR models from both regulatory and risk management perspectives.

Overall, from regulatory perspective, the empirical results reveal that most VaR models have satisfactory performance with small number of violations during pre-crisis period, while the number of violations, mean deviation of violations, and maximum deviation of violations dramatically increase during crisis period. Furthermore, multivariate models incur lower number of violations compared to univariate models, while DCC and ADCC models perform better than CCC models during crisis period. This in turn indicates that multivariate models are more favourable to regulators, compared to univariate models. In addition, the assumption that market shocks follow Student-*t* distribution leads to more accurate and conservative VaR estimations over both sub-sample periods. From risk management perspective, however, portfolio models produce slightly higher regulatory capital requirement and weaker goodness of fit, while most univariate models produce more than 10 violations in 250 business days across most sample countries. Furthermore, there is mixed evidence on the choice of portfolio models among CCC, DCC, and ADCC models.

These findings have several important implications for regulators and policymakers. They underline the necessity of imposing more capital requirements for internal VaR models during crisis periods. This is mainly because most VaR models are likely to fail to perform satisfactorily during periods of financial crisis. As a solution for this issue, the 2009 amendment to the Basel Accord proposed adding stressed VaR to the calculation of market risk capital charges. However, adding stressed VaR to capital charges during a non-crisis state may lead to excessive capital requirements, which may in turn increase risk-taking appetite of bank managers. Another striking implication is that none of VaR models considered in this study is able to pass all specification tests and satisfy both regulators and risk managers concurrently. Indeed, this underlines the need for further research on developing better performing VaR models, particularly during crisis periods.

CHAPTER THREE

HOUSE PRICES AND EVOLUTION OF NONPERFORMING LOANS: EVIDENCE FROM THE UNITED STATES

3.1. INTRODUCTION

The recent subprime mortgage crisis in the United States has demonstrated the key role that house prices play in destabilising the financial system. From the late 1990s, there was a sharp increase in subprime mortgages fuelled by low interest rates and lax lending standards. However, while the quality of banks' loan portfolios was deteriorating by the constant growth of the subprime mortgages, the default rates remained artificially low due to rapid house price appreciation. These protracted booms in house prices and low default rates encouraged banks to heavily invest in the real estate market as well as mortgage related securities. This further increased house prices and led to the creation of a speculative real estate bubble, which eventually burst in the subsequent years.

The collapse of real estate bubble exerted enormous pressure on banks that were highly exposed to the real estate market. In particular, many banking institutions suffered from severe liquidity shortages due to a sharp increase in their nonperforming real estate loans. Falling house prices undermined the value of real estate collaterals, which motivated many subprime mortgage borrowers to default on their loan repayments. Higher default rates in turn led to credit contraction and tightening of lending standards by banks. As a consequence, housing demand substantially dropped, while housing supply was increasing by the rising number of real estate foreclosures. This further reduced house prices and exacerbated deteriorating credit market conditions, which severely affected the real economy and led to high nonperforming loans across all loan categories.

In the light of the recent events, it is clear that understanding how house prices affect the quality of loan portfolios is of crucial importance for financial institutions and regulators interested in maintaining financial stability. In this context and due to lack of empirical works on the linkage between house prices and quality of loan portfolios, dynamic panel data models are employed in this chapter to empirically investigate the impact of house price fluctuations on the evolution of nonperforming loans across the US banking institutions. This analysis is further developed by examining how this relationship varies across different loan categories, different types of banking institutions, and different bank size.

This chapter contributes to the existing literature in several ways. First, to the best of my knowledge, this study is among few studies that empirically examine the impact of house prices on the quality of loan portfolios at bank-level.[8] It is argued that house prices largely affect the performance of loan portfolios as (*i*) real estate loans usually form a large portion of a bank's aggregate loan portfolio, (*ii*) real estate assets are widely used as collateral for other loan categories to secure the loan repayments (see, e.g., Goodhart and Hofmann, 2008; Davis and Zhu, 2009). However, most previous studies, including Reinhart and Rogoff (2008), Reinhart and Rogoff (2009), and Barrell *et al.* (2010), have concentrated on the role of house prices in undermining the banking system as a whole, and far less is known on how individual banks are affected by swings in house prices. This chapter aims to fill this gap.

Second, this Chapter investigates how different loan categories are affected by house price developments. Using aggregate nonperforming loan to examine the linkage between house prices and the quality of loan portfolios may be challenged as the composition of loan portfolios varies widely across banking institutions (see, e.g., Louzis *et al.*, 2012). Therefore, it is of crucial importance to investigate the sensitivity of different loan categories to house price fluctuations, which helps financial regulators

[8] Closely related to this aspect of this study, Davis and Zhu (2009) investigate the impact of changes in commercial property prices on various loan portfolio performance indicators including nonperforming loans.

provide better regulatory practices for individual banks with different loan portfolio compositions.

Third, potential differences between determinants of nonperforming loans across different types of the US banking institutions have remained undetected, despite their important regulatory implications. It is argued that a bank's lending policies reflect its risk attitude, which in turn depends on its mission and institutional structure (see, e.g., Salas and Saurina, 2002). This Chapter adds to existent credit risk literature by examining if the impact of house prices on the evolution of nonperforming loans varies across two types of banking institutions: namely commercial banks (CB) and saving institutions (SI).[9]

Fourth, this chapter constitutes a first attempt to assess the role of bank size on the linkage between house prices and nonperforming loans. Sensitivity of a bank to real estate market is highly associated with its lending strategies, which in turn greatly depend upon its size and complexity. In general, larger banks can benefit from economies of scale, better access to external funds, and more diversified borrowers and products, while their 'too-big-to-fail' status can create moral hazard incentives to take excessive risks (see, e.g., Tabak *et al.,* 2011; De Haan and Poghosyan, 2012). Accordingly, it is examined if larger banks are more vulnerable to swings in house prices, compared to smaller banks.

Finally, the study at hand is among the first studies that investigate the impact of state-level house price fluctuations on evolution of nonperforming loans during both boom and bust periods. It is argued that the dynamics of house prices vary widely both over time and across geographical regions (see, e.g., Holly *et al.*, 2010). A close look at the US state-level data reveals that the recent boom and bust in the house prices were non-uniform across US States. While some States such as California and Florida experienced substantial changes in house prices over both boom and bust periods, some States such as Vermont and Montana only underwent rapid house price appreciation, and some other States such as Georgia and Michigan only faced large declines over the bust period. These substantial variations in regional house price dynamics reflect differences in the housing market supply and demand, which in turn depend on

[9] Savings institutions in this study include all U.S. savings banks as well as savings and loan associations.

demographic and socio cultural factors, local economic conditions, regional regulations and jurisdictions, and local financial system. Although these factors can markedly contribute to the diversity of credit risk within the US, the impact of time and regional variations in house prices on the evolution of credit risk has been largely neglected by the literature.

In a nutshell, the empirical results of this chapter reveal that house prices significantly affect the quality of banks' loan portfolios. More specifically, the findings clearly show that there is a strong negative relation between house prices and nonperforming loans in individual banks. In addition, it is found that real estate loans are more sensitive to house price fluctuations compared to other types of loans. Also, while house prices have significant impact on the quality of loan portfolios across savings banks and commercial banks, the magnitude of its impact varies depending on the type and mission of the institutions. Finally, it is found that the impact of falling house prices on credit risk is more pronounced in large banks, compared to small banks.

The remainder of this chapter is organised as follows. Section 3.2 reviews relevant literature and develops the empirical hypotheses to be tested. Section 3.3 introduces the empirical model under consideration, the estimation procedure, and control variables. In Section 3.4, a detailed description of the data under consideration is provided. Section 3.5 discusses the empirical results associated with each hypothesis while Section 3.6 concludes and makes several suggestions regarding policy implications.

3.2. EMPIRICAL HYPOTHESES

Credit risk refers to the risk that a borrower fails to make a scheduled payment on any type of debt. This has been one of the major risks faced by banking institutions, and it is therefore not surprising that a tremendous amount of literature has dealt with modelling credit risk by investigating the factors affecting the risk attitude of both lenders and borrowers.

A main strand of research postulates that credit risk is tightly linked to business cycles (see, e.g., Pesaran *et al.*, 2006; Koopman *et al.*, 2005; Koopman and Lucas, 2005; Quagliariello, 2007, Fei *et al.,* 2012, among others). According to this literature, lending standards and borrowers' default and financing policies are closely related to the state of the economy in different phases of the business cycle. Most importantly, it is argued that the impact of macroeconomic conditions on credit risk is stronger during macroeconomic downturn, indicating an asymmetric pattern in the linkage between business cycle and credit risk (Marcucci and Quagliariello, 2009).

One of the main macroeconomic factors that can play a key role in the evolution of credit risk is house price cycle. On the one hand, changes in house prices can largely affect the riskiness of households and mortgage borrowers as housing is a major component of household wealth (Flavin and Yamashita, 2002), and also wealth effects of housing are greater than other financial assets (Case *et al.,* 2005). On the other hand, real estate assets and mortgage related securities form a major component of banks' balance sheets as most banks are actively involved in different types of real estate investments, including mortgage lending. Accordingly, it is argued that lending policies and risk taking behaviour of banks are greatly affected by house price cycles (see, e.g., Davis and Zhu, 2009; Davis and Zhu, 2011). Furthermore, house price busts have been often associated with financial instability and banking crisis in the past.

Therefore, understanding the drivers of house price cycles is of crucial importance and can shed light on the linkage between housing prices and credit risk. Like any other assets, equilibrium house prices are determined by a wide range of factors influencing supply and demand in the housing market. Housing supply strongly depends on the real construction costs as well as physical and regulatory constraints while the main drivers of housing demand are macroeconomic fundamentals such as local population growth, real disposable income, interest rate, and unemployment rate, suggesting that house prices and business cycles may move together (see, e.g., Leamer, 2007; Davis and Heathcote, 2005). However, actual house prices often deviate from the long-run equilibrium determined by supply and demand fundamentals. Koetter and Poghosyan (2010) point out that sustained deviations from long-run equilibrium occur more frequently in the housing market compared to financial markets because of (*i*) decentralized trading of real estate, as a non-standardized asset, which implies imperfect information and high transaction costs, and (*ii*) inelastic housing supply due to construction lags and limited land availability.

Furthermore, recent consensus literature highlights the central role of financial sector in fuelling such deviations. According to this literature, banks' lending behaviour greatly amplifies the effects of small income shocks through the real economy by altering the value of borrowers' net-worth. In an influential paper, Bernanke *et al.* (1996) refer to this amplification mechanism as the "financial accelerator" or "credit multiplier". The main idea behind the financial accelerator is the interplay between borrowers' net worth and their borrowing capacity that arises due to credit market imperfections and asymmetric information between lenders and borrowers in the credit market. In this context, the financial accelerator mechanism can offer an explanation to changes in house prices beyond their fundamental values. Prospective borrowers are usually required to put up collateral to secure their loan repayments. Collateralised assets are often in the form of real estate, thereby linking aggregate borrowing capacity of firms and households to house prices. Rising house prices increase the value of real estate collaterals and feeds to greater net-worth for borrowers, which in turn further increases the borrowing capacity of firms and households (see, e.g., Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Iacoviello, 2005).

On the other hand, rising house prices boost the value of the pledged collaterals, thereby reducing the likelihood of borrowers' defaults. This notionally improves asset quality and encourages banks to expand their real estate lending, which in turn leads to a positive feedback loop between house prices, real estate lending, and external financing capacity of firms and individuals. Empirical literature presents a two-way relationship between real estate lending and house prices. Among others, Mora (2008) finds empirical evidence that bank lending deeply affects the real estate market while Gimeno and Martinez-Carrascal (2010) and Gelarch and Peng (2005) show that real estate lending policies depends on house price behaviour.

The co-movement of credit cycles and macroeconomic variables including house prices implies procyclicality in the banking system where most banks take same policy actions as they are systematically exposed to similar conditions. This in turn exacerbates swings in the house prices and real economy. It is argued that procyclicality and trend-chasing behaviour in bank lending occurs in both lending level (Borio *et al.*, 2001; Berger and Udell, 2004) and lending concentration (Mei and Saunders, 1997). Rajan (1994) describes a similar process in real estate lending and suggests that bank managers have strong incentives for herding behaviour, particularly when regulatory oversight is lax. More importantly, Piazzesi and Schneider (2009) show that momentum forecasts by even a small number of optimistic investors significantly affect house prices. Therefore, procyclical behaviour in the housing market can feed to a rapid growth spiral and increase the speed of house price deviations from their fundamental values, which may ultimately lead to the creation of a housing bubble. Eventually, when the housing bubble bursts, the real economy suffers from severe consequences of reverse developments in house prices. Hott (2011) argues that falling house prices stem from sudden and fundamental changes in investors' irrational expectations about house prices as a consequence of disaster myopia. In this context, corrections in house prices towards equilibrium can lead to reverse procyclical behaviour in the banking sector, which is often a prolonged process (Black *et al.*, 2006).

In general, adverse fluctuations in house prices have a procyclical impact on borrowers' net-worth and, as a result, their ability to raise external finance. Reduced borrowing capacity of firms and households is associated with less spending, which further reduces house prices and triggers a feedback loop between house prices and credit market conditions. This in turn propagates financial and economic downturn. On the other hand, excessive risk accumulations during booming period heavily expose financial institutions to the real estate market and, as a result, banks severely suffer from high loan losses when house prices drop. This is consistent with the idea that risk builds up during booms and materializes itself during periods of economic downturns (see, for example, Borio and Lowe, 2002; Pesola, 2011).

Against this background and despite the abundance of theoretical works on house prices and financial stability, research that follows this line of literature is rather silent on the linkage between housing market and loan performance. In particular, researchers have largely neglected the impact of house price fluctuations on the evolution of NPL while NPL is commonly used as a key indicator to trace financial vulnerabilities and banking crises (see, e.g., Demirgüc-Kunt and Detragiache, 2005;

Barrell *et al.*, 2010). To narrow this gap, this chapter builds up on existing literature and offers four empirical hypotheses regarding the impact of house price fluctuations on the quality of banks' loan portfolios. More specifically, the empirical hypotheses are formulated as follows.

Hypothesis 1: *House prices fluctuations heavily affect the quality of banks' loan portfolios.*

Broadly speaking, house price fluctuations largely affect the debt servicing capacity of households and mortgage borrowers by altering their collateral position. This in turn influences homeowners' decision process and determines those situations where default becomes the best financial alternative available for borrowers (see, for example, Kau *et al.*, 1994; Daglish, 2009, among others). Moreover, changes in house prices may induce substantial spillover effects on the performance of other loan categories where real estate is widely used as collateral to secure loan repayments. Thus, it is expected that changes in house prices lead to significant variations in a bank's aggregate nonperforming assets.

Hypothesis 2: *Real estate loans are more sensitive than other types of loans to house price fluctuations.*

Loan categories mainly vary in terms of the type of borrowers and the collateralised assets pledged to secure loan repayment. A fall in the market value of collaterals deteriorates borrowers' equity position, which can play a key role in borrowers' decision to default when they face financial distress. Thus, compared to other loan categories, real estate loans are expected to be more sensitive to adverse fluctuations in house prices as they are primarily secured by real estate while other loan types are either unsecured or secured with assets other than real estate.

Hypothesis 3: *House price changes have a non-uniform impact on the quality of loan portfolios in different types of depositary institutions.*

Lending policies and risk taking behaviour of banks are highly associated with a wide range of internal factors, including a bank's mission, organisational structure, ownership structure, depositor type, regulatory framework, and agency problems (see, e.g., Salas and Saurina, 2002; Laeven and Levine, 2009, for a review). In this context, savings institutions greatly vary from commercial banks. In particular, savings institutions are traditionally community-oriented organizations mandated to concentrate on residential mortgages to promote home ownership, whereas commercial banks are allowed to make various types of loans, including commercial and industrial loans.[10] Accordingly, savings institutions are expected to have developed more expertise in real estate lending, which may enable them to better forecast the dynamics of housing markets. Thus, compared to commercial banks, savings institutions are likely to be less affected by adverse house price fluctuations.

Hypothesis 4: *Larger banking institutions are more sensitive to falling house prices due to rapid deterioration of their asset quality during boom period.*

Sensitivity of a bank to real estate market is highly associated with its lending strategies which in turn greatly depend upon its size and complexity. Better access to external financing and ability to offer a greater range of financial products in larger banks enables them to quickly adjust their lending policies with soaring house prices. In addition, larger banks benefit from their 'too-big-to-fail' status as well as strong political and regulatory connections which create moral hazard incentives for their managers. This in turn may lead to excessive risk accumulations and high exposures to the housing market during boom period. Therefore, larger banks are expected to experience higher loan losses when house prices drop (see, e.g., De Nicoló, 2000; Tabak *et al.*, 2011; De Haan and Poghosyan, 2012).

[10] For a detailed discussion about differences between commercial banks and savings institutions see Madura (2014).

3.3. EMPIRICAL FRAMEWORK

3.3.1. Econometric methodology

In this chapter dynamic panel models are adopted to investigate the impact of real estate prices on the evolution of NPLs in individual US banks. NPL is defined as the sum of loans past due more than 90 days and still accruing interest plus nonaccrual loans that are no longer accruing interest as a percentage of total gross loans. In this case, using dynamic specification to model NPL is essential to account for time persistence of NPL and to capture the effect of omitted variables (see, for instance, Nkusu, 2011; Salas and Saurina, 2002). In general, a dynamic panel data model is specified as

$$y_{it} = \alpha y_{i,t-1} + \boldsymbol{x}'_{\boldsymbol{it}}\boldsymbol{\beta} + u_{it}, \qquad |\alpha| < 1; \tag{3.1}$$

where the subscript $i = 1, \dots, N$ indexes cross sectional units and $t = 1, \dots, T$ denotes time dimension,[11] $y_{i,t-1}$ is the lag of dependent variable, α is a scalar; $\boldsymbol{x}'_{\boldsymbol{it}}$ is $1 \times k$ vector of remaining explanatory variables, $\boldsymbol{\beta}$ is $k \times 1$ vector of coefficients to be estimated; and u_{it} is the error term. The error term consists of two orthogonal components: the time-invariant unobservable individual-specific effect, η_i, and idiosyncratic disturbance term, ε_{it}, meaning that $u_{it} = \eta_i + \varepsilon_{it}$.

One of the crucial assumptions for unbiasedness property of the OLS estimator is the exogeneity of explanatory variables, meaning that explanatory variables are uncorrelated with u_{it}, $E(u_{it}|x_{it}) = 0$. However, in dynamic models this assumption is violated by inclusion of the lagged dependent variable in the set of explanatory variables. The lagged dependent variable is a function of η_i and, therefore, correlated with the error term, $u_{it} = \eta_i + \varepsilon_{it}$. In this case, using the OLS estimation method produce biased and inconsistent estimates (see Blundell and Bond, 1998; Bond, 2002). To address this issue, Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998) suggested to use of the generalized method of moments GMM estimation method.

[11] Note that in unbalanced panels, T varies among different cross-sections.

Arellano and Bond (1991) proposed to remove the individual effects, η_i, through the first difference transformation as below

$$\Delta y_{it} = \alpha \Delta y_{i,t-1} + \Delta \boldsymbol{x}'_{it} \boldsymbol{\beta} + \Delta \varepsilon_{it}, \tag{3.2}$$

where Δ is the first difference operator. Although this transformation removes the individual specific effects, two major sources of bias remain in the regression model. The first source of bias stems from high correlation of $\Delta y_{i,t-1}$ with $\Delta \varepsilon_{it}$ whereas the second source is the possible endogeneity of other explanatory variables. As the authors point out, the first difference transformation is crucial to obtain valid moment conditions. It allows to take $y_{i,t-2}$ as an instrument for $\Delta y_{i,t-1}$. This instrument is by construction highly correlated with $\Delta y_{i,t-1}$ and not correlated with $\Delta \varepsilon_{it}$, for $t = 3, \dots, T$, given that ε_{it} are not serially correlated. Similar technique can be used for other explanatory variables.

When x_{it} are strictly exogenous, current and lagged values of x'_{it} are not correlated with $\Delta \varepsilon_{it}$. Therefore, adding extra valid instruments in each period, the instrument matrix will have the following form[12]

$$Z_i = \begin{bmatrix} y_{i1}, x_{i1}, \dots, x_{iT} & 0 & \cdots & 0 \\ 0 & y_{i1}, y_{i2}, x_{i1}, \dots, x_{iT} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & \cdots & y_{i1}, \dots, y_{i,T-2}, x_{i1}, \dots, x_{iT} \end{bmatrix}, \tag{3.3}$$

where rows correspond to the equation (3.2) for periods *t=3, 4, …, T* and for *i*-th individual. This instrument matrix corresponds to the following $(T-2)(T-1)/2$ moment conditions:

$$E[Z'_i \Delta \varepsilon_i] = 0, \quad i = 1, 2, \dots, N; \tag{3.4}$$

where $\Delta \varepsilon_i = (\Delta \varepsilon_{i3}, \Delta \varepsilon_{i4}, \dots, \Delta \varepsilon_{iT})'$. Equation (3.4) can be split into following equations

[12] This instrument matrix can be easily modified for predetermined or endogenous explanatory variables. When x_{it} are endogenous, $E(\varepsilon_{it}|x_{it}) \neq 0$ and $E(\varepsilon_{i,t-1}|x_{i,t-1}) \neq 0$. Therefore, x_{is} $(s = 1, 2, \dots, t-2)$ can be used as valid instruments as $E(\varepsilon_{it}|x_{i,t-2}) = 0$. Also, x_{is} $(s = 1, 2, \dots, t-1)$ can be used as instruments when x_{it} are predetermined or weakly exogenous, meaning that there is a feedback from $\varepsilon_{i,t-1}$ to x_{it} and therefore $E(\varepsilon_{i,t-1}|x_{it}) \neq 0$ but $E(\varepsilon_{i,t-1}|x_{i,t-1}) = 0$.

$$E\left[y_{i,t-s}\Delta\varepsilon_i\right] = 0, \quad t = 3, \dots, T \text{ and } s \geq 2; \tag{3.5}$$

$$E\left[x_{i,t-s}\Delta\varepsilon_i\right] = 0, \quad t = 3, \dots, T \text{ and all } s. \tag{3.6}$$

These orthogonality restrictions, $E[Z_i'\Delta\varepsilon_i] = 0$, provide preliminary requirements for the GMM estimation. Multiplying by the instrument matrix, equation (3.2) takes the following vector form

$$Z'\Delta y = Z'\Delta y_{-1}\alpha + Z'\Delta X\beta + Z'\Delta\varepsilon, \tag{3.7}$$

where ΔX is the stacked matrix of observations on Δx_{it}. Accordingly, one-step and two-step form of the GMM estimator of (α, β') are obtained from

$$\begin{pmatrix}\hat{\alpha}\\ \hat{\beta}\end{pmatrix} = ([\Delta y_{-1}, \Delta X]'ZA_N Z'[\Delta y_{-1}, \Delta X])^{-1}([\Delta y_{-1}, \Delta X]'ZA_N Z'\Delta y). \tag{3.8}$$

Two choices for A_N result in two alternative types of GMM estimators. A one-step GMM estimator is obtained by defining A_N as follow

$$A_N = \left(\frac{1}{N}\sum_{i}^{N} Z_i' G Z_i\right)^{-1}, \tag{3.9}$$

where G is the following $(T-2)\times(T-2)$ matrix with twos in the main diagonals, minus ones in the first sub-diagonals, and zeros otherwise

$$G = \begin{bmatrix} 2 & -1 & \dots & 0 & 0 \\ -1 & 2 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 2 & -1 \\ 0 & 0 & \dots & -1 & 2 \end{bmatrix}. \tag{3.10}$$

In a two-step estimator, A_N is defined as

$$A_N = \left(\frac{1}{N}\sum_{i}^{N} Z_i'\Delta\hat{\varepsilon}_i\Delta\hat{\varepsilon}_i' Z_i\right)^{-1}, \tag{3.11}$$

where $\Delta\hat{\varepsilon}_i = (\Delta\widehat{\varepsilon_{i3}}, \Delta\widehat{\varepsilon_{i4}}, \dots, \Delta\widehat{\varepsilon_{iT}})$ are the differenced residuals from the preliminary consistent estimator of $\begin{pmatrix}\hat{\alpha}\\ \hat{\beta}\end{pmatrix}$.

Although the first-differenced GMM model of Arellano and Bond (1991) delivers consistent estimators, it suffers from some important shortcomings. One of the main shortcomings is that the first difference transformation is likely to enlarge gaps in unbalanced panels and it is even possible that whole dataset vanishes in this transformation. In addition, Blundell and Bond (1998) point out the first-differenced GMM estimators are expected to perform poorly when instruments are weak.[13] In other word, as weak instruments become less informative, the first-differenced GMM estimators suffer from finite sample size distortion problem, particularly when the number of time periods available is small. To address this problem Blundell and Bond (1998) propose a new framework known as system GMM to estimate dynamic panel data models. Their basic idea is to simultaneously estimate a system of two equations; one in first differences and the other one in levels. By adding the second equation $(T-2)$ extra moment conditions can be obtained in addition to the moment conditions of the first-differenced model. Therefore, we can exploit $y_{i,t-2}$ as instruments for equations in first differences as well as $\Delta y_{i,t-1}$ as instruments for equations in levels, as suggested by Arellano and Bover (1995). The vector of errors and matrix of instruments for individual *i* for this system can be written as

$$u_i^+ = \begin{bmatrix} \varepsilon_{i3} - \varepsilon_{i2} \\ \vdots \\ \varepsilon_{iT} - \varepsilon_{i,T-1} \\ \eta_i + \varepsilon_{i3} \\ \vdots \\ \eta_i + \varepsilon_{iT} \end{bmatrix}, \qquad Z_i^+ = \begin{bmatrix} \boldsymbol{Z_i} & 0 & 0 & \cdots & 0 \\ 0 & \Delta y_{i2} & 0 & \cdots & 0 \\ 0 & 0 & \Delta y_{i3} & \cdots & 0 \\ \cdot & \cdot & \cdot & \cdots & 0 \\ 0 & 0 & 0 & \cdots & \Delta y_{i,T-1} \end{bmatrix}. \tag{3.12}$$

The moment conditions in system GMM are as follows

[13] Weak instruments are uncorrelated with the error term but they are only weakly correlated with the endogenous variable. Weak instrument problem in the case of the first-differenced GMM estimator usually occurs when time series are persistent $(\alpha \to 1)$ and/or the relative variance of the fixed effects increases $(\sigma_\eta^2/\sigma_\varepsilon^2 \to \infty)$.

$$E(Z_i^{+'} u_i^+) = 0, \tag{3.13}$$

where new moment conditions are defined as

$$E\left[u_{it}\Delta y_{i,t-1}\right] = E\left[(\eta_i + \varepsilon_{it})\Delta y_{i,t-1}\right] = 0, \tag{3.14}$$

and

$$E\left[u_{it}\Delta x_{i,t-1}\right] = E\left[(\eta_i + \varepsilon_{it})\Delta x_{i,t-1}\right] = 0. \tag{3.15}$$

The key idea behind the system GMM estimator is to simultaneously estimate a system of two equations: one in first-differences and the other one in levels. Accordingly, the lagged level values are used to instrument first-differenced equation, while the lagged first-differenced values are used to instrument the equation in levels. Once the instruments matrix is constructed, the two-step system GMM estimator can be calculated.

This chapter adopts two-step system GMM estimator with Windmeijer's (2005) finite sample correction. In general, system GMM outperforms difference GMM and other preliminary models by producing less biased and more precise estimates, especially when α is large (Blundell and Bond, 1998). In addition, the two-step GMM estimator is more efficient and also relaxes the assumption of homoscedasticity in the error terms (Blundell and Bond, 1998; Arellano and Bond, 1991). Finally, due to its dependence on estimated residuals, the two-step GMM estimator may impose a severe downward bias on estimated asymptotic standard errors, particularly in small samples. Therefore, the finite sample correction technique proposed by Windmeijer (2005) is applied to address this issue and provide corrected variance estimates, leading to more reliable asymptotic statistical inference.[14]

Furthermore, the consistency of the GMM estimators relies upon the validity of instrumental variables in a sense that they are uncorrelated with the errors in the first-

[14] Robust standard errors are reported to account for potential problems that may arise from heteroskedasticity and clustering of observations within banks while using the Windmeijer's (2005) finite sample correction in the GMM models.

differenced equation as well as the fundamental assumption that the errors, ε_{it}, are serially uncorrelated. To test the overall validity of instruments, the Hansen specification test is used (see Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Under the null hypothesis of valid moment conditions, the Hansen test statistic for over-identifying restrictions is asymptotically distributed as chi-square. In addition, Arellano and Bond (1991) propose a test to assess the assumption of no serial correlation in the error terms. This test is based on the hypothesis that there is no second-order serial correlation in the residuals of the first-difference equation, $E[\Delta\varepsilon_{it}\Delta\varepsilon_{i,t-2}] = 0$. This hypothesis is rejected if the ε_{it} are serially autocorrelated which undermines the consistency of the GMM estimators.

3.3.2. Empirical model

In order to investigate the linkage between house price fluctuations and evolution of NPLs, equation (3.1) takes the following form

$$NPL_{it}^{h} = \alpha NPL_{i,t-1}^{h} + \boldsymbol{S}_{\boldsymbol{t}}'\boldsymbol{\beta} + \boldsymbol{I}_{\boldsymbol{i,t-1}}'\boldsymbol{\gamma} + \eta_i + \varepsilon_{it}, \qquad (3.16)$$

where subscript *h* denotes the definition of NPL regarding the corresponding hypothesis under consideration while subscripts *i* and *t* denote banks and time, respectively; $\boldsymbol{I}_{\boldsymbol{i,t-1}}$ is a vector of idiosyncratic variables and $\boldsymbol{S}_{\boldsymbol{t}}$ is a vector of systematic variables including house price fluctuations; $\alpha, \boldsymbol{\beta}, \text{and}\, \boldsymbol{\gamma}$ are regression coefficients; and ε_{ijt} is the disturbance term.

As for the dependent variable, NPL_{it} is defined as a percentage of nonperforming loans to total gross loans with regards to the hypothesis under consideration. Some authors, including Salas and Saurina (2002), have suggested to apply a logarithmic transformation on NPL to allow it to vary in the range $(-\infty, \infty)$. However, Quagliariello (2007) argues that since NPL typically takes values in the range (0, 0.10), such transformation does not seem to be very useful.

Furthermore, to avoid potential omitted variable issue in this analysis, a broad set of idiosyncratic and systematic variables are included in the regression as control variables. This section reviews control variables used in this study along with their expected impact on the evolution of NPL. In addition, for ease of interpretation, a detailed definition of these variables is given in Table A3.1.

I. Systematic factors

In addition to house price fluctuations, the column entries of the matrix $\boldsymbol{S_t}$ in equation (3.16) include the following systematic factors:

Real gross domestic products (GDP_t): Real GDP growth is widely used as a proxy for general macroeconomic conditions and business cycles. A well-established empirical literature documents that changes in macroeconomic conditions translate into changes in the quality of loan portfolios (see, e.g., Quagliariello, 2007; Pesola, 2011; Marcucci and Quagliariello, 2009). According to this literature, an expansionary phase of the economy is often associated with low level of NPLs as borrowers' debt servicing capacity improves owing to (i) higher stream of income for firms and households, and (ii) rising asset prices. However, as economic upturn continues, banks risk appetite gradually increases and banks become more vulnerable to macroeconomic shocks. Subsequently, when recession begins, NPLs increases and banks tighten access to credit as economic prospects worsen. Therefore, NPLs are expected to illustrate an inherent cyclical pattern moving in line with economic cycles.

Unemployment rate (U_t): Unemployment rate is another key indicator of macroeconomic conditions and business cycle and is widely used as a determinant of NPL in previous studies (see, e.g., Louzis *et al.,* 2012; Nkusu, 2011). Rising unemployment rate undermines ability of subprime borrowers to settle their obligations and may encourage them to default or terminate their loan contracts. In this regard, higher unemployment rate is expected to result in higher NPLs.

Real interest rate (IR_t): Real interest rate is defined as the lending interest rate adjusted for inflation measured by the consumer price index. A rise in interest rate indicates higher borrowing costs, which in turn attenuates borrowers' debt servicing capacity. In particular, subprime borrowers and adjustable rate mortgage borrowers are likely to be very sensitive to changes interest rates as they are usually charged with higher interest rates compared to prime borrowers in order to compensate the banks for higher risk premiums of subprime loans (see, e.g., Demyanyk and Van Hemert, 2011; Daglish, 2009).

It should be noted that, following previous studies, systematic variables are treated as exogenous variables in this analysis (see, e.g., Louzis *et al.,* 2012). In addition, due to high correlations between contemporaneous and lagged values of macroeconomic variables and to avoid multicollinearity issues, only contemporaneous macroeconomic variables in the empirical model.

II. Idiosyncratic factors

As far as idiosyncratic factors are concerned, the column entries of the matrix $\boldsymbol{I_{it}}$ in equation (3.16) are as follows:

Capital ratio (CR_{it}): Capital ratio is defined as total equity as a percentage of total assets. Several papers have investigated the relationship between level of bank capitalization and evolution of NPLs. In their seminal paper, Keeton and Morris (1987) argue that banks with aggressive risk taking behaviour are less willing to back their assets by equity. They mention high loan to asset ratio, reliance on volatile sources of funds and low equity to asset ratio as three features of banks that are willing to make loans with a higher probability of default. Furthermore, Berger and DeYoung (1997) examine moral hazard hypothesis and provide strong evidence that low capitalization of banks is associated with relatively high level of NPLs. The proposed justification links the increasing risk taking appetite on the part of banks' managers due to moral hazard incentives when banks are highly leveraged.

Loan to asset ratio (LA_{it}): Several papers have documented loan to asset ratio as an indicator of riskiness of bank's asset portfolio as loans are riskier and less liquid compared to other types of bank assets such as cash, reserves, and government bonds (see, e.g., Wheelock and Wilson, 2000; Davis and Zhu, 2009). Dell'Ariccia and Marquez (2006) argue that making loan involves an inherent risk of maturity transformation, where short-term deposits are converted into long-term loans. Therefore, higher lending may imply higher risk of maturity transformation and is likely to be linked with relax lending standards and weak internal controls as banks may sacrifice their long-term stability in favour of short-term reputation concerns.

Accordingly, higher loan to asset ratio is expected to be associated with higher riskiness and NPLs across banks.

Inefficiency (INE_{it}): Inefficiency is defined as the ratio of non-interest expenses to the sum of interest and non-interest income. Net interest expenses in this definition don't include the amortization expenses of intangible assets. The relationship between inefficiency and NPL is complex. In an early study, Berger and DeYoung (1997) propose two possible hypotheses on the linkage between NPL and cost efficiency. On one hand, bad management hypothesis indicates that inefficiency may be the result of low quality of managerial skills in banks, which subsequently leads to higher level of NPLs. On the other hand, according to the skimping hypothesis, inefficiency may be associated with lower NPL because inefficient banks incur higher costs and expend more resources to monitor borrowers. Inefficient banks with risk-averse managers tend to trade off reduced income for reduced asset risk. Podpiera and Weill (2008) and Louzis *et al*. (2012) provide empirical evidence in favour of the bad management hypothesis, while Salas and Saurina (2002) and Shehzad *et al.* (2010) estimate insignificant effect of efficiency on impaired loans.

Net interest margin (NIM_{it}): Net interest margin is defined as the net interest income as a percentage of average earning assets. NIM_{it} can be used as a proxy for both profitability and riskiness of a loan portfolio. However, the linkage between profitability and NPL is ambiguous. Louzis *et al*. (2012) refer to the bad management hypothesis and argue that high profitability is a sign of efficient management and is therefore associated with lower NPL. Also, Salas and Saurina (2002) argue that banks with low net interest margin are more pressured to revenue creation and may change their credit policy and make riskier loans. Thus, low net interest margin is associated with higher NPLs in the future. On the other hand, Quagliariello (2007) argues that higher net interest margin is associated with riskier loan portfolios as banks charge higher interest rate on riskier borrowers. From this point of view, low net interest margin is associated with lower NPLs.

Log of total assets ($SIZE_{it}$): Some papers have investigated the linkage between diversification and NPLs by employing bank size as a proxy for diversification opportunities. For instance, Salas and Saurina (2002) report a negative relationship between NPLs and bank size. According to their view, large banks have better risk management practices which eventually lead to lower credit risk and NPLs.

Loan portfolio concentration (LC_{it}): Loan portfolio concentration is an indicator of a bank's lending policies, which can largely affect the quality of its loan portfolio. Loan portfolio concentration in this study is defined as the Herfindahl–Hirschman index of three major loan categories in a bank: real estate loans, commercial and industrial loans, and consumer loans. Higher loan portfolio concentration in a bank indicates that the bank is more exposed to certain markets and may severely suffer when those markets crash (Rossi *et al.,* 2009). On the other hand, banks that specialise their lending activities to certain sectors may develop their expertise in those sectors. Therefore, they have better knowledge and understanding of market conditions, making their portfolios less risky (Tabak *et al.,* 2011). Overall, an asymmetric linkage between loan portfolio concentration and NPL is expected. In other words, more concentrated banks face less NPL during economic expansion, while less diversified banks suffer from higher NPL during crisis period.

As for idiosyncratic factors, it is a common practice to use lagged bank-specific variables in modelling NPL and loan losses (see, e.g., Berger and DeYoung, 1997; Tabak *et al.*, 2011; Louzis *et al.*, 2012; Davis and Zhu, 2009). Notably, inclusion of lagged variables is crucial for (*i*) avoiding simultaneity effects between NPL and bank-specific variables, and (*ii*) accounting for the potential time delay between changes in managerial decisions and changes in the quality of loan portfolios as reported in the balance sheet data. This in turn allows to consider bank-specific variables as exogenous variables, which is essential to overcome the problem of too many instruments pointed out by Roodman (2009).

3.4. DATA

This study is based on annual panel data of the US banking institutions over the period 1999-2012. The dataset comprises a combination of macroeconomic and idiosyncratic variables obtained from different sources. Bank specific variables were extracted from the Federal Deposit Insurance Corporation (FDIC) database, which provides balance sheet and income statement data for individual insured banks in the US banking system.[15]

House prices were retrieved from the Federal Housing Finance Agency (FHFA) database, which provides state-level House Price Index (HPI) data.[16] State-level GDP growth rate and unemployment rate data were retrieved from the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS), respectively. Finally, interest rate and inflation rate were obtained from the Federal Reserve Economic Data (FRED). Note that house prices, GDP growth rates and interest rates are considered in real terms.

Table 3.1. Geographical distribution of sample banks throughout U.S. states.

State	Abb.	Number of Banks	State	Abb.	Number of Banks	State:	Abb.	Number of Banks
Alabama	AL	232	Kentucky	KY	360	North Dakota	ND	131
Alaska	AK	10	Louisiana	LA	236	Ohio	OH	449
Arizona	AZ	97	Maine	ME	49	Oklahoma	OK	361
Arkansas	AR	267	Maryland	MD	182	Oregon	OR	77
California	CA	618	Massachusetts	MA	258	Pennsylvania	PA	401
Colorado	CO	280	Michigan	MI	253	Rhode Island	RI	21
Connecticut	CT	109	Minnesota	MN	602	South Carolina	SC	160
Delaware	DE	63	Mississippi	MS	141	South Dakota	SD	128
D.C.	DC	12	Missouri	MO	532	Tennessee	TN	330
Florida	FL	562	Montana	MT	123	Texas	TX	1054
Georgia	GA	559	Nebraska	NE	359	Utah	UT	91
Hawaii	HI	21	Nevada	NV	61	Vermont	VT	29
Idaho	ID	32	New Hampshire	NH	53	Virginia	VA	247
Illinois	IL	1028	New Jersey	NJ	226	Washington	WA	154
Indiana	IN	300	New Mexico	NM	92	West Virginia	WV	131
Iowa	IA	535	New York	NY	322	Wisconsin	WI	446
Kansas	KS	460	North Carolina	NC	186	Wyoming	WY	64

[15] The FDIC was established in 1933 in response to large number of bank failures during the Great Depression that started in the late 1920s. The main mission of the FDIC is to promote public confidence in the US banking system by providing deposit insurance for up to $250,000 per account in membered banks. Also, the FDIC directly monitors and supervises more than half of the banking institutions in the US to preserve and promote sound banking practices. As of December 2012, the FDIC insured deposits at 7,009 banking institutions with total assets of over 14.5 trillion US dollars.

[16] The HPI is derived from data provided by Fannie Mae and Freddie Mac and is a measure of average house price changes in repeat sales or refinancings on the same single-family properties. The HPI data was available on quarterly basis and I converted it to yearly data by simple averaging.

The dataset was then refined by excluding (i) banks with less than 8 consecutive observations on all variables when full sample is considered,[17] (ii) banks that report unusual values reflecting measurement errors or anomalous transactions such as major asset sales,[18] (iii) banks that are headquartered in the U.S. territories such as Puerto Rico and Guam, and (iv) insured U.S. branches of foreign chartered institutions. The resulting sample is an unbalanced panel consisting of 106,276 annual observations from 8,367 US banking institutions. Table 3.1 presents the geographical distribution of the sample after cleaning and filtering the data, for a brief review. Also, Table 3.2 lists all explanatory variables used in this study, together with their expected signs, acronyms, and data sources.

Table 3.2. Summary of explanatory variables, acronyms, units, and data sources.

Variables	Acronym	Expected sign	Units	Source
Bank-specific variables:				
Loan portfolio concentration	LC_{it}	+	Percentage	FDIC Institution Directory
Loan to asset ratio	LA_{it}	+	Percentage	FDIC Institution Directory
Capital ratio	CR_{it}	-	Percentage	FDIC Institution Directory
Inefficiency	INE_{it}	-/+	Percentage	FDIC Institution Directory
Net interest margin	NIM_{it}	-/+	Percentage	FDIC Institution Directory
Size	$SIZE_{it}$	-/+	Logarithm	FDIC Institution Directory
Local economic conditions*:				
Real GDP growth	GDP_t	-	Percentage	Bureau of Economic Analysis
Real interest rate	IR_t	+	Percentage	Federal Reserve
Unemployment rate	U_t	+	Percentage	Bureau of Labor Statistics
Real house price growth	HP_t	-	Percentage	Federal Housing Finance Agency

*Data on nominal GDP growth rate, interest rate, and house prices are adjusted for inflation by using national-level consumer price index data obtained from the International Financial Statistics (IFS) database.

[17] When sub-samples are under consideration, banks with less than 6 consecutive observations are dropped from the sample.

[18]Unusual values are defined as loan/assets >1, equity/assets >1, nonperforming loans/assets >1, and net interest margins>100% or net interest margins<-100%.

Table 3.3 summarises the descriptive statistics of the variables used in this analysis over the period 1999-2012. For each variable, mean, descriptive statistics of the 25th and 75th percentiles are included. It appears that, on average, 1.534% of total gross loans in the US banks are nonperforming. More interestingly, sample banks, on average, faced higher NPL in real estate loans, compared to other loan categories. Average HHI is 0.610, indicating that loan portfolios of the US banks are highly concentrated on specific sectors. In addition, loans form, on average, 63.917% of asset portfolios in the sample banks, meaning that the U.S. banks are more concentrated lending activities. Overall, the sample banks seem to be well capitalized as indicated by 10.842% of average capital ratio. However, this indicator has a relatively large standard deviation, suggesting that level of capitalization varies widely among sample banks. Average NIM is 4.047%, indicating that the sample consists of bank with profitable and efficient loan portfolios. Finally, the sample includes large banks with average log of total assets of 11.875.

Table 3.3. Descriptive statistics.

	Mean	Median	Std. Dev.	Skewness	Kurtosis
NPL_{it}	1.534	0.774	2.456	5.870	82.270
$RENPL_{it}$	1.613	0.660	2.879	5.644	71.504
$CINPL_{it}$	1.469	0.331	3.762	10.661	203.642
$CNPL_{it}$	0.863	0.290	2.306	15.938	453.234
LC_{it}	0.610	0.573	0.173	0.652	2.422
LA_{it}	63.917	65.871	15.584	-0.706	3.656
CR_{it}	10.842	9.768	4.916	6.197	76.090
INE_{it}	0.715	0.667	0.414	10.525	189.419
NIM_{it}	4.047	3.997	1.118	4.460	73.447
$SIZE_{it}$	11.875	11.723	1.352	1.148	6.349
GDP_t	1.875	1.970	2.402	-0.377	4.856
IR_t	3.050	3.041	1.733	0.103	1.763
U_t	5.647	5.233	1.940	1.034	3.826
HP_t	0.701	1.113	4.945	0.095	5.775

Table 3.4. Cross-correlation between variables, 1999-2012.

	NPL_{it}	$RENPL_{it}$	$CINPL_{it}$	$CNPL_{it}$	$LC_{i,t-1}$	$LA_{i,t-1}$	$CR_{i,t-1}$	$INE_{i,t-1}$	$NIM_{i,t-1}$	$SIZE_{i,t-1}$	GDP_t	IR_t	U_t	HP_t
NPL_{it}	1													
$RENPL_{it}$	**0.90**	1												
$CINPL_{it}$	**0.48**	**0.27**	1											
$CNPL_{it}$	**0.21**	**0.16**	**0.13**	1										
$LC_{i,t-1}$	**0.12**	**0.11**	**0.04**	**0.02**	1									
$LA_{i,t-1}$	**0.06**	**0.07**	**0.03**	**0.02**	**0.19**	1								
$CR_{i,t-1}$	**-0.02**	**-0.04**	**-0.02**	**-0.01**	**0.09**	**-0.37**	1							
$INE_{i,t-1}$	**0.16**	**0.01**	0.00	**-0.01**	**0.05**	**-0.13**	**0.32**	1						
$NIM_{i,t-1}$	**-0.04**	**-0.05**	0.00	**0.02**	**-0.16**	**0.12**	**-0.06**	**-0.09**	1					
$SIZE_{i,t-1}$	**0.09**	**0.10**	**0.02**	**-0.02**	**0.23**	**0.20**	**-0.23**	**-0.14**	**-0.02**	1				
GDP_t	**-0.16**	**-0.17**	**-0.05**	**-0.03**	**-0.10**	**-0.09**	**-0.02**	**-0.01**	**0.05**	**-0.05**				
IR_t	**-0.17**	**-0.18**	**-0.04**	**-0.01**	**-0.08**	**0.01**	**0.08**	**-0.02**	**0.04**	**-0.09**	**0.13**	1		
U_t	**0.30**	**0.32**	**0.10**	**0.04**	**0.21**	**0.05**	0.00	**0.05**	**-0.06**	**0.17**	**-0.39**	**-0.54**	1	
HP_t	**-0.28**	**-0.30**	**-0.08**	**-0.04**	**-0.07**	**-0.07**	**-0.02**	**-0.02**	**0.04**	**-0.05**	**0.43**	**0.34**	**-0.54**	1

Note: Coefficients in bold are significant at 5% level

Table 3.4 reports the cross-correlation matrix of variables used in this study. For the consistency of the correlation matrix with the regression analysis, lagged values of bank-specific variables were used for calculating correlation coefficients among variables. The correlation matrix shows that among bank specific variables, real estate NPL (RENPL) has the highest correlation with macroeconomic variables in crisis period. Not surprisingly, aggregate NPL is also highly correlated with macroeconomic factors, which is perhaps because aggregate NPL is largely driven by real estate NPL. Correlations between NPL and macroeconomic factors are significantly lower for other loan categories. Furthermore, NPL and RENPL are significantly correlated with all bank-specific variables, indicating that NPL is a function of both systematic and idiosyncratic factors. Nevertheless, correlation coefficients between bank-specific variables and NPL in other loan categories are rather different in terms of magnitude and significance level.

3.5. EMPIRICAL RESULTS

In this section, the estimated results of equation (3.16) are reported. In order to investigate potential asymmetric impact of house prices on the evolution of NPLs during boom and bust periods, the sample was split into two sub-sample periods, 1999-2005 and 2006-2012. Accordingly, each table includes three pairs of estimation results with respect to three alternative sample periods; the whole period and two sub-sample periods.

Furthermore, one of the main arguments of this Chapter is that NPL is highly affected by regional macroeconomic conditions. However, after eliminating legal restrictions on intrastate and interstate branching during late 20th century, some U.S. banks either spread their branches to other states or acquired banks in other states and converted them into their branches. These banks, therefore, are less exposed to local economies and investigating the regional macroeconomic developments on their problem loans might be irrelevant. In order to account for this issue, the Summary of Deposit (SOD) database provided by the FDIC was used in this study to distinguish between intrastate and interstate banks. The intrastate banks are defined as those that operate in one state while interstate banks operate in multiple states and have offices in more than one state. In this study the mid-sample year was chosen as the reference year for distinguishing interstate and intrastate banks in the sample.[19] Therefore, within each pair of estimations, the first estimated equation represents all banks including intrastate and interstate banks while only the intrastate banks are included in the second equation.[20]

[19] Despite removing the intrastate and interstate branching restrictions, most U.S. banks are still operating locally. This is in particular evident in pre-crisis sample where less than 500 banks operate in more than one state. Furthermore, the main activities of those interstate banks were carried out in the state where their headquarters were located.

[20] Due to lack of state-level NPL data for interstate banks, a separate analysis on interstate banks is not carried out in this study.

3.5.1. House price fluctuations and aggregate NPL

Table 3.5 presents the estimation results regarding the first hypothesis. Here, NPL is defined as the aggregate NPL in loan portfolio of a bank as a percentage of total gross loans. Results are reported for three pairs of equations, corresponding to three sampling periods under consideration. Equations (I) and (II) represent the results for the whole period, 1999-2012; equations (III) and (IV) show the estimation results for pre-crisis period, 1999-2005, while equations (V) and (VI) show the estimation results for the crisis period, 2006-2012. In addition, equations (I), (III), and (VI) represents the results for all sample banks while other equations are related to estimation results for intrastate banks only.

From Table 3.5 it appears that estimated coefficients for changes in house prices are negative and statistically significant in all models, regardless of the period under consideration. These empirical results strongly support hypothesis one that the quality of loan portfolios is highly sensitive to house price fluctuations. Furthermore, it should be noted that the estimated coefficients are approximately six times higher in crisis period, compared to pre-crisis period. This indicates that house price fluctuations have asymmetric effects on NPL. In other words, rising house prices have slight impact on the evolution of NPL, while falling house prices are associated with large increase in NPL levels in banks.

As far as other macroeconomic factors are concerned, it appears that estimated coefficients on real GDP growth and unemployment rate as well as other main indicators of general macroeconomic conditions are statistically significant and carry the expected signs. Real GDP growth enters in equations with negative sign, while unemployment rate takes on positive sign across all equations. This suggests that NPL dynamics and business cycles are procyclical, which is consistent with the findings of Marcucci and Quagliariello (2008). In addition, the estimated coefficients on real interest rate are positive and statistically significant across all equations, indicating that NPL level is highly associated with borrowing costs.

Furthermore, similar to house price fluctuations, other macroeconomic factors have asymmetric impact on the evolution of NPL during different phases of business cycles. In other words, the impact of all macroeconomic variables on NPL is more pronounced during crisis period. This finding is consistent with asymmetric effects of the business cycle on bank credit risk found by Marcucci and Quagliariello (2009).

Table 3.5. GMM estimation results of NPL for all banking institutions

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.689***	0.692***	0.608***	0.610***	0.704***	0.712***
	(0.020)	(0.021)	(0.069)	(0.070)	(0.023)	(0.022)
GDP_t	-0.041***	-0.039***	-0.019***	-0.019***	-0.042***	-0.038***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
IR_t	0.035***	0.035***	0.027***	0.029***	0.066***	0.065***
	(0.004)	(0.005)	(0.006)	(0.006)	(0.008)	(0.008)
U_t	0.102***	0.099***	0.033***	0.038***	0.081***	0.078***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
HP_t	-0.051***	-0.051***	-0.010***	-0.011***	-0.068***	-0.069***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)
$LC_{i,t-1}$	0.425***	0.405***	-0.115**	-0.099***	0.632***	0.629***
	(0.053)	(0.056)	(0.049)	(0.048)	(0.105)	(0.113)
$LA_{i,t-1}$	0.008***	0.008***	0.003***	0.003***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$INE_{i,t-1}$	0.041	0.006	-0.090***	-0.112***	0.031	-0.103
	(0.041)	(0.031)	(0.032)	(0.037)	(0.149)	(0.115)
$SIZE_{i,t-1}$	0.035***	0.034***	-0.046***	-0.053***	0.054***	0.034**
	(0.007)	(0.008)	(0.010)	(0.012)	(0.014)	(0.014)
$CR_{i,t-1}$	-0.005**	-0.004	0.004***	0.003*	-0.001	0.002
	(0.002)	(0.003)	(0.001)	(0.002)	(0.006)	(0.006)
$NIM_{i,t-1}$	0.004***	0.038***	0.037***	0.041***	0.040**	0.032*
	(0.010)	(0.010)	(0.009)	(0.009)	(0.020)	(0.018)
Constant	-1.289***	-1.235***	0.487***	0.554***	-1.820***	-1.473***
	(0.113)	(0.114)	(0.201)	(0.213)	(0.282)	(0.247)
No. of Observations	97,898	91,497	50,557	48,164	36,283	33,143
Number of banks	8,367	7,821	7,337	6,986	6,081	5,554
AR(1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test, p-value	0.779	0.913	0.582	0.552	0.844	0.924
Hansen test, p-value	0.194	0.197	0.154	0.147	0.115	0.264
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of nonperforming loans to total gross loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

In general, significant coefficients on most bank-specific variables across estimated equations outlines the importance of idiosyncratic factors in explaining NPL. The estimated coefficient on the lagged dependent variable is positive and significant at 1% level across all equations. However, compared to pre-crisis period, these coefficients are higher in crisis period, indicating that NPL is more persistent and sticky during crisis period.

The empirical results show that the estimated coefficient for loan portfolio concentration is significant across all equations, but it gets different signs for the two sub-sample periods: it is positive during pre-crisis period and negative during crisis period. One possible explanation for this finding is that higher loan portfolio concentration usually indicates higher ratio of real estate loans to total gross loans in most US banks. Therefore, it is not surprising that banks with higher ratio of real estate loans to total loans experienced less NPLs when house prices were rising, while they dramatically suffered from high NPLs when housing bubble collapsed. Furthermore, loan to total assets appear to be positive and significant in all periods, which is consistent with the results of Davis and Zhu (2009). This indicates that banks with more reliance on their interest income have less liquidity and face more NPLs than their counterparts with more diversified sources of income.

The impact of bank size on NPL varies across different periods under consideration. Smaller banks suffered from higher NPL levels during boom period. This indicates that smaller banks have less market power, less economies of scale, and less diversification opportunities among their customers and products (see, for instance, Salas and Saurina, 2002). On the other hand, larger banks have suffered from higher NPLs during crisis period. In fact, larger banks have higher agency costs and more difficulties in monitoring the quality of their loan portfolios. Also, larger banks may be more exposed to credit risk because of being engaged in complex financial innovations such as mortgage-related derivatives. Therefore, riskier portfolios may have left them more exposed to credit risk after the burst of the housing bubble.

The sign of NIM_{it} is positive and significant across all periods, indicating that higher NIM_{it} is associated with riskier portfolios (see Quagliariello, 2007). Furthermore, confining this analysis to intrastate banks, it appears that the estimated coefficients for intrastate banks are very similar to those obtained with the sample of all banks, with the exception of INE_{it}.

Table 3.5 also reports the results for the Hansen test of over-identifying restrictions and Arellano and Bond (1991) test for autocorrelation in the first difference residuals. Results show that the instruments are valid for the regressions and that the null hypothesis of no serial correlation cannot be rejected. In Summary, the empirical results strongly support the hypothesis that there is a close relationship between credit risk and house price fluctuations. Also, an asymmetric impact of house prices and other macroeconomic variables on the dynamics of NPL is found. These findings remain robust when analysis is confined to intrastate banks.

3.5.2. House prices and NPL in different loan categories

In this section, hypothesis two is tested. Three loan categories are used in this analysis: real estate loans, commercial and industrial loans, and consumer loans. It should be noted that the number of banks and observations are reduced when considering different loan categories because some banks heavily invest in specific types of loans and have no recorded data for other loan categories. Table 3.6 presents the system GMM estimation results of model (3.16) where NPL_{it}^{h} is defined as real estate NPL as a percentage of total real estate loans.

The results show that real estate NPL (RENPL) is highly sensitive to macroeconomic conditions. The coefficient of house price fluctuations remains negative and significant in all equations and for whole sample and the intrastate subsample. This indicates that house prices have remarkably affected the evolution of real estate NPL in different economic conditions. However, this impact is much stronger during the crisis period, indicating an asymmetric linkage between house prices and RENPL. The same asymmetric pattern is observed for other macroeconomic variables.

As regards the bank-specific factors, empirical results in Table 3.6 show that quality of real estate loan portfolios is highly affected by idiosyncratic factors, particularly in the first sample period. While all estimated coefficients of bank-specific factors are statistically significant during pre-crisis period, only LC_{it}, LA_{it}, and $SIZE_{it}$

remain significant during crisis period. In addition, the estimated coefficient of lagged RENPL is higher during crisis period, indicating higher time persistence in RENPL during economic downturn.

Table 3.6. GMM estimation results of real estate NPL.

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
Variables	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.714***	0.721***	0.660***	0.671***	0.672***	0.685***
	(0.028)	(0.030)	(0.069)	(0.069)	(0.027)	(0.028)
GDP_t	-0.051***	-0.049***	-0.026***	-0.027***	-0.048***	-0.045***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
IR_t	0.036***	0.036***	0.034***	0.034***	0.079***	0.080***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.011)	(0.011)
U_t	0.097***	0.092***	0.039***	0.042***	0.099***	0.093***
	(0.011)	(0.012)	(0.010)	(0.011)	(0.012)	(0.013)
HP_t	-0.062***	-0.062***	-0.009***	-0.009***	-0.094***	-0.096***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.007)	(0.007)
$LC_{i,t-1}$	0.448***	0.441***	-0.066	-0.023	0.526***	0.574***
	(0.067)	(0.072)	(0.065)	(0.060)	(0.141)	(0.154)
$LA_{i,t-1}$	0.006***	0.007***	0.002**	0.002**	0.007***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$INE_{i,t-1}$	-0.054	-0.004	-0.120**	-0.165***	-0.052	-0.090
	(0.060)	(0.047)	(0.047)	(0.057)	(0.151)	(0.121)
$SIZE_{i,t-1}$	0.055***	0.046***	-0.059***	-0.075***	0.084***	0.047**
	(0.009)	(0.011)	(0.014)	(0.019)	(0.018)	(0.019)
$CR_{i,t-1}$	-0.004	-0.003	0.005*	0.005*	-0.005	-0.001
	(0.004)	(0.005)	(0.003)	(0.003)	(0.009)	(0.010)
$NIM_{i,t-1}$	0.095***	0.095***	0.052***	0.053***	0.114***	0.144***
	(0.015)	(0.015)	(0.012)	(0.013)	(0.033)	(0.033)
Constant	-1.630***	-1.490***	0.5830**	0.748**	-2.361***	-1.860***
	(0.163)	(0.169)	(0.284)	(0.326)	(0.373)	(0.358)
No. of Observations	84,478	78,315	39,763	37,531	31,334	28,264
Number of banks	6,937	6,415	5,758	5,431	5,249	4,734
AR(1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test, p-value	0.649	0.699	0.198	0.189	0.489	0.476
Hansen test, p-value	0.288	0.258	0.441	0.449	0.26789	0.291
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of real estate nonperforming loans to total gross real estate loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

Table 3.7. GMM estimation results of commercial and industrial NPL.

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
Variables	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.317***	0.332**	0.350***	0.352***	0.472***	0.452***
	(0.135)	(0.148)	(0.034)	(0.035)	(0.114)	(0.120)
GDP_t	-0.017***	-0.017***	-0.016**	-0.016**	-0.013	-0.008
	(0.006)	(0.006)	(0.008)	(0.008)	(0.011)	(0.012)
IR_t	0.027***	0.027***	0.072***	0.075***	0.039**	0.045**
	(0.010)	(0.010)	(0.015)	(0.016)	(0.017)	(0.018)
U_t	0.130***	0.126***	0.125***	0.137***	0.130***	0.133***
	(0.020)	(0.022)	(0.022)	(0.023)	(0.022)	(0.023)
HP_t	-0.024***	-0.023***	0.001	0.003	-0.031***	-0.034***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.009)	(0.010)
$LC_{i,t-1}$	0.688*	-0.619	0.775**	0.897***	0.781	0.938***
	(0.398)	(0.413)	(0.268)	(0.300)	(0.534)	(0.651)
$LA_{i,t-1}$	0.005**	0.005**	0.002	0.002	0.008**	0.007**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
$INE_{i,t-1}$	0.185**	0.164*	0.153	0.132	0.568*	0.496
	(0.090)	(0.092)	(0.217)	(0.227)	(0.341)	(0.372)
$SIZE_{i,t-1}$	-0.108***	-0.122***	-0.202***	-0.252***	-0.153***	-0.214***
	(0.033)	(0.045)	(0.025)	(0.033)	(0.041)	(0.062)
$CR_{i,t-1}$	-0.017**	-0.016**	0.010	0.009	0.003	-0.002
	(0.007)	(0.008)	(0.009)	(0.009)	(0.011)	(0.011)
$NIM_{i,t-1}$	0.033	0.035	0.017	0.017	-0.010	-0.004
	(0.024)	(0.021)	(0.022)	(0.022)	(0.029)	(0.030)
Constant	0.893**	1.035*	1.899****	2.328***	0.699	1.483**
	(0.427)	(0.551)	(0.430)	(0.505)	(0.504)	(0.670)
No. of Observations	73,204	67,621	29,803	27,956	19,261	16,862
Number of banks	6,096	5,628	4,312	4,402	3,223	2,821
AR(1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test, p-value	0.297	0.320	0.924	0.914	0.192	0.423
Hansen test, p-value	0.162	0.165	0.336	0.328	0.382	0.282
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of commercial and industrial nonperforming loans to total gross commercial and industrial loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

Table 3.8. GMM estimation results of consumer NPL.

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.316***	0.346****	0.232**	0.219**	0.380***	0.352***
	(0.086)	(0.095)	(0.107)	(0.108)	(0.121)	(0.132)
GDP_t	-0.013***	-0.014***	-0.001	-0.001	-0.017***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
IR_t	0.010**	0.010**	0.010	0.008	0.018**	0.019*
	(0.005)	(0.005)	(0.009)	(0.010)	(0.009)	(0.010)
U_t	0.019***	0.019***	0.021	0.029*	0.014	0.014
	(0.006)	(0.006)	(0.014)	(0.015)	(0.010)	(0.011)
HP_t	-0.001	-0.001	-0.001	0.002	-0.012*	-0.014**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)
$LC_{i,t-1}$	0.217**	0.216**	0.667***	0.792***	0.747***	0.934***
	(0.090)	(0.100)	(0.213)	(0.232)	(0.241)	(0.276)
$LA_{i,t-1}$	0.003***	0.003***	0.001	0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$INE_{i,t-1}$	-0.070	-0.099	-0.140	-0.240	0.073	-0.003
	(0.065)	(0.067)	(0.173)	(0.184)	(0.133)	(0.130)
$SIZE_{i,t-1}$	-0.051***	-0.063***	-0.162***	-0.207***	-0.080***	-0.132***
	(0.011)	(0.015)	(0.028)	(0.036)	(0.026)	(0.039)
$CR_{i,t-1}$	-0.001	-0.003	0.020**	0.010**	0.009	0.003
	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)	(0.006)
$NIM_{i,t-1}$	0.001	-0.004	0.010	0.008	0.025	0.019
	(0.010)	(0.011)	(0.016)	(0.017)	(0.024)	(0.025)
Constant	0.696***	0.847***	2.215***	2.683***	1.005***	1.682***
	(0.167)	(0.209)	(0.494)	(0.578)	(0.330)	(0.431)
No. of Observations	77,095	71,631	36,809	34,807	20,347	18,184
Number of banks	6,434	5,973	45,330	5,036	3,404	3,042
AR(1) test, p-value	0.000	0.000	0.001	0.002	0.000	0.001
AR(2) test, p-value	0.225	0.127	0.127	0.143	0. 992	0.929
Hansen test, p-value	0.297	0.265	0.159	0.239	0.214	0.266
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of consumer nonperforming loans to total gross consumer loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

The estimation results for commercial and industrial NPL (CINPL) are presented in Table 3.7. These results show that the determinants of CINPL are quite similar to those of RENPL. In general, CINPL is mainly driven by macroeconomic factors rather than bank-specific variables. All macroeconomic variables significantly affect the quality of commercial loan portfolios in both sub-sample periods, except house prices for which the estimated coefficients are insignificant during the first sample period. However, house prices significantly contributed to CINPLs in the second sub-period, perhaps due to spillover effects of falling house prices and deterioration of aggregate liquidity position in the financial system.

Among idiosyncratic factors, bank size appears to be significant and negative across all periods and when all banks are considered. This reflects economies of scale and better diversification opportunities in larger banks. Also, LA has a positive significant impact on CINPL across all periods for intrastate banks.

Estimation results for consumer NPL (CNPL) are presented in Table 3.8. As for the consumer NPL, the estimation results show that dynamics are rather different from other loan categories. The only bank-specific factor that consistently affects the quality of consumer loan portfolios is the banks size, which is negative and significant across all equations. This indicates that larger banks faced less CNPLs because they have more diversified credit portfolios and more scale efficiency.

As for systematic factors, the results indicate that all macroeconomic variables have asymmetric impact on CNPL over two sub-sample periods. While real interest rate is the only macroeconomic variable that significantly contributes to CNPLs in the first sample period, its impact become insignificant during crisis period and quality of consumer loans are significantly affected by other macroeconomic variables. More specifically, unexpected shocks arising from rising unemployment rate, falling house prices and adverse economic growth largely affected borrower's wealth in the second period. This implies that borrowers can no longer use their wealth as a buffer to service their debt (see, for example, Nkusu, 2011; Rinaldi and Sanchis-Arellano, 2006).

To summarise the results, comparing the estimation results of NPL in different loan categories, there is clear support for hypothesis two suggesting that different loan categories have different dynamics towards macroeconomic and bank-specific factors.

In general, there is empirical evidence that NPL dynamics of all loan categories are highly sensitive to adverse movements of house prices during the second period, with real estate loans being the most sensitive category to house price fluctuations. RENPL is also the most sensitive category to GDP growth, which can be considered as a general proxy for business cycle. These results clearly contradict the empirical findings of Louzis *et al.* (2012) that mortgage loans are the least sensitive category to macroeconomic developments.[21] Furthermore, RENPL is the most persistent category of NPL across all sample periods. Finally, sensitivity of NPL to various institutional factors varies among different loan categories, with RENPL being most sensitive to LC_{it} and LA_{it}, while CINPL and CNPL are highly responsive to bank size.

3.5.3. Organisational structure and aggregate NPL

We now extend our analysis to different types of depository institutions. In order to do so, we follow the FDIC charter type classification and split the depository institutions in our sample into commercial and savings institutions. The two types of institutions are functionally similar as they both accept deposits and issue loans. However, savings institutions are traditionally community oriented organizations that specialize in mortgage lending, whereas commercial banks make various types of loans including commercial and industrial loans.[22]

The GMM estimation results for the commercial and savings institutions are presented in Tables 3.9 and 3.10, respectively. From Table 6 it emerges that the quality of loan portfolios of the commercial banks is highly sensitive to the house price movements. Notably, the estimated coefficients of HP_t are negative and statistically significant across all the periods. In addition, all other macroeconomic factors as well as some bank-specific factors, such as LC_{it}, LA_{it}, and $SIZE_{it}$, significantly contribute to the NPL in commercial banks.

[21] However, it should be noted that real estate loan category, in this paper, includes all type of loans backed by real estate.

[22] Federally chartered savings institutions are currently allowed to extend their nonmortgage lending up to 30% of their assets.

From Table 3.10, however, it appears that the NPL dynamics are rather in the savings institutions. Unlike commercial banks, savings institutions are less sensitive to the institutional factors. More specifically, none of the bank-specific variables has a remarkable impact on NPL in the savings institutions. However, the estimated coefficients of the lagged dependent variables are slightly higher in the savings institutions, suggesting that NPL are more persistent in savings institutions. As regards the systematic factors, it is found that the quality of loan portfolios of the savings institutions is significantly affected by the macroeconomic variables. In particular, the NPL dynamics in the savings institutions are highly sensitive to the business cycle (see also Salas and Saurina, 2002). The results also show that the impact of the macroeconomic factors on NPL is stronger in the second period, which is consistent with the findings of Marcucci and Quagliariello (2009).

As in the case of commercial banks, the estimated coefficients of HP_t are negative and statistically significant in all the equations when savings institutions are considered. However, compared to the commercial banks, the impact of HP_t on the NPL in the savings institutions is higher during the first period and lower in the second period. This indicates that commercial banks are more sensitive to house price developments in downturns. One possible explanation is that, like savings institutions, commercial banks become heavily exposed to the housing markets during a booming period. However, commercial banks do not specialize in mortgage lending and may invest in riskier real estate loans. Accordingly, commercial banks may suffer from higher loan losses when house prices drop. The results in Table 3.10 also show that the impact of house prices on the NPL is stronger during the second period for both types of banks, which lends support to the findings of Pan and Wang (2013), who show that the impact of house price fluctuations on credit risk is stronger when the growth of personal income falls below a certain threshold level.

In light of these results, we conclude that house price fluctuations significantly affect the quality of loan portfolios across the two types of institutions, while the magnitude of the impact varies across commercial and savings institutions during different macroeconomic conditions. These results represent evidence in favour of hypothesis 3.

Table 3.9. GMM estimation results of NPL for commercial banks.

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.683***	0.666***	0.663***	0.661***	0.696***	0.696***
	(0.023)	(0.023)	(0.079)	(0.080)	(0.025)	(0.024)
GDP_t	-0.039***	-0.035***	-0.020***	-0.021***	-0.043***	-0.039***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
IR_t	0.036***	0.035***	0.034***	0.034***	0.068***	0.065***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)
U_t	0.096***	0.099***	0.034***	0.036***	0.071***	0.071***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
HP_t	-0.052***	-0.053***	-0.008***	-0.008***	-0.069***	-0.069***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
$LC_{i,t-1}$	0.727***	0.690***	-0.228***	-0.209***	1.139***	1.092***
	(0.071)	(0.076)	(0.054)	(0.060)	(0.142)	(0.156)
$LA_{i,t-1}$	0.009***	0.008***	0.004***	0.004***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$INE_{i,t-1}$	0.012	0.009	-1.172***	-0.180***	-0.017	-0.006
	(0.024)	(0.025)	(0.044)	(0.044)	(0.081)	(0.089)
$SIZE_{i,t-1}$	0.031***	0.030***	-0.040***	-0.048***	0.040***	0.026*
	(0.007)	(0.008)	(0.012)	(0.015)	(0.013)	(0.015)
$CR_{i,t-1}$	-0.001	-0.001	0.004**	0.004**	0.004	0.006
	(0.002)	(0.003)	(0.002)	(0.002)	(0.007)	(0.007)
$NIM_{i,t-1}$	0.008	0.009	0.037***	0.037***	-0.018	-0.011
	(0.008)	(0.009)	(0.009)	(0.009)	(0.016)	(0.016)
Constant	-1.294***	-1.276***	0.422***	0.492***	-1.688***	-1.547***
	(0.099)	(0.106)	(0.205)	(0.235)	(0.214)	(0.229)
No. of Observations	82,427	77,6663	42,5348	40,800	30,447	28,040
Number of banks	7,056	6,652	6,173	5,919	5,101	4,698
AR(1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test, p-value	0.239	0.430	0.171	0.175	0.997	0.948
Hansen test, p-value	0.179	0.201	0.165	0.169	0.159	0.288
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of nonperforming loans to total gross loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

Table 3.10. GMM estimation results of NPL for savings banks

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.695***	0.712***	0.718***	0.708***	0.767***	0.763***
	(0.044)	(0.045)	(0.100)	(0.099)	(0.039)	(0.060)
GDP_t	-0.038***	-0.044***	-0.016**	-0.014*	-0.047***	-0.042***
	(0.009)	(0.011)	(0.007)	(0.008)	(0.011)	(0.012)
IR_t	0.043***	0.038***	0.028*	0.028	0.067***	0.067***
	(0.011)	(0.012)	(0.016)	(0.017)	(0.019)	(0.021)
U_t	0.136****	0.112***	0.037**	0.044**	0.085***	0.087***
	(0.021)	(0.021)	(0.017)	(0.019)	(0.019)	(0.028)
HP_t	-0.049***	-0.048***	-0.015**	-0.015***	-0.059***	-0.061***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.012)	(0.013)
$LC_{i,t-1}$	0.313*	0.494**	0.170*	-0.191*	0.412	0.664*
	(0.172)	(0.201)	(0.087)	(0.099)	(0.265)	(0.341)
$LA_{i,t-1}$	0.003*	0.002**	0.001	0.001	0.004	0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
$INE_{i,t-1}$	0.129	-0.038	0.017	0.027	0.262	-0.478
	(0.162)	(0.134)	(0.030)	(0.039)	(0.514)	(0.405)
$SIZE_{i,t-1}$	0.045**	0.031	-0.021*	-0.026*	0.092*	0.024
	(0.022)	(0.025)	(0.012)	(0.015)	(0.048)	(0.043)
$CR_{i,t-1}$	-0.014*	-0.017*	-0.003	-0.004	-0.004	-0.008
	(0.008)	(0.009)	(0.003)	(0.003)	(0.011)	(0.014)
$NIM_{i,t-1}$	0.158***	0.172***	0.066*	0.080*	0.284***	0.207*
	(0.064)	(0.069)	(0.038)	(0.043)	(0.108)	(0.108)
Constant	-1.618***	-1.437***	-0.107	-0.111	-3.021**	-1.444
	(0.481)	(0.486)	(0.262)	(0.299)	(0.1.288)	(1.098)
No. of Observations	15,471	13,831	8,023	7,364	5,836	5,103
Number of banks	1,311	1,169	1,164	1,067	980	856
AR(1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test, p-value	0.578	0.551	0.187	0.121	0.492	0.345
Hansen test, p-value	0.231	0.255	0.134	0.171	0.249	0.345
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of nonperforming loans to total gross loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

3.5.4. NPL determinants in large and small banks

Hypothesis four in Section 3.2 is tested by investigating the impact of house price fluctuations on large and small banks. Following the FDIC and Federal Reserve guidelines, small banks are defined as those with average total assets of less than $500 million during the sample period. This study only divides the sample into large and small banks to ensure that there is reasonable number of banks in each category. Tables 3.11 and 3.12 present the estimation results for large banks and small banks, respectively.

In general, the system GMM estimation results for small banks are very similar to those of all sample banks, indicating that the results in Table 3.5 are mainly driven by small banks. This is because the sample under consideration includes a relatively large number of small banks compared to large banks. As for the systematic factors, the results show that all macroeconomic variables significantly contribute to the evolution of NPL across small banks and over all sample periods. Also, the impact of macroeconomic variables is more pronounced during the second sub-sample period.

As for bank-specific variables, LA_{it} and NIM_{it} have positive and significant impact on NPL of small banks across all estimated models. The coefficients on LC_{it} and $SIZE_{it}$ are also significant across all sample periods, but they obtain different signs in the two sub-sample periods. They enter into equations with negative sign during the first sub-sample period and with a positive sign in the second sub-sample periods.

The estimation results in Table 3.12, however, show that determinants of NPL are rather similar in large and small banks, with a few notable exceptions. Specifically, the impact of falling house prices on NPL is more pronounced in large banks. This can be attributed to reliance on 'too-big-to-fail' guarantees creating excessive moral hazard as well as higher agency costs in large bank. Eventually, higher credit risk accumulation during economic expansion results in higher NPL when house prices drop. On the other hand, small banks suffer less from falling house prices, while they benefit more from rising house prices. One possible explanation is that small banks have limited access to external funding and might have greater incentives to efficiently monitor the riskiness of their portfolios. This in turn may prevent excessive accumulation of credit risk during booming period. Another striking finding is that large banks are more sensitive to

Table 3.11. GMM estimation results of NPL for banks with total assets of less than $500 million.

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.772***	0.682***	0.457***	0.457***	0.703***	0.703***
	(0.017)	(0.028)	(0.057)	(0.058)	(0.025)	(0.025)
GDP_t	-0.037***	-0.033***	-0.017***	-0.017***	-0.037***	-0.037***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
IR_t	0.035***	0.033***	0.016**	0.015*	0.057***	0.055***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.009)	(0.009)
U_t	0.064***	0.086***	0.036***	0.036***	0.075***	0.075***
	(0.007)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
HP_t	-0.048***	-0.052***	-0.011***	-0.011***	-0.065***	-0.064***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
$LC_{i,t-1}$	0.348***	0.394***	-0.361***	-0.357***	0.783***	0.759***
	(0.060)	(0.064)	(0.062)	(0.063)	(0.136)	(0.142)
$LA_{i,t-1}$	0.008***	0.008***	0.002**	0.002**	0.010***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$INE_{i,t-1}$	0.004	0.013	-0.006	-0.006	-0.006	0.012
	(0.012)	(0.014)	(0.005)	(0.005)	(0.041)	(0.059)
$SIZE_{i,t-1}$	0.060***	0.048***	-0.071***	-0.074***	0.070***	0.059***
	(0.009)	(0.011)	(0.018)	(0.018)	(0.020)	(0.017)
$CR_{i,t-1}$	0.001	0.003	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
$NIM_{i,t-1}$	0.034***	0.034***	0.052***	0.053***	0.035*	0.036*
	(0.009)	(0.009)	(0.015)	(0.015)	(0.019)	(0.019)
Constant	-1.453***	-1.394***	1.105***	1.137***	-1.981***	-1.843***
	(0.119)	(0.139)	(0.299)	(0.305)	(0.251)	(0.253)
No. of Observations	70,483	68,482	27,239	26,849	28,614	27,335
Number of banks	5,762	5,594	4,698	4,630	4,823	4,605
AR(1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test, p-value	0.813	0.731	0.908	0.908	0.353	0.344
Hansen test, p-value	0.209	0.210	0.223	0.220	0.263	0.280
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of nonperforming loans to total gross loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

Table 3.12. GMM estimation results of NPL for banks with total assets of more than $500 million.

	I	II	III	IV	V	VI
	1999-2012		1999-2005		2006-2012	
	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$NPL_{i,t-1}$	0.547***	0.527***	0.687***	0.714***	0.644***	0.742***
	(0.057)	(0.059)	(0.129)	(0.143)	(0.069)	(0.047)
GDP_t	-0.062***	-0.058***	-0.023***	-0.024***	-0.078***	-0.073***
	(0.010)	(0.010)	(0.007)	(0.008)	(0.015)	(0.017)
IR_t	0.049***	0.051***	0.045***	0.050***	0.114***	0.112***
	(0.014)	(0.016)	(0.011)	(0.013)	(0.020)	(0.022)
U_t	0.192***	0.190***	0.035**	0.042**	0.128***	0.073***
	(0.027)	(0.030)	(0.015)	(0.018)	(0.036)	(0.028)
HP_t	-0.057***	-0.060***	-0.008**	-0.009**	-0.083***	-0.084***
	(0.005)	(0.005)	(0.003)	(0.004)	(0.013)	(0.014)
$LC_{i,t-1}$	1.019***	1.036***	0.032	0.039	1.069***	0.713**
	(0.159)	(0.178)	(0.064)	(0.065)	(0.283)	(0.288)
$LA_{i,t-1}$	0.010***	0.009***	0.002	0.001	0.015***	0.008**
	(0.002)	(0.002)	(0.001)	(0.002)	(0.005)	(0.004)
$INE_{i,t-1}$	0.117*	0.156**	-0.003	-0.001	0.168**	-0.081
	(0.070)	(0.077)	(0.048)	(0.055)	(0.071)	(0.217)
$SIZE_{i,t-1}$	0.061***	0.077***	0.021***	0.040***	0.064	-0.069
	(0.020)	(0.027)	(0.008)	(0.014)	(0.053)	(0.049)
$CR_{i,t-1}$	0.001	-0.007	0.003	0.001	0.025	0.022
	(0.012)	(0.007)	(0.002)	(0.002)	(0.030)	(0.032)
$NIM_{i,t-1}$	-0.008	-0.003	0.017	0.017	-0.058**	-0.044**
	(0.018)	(0.018)	(0.020)	(0.021)	(0.028)	(0.021)
Constant	-2.491***	-2.603***	-0.540***	-0.807***	-3.036***	-0.204
	(0.380)	(0.454)	(0.201)	(0.287)	(0.936)	(0.815)
No. of Observations	11,176	8,374	4,137	3,403	4,186	2,866
Number of banks	967	700	705	580	716	489
AR(1) test, p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) test, p-value	0.946	0.702	0.941	0.925	0.492	0.898
Hansen test, p-value	0.102	0.0966	0.127	0.141	0.137	0.0901
Wald test, p-value	0.000	0.000	0.000	0.000	0.000	0.000

The dependent variable is the ratio of nonperforming loans to total gross loans. All banks are considered in models (I), (III), and (VI), while interstate banks are excluded in models (II), (IV), and (VI). All models are estimated using the dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's finite sample correction. Huber-White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

business cycles as indicated by GDP. This finding has important regulatory implications as the failure of a large bank can have severe impact on the banking system and the economy.

As for idiosyncratic factors, the empirical results for large banks reveal that all bank-specific variables are insignificant during the first sample period, with the exception of $SIZE_{it}$ that takes a positive sign. This indicates that NPL in large banks is mostly driven by macroeconomic conditions and larger banks face higher NPL. This is also consistent with positive linkage between bank size and risk taking found in De Nicoló (2000) and Tabak *et al.* (2011). However, some idiosyncratic factors such as LC_{it}, LA_{it}, and NIM_{it} significantly affect NPL in the second sub-period. Furthermore, NPL appears to be highly persistence in large banks over both sample periods, while the estimated coefficients on lagged NPL take high value only in the second sub-sample period for small banks.

To summarize, the empirical findings strongly support hypothesis four which postulates that falling house price have greater impact on the quality of loan portfolios in large banks, compared to small banks. In addition, large banks are more responsive to business cycles and are less sensitive to idiosyncratic factors during economic expansion.

3.6. CONCLUSIONS

The collapse of house price bubble in the US triggered the recent financial crisis. The US banking institutions suffered heavily from falling house prices, while they had a marked contribution to the creation of house price bubble through their lending behaviour in pre-crisis period. Using a large panel of the insured banking institutions in the US, this chapter applies dynamic panel models to investigate the linkage between house price fluctuations and evolution of nonperforming loans over three periods. Furthermore, in order to account for banking deregulation in the US, the analysis is carried out on all banks as well as intrastate banks.

Overall, the empirical results suggest that nonperforming loans across US banks can be explained by a mixture of idiosyncratic and systematic factors used in this study. With respect to hypothesis one, a strong negative linkage between house price fluctuations and NPL is detected i.e. falling house prices are tightly linked to rising NPL levels. In addition, the linkage between house prices and credit risk is asymmetric, meaning that the impact of house price fluctuations on NPL is stronger during crisis period.

With respect to hypothesis two, strong evidence that the impact of house price fluctuations widely vary across different loan categories is found, with real estate loans being the most responsive loan category. Moreover, real estate NPLs as well as commercial and industrial NPLs are very sensitive to business cycle indicators, such as GDP growth and unemployment rate. Also, sensitivity of NPL to various institutional factors vary among different loan categories, with real estate NPL being most sensitive to loan portfolio concentration while commercial NPL and consumer NPL being most responsive to bank size.

The test of Hypothesis 3 reveals that different types of depository institutions react differently to the housing prices. In particular, our results show that commercial banks are more sensitive to the house price movements during downturns. However, this finding can be challenged by the fact that I have different number of savings and commercial banks in this analysis. Moreover, it is found that bank-specific determinants of NPL vary across commercial and savings institutions and over different economic conditions. As for the fourth hypothesis, strong evidence is found that falling house prices have greater impact on the evolution of NPL in large banks during crisis period. In addition, large banks are more sensitive to business cycle fluctuations.

These findings have several important implications for regulators and policymakers. They underline the need for closely monitoring the exposure of each bank to house price fluctuations. This indicates that house price fluctuations can be considered as an important macroeconomic indicator to assess financial stability. Also, it is of crucial importance to control and monitor the aggregate lending level in the housing markets in different regions to ensure smooth flow of house prices and to avoid creation of severe macroeconomic imbalances such as housing bubble. As regards the loan categories, different regulatory frameworks have to be designed for assessing the credit risk exposure of different types of loans. Finally, regulators have to carefully monitor the exposure of large banks to housing markets as falling house prices triggers a sharp increase in their NPL, which can eventually destabilise the whole banking system.

APPENDIX A3

Table A3.1. Variable definitions

Variable	Definition
NPL_{it}	(Loans that are past due more than 90 days and still accruing interest plus nonaccrual loans that are no longer accruing interest)/total gross loans
$RENPL_{it}$	Nonperforming real estate loans/total real estate loans
$CINPL_{it}$	Nonperforming commercial and industrial loans/total commercial and industrial loans.
$CNPL_{it}$	Nonperforming consumer loans/total consumer loans
LC_{it}	The Herfindahl–Hirschman index (HHI) of loan portfolio composition in each bank. We define three major categories of loans; real estate loans, commercial loans, and consumer loans. If PL_{jt} represents the portfolio shares of each loan category, then $HHI_{jt} = \sum_{n=1}^{3}(PL_{jt})_n^2$ is defined as the HHI of bank *j* at time *t*.
LA_{it}	Total gross loan/ total assets
CR_{it}	Total capital equity/total assets
INE_{it}	The ratio of non-interest expenses to the sum of interest and non-interest income. Net interest expenses don't include the amortization expenses of intangible assets.
NIM_{it}	Net interest income (total interest income minus total interest expenses)/average earning assets Net interest expenses don't include the amortization expenses of intangible assets.
$SIZE_{it}$	log of total assets
GDP_t	The state-level Gross Domestic Product (GDP) adjusted for the inflation according to national prices for the goods and services produced within the state.
IR_t	The lending interest rate adjusted for inflation measured by the consumer price index.
U_t	The percentage of labour force without work but available to work and actively seeking employment.
HP_t	The growth rate of house price index adjusted for inflation as measured by the national level consumer price index. The house price index is estimated using sales price and appraisal data.

CHAPTER FOUR

CAPITAL INFUSIONS AND STABILITY OF RECIPIENT BANKS

4.1. INTRODUCTION

In the wake of Lehman Brothers' bankruptcy, the U.S. financial system experienced an unprecedented liquidity shock due to widespread panic and lack of confidence among investors and financial institutions. As a response, the U.S. Congress passed the Emergency Economic Stabilization Act (EESA) of 2008 and authorised the Department of the Treasury to establish the Troubled Asset Relief Program (TARP) and to disburse up to $700 billion to bailout the US financial system. Under TARP, the Department of the Treasury created the Capital Purchase Program (CPP) to stabilise the banking system by injecting capital into viable banks. Over the course of this program, 707 banking institutions of all sizes in 48 states received capital assistance.

TARP, as the largest ever government intervention in the US financial sector, has intensified a vigorous debate concerning the effectiveness of capital injection programs as reliable instruments to restore banking stability during periods of financial distress. Providing capital assistance to viable banks during financial crisis was politically justified as an essential strategy to rescue the U.S. financial system from imminent collapse. In this context, TARP funds were intended (*i*) to restores confidence in the banking industry by keeping large institutions facing temporary liquidity problems afloat, (*ii*) to stimulate healthy recipients to promote lending activities, and through that, resolving the 'loan freeze problem' and restarting the economy.

Nevertheless, many pundits and researchers have raised serious concerns regarding the implementation of TARP which may largely distort the program from serving taxpayers in the manner it was intended. First, it is argued that governmental assistance distorts banking competition and induces increased risk-taking incentives for non-recipient banks, thereby destabilising the banking system (see Hakenes and Schnabel, 2010; Gropp *et al.*, 2011;, among others). On the other hand, capital infusions may undermine financial stability of recipient banks due to lack of transparency in the selection of qualifying institutions and insufficient monitoring of a recipient bank's investment strategy ex post. As a consequence, government protection may create moral hazard incentives on the part of supported banks, resulting in excessive risk-taking and instability (see, e.g., Farruggio *et al.*, 2013; Elyasiani *et al.*, 2014; Black and Hazelwood, 2013). In addition, many recipient banks used TARP funds for purposes other than promoting lending activities which was the primary objective of TARP to restore credit flow in the economy.

Furthermore, a comprehensive assessment of TARP reveals that a considerable number of TARP recipients have faced significant distressing experiences, such as failure or missing their TARP dividend payments. This gives rise to following questions: does capital infusion enhance stability of recipient banks? Are recipients of governmental capital assistance attractive acquisition targets? Does size of a bailout recipient affect its survival likelihood? This study attempts to provide answer to these questions by empirically investigating the impact of capital infusions on financial stability of TARP recipients. With this target in mind, the Cox proportional hazard model with time varying covariates is estimated. This model allows to investigate if receiving capital assistance affects the likelihood of failure or acquisition of banks controlled by a TARP recipient's holding company.

The empirical results in this chapter reveal that capital infusions do not play a significant role in stabilising recipient banks, perhaps due to severe impediments in implementation of these programs. Providing capital assistance did not help recipient banks avoid technical insolvency even though larger institutions may avoid regulatory closure. Smaller recipients were also less likely to avoid regulatory closure. Furthermore, capital infusions significantly increased acquisition likelihood of recipients before repayment of TARP funds, disregarding their sizes and financial health. These findings have important policy implications and can help regulators and policymakers to provide better rescue strategies and supervisory practices in response to likewise crises in the future.

This study contributes to the existing literature in several ways. First, to the best of my knowledge, this is the first study that analyses the impact of governmental capital assistance on failure and acquisition of recipient banks. Most previous TARP studies can be classified in two strands: the first strand concentrates on financial health of TARP banks throughout the program (see Duchin and Sosyura, 2012; Bayazitova and Shivdasani. 2012; Wilson and Wu, 2012, among others), while the second strand of literature investigates stock price performance of CPP recipients in response to various TARP events (see, e.g., Veronesi and Zingales, 2010; Kim and Stock, 2012; Liu *et al.*, 2013; Farruggio *et al.*, 2013).

Second, most previous TARP studies analyse the performance of TARP recipients at bank holding level, while TARP studies at bank level are scarce. An important contribution is Li (2013) which investigates financial characteristics of CPP recipients as well as the stimulus effect of TARP funds on a recipient bank's loan supply. The present Chapter adds to the literature by investigating the impact of TARP funds on stability of banking institutions controlled by a TARP recipient. This is of paramount importance for providing better regulatory practices.

Finally, most recent studies, including Cole and White (2012) and Berger and Bouwman (2013), have examined various factors affecting bank failures during the recent financial crisis, while far less is known about the financial characteristics of acquired banks. This chapter contributes to existing literature by documenting financial determinants of the U.S. banks takeover during the recent financial crisis.

The remainder of this chapter is organised as follows. In Section 4.2, a brief introduction to TARP is provided and relevant empirical hypotheses are presented. Section 4.3 describes data and sources, econometric model and variables employed in this study. Empirical results are discussed in Section 4. 4. Finally, Section 4.5 concludes and makes some suggestions regarding policy implications.

4.2. EMPIRICAL HYPOTHESES

This Section provides a brief introduction to TARP and posits the empirical hypotheses.

4.2.1 Troubled Asset Relief Program

The U.S. financial system experienced a severe liquidity crisis in September 2008 when a series of distressing events occurred in various key industries. On September 7, 2008, the Federal Housing Finance Agency (FHFA) placed two major Government Sponsored Enterprises (GSE), Freddie Mac and Fannie Mae, into government conservatorship run by the FHFA in order to ensure financial soundness of these two troubled companies and stabilise the mortgage market. This was the most significant U.S. government intervention in private sector in decades.

A week later, the largest bankruptcy filing in the history of U.S. financial system occurred when the Lehman Brothers Holding Inc. filed for bankruptcy on September 15, 2008.[1] Consequently, many other financial institutions linked to the Lehman Brothers Holding Inc. incurred significant losses. For instance, the day after, the Reserve Primary Fund, one of the oldest and largest U.S. money market mutual funds, broke the buck due to writing off its debt securities issued by Lehman Brothers Holdings Inc. The failure of the Reserve Primary Fund triggered a run on many other money market mutual funds, which played a pivotal role in providing liquidity in the market place.[2]

The American International Group Inc. (AIG) was another major financial institution facing liquidity difficulties in the tumultuous month of September. The company suffered from significant losses on its investments on a wide range of financial instruments and dramatic decline in its stock price. Consequently, the AIG's credit

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[1] On the same day, Merrill Lynch & Co., an investment bank giant that was facing significant losses attributed to its exposure to Collateralised Debt Obligations (CDOs), was acquired by Bank of America.

[2] In response to rising anxiety in money market, the U.S. Department of the Treasury launched a temporary guarantee program on September 19, 2008. This program provides up $50 billion from the Exchange Stabilization Fund to guarantee to restore the net asset value (NAV) of a participating money market mutual fund to $1 in the event it breaks the buck.

rating was downgraded by various credit rating agencies, which obliged the company to post significant amount of additional collateral. Unable to meet mounting demands for additional collateral, the company experienced a severe liquidity crisis, which placed the AIG on the verge of collapse.[3]

With worsening financial conditions, many banks that were already struggling with their mortgage portfolios, started to experience dramatic deposit outflows. Among them was the Washington Mutual Bank (WaMu), the U.S. largest savings and loan association with total assets of over $300 million, which was declared insolvent by the Office of Thrift Supervision (OTS) and placed into receivership of the FDIC on September 25, 2008.[4] The failure of WaMu was the largest bank failure in the history of the U.S. banking system, which intensified the pressure on other banking institutions including large banks with 'too-big-to-fail' status.[5]

For the first time in generations, the whole financial system in the U.S. was on the verge of collapse due to a widespread panic and lack of trust among investors and financial institutions. It was out of these distressing conditions that a bipartisan majority of Congress passed and President Bush signed into law the Emergency Economic Stabilization Act (EESA) on October 3, 2008. The EESA authorised the Department of the Treasury to establish Troubled Asset Relief Program (TARP) to stem the panic, restore confidence in the financial markets, and restart economic growth.

Under the TARP, the Department of the Treasury was authorised to either purchase or insure up to $700 billion of troubled mortgage-related assets of financial institutions in order to clean up their balance sheets, enhance market liquidity and stabilise housing and financial markets. However, on October 14, the Department of the Treasury announced a revised version of the original TARP plan and launched Capital

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[3] In an attempt to avoid the disastrous repercussions of AIG collapse, the Federal Reserve Board authorised the Federal Reserve Bank of New York to provide an emergency loan of up to $85 billion to the company on September 16, 2008.

[4] On the same day, all assets, deposits, certain liabilities, and banking operations of WaMu were acquired by the JPMorgan Chase for a mere $1.9 billion and at no cost to the FDIC.

[5] For instance, the day after the seizure of WaMu, Wachovia, the fourth largest U.S. bank at that time, appeared to be on the verge of failure due to large deposit outflows and significant decline in its stock price. Eventually, the banking operations of Wachovia Corporation were acquired by Wells Fargo on October 3, 2008.

Purchase Program (CPP) as an initial program, which was later followed by several other programs under TARP.[6]

The CPP, as the largest program launched under the TARP, was designed to purchase up to $250 billion of preferred stock and equity warrants from viable financial institutions. Warrants are derivative securities that give the holder the right to purchase a stock at a specific exercise price until the expiration date. For each CPP investment in a publicly traded company, the Treasury received warrants to purchase shares of common stock equal to 15% of the senior preferred stock investment. These warrants are exercisable at any time over a ten year period and with exercise prices set at the 20-trading day trailing average stock price of a company as of the investment date.[7]

On October 28, 2008, the initial round of CPP investments, $115 billion, was allocated to eight giant banking institutions.[8] Over the course of the program, 707 financial institutions, in 48 states, received approximately $205 billion as CPP investments through December 29, 2009.[9] In return, the CPP participating banks were subject to certain requirements. The shares purchased by the Treasury under CPP have dividend rate of 5% per year for the first five years and 9% per year afterwards. Also, the Treasury established certain standards and rules applicable to executive compensation practices of CPP recipients, for so long as the Treasury owns their shares or warrants.

[6] In general, the TARP created 13 different programs which can be broken down into five major programs; namely Bank Investment Programs, Credit Market Programs, AIG Assistance Program, Automobile Industry Support, and Housing Programs.

[7] Upon the redemption of the senior preferred stock investment, an institution can either repurchase its warrants at the fair market value, or the Treasury would sell the warrants to third parties through public auction.

[8] The first recipients of the CPP investments were Bank of America Corp., Goldman Sachs Group Inc., JPMorgan Chase & Co., Wells Fargo & Co., Bank of New York Mellon Corp., Citigroup Inc., State Street Corp, and Morgan Stanley. To be eligible for TARP funds, Goldman Sachs Group and Morgan Stanley converted from investment banks to bank holding companies in September 2008.

[9] The treasury also purchased $20 billion in preferred stock from Bank of America Corp. and Citigroup Inc. However, since the CPP was notionally designed for viable institutions, this assistance came under a new program called under the Targeted Investment Program (TIP) which was designed to provide additional funds to stabilise institutions that were considered to be systematically significant.

Some CPP terms and conditions were amended on February 17, 2009, when President Obama signed into law the American Recovery and Reinvestment Act (ARRA). Among other changes, ARRA imposed more restrictions on the executive compensation practices of CPP recipients. Also, the enactment of ARRA eliminated the three year waiting period and allowed recipient banks to repay the CPP funds and exit the program, subject to consultation with the appropriate Federal banking agency.

TARP authority was amended by Dodd–Frank Wall Street Reform and Consumer Protection Act which reduced the authorized amount to $475 billion. The Treasury's authority to make investment under TARP expired on October 3, 2010, and since then the Treasury has been focusing on winding down remaining TARP investments. Of approximately $245 billion disbursed to banking institutions under Bank Support Programs, the Treasury has received total cash back of approximately $273 billion including net capital repayments, interest and dividends, and warrant proceeds, as of September 2013.

4.2.2. Development of empirical hypothesis

The largest ever government intervention in the US banking system has prompted researchers to evaluate the effectiveness of emergency capital injections on financial performance of recipient institutions. Yet, there is no consensus in the literature on how efficiently bank recapitalisation works. In general, stability of a TARP recipient is likely to be affected by three key factors: initial financial health, market perception towards TARP investment, and recipient's reinvestment strategies ex post.

Theoretically, it is argued that the effectiveness of equity capital infusions predominantly depends upon financial health of recipient banks ex ante. Diamond and Rajan (2005, 2011) point out that capital infusions to impaired banks with highly illiquid asset portfolios are not only of no use to help these banks survive and avoid under-priced fire sales but also may destroy their healthier counterparts. Empirical evidence by Bayazitova and Shivdasani (2012) indicates that, compared to non-recipients, TARP recipients tended to be larger, with less stable funding resources, weaker capital ratios, greater derivative exposures, and better performing loan portfolios. Furthermore, several studies point out the key role that political and regulatory connections played in distribution of TARP funds (see Duchin and Sosyura, 2012; Li, 2013). These studies suggest that some recipient banks were not healthy at all, while TARP was notionally designed for healthy and viable institutions. Accordingly, Cornett *et al.* (2013) account for heterogeneity in financial health of TARP recipients and show that performance of recipient banks greatly differs with respect to their pre-crisis health: healthier and larger banks are significantly more likely to repay their TARP funds and less likely to miss their dividend payments.

Another important factor that affects the stability of recipient banks is market perception and sentiment towards recipients, which can greatly affect their stock price performance as well as their access to external funding and liquidity. Indeed, the existing literature provides two divergent views on the relationship between receiving bailout funds and stability of recipient banks in the short-run. On the one hand, some authors support 'bailout-stability' view and argue that capital assistance enhances stability of recipient banks in the short-run by improving their capital and liquidity position during adverse financial conditions (see Mehran and Thakor, 2011; Bayazitova and Shivdasani, 2012). Furthermore, capital infusions may be considered as a positive signal about financial health of bailout recipients, particularly considering that TARP funds were designed for viable banks only. Also, investors may assume that TARP recipients are under government's protection and will be bailed out again by the government, in case of future distress (see Duchin and Sosyura, 2014).

By contrast, advocates of 'bailout-fragility' view argue that capital infusions may serve as a distress signal about financial health of a recipient bank. Hoshi and Kashyap (2010) argue that applying for government funds may reduce the value of a bank's existing equity by indicating that the bank is either unable to raise external funds elsewhere or its potential future loss is likely to be higher than the previously disclosed amount. Furthermore, capital infusions may induce debt overhang problem as government securities have priority over common shares in terms of claim on earnings and dividend payments. This can further undermine the current market value of a recipient's existing equity. In general, previous studies have provided conflicting empirical evidence on how investors reacted to capital injections; Elyasiani *et al.* (2014) reveal that investors reacted positively to TARP injections, while others, including

Farruggio *et al.* (2013) and Fratianni and Marchionne (2013), find a significantly negative market response to capital infusions.

The impact of capital infusions on long-run stability of a recipient bank mainly depends upon the bank's risk-taking behaviour and reinvestment strategy ex post. On the one hand, increased capitalisation of supported banks may reduce their risk-taking incentives, which, in turn, enhances their likelihood of survival and long-run stability (Duchin and Sosyura, 2014). Equally important, liquid capital infusions when financial markets are highly illiquid distorts market conditions and gives bailout recipients the advantage to better seize profitable investment opportunities at deep discounts. Thus, skilful managers can use this cheap source of financing to reduce the bank's risk level via diversification of asset portfolios, thereby promoting the bank stability (Farruggio *et al.*, 2013).

On the other hand, advocates of 'bailout-fragility' view argue that bailout recipients may be more fragile in the long run. In particular, capital injections may induce higher risk-taking by a protected bank due to increasing moral hazard incentives on the part of the bank's managers (see, e.g., Dam and Koetter, 2012; Duchin and Sosyura, 2014). Moreover, one of the primary purposes of TARP was to promote lending activities through TARP recipients. Lending cash liquid to risky borrowers during a period of financial distress can largely deteriorate the quality of loan portfolios in protected banks (Black and Hazelwood, 2013; Elyasiani, 2014).

Building up on the existing literature, the empirical hypotheses about the impact of governmental capital assistance on bank stability are formulated as follows.

Hypothesis 1: *Although government bailout is not effective in preventing recipient banks from technical insolvency, larger recipients may avoid regulatory closure.*

Several reasons can be provided for this hypothesis. First, in the presence of political and regulatory connections, some unhealthy and highly illiquid banks may receive government funds. This, in turn, may question and stigmatise financial health of other recipients, and hence limit their access to external financing, reduce their share prices, and trigger deposit outflows. Furthermore, having no clear guidance and restrictions as to how the government funds should be used may generate ex ante moral hazard incentives on the part of bank managers, particularly if participating in bailout program restricts managers' compensation. More importantly, when facing financial distress, larger banks are more likely to avoid regulatory closure due to better political and regulatory connections as well as having 'too-big-too-fail' status, which ease their access to liquidity and external funding.

Hypothesis 2: *Bailout recipients are attractive acquisition targets, regardless of their size and financial health, particularly before the repayment of the bailout funds.*

There are three main reasons why the bailout recipients are more likely to be acquired before capital repayments. Over time, many TARP recipients struggled with (*i*) public stigma and pressure attached to the TARP investment, (*ii*) reduced share prices due to market uncertainty and stigma, (*iii*) potential debt overhang problems, and (*iv*) various restrictions on executive compensations. This may incentivise managers of recipient banks to trade some of their subsidiaries to repay government funds and exit TARP. Furthermore, some recipients that used TARP money to acquire other banks with great bargains during liquidity crisis may sell their less efficient subsidiaries to other banking institutions. Finally, recipients that are expected to face imminent failures may be acquired by other banks under regulatory pressures as well as possibilities of renegotiating TARP terms for acquiring institutions.

4.3. ECONOMETRIC METHODOLOGY

The literature of bank failure features logistic models (logit) and hazard models as two widely used empirical approaches to investigate and predict bank failures. Logit models are used to identify various risk fundamentals affecting the probability of bank failures in cross-sectional data and over a specific year (see, for instance, Kolari *et al.,* 2002; Cole and White, 2012). The main shortcoming of logit models in modelling bank failures is that they are static models and do not adjust for time, while the risk of failure may change over time, particularly when the sampling period is long.[10]

One way to address this issue is to apply hazard models. Hazard models are widely employed to analyse time to failure, that is the time it takes for a bank to fail or become distressed (see, for instance, Calomiris and Mason, 2003; Mannasoo and Mayes, 2009). Shumway (2001) shows that apart from their advantages in accounting for time and time varying covariates, hazard models also outperform single-period logit models in out of sample prediction of bankruptcy.

Following Wheelock and Wilson (2000), Hannan and Pilloff (2009), and Goddard *et al.* (2014), the Cox (1972) proportional hazard model with time varying covariates is applied in this study to investigate the impact of various risk fundamentals including TARP indicators on the timing of closures, technical failures and acquisitions of U.S. commercial banks during the recent financial crisis. In this Section, the Cox proportional hazard model in the competing risks framework is briefly reviewed.[11]

Let T_i represent the exit time of bank i, meaning that bank i is observed at J_i distinct quarters $t_{i1} < t_{i2} < \cdots < t_{iJ_i} < T_i$ under the risk of disappearance. As T_i is a random variable, it has a cumulative distribution function, $P_i(t) = \Pr(T_i \leq t)$, and a probability density function, $p_i(t) = dP_i(t)/dt$. The cumulative density function gives us probability of $T_i \leq t$ which indicates the probability of the *i*-th bank exiting before some specified time, t. A more relevant definition in survival analysis is the survivor function, which is the complement of cumulative distribution function and can be defined as

$$S_i(t) = \Pr(T_i > t) = 1 - P_i(t). \tag{4.1}$$

[10] Panel logit models have been used in a number of studies to cover a period of banking failures (see, e.g., Poghosyan and Čihak, 2011; Gonzalez-Hermosillo, 1999). However, they are not as popular as cross sectional logit in this line of literature, particularly when number of failed banks is relatively small. An alternative approach in this case is to apply discrete time hazard models that are based on logistic models and can account for heterogeneity in panel data (see, for instance, Mannasoo and Mayes, 2009; Shumway, 2001).

[11] Interested readers can refer to Kalbfleisch and Prentice (2011) for a more extensive discussion.

The object of primary interest in survival analysis is to estimate the hazard function, which is defined as the instantaneous risk of a bank disappearing at time *t* conditional upon its existence up to time *t*. This Chapter distinguishes between two types of bank exit: exit due to failure and exit due to acquisition. Accordingly, the hazard function for each type of bank exit can be specified as

$$h_l(t) = \lim_{dt \to 0} \frac{\Pr(t \leq T_i < t + dt, L = l | T_i \geq t)}{dt} = \frac{p_{l,i}(t)}{S_{l,i}(t)}, \qquad (4.2)$$

where $l=1$ denotes failure and $l=2$ denotes acquisition. According to the Cox hazard model, the hazard function for type *l* exit takes the following form

$$h_{l,i}\left(t \middle| \boldsymbol{x_{l,i}(t)}\right) = h_{lo}(t) \exp\left(\boldsymbol{x_{l,i}(t)\beta_l}\right), \qquad (4.3)$$

where $h_{lo}(t)$ is an unspecified baseline hazard function, $\boldsymbol{x_{l,i}(t)}$ is a $1 \times k$ vector of time varying covariates, and $\boldsymbol{\beta_l}$ is a $k \times 1$ vector of coefficients to be estimated. The Cox model is a semi-parametric model as it includes a parametric part, $\exp(\boldsymbol{x_{l,i}(t)\beta_l})$, as well as a nonparametric part, which is the unspecified baseline hazard function, $h_{lo}(t)$. The baseline hazard function only varies over time and is assumed to be the same for all banks at time *t*, indicating that the Cox model is a proportional hazard model, and the relative hazard of two banks at time t can be expressed as[12]

$$\frac{h_{lo}(t)\exp(\boldsymbol{x_{l,j}(t)\beta_l})}{h_{lo}(t)\exp(\boldsymbol{x_{l,m}(t)\beta_l})} = \frac{\exp(\boldsymbol{x_{l,j}(t)\beta_l})}{\exp(\boldsymbol{x_{l,m}(t)\beta_l})}. \qquad (4.4)$$

The Cox model can be estimated by maximising the partial likelihood function. Let T_j be the exit time and *d* be the number of distinct observed exit times. The Cox likelihood function can be defined as

[12] Although the Cox proportional hazard model accounts for individual heterogeneity among banks exiting at different times, it does not capture unobserved heterogeneity among banks. However, Mannasoo and Mayes (2009) argue that such unobserved heterogeneity can be neglected perhaps due to major commonalities among banking institutions in terms of banking activities and regulations.

$$L(\boldsymbol{\beta_l}) = L_1(\boldsymbol{\beta_l})L_2(\boldsymbol{\beta_l}) \dots L_d(\boldsymbol{\beta_l}) = \prod_{j=1}^{d} \frac{\exp\big(\boldsymbol{x_{l,j}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)}{\sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)}. \tag{4.5}$$

where L_j represents the conditional probability of bank exit at time T_j, and R_j is the set of banks that are at risk of exit due to event l at time T_j. Thus, the corresponding log likelihood function is given by

$$l(\boldsymbol{\beta_l}) = \sum_{j=1}^{d} l_j(\boldsymbol{\beta_l}) = \sum_{j=1}^{d} \left[\boldsymbol{x_{l,j}}(\boldsymbol{t_j})\boldsymbol{\beta_l} - \log\left(\sum\nolimits_{i\in R_j} exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)\right)\right]. \tag{4.6}$$

The above log likelihood function is a partial log likelihood function as it is confined to d distinct exit times and does not consider times when there is no exit. Nonetheless, it can be treated as an ordinary log likelihood and the estimate of $\boldsymbol{\beta_l}$ can be obtained by maximising the partial log likelihood function. In other words, $\widehat{\boldsymbol{\beta}}_{\boldsymbol{l}}$ is the unique solution of the following equation

$$\frac{\partial l(\boldsymbol{\beta_l})}{\partial \boldsymbol{\beta_l}} = \sum_{j=1}^{d} \left[\boldsymbol{x_{l,j}}(\boldsymbol{T_j}) - \frac{\sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)\boldsymbol{x_{l,i}}(\boldsymbol{T_j})}{\sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)}\right] = 0. \tag{4.7}$$

The resulting $\widehat{\boldsymbol{\beta}}_{\boldsymbol{l}}$ is consistent and asymptotically normal with mean $\boldsymbol{\beta_l}$ and variance-covariance matrix equal to the matrix of the second derivatives of the Cox log partial likelihood function with respect to $\boldsymbol{\beta_l}$.

$$\begin{aligned} &\frac{\partial^2 l(\boldsymbol{\beta_l})}{\partial \boldsymbol{\beta_l}^2} \\ &= -\sum_{j=1}^{d} \left(\frac{\sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{x'_{l,j}}(\boldsymbol{T_j})}{\sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)}\right. \\ &\left. - \frac{\sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)\boldsymbol{x_{l,i}} \times \sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)\boldsymbol{x'_{l,j}}(\boldsymbol{T_j})}{\left[\sum_{i\in R_j} \exp\big(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\big)\right]^2}\right). \end{aligned} \tag{4.8}$$

Once the coefficients are estimated, the baseline hazard and its corresponding survivor function can be obtained. It should be noted that the abovementioned estimation method is based on the assumption that bank exits are not tied, which is often violated. To handle tied exits, Breslow (1974) develops an approximation of the Cox partial likelihood function which takes the following form

$$L(\boldsymbol{\beta_l}) = \prod_{j=1}^{d} \frac{\exp(\boldsymbol{x_{l,j}}(\boldsymbol{T_j})\boldsymbol{\beta_l})}{\sum_{i \in R_j} \exp(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l})} \approx \prod_{j=1}^{d} \frac{\exp(\sum_{i \in D_j} \boldsymbol{x_{l,i}}(\boldsymbol{T_j}))\boldsymbol{\beta_l})}{\left[\sum_{i \in R_j} \exp\left(\boldsymbol{x_{l,i}}(\boldsymbol{T_j})\boldsymbol{\beta_l}\right)\right]^{d_j}}, \tag{4.9}$$

where d_j be the number of tied exit times due to event *l* and D_j be the number of tied exits due to event *l* at time t_j. This approximation works well when the number of tied exits at each exit time t_j is relatively smaller than the number of banks at risk, R_j.

In principle, one of the main advantages of using the partial likelihood approach to estimate the hazard function is that it avoids problems associated with potential endogeneity of time varying covariates with respect to the exit time, T_i.[13] In addition, the Cox proportional hazard model has an advantage over parametric models as it avoids having to make any arbitrary and possibly wrong assumption about the functional form of the baseline hazard. However, the estimate of $\boldsymbol{\beta_l}$ is more efficient in parametric models where the baseline hazard is correctly specified. In other words, the cost of making no assumption about the shape of the baseline hazard function is a loss in efficiency.

4.4. DATA AND VARIABLES

4.4.1. Data description

To investigate the impact of TARP investment on the performance of recipient institutions, Call report data for all commercial banks in the U.S. were obtained from

[13] See Wheelock and Wilson (2000) and Lancaster (1992) for detailed discussion.

the FDIC Institution Directory database.[14] Data were collected over the period 2007Q1-2012Q4, which covers the recent U.S. banking crisis. The dataset was then refined by removing (*i*) banks with missing observations, (*ii*) de novo banks that have been in operation since the beginning of 2007, (*iii*) banks that are not headquartered in the U.S. states,[15] (*iv*) insured U.S. branches of foreign chartered institutions, and (*v*) banks that voluntarily relinquished the FDIC insurance or were closed without government assistance. The resulting sample consists of 7,405 commercial banks with 158,654 covering the period 2007Q1-2012Q4.

4.4.2. Failure and acquisition identification

In this study, the exit indicator is defined as a binary dummy variable, which takes value one if a bank disappears, and zero otherwise. Two types of exits are considered in this study: exit due to failure and exit due to acquisition. The most widely used failure indicator is regulatory closure which occurs when a bank is declared insolvent and placed in receivership by its primary regulator. In such events, the FDIC, as the main receiver of the insured institutions, receives the insolvent bank and either liquidates its assets or transfer its assets to an acquiring institution. The list of closed banks, their closing dates, as well as their acquiring institutions is disclosed by the FDIC. The list includes 398 commercial banks were closed and received by the FDIC over the sample period.

In addition to the closed banks, many other U.S. banks became insolvent on a mark-to-market basis at some point during the recent financial crisis. However, these banks were allowed to remain in operation either subject to various regulatory enforcement actions or because they were effectively bailed out by the TARP. Thus, a framework is established to identify banks that became technically insolvent during the

[14] Savings banks and savings and loan associations are not considered in this study as they have different organisational structure, objectives, and regulatory restrictions, compared to commercial banks.

[15] These are the banks that are headquartered in the U.S. territories such as Puerto Rico, Guam, Northern Marianas, U. S. Virgin Islands and American Samoa.

recent crisis. Accordingly, two criteria are defined for technical insolvency: technical insolvency occurs (*i*) if a bank was closed by its primary regulatory, or (*ii*) if a bank is critically undercapitalised meaning that it has tangible equity to total assets of less than 2%, where tangible equity is total equity minus goodwill, or (*iii*) if a bank is unable to provide sufficient coverage against its nonperforming assets,[16] where sufficient coverage for a bank means that sum of its equity and loan loss reserves is equal or more than half of its nonperforming assets.[17] The insolvency date is taken as the earliest time a bank meets either of these criteria.

Using these criteria it was found that 580 commercial banks became technically insolvent over the sample period. Of those, 182 banks remained in operation and 398 banks were closed down by their primary regulators. This framework seems to be very helpful and informative to identify technical insolvency as picks up approximately 90% of banks that were closed down by regulators.

The second type of exit investigated in this study is exit due to acquisition. The data on the U.S. bank acquisitions were obtained from the FDIC Institution Directory database, which provides detailed information on acquired institutions, their corresponding acquiring institutions, and acquisition date. Some acquisitions were related to banks that were technically insolvent and their regulatory closures were imminent while other acquired institutions were healthy.[18] Thus, similar to the analysis of bank failures, technical insolvency criteria was used to distinguish between different types of acquisitions based on financial health of the acquired banks. There were 1,167

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[16] Nonperforming assets include assets past due 30-89 days and still accruing interest, assets past due 90 days, or more, and still accruing interest, assets in nonaccrual status, and real estate acquired through foreclosures.

[17] This definition follows standard IMF stress-testing practices by implicitly assuming 50% Loss Given Default (LGD) for nonperforming assets. A more conservative approach could be assuming 100% LGD for nonperforming loans (see González-Hermosillo, 1999).

[18] When a bank fails, the FDIC either liquidates its assets or sells the bank to an acquiring institution, often with financial assistance. The definition of bank acquisition in this study does not include failed bank acquisitions as (*i*) this cause an overlap between the definitions of the competing risks, (*ii*) the process of failed bank acquisition is substantially different from acquisition of operating banks, and it often requires government financial assistance.

commercial banks that were acquired over the sample period. Of those, 20 banks were technically insolvent when they were acquired.

4.4.3. Explanatory variables

To evaluate the impact of TARP investments on stability of recipient banks, hazard functions are estimated based on equation (4.3) as the main empirical model of this Chapter. The column entries of the matrix $\boldsymbol{x}_{l,i}(\boldsymbol{t})$ in equation (4.3) include TARP indicators as well as a broad set of control variables. TARP transactions data were retrieved from Transaction Investment Program Reports provided by the U.S. Department of the Treasury. Then, the Federal Reserve identification number (RSSDID) of each recipient institution was hand-collected by referring to the Federal Reserve Board National Information Center database. The RSSDID was later used to match recipient holding companies with their subsidiaries.[19] This study assumes that all subsidiaries of a recipient bank holding company received a fraction of the TARP funds and were affected by TARP investment. Therefore, over the time span of this study, 852 commercial banks obtained TARP money, either directly or through their associated holding companies.

The CPP investments had two major components; senior preferred stocks and equity warrants. To exit TARP, a recipient bank was required to redeem the amount of capital invested in the bank under CPP. Also, upon the redemption of the senior preferred stock investment, an institution could either repurchase its warrants at the fair market value, or the Treasury would sell the warrants to third parties through public auction. Therefore, there were three major TARP transactions for each recipient institution; capital injection, capital repayment, and disposition of warrants. Accordingly, in this study, the impact of TARP investments on the survival likelihood of the recipient banks is investigated by considering three alternative TARP indicators. TARP1 is a dummy variable that takes value of one if a bank or its bank holding

[19] Similar approach was used to identify recipient institutions that were not controlled by a bank holding company.

company received capital infusions under TARP, and zero otherwise. This variable measures the general impact of TARP funds disregarding the potential impact of repayment or final disposition of TARP investment on bank stability. TARP2 is a dummy variable that takes value of one from the time a bank or its bank holding company received capital infusion up to the capital repayment date, and zero otherwise. TARP3 is a dummy variable that takes value of one from the time a bank or its bank holding company received capital infusion up to the final disposition date, and zero otherwise. In fact, the main difference between TARP2 and TARP3 is that the latter controls for the impact of disposition of equity warrants, while the former only considers the transactions related to injection and repayments of senior stocks.

In addition to TARP indicators and to avoid potential omitted variable bias, this study employs a comprehensive set of control variables that have been frequently used in the literature as determinants of bank failures and acquisitions. In principle, selected explanatory variables include several characteristics of banking institutions including CAMELS indicators,[20] size, age, and ownership structure.

Furthermore, additional explanatory variables are included to serve as proxies for banking sector concentration and competition as well as local economic conditions.[21] Control variables used in this analysis as well as their potential impact on bank failure and acquisition are discussed below. Also, a summary of the explanatory variables under consideration, their expected impact on bank exit, and data sources are presented in Tables 4.1 and 4.2.

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[20] CAMELS rating system is a supervisory rating system to assess the stability of individual banks. CAMELS stands for Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk. During an on-site bank examination, supervisory regulators assess financial health of a bank and assign a score from one (best) to five (worst) for each of the six CAMELS components in addition to the overall rating of a bank's financial condition.

[21] Table A4.1 illustrates the geographical distribution of all banks, closed banks, and acquired banks in each State. It can be seen that bank closures and acquisitions are more clustered in certain States, suggesting that state-level banking sectors and local economic conditions may play key roles in bank exits.

Table 4.1. Variable acronyms and definitions

	Variable	Explanation
Capital adequacy	CAP_{it}	Total equity capital/total assets
Asset quality	NPL_{it}	Nonperforming loans/total assets
	ORE_{it}	Other real estate owned/total assets
Management capability:	MNG_{it}	Total noninterest expenses minus /sum of net interest income and noninterest income
Earnings:	$EARN_{it}$	Net income after taxes/total assets
Liquidity:	JCD_{it}	Jumbo certificate of deposits/total assets
	$LOAN_{it}$	Total loans/total assets
	$FEDF_{it}$	(Federal funds purchased-federal funds sold)/total assets
Sensitivity to market:	$COML_{it}$	Commercial and industrial loans/total assets
	REL_{it}	Real estate loans/total assets
Miscellaneous factors:	$SIZE_{it}$	Log of total assets
	AGE_{it}	Log of bank's age in years
	$HOLD_{it}$	1 if 25% or more of a bank's shares are held by a multibank holding company, 0 otherwise.
Government bailout:	$TARP1_{it}$	1 if the bank or its bank holding company received assistance through CPP under TARP program, 0 otherwise.
	$TARP2_{it}$	1 if the bank or its bank holding company received CPP investment and before capital repayment, 0 otherwise.
	$TARP3_{it}$	1 if the bank or its bank holding company received CPP investment and before final disposition, 0 otherwise.
State level banking sector	$CONC_t$	Share of the five largest banks' deposits to total deposits in each state.
Local Economic Conditions	HPI_t	The state-level growth rate of house price index adjusted for inflation as measured by the national level consumer price index.
	UNE_t	The state-level percentage of labour force without work but available to work and actively seeking employment.
	$INCO_t$	The state-level growth rate of personal income adjusted for the inflation according to national prices.

Table 4.2. Variables, their expected effects on failure and acquisitions, their units and data sources

Variable	Expected sign on		Unit	Data source
	Failure	Acquisition		
Bank specific variables				
CAP_{it}	-	-/+	Percentage	FDIC Institution Directory
NPL_{it}	+	-/+	Percentage	FDIC Institution Directory
ORE_{it}	+	-/+	Percentage	FDIC Institution Directory
MNG_{it}	+	-/+	Percentage	FDIC Institution Directory
$EARN_{it}$	-	-/+	Percentage	FDIC Institution Directory
JCD_{it}	+	-/+	Percentage	FDIC Institution Directory
$EARN_{it}$	+	-/+	Percentage	FDIC Institution Directory
$FEDF_{it}$	-/+	-/+	Percentage	FDIC Institution Directory
$COML_{it}$	+	-/+	Percentage	FDIC Institution Directory
REL_{it}	+	-/+	Logarithm	FDIC Institution Directory
$SIZE_{it}$	-	-	Percentage	FDIC Institution Directory
AGE_{it}	-	-	Logarithm	FDIC Institution Directory
$HOLD_{it}$	-	-/+	Level	FDIC Institution Directory
Government bailout				
$TARP1_{it}$	-/+	-/+	Level	Department of the Treasury
$TARP2_{it}$	-/+	-/+	Level	Department of the Treasury
$TARP3_{it}$	-/+	-/+	Level	Department of the Treasury
State level banking sector				
$CONC_{t}$	-/+	-/+	Percentage	FDIC Summary of Deposits
Local Economic Conditions				
HPI_{t}	-	-/+	Percentage	Federal Housing Finance Agency
UNE_{t}	+	-/+	Percentage	Bureau of Labor Statistics
$INCO_{t}$	-	-/+	Percentage	Bureau of Economic Analysis

I. CAMELS rating system

Capital to asset ratio (CAP_{it}): It is a general consensus that bank's equity can serve as a cushion to absorb shocks and effectively help to increase the survival time (see Berger and Bouwman, 2013, for a detailed discussion). However, the relationship between capital and acquisition is ambiguous. Most previous studies, including Wheelock and Wilson (2000) and Moore (1997), report a negative linkage between capital ratio and likelihood of acquisition. Yet, Hannan and Pilloff (2009) argue that a reverse direction is also possible as banks with higher capital ratios might be less efficient in maximising their deposit insurance. In addition, well-capitalised banks can be very attractive targets for acquiring banks seeking to increase their capital level in order to maintain their minimum capital requirement.

Nonperforming loans to total assets (NPL_{it}): Nonperforming loan (NPL) is a measure of *ex post* credit risk and is often employed as a proxy for a bank's asset quality. High NPL indicates pervasive problems in a bank's lending activities and is hypothesized to be positively associated with the probability of failure and acquisitions, i.e., banks with higher NPL are more likely to be closed or acquired.

Other real estate owned to total assets (ORE_{it})*:* other real estate owned assets reflect non-earning bank assets primarily consisting of foreclosed real estate. ORE has been used as a proxy for asset quality in a number of studies, including Cole and Gunther (1998) and Wheelock and Wilson (2000). Higher ORE implies higher nonearning and substandard assets, which increases the probability of closure and timing of acquisition.

Inefficiency ratio (MNG_{it}): various measures of inefficiency, including cost to income ratio, cost efficiency, and nonparametric technical inefficiency measure based on Data Envelopment Analysis (DEA), have been used in the literature as a proxy for management quality in banks. This chapter uses inefficiency ratio defined as the ratio of noninterest expenses to the sum of net interest income and noninterest income as a measure of inefficiency.[22] In principle, inefficiency makes banks more likely to fail and less attractive to be acquired.

Return on Assets ($EARN_{it}$): Return on assets (ROA) is defined as net income after tax as a percentage of total assets, which is included in the hazard regression as a proxy for bank's earning, the fourth CAMELS component. In general, higher ROA reflects more efficient management skills and less financial difficulties in a bank. Thus, it is expected to have a negative impact on the probability of failure and acquisition.

[22] Amortisation expenses of intangible assets are not included in the calculation of noninterest expenses in the definition of inefficiency.

Jumbo Certificates of Deposit (JCD_{it}): Jumbo CDs are time deposits with denominations greater than $100,000, which was the standard FDIC maximum deposit insurance coverage limit per depositor, per insured depository institutions.[23] JCD is often used as a proxy for liquidity (see, for instance, Shaffer, 2012; González-Hermosillo, 1999; Cole and Gunther, 1995). Higher JCDs implies higher funding costs and can be indicative of riskier and more aggressive growth strategies. Thus, banks heavily relying on JCDs are more likely to fail while being less attractive for acquirers.

Gross loan to total assets ($LOAN_{it}$): Loans are typically considered to be less liquid and more risky compared to other bank assets such as investment securities (see, e.g., DeYoung, 2003; Wheelock and Wilson, 2000). Therefore, higher concentration on lending activities implies lower liquidity, which can increase the risk of failure and make banks less attractive targets for acquisition.

Net federal funds purchased[24] ($FEDF_{it}$): Federal funds are unsecured interbank loans from banks with excess reserves to banks with insufficient reserves. Net federal funds purchased can be used as a proxy for liquidity (see, for instance, Wheelock and Wilson, 2000). Higher net purchased funds can be indicative of liquidity problems which make banks more likely to be closed.

Percentage of commercial and industrial loans to total assets ($COML_{it}$): a commercial bank with higher ratio of commercial and industrial loans is more likely to face distress due to higher nonperforming loans during adverse economic conditions, particularly if a large fraction of these loans are not secured by collaterals.

Real estate loans as a percentage of total gross loans ($RELN_{it}$): It is argued that quality of loan portfolios is highly sensitive to real estate price fluctuations (see, for instance, Hott, 2011; Goodhart and Hofmann, 2007). In this study, RELN is used as a proxy for sensitivity to real estate market risk.[25] Since the quality of loan portfolios is highly

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[23] In October, 2008, the insurance coverage limit was temporarily raised to $250,000 through December, 2010, and was later extended through December, 2013. Later on, in July, 2010, President Obama signed the Dodd-Frank Wall Street Reform and Consumer Protection Act and, as a result, the insurance coverage limit was permanently increased to $250,000.

[24] This definition includes repurchase agreements as well.

[25] Another possible indicator of sensitivity to market risk is the loan portfolio concentration measured by Herfindahl–Hirschman Index of various loan categories (see, for instance, Berger and Bouwman, 2013;

sensitive to real estate market real estate loans are defined as loans secured primarily by real estate. In principle, banks heavily relying on real estate loans are likely to experience significant losses during adverse real estate market conditions, indicating that they are more likely to be closed and less likely to be acquired.

II. Miscellaneous bank-specific factors

Log of total assets ($SIZE_{it}$): Bank size is widely used in previous studies of bank failure and acquisition (see, for instance, Shaffer, 2012; Cole and Gunther, 1995; Arena, 2008). Larger banks benefit from economies of scales, more opportunities to diversify their products and credit portfolios, and more flexible access to external funds. Moreover, larger banks hold 'too-big-to-fail' regulatory status, which indicates that regulatory closure of larger institutions is very complex and might impose high costs to the FDIC as well as the overall economy. In general, larger banks are less likely to be closed or acquired.

Log of bank's age in years (AGE_{it}): Due to their established reputation, older banks are considered to be more reliable and trustworthy for depositors and other financial institutions. Thus, mature banks are more stable and better equipped to face adverse economic conditions and are less likely to be closed or acquired.

Multi-Bank Holding Company (MBHC) affiliation ($HOLD_{it}$): This study employs a dummy variable to distinguish between MBHC affiliates from other banking institutions, including independent banks as well as affiliates of one-bank holding companies. In principle, bank holding companies benefit from less regulatory restrictions and better access to liquidity and external funding. Ashcraft (2008) argues that MBHC affiliation is a source of strength as MBHCs can provide managerial and financial supports to their subsidiaries and help them avoid liquidity shortage and recover from financial distress during adverse economic conditions. On the other hand, I expect a positive relationship between MBHC affiliation and probability of being

DeYoung and Torna, 2013). However, only RELN is included in the hazard model because RELN and loan concentration ratios are highly correlated and RELN seems to be more relevant as the recent banking crisis had its roots in adverse fluctuations in real estate market.

acquired as MBHC facing financial distress may trade their affiliates in order to survive or to acquire more efficient and profitable institutions.

III. Banking sector concentration

Percentage of deposits held by top five banks in a state ($CONC_t$): This chapter controls for local market concentration and competition by measuring deposit concentration in five largest banks in each State. The data on branch office deposits for all FDIC-insured institutions was obtained from the FDIC Summary of Deposit (SOD).[26] In general, there are conflicting theoretical views on the relationship between banking sector concentration and bank stability. Some previous studies advocate 'concentration-stability' view and argue that a more concentrated banking system increases franchise value and make banks less likely to fail (see, e.g., DeYoung, 2003). Others, including Boyd and De Nicolo (2005), argue that there is potential fundamental risk-incentive mechanisms that makes bank take on more risk and impose higher interest spreads in less competitive banking sectors. According to this 'concentration-fragility' view, banks are more stable and less likely to fail in a more competitive banking system.

IV. Local economic conditions

Percentage change in state-level real House Price Index (HPI_t): It was shown in the previous chapter that house price fluctuations significantly affect financial stability of banks. Therefore, it is of crucial importance to control for the impact of house prices on bank exits by including the growth of state-level HPI which is adjusted for inflation as measured by the national level consumer price index. The data on HPI was obtained

[26] Deposit data is used as it is the only branch-level information available in the FDIC database. In addition, since the FDIC-SOD data are only reported on annual basis, the quarterly COMP data is obtained by interpolating annual COMP data.

from the Federal Housing and Finance Agency (FHFA) database.[27] Broadly speaking, banks are exposed to the housing market from several fronts, including direct investment in housing market, investment in real estate loans, investment in any other types of loans secured by real estate, and investment in securities tied to real estate, such as mortgage-backed securities. Thus, performance of banking institutions is highly sensitive to house price fluctuations. Daglish (2009) argues that house price depreciations deteriorate the quality of loan portfolios by reducing the value of pledged collaterals and increasing the probability of default on part of subprime borrowers. Thus, when confronting falling house prices, banks are more likely to fail while being less likely to be acquired.

State-level unemployment rate (UNE_t): To control for local economic imbalances, this study uses the state-level unemployment rate, which can be a proxy for the level of real economic activities in each state. Higher unemployment rate implies a permanent decline in real economic activities and is expected to make banks more likely to fail and less likely to be acquired.

Percentage change in state-level real personal income ($INCO_t$): another indicator of local economic conditions used in this chapter is the growth of state-level per income adjusted for inflation as measured by the national level consumer price index. Aubuchon and Wheelock (2010) show that the state-level bank failure rate is negatively associated with the growth of state-level real per capita income during the recent financial crisis. Thus, higher real personal income is expected to have a negative impact of the likelihood of bank failure.

4.5. EMPIRICAL RESULTS

In this section, the univariate analyses of covariates used in this study is presented. Accordingly, potential differences between these covariates among survived

[27] The HPI is a measure of average price fluctuations of single-family properties in repeat sales or refinancings of the same single-family properties. The HPI is calculated based on repeat transaction data of mortgages purchased or securitised by the Federal National Mortgage Association (Fannie Mae) or the Federal Home Loan Mortgage Corporation (Freddie Mac).

banks, closed banks, and acquired banks are examined. Then, the empirical results of the Cox proportional hazard estimations are presented to evaluate the impact of capital infusions on bank disappearance during the recent crisis.

4.5.1. Univariate analysis

Table 4.3 presents descriptive statistics of the covariates used in this study based on 158,654 observations on 7,405 U.S. commercial banks. For each covariate, the mean, standard deviation, the first quartile, median, and the third quartile are reported. From Table 4.3 it appears that, on average, the sample banks are well-capitalised with equity capital ratio of over 11%. However, the standard deviation of capital ratio is relatively large, indicating that some banks were critically undercapitalised. The sample banks, on average, have 1.53% of nonperforming loans to total assets and 0.65% of real estate foreclosure to total assets, meaning that many sample banks suffered from high levels of troubled assets during the recent crisis. Liquidity indicators also have relatively large standard deviations, suggesting that level of liquidity significantly varies among sample banks. Another interesting finding is that the sample banks were highly concentrated in real estate lending with real estate loans covering, on average, 67.5% of their loan portfolios. Furthermore, these results suggest that many sample banks operated in highly concentrated banking sectors and adverse economic conditions.

In general, the findings from the descriptive statistics reveal that many covariates have relatively large standard deviations, indicating that financial characteristics widely vary among sample banks. To take this important feature of the data into account, a mean comparison test with Welch (1947) approximation was conducted to investigate potential variations among mean values observed for survived banks, closed banks, and acquired banks.[28] Table 4.4 presents the results of mean comparison test. It emerges that for most variables considered, the mean values for survived banks are statistically different from the mean values observed for closed

[28] The mean comparison test examines the null hypothesis that the means of two groups of banks are equal i.e. $\mathrm{H_0}: \mathrm{diff} = \mathrm{mean(group1)} - \mathrm{mean(group2)} = 0$. The mean comparison test applied in this study is a t-test with Welch approximation to account for possible unequal variances between the two groups of banks.

banks and acquired banks. Compared to banks that disappeared, survived banks were older and with less real estate loans in their loan portfolios, higher commercial and industrial loans, lower reliance on lending activities, and more efficient.

Despite these similarities between characteristics of closed banks and acquired banks in comparison with survived banks, the mean comparison tests produce contrasting outcomes when other explanatory variables are taken under consideration. Compared to survived banks, the results indicate that the mean values of NPL, ORE, and JCD are significantly higher in closed banks and lower in acquired banks. On the other hand, closed banks operated in States with larger declines in house prices, while acquired banks were located in states experiencing better housing market conditions.

Table 4.3. Summary statistics of explanatory variables.

	Mean	SD	Q1	Median	Q3
CAP_{it}	11.19	6.07	8.68	10.05	12.13
NPL_{it}	1.52	2.23	0.24	0.80	1.88
ORE_{it}	0.65	1.40	0.00	0.15	0.68
MNG_{it}	0.75	2.28	0.59	0.69	0.82
$EARN_{it}$	0.50	2.60	0.28	0.80	1.26
JCD_{it}	16.21	8.83	10.08	14.85	20.86
$LOAN_{it}$	63.66	16.35	54.34	66.15	75.41
$FEDF_{it}$	-1.66	7.16	-3.47	-0.18	0.48
$COML_{it}$	14.77	10.88	7.05	12.21	19.81
$RELN_{it}$	68.5	19.66	58.04	72.65	82.83
$SIZE_{it}$	12.01	1.33	11.15	11.87	12.67
AGE_{it}	3.89	1.03	3.26	4.38	4.66
$HOLD_{it}$	0.18	0.39	0.00	0.00	0.00
$TARP1_{it}$	0.08	0.27	0.00	0.00	0.00
$TARP2_{it}$	0.06	0.24	0.00	0.00	0.00
$TARP3_{it}$	0.06	0.24	0.00	0.00	0.00
$CONC_{t}$	47.83	13.37	37.61	50.52	55.87
HPI_{t}	-3.60	4.22	-5.51	-3.06	-0.93
UNE_{t}	7.00	2.30	5.08	6.90	8.68
$INCO_{t}$	1.16	3.37	-0.52	1.51	3.35

Table 4.4. Univariate mean comparison test for survived, failed and acquired commercial banks.

	Survived		Closed		Acquired		Survived vs. Closed		Survived vs. Acquired		Acquired vs. Closed	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	t-difference		t-difference		t-difference	
CAP_{it}	11.281	0.0697	8.0792	0.1370	12.047	0.2326	20.828	***	-3.155	***	14.696	***
NPL_{it}	1.3838	0.0178	5.5028	0.1444	1.1991	0.0399	-28.30	***	4.2273	***	-28.72	***
ORE_{it}	0.6057	0.0123	2.0423	0.1011	0.3423	0.0172	-14.11	***	12.469	***	-16.58	***
MNG_{it}	0.7376	0.0054	1.0691	0.1485	0.7696	0.0140	-2.232	**	-2.151	**	-2.008	**
$EARN_{it}$	0.6564	0.0183	-3.023	0.1004	-0.847	1.1237	36.055	***	1.3376		1.9287	*
JCD_{it}	16.043	0.1004	22.401	0.4713	15.013	0.2299	-13.20	***	4.1011	***	-14.09	***
$LOAN_{it}$	63.076	0.1963	75.048	0.4503	65.404	0.4901	-25.24	***	-4.410	***	-15.13	***
$FEDF_{it}$	-1.585	0.0653	-1.809	0.2732	-2.824	0.3114	0.7984		3.8963	***	-2.451	**
$COML_{it}$	14.896	0.1358	11.617	0.4386	14.095	0.2957	7.1409	***	2.4910	**	4.666	***
$RELN_{it}$	67.860	0.2497	82.125	0.6597	70.856	0.5544	-19.93	***	-4.541	***	-13.08	***
$SIZE_{it}$	11.997	0.0171	12.487	0.0576	12.003	0.0445	-8.159	***	-0.144		-6.645	***
AGE_{it}	3.9576	0.0130	2.9770	0.0566	3.6079	0.0327	16.878	***	9.9494	***	9.6522	***
$HOLD_{it}$	0.1547	0.0045	0.1242	0.0161	0.5549	0.0139	1.8328	*	-27.28	***	20.250	***
$TARP1_{it}$	0.0791	0.0029	0.0262	0.0061	0.0727	0.0057	7.7962	***	1.004		5.5747	***
$TARP2_{it}$	0.0570	0.0023	0.0255	0.0060	0.0638	0.0051	4.9163	***	-1.225		4.8799	***
$TARP3_{it}$	0.0612	0.0024	0.0262	0.0061	0.0660	0.0052	5.3164	***	-0.852		4.9641	***
$CONC_{t}$	0.4764	0.0017	0.5153	0.0057	0.4840	0.0039	-6.531	***	-1.639		-4.619	***
HPI_{t}	-3.497	0.0319	-6.198	0.2279	-2.692	0.1097	11.740	***	-7.044	***	13.863	***
UNE_{t}	7.0380	0.0194	7.0387	0.0639	5.7596	0.0480	-0.101		24.682	***	-16.01	***
$INCO_{t}$	1.2012	0.0140	0.1509	0.0623	1.7022	0.0499	16.441	***	-9.655	***	19.417	***
Banks	5840		398		1167							

Note. The mean comparison test examines the null hypothesis that the means of two groups of banks are equal i.e. $\mathrm{H_0: diff = mean(group1) - mean(group2) = 0}$. The mean comparison test applied in this study is a t-test with Welch approximation to account for possible unequal variances between the two groups of banks. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Table 4.5. Cross correlation matrix of explanatory variables.

	CAP_{it}	NPL_{it}	ORE_{it}	MNG_{it}	$EARN_{it}$	JCD_{it}	$LOAN_{it}$	$FEDF_{it}$	$COML_{it}$	$RELN_{it}$	$SIZE_{it}$	AGE_{it}	$HOLD_{it}$	$TARP_{it}$	$COMP_{it}$	HPI_t	UNE_t	$INCO_t$
CAP_{it}	1																	
NPL_{it}	**-0.151**	1																
ORE_{it}	**-0.138**	**0.508**	1															
MNG_{it}	0.003	**0.061**	**0.047**	1														
$EARN_{it}$	**0.201**	**-0.381**	**-0.261**	**-0.076**	1													
JCD_{it}	**-0.147**	**0.171**	**0.165**	**0.019**	**-0.114**	1												
$LOAN_{it}$	**-0.282**	**0.204**	**0.088**	-0.005	**-0.109**	**0.21**	1											
$FEDF_{it}$	**-0.23**	**0.047**	**0.024**	**-0.021**	**0.022**	**-0.067**	**0.212**	1										
$COML_{it}$	**-0.028**	**-0.109**	**-0.139**	**-0.016**	**0.057**	**-0.021**	**0.25**	**0.031**	1									
$RELN_{it}$	**-0.257**	**0.25**	**0.233**	**0.018**	**-0.181**	**0.12**	**0.31**	**0.138**	**-0.659**	1								
$SIZE_{it}$	**-0.149**	**0.129**	**0.034**	**-0.024**	**-0.013**	**-0.021**	**0.193**	**0.315**	**-0.12**	**0.222**	1							
AGE_{it}	**-0.087**	**-0.15**	**-0.124**	**-0.037**	**0.173**	**-0.251**	**-0.225**	**0.061**	**0.06**	**-0.165**	**-0.064**	1						
$HOLD_{it}$	**0.065**	**-0.025**	**-0.046**	**-0.01**	**0.017**	**-0.072**	0.003	**0.054**	**0.026**	**-0.026**	**0.106**	**-0.007**	1					
$TARP_{it}$	**-0.036**	**0.128**	**0.063**	**0.005**	**-0.085**	**0.039**	**0.089**	**0.069**	**-0.028**	**0.097**	**0.21**	**-0.101**	**0.062**	1				
$CONC_t$	**0.061**	**0.117**	**0.11**	**0.014**	**-0.058**	**0.073**	**0.044**	-0.001	**-0.144**	**0.116**	**0.22**	**-0.246**	**-0.052**	**0.081**	1			
HPI_t	**-0.006**	**-0.232**	**-0.14**	**-0.022**	**0.161**	**-0.039**	**-0.106**	**-0.052**	**0.117**	**-0.181**	**-0.109**	**0.192**	**0.005**	**-0.105**	**-0.226**	1		
UNE_t	**-0.043**	**0.304**	**0.231**	**0.022**	**-0.154**	**0.126**	0.002	**0.096**	**-0.275**	**0.277**	**0.165**	**-0.114**	**-0.047**	**0.211**	**0.2**	**-0.414**	1	
$INCO_t$	**0.018**	**-0.138**	**-0.052**	**-0.013**	**0.119**	**-0.04**	**-0.074**	**-0.053**	**0.096**	**-0.125**	**-0.054**	**0.059**	-0.001	**-0.107**	**-0.039**	**0.286**	**-0.447**	1

Note. Coefficients in bold are significant at 5% level

To take into account the differences between closed banks and acquired banks, the mean comparison test for acquired banks and closed banks is included in the last column of the Table 4.4. The results indicate that for all variables considered, mean values observed for acquired banks significantly differ from those for closed banks. As expected, closed banks have lower capital ratios, higher troubled assets, less liquidity, and more real estate loans, compared to acquire banks. Also, acquired institutions are headquartered in states with better economic conditions and less concentrated banking sectors. In general, the results obtained from mean comparison tests suggest that the set of variables considered in this study may help explain why some banks disappear, under the hazard regression analysis framework.

The pairwise correlation coefficients among covariates used in this study are reported in Table 4.5. It emerges that most covariates are significantly correlated, while the magnitude of correlations varies among explanatory variables. Not surprisingly, there is a very high positive correlation between nonperforming assets and real estate foreclosures, while the real estate loans to total loans and commercial loans to total assets are negatively correlated. Other correlation coefficients are reasonably small and do not seem to cause potential multicollinearity problems between explanatory variables.

4.5.2. Failure hazard estimation

In this section, the results of the estimated Cox proportional hazard models with time-varying covariates are reported to examine the factors affecting the survival time of the US commercial banks during the recent crisis, with special focus given to the role of capital infusions. Table 4.6 reports the estimated results of time-to-failure hazard model as specified in equation (4.3) with $l=1$. Three pairs of equations are presented with respect to three alternative measures of capital infusions discussed earlier. Within each pair of equations, two definitions of bank failure are used: regulatory closure and technical insolvency. Models (I) and (II) include TARP1 as a proxy for receiving capital infusions, models (III) and (IV) include TARP2 representing the interval a bank holds bailout funds, while models (V) and (VI) include TARP3 indicating the time interval of receiving capital assistance and final disposition transactions.

In this study the estimated coefficients are reported rather than hazard ratios. However, the hazard ratio of a covariate can be obtained by exponentiating its estimated coefficient. Each exponentiated coefficient represents the respective change in failure hazards for a one-unit change in the corresponding covariate, holding other covariates constant. A positive coefficient indicates that a rise in the corresponding covariate increases the failure hazard, while a negative coefficient indicates that an increase in the relevant covariate reduces the failure hazard and increases the survival likelihood. Also, in order to evaluate its overall statistical significance and goodness of fit of each estimated model, its pseudo R-squared, and Wald test statistics are reported.[1]

In general, the empirical results in Table 4.6 show that most covariates significantly affect the survival likelihood of the US commercial banks. These results are robust in terms of signs and magnitude of coefficients across all models. Not surprisingly, deteriorating CAMELS indicators significantly undermine survival likelihood of commercial banks. In particular, it appears that banks with lower capital ratios are at higher risk of closure. This result is consistent with Berger and Bouwman's (2013) view that capital enhances the survival likelihood of banks during banking crises. This is also consistent with the Prompt Corrective Action (PCA) under the US regulatory framework, which penalizes banks with progressively deteriorating capital ratios and eventually closes banks that are critically undercapitalized.

Furthermore, the empirical results reveal that higherNPL_{it} and ORE_{it} are associated with shorter time to closure, indicating that banks with more troubled assets are less likely to survive during the crisis period. In addition, the FDIC closure is more likely for banks with higher Jumbo certificate of deposit in their asset portfolios. As regards the composition of loan portfolios, empirical results show that higher fraction of real estate loans to total loans and higher commercial and industrial loans are associated with higher failure hazards. Coming to the liquidity indicators, no robustly significant

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[1] The goodness of fit in estimated models can be compared using the reported pseudo R^2 calculated as follows

$$pseudoR^2 = 1 - lnL_f/lnL_i$$

where lnL_n is the log-likelihood of the null model where all covariates are dropped, and lnL_f is the log-likelihood of the model with all covariates under consideration.

Table 4.6. Failure hazard estimation results for the US commercial banks.

Variables	I Closure	II Insolvency	III Closure	IV Insolvency	V Closure	VI Insolvency
CAP_{it}	-0.481***	-0.416***	-0.481***	-0.417***	-0.481***	-0.417***
	(0.031)	(0.028)	(0.031)	(0.028)	(0.031)	(0.028)
NPL_{it}	0.074***	0.076***	0.074***	0.076***	0.074***	0.076***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
ORE_{it}	0.057***	0.063***	0.058***	0.063***	0.058***	0.063***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)
$COML_{it}$	0.063***	0.061***	0.064***	0.060***	0.063***	0.060***
	(0.018)	(0.016)	(0.018)	(0.016)	(0.018)	(0.016)
REL_{it}	0.046***	0.052***	0.046***	0.052***	0.046***	0.052***
	(0.014)	(0.012)	(0.014)	(0.012)	(0.014)	(0.012)
MNG_{it}	-0.004**	-0.003	-0.004**	-0.003	-0.004*	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$EARN_{it}$	0.058***	0.046***	0.058***	0.046***	0.058***	0.046***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
JCD_{it}	0.008*	0.009**	0.009*	0.010**	0.009*	0.010**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
$LOAN_{it}$	-0.004	-0.005	-0.004	-0.005	-0.004	-0.005
	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)
$FEDF_{it}$	-0.049***	-0.032***	-0.049***	-0.032***	-0.049***	-0.032***
	(0.011)	(0.009)	(0.011)	(0.009)	(0.011)	(0.009)
$SIZE_{it}$	0.166***	0.020	0.159***	0.014	0.159***	0.014
	(0.061)	(0.051)	(0.059)	(0.050)	(0.059)	(0.050)
AGE_{it}	-0.106	-0.104*	-0.104	-0.101*	-0.104	-0.101*
	(0.068)	(0.059)	(0.068)	(0.059)	(0.068)	(0.059)
$HOLD_{it}$	-0.463*	-0.108	-0.470*	-0.114	-0.469*	-0.114
	(0.251)	(0.195)	(0.251)	(0.195)	(0.251)	(0.195)
$TARP1_{it}$	-0.601**	-0.114				
	(0.270)	(0.160)				
$TARP2_{it}$			-0.574**	0.002		
			(0.277)	(0.160)		
$TARP3_{it}$					-0.534**	-0.011
					(0.270)	(0.158)
$CONC_t$	0.011**	0.012***	0.0113**	0.012***	0.011**	0.012***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
HPI_t	-0.033**	-0.028*	-0.034**	-0.029*	-0.034**	-0.029*
	(0.017)	(0.015)	(0.017)	(0.015)	(0.017)	(0.015)
UNE_t	-0.006	0.030	-0.007	0.028	-0.007	0.029
	(0.045)	(0.036)	(0.045)	(0.036)	(0.045)	(0.036)
$INCO_t$	-0.064	-0.052	-0.064	-0.052	-0.064	-0.052
	(0.040)	(0.035)	(0.040)	(0.035)	(0.040)	(0.035)
Observations	158,654	157,221	158,654	157,221	158,654	157,221
# banks	7405	7405	7405	7405	7405	7405
# acquisitions	398	580	398	580	398	580
LLF	-2122	-3376	-2123	-3376	-2123	-3376
Pseudo R^2	0.393	0.336	0.393	0.336	0.393	0.336
Wald test	2023	2684	2018	2682	2023	2682

All models are estimated by the Cox proportional hazard model with time varying covariates. Models I and II, III and IV, and V and VI employ TARP1, TARP2, and TARP3, respectively, as proxies for government bailout. LLF indicates log likelihood function. The pseudo R^2 evaluates the goodness of fit by comparing the log-likelihood of estimated models with the log-likelihood of constant-only model. The Wald test evaluates the overall significance of the estimated coefficients. Robust standard errors are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

linkage between LA_{it} and probability of regulatory closure is found, while higher JCD_{it} and lower net Federal funds purchases are associated with higher likelihood of failure. Contrary to the results reported by Wheelock and Wilson (2000), it is found that banks with more managerial efficiency and more profitability are at greater risk of failure. This may reflect the fact that most closed banks incur significant losses a few quarters before they are closed down. Also, moral hazard incentives are higher for managers of banks with imminent regulatory closure. Therefore, it is not surprising that improving short-term profitability and efficiency is associated with lower survival likelihood.

In addition to CAMELS indicators, a positive relationship is found between bank size and probability of closure, although this relationship becomes insignificant when considering technical insolvency. This may reflect the complexity of operations and products as well as higher agency costs among larger banks. Also, the results indicate that MBHC affiliates are at lower risk of regulatory closure, which is consistent with Ashcraft's (2008) explanation that MBHC affiliation is a source of strength as MBHCs can provide managerial and financial supports to their subsidiaries during financial crises.

Furthermore, state-level local economic conditions and banking sector concentrations largely affect the failure hazards of the US commercial banks. Banks operating in more concentrated banking sectors are more likely to fail. This is consistent with Boyd and De Nicolo's (2005) view that banks take on riskier portfolios in less competitive banking sectors. Also, adverse house price fluctuations significantly increase the failure hazards, perhaps due to deteriorating the value of mortgage related securities as well as collateralized assets in the form of real estate.

From Tables 4.8 and 4.9, it can be inferred that most bank-specific variables have similar signs, whereas the magnitude of their impact on failure hazards differs across large and small bank models. The only significant variable with different signs on the estimated coefficients is the bank size, which appears as a negative coefficient for small banks but a positive coefficient for large banks. These contrasting findings suggest that larger banks in the small bank sample are less likely to fail, reflecting scale

Table 4.7. Failure hazard estimation results for small banks.

	I	II	III	IV	V	VI
Variables	Closure	Insolvency	Closure	Insolvency	Closure	Insolvency
CAP_{it}	-0.485***	-0.402***	-0.485***	-0.402***	-0.485***	-0.402***
	(0.035)	(0.028)	(0.035)	(0.028)	(0.035)	(0.028)
NPL_{it}	0.091***	0.092***	0.091***	0.092***	0.091***	0.092***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
ORE_{it}	0.091***	0.093***	0.091***	0.093***	0.091***	0.093***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
$COML_{it}$	0.056**	0.058***	0.056**	0.057***	0.056**	0.058***
	(0.028)	(0.021)	(0.028)	(0.021)	(0.028)	(0.021)
REL_{it}	0.042**	0.046***	0.042**	0.046***	0.042**	0.046***
	(0.020)	(0.015)	(0.020)	(0.015)	(0.020)	(0.015)
MNG_{it}	-0.004	-0.003	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)
$EARN_{it}$	0.052***	0.038***	0.052***	0.038***	0.052***	0.038***
	(0.010)	(0.007)	(0.010)	(0.007)	(0.010)	(0.007)
JCD_{it}	0.006	0.004	0.006	0.004	0.006	0.004
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
$LOAN_{it}$	-0.010	-0.007	-0.010	-0.007	-0.010	-0.0075
	(0.011)	(0.008)	(0.011)	(0.008)	(0.011)	(0.008)
$FEDF_{it}$	-0.034**	-0.025**	-0.034**	-0.025**	-0.034**	-0.025**
	(0.014)	(0.011)	(0.014)	(0.011)	(0.014)	(0.011)
$SIZE_{it}$	-0.274**	-0.293***	-0.276**	-0.296***	-0.276**	-0.296***
	(0.124)	(0.104)	(0.124)	(0.104)	(0.124)	(0.104)
AGE_{it}	-0.214***	-0.197***	-0.213***	-0.196***	-0.213***	-0.196***
	(0.082)	(0.071)	(0.082)	(0.071)	(0.082)	(0.071)
$HOLD_{it}$	-0.422	0.191	-0.422	0.190	-0.422	0.190
	(0.258)	(0.181)	(0.258)	(0.181)	(0.258)	(0.181)
$TARP1_{it}$	-0.104	-0.235				
	(0.348)	(0.248)				
$TARP2_{it}$			-0.076	-0.174		
			(0.349)	(0.248)		
$TARP3_{it}$					-0.081	-0.187
					(0.348)	(0.248)
$CONC_t$	0.011*	0.014**	0.011*	0.014**	0.011*	0.014**
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
HPI_t	-0.044*	-0.019	-0.044*	-0.019	-0.044*	-0.019
	(0.023)	(0.019)	(0.023)	(0.019)	(0.023)	(0.019)
UNE_t	-0.064	-0.006	-0.065	-0.007	-0.065	-0.007
	(0.059)	(0.043)	(0.059)	(0.043)	(0.059)	(0.043)
$INCO_t$	-0.054	-0.065	-0.054	-0.065	-0.054	-0.065
	(0.051)	(0.043)	(0.051)	(0.043)	(0.051)	(0.043)
Observations	116,616	115,555	116,616	115,555	116,616	115,555
# banks	5378	5378	5378	5378	5378	5378
# acquisitions	233	361	233	361	233	361
LLF	-1108	-1942	-1108	-1942	-1108	-1942
Pseudo R^2	0.439	0.364	0.439	0.364	0.439	0.364
Wald test	2009	2586	2009	2584	2009	2585

All models are estimated by the Cox proportional hazard model with time varying covariates. Models I and II, III and IV, and V and VI employ TARP1, TARP2, and TARP3, respectively, as proxies for government bailout. LLF indicates log likelihood function. The pseudo R^2 evaluates the goodness of fit by comparing the log-likelihood of estimated models with the log-likelihood of constant-only model. The Wald test evaluates the overall significance of the estimated coefficients. Robust standard errors are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Table 4.8. Failure hazard estimation results for large banks.

	I	II	III	IV	V	VI
Variables	Closure	Insolvency	Closure	Insolvency	Closure	Insolvency
CAP_{it}	-0.657***	-0.566***	-0.663***	-0.567***	-0.658***	-0.568***
	(0.044)	(0.039)	(0.044)	(0.039)	(0.044)	(0.039)
NPL_{it}	0.046***	0.045***	0.046***	0.045***	0.047***	0.045***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)
ORE_{it}	0.035	0.044*	0.035	0.045*	0.035	0.045*
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
$COML_{it}$	0.086***	0.059**	0.090***	0.056**	0.087***	0.056**
	(0.023)	(0.026)	(0.023)	(0.023)	(0.023)	(0.026)
REL_{it}	0.051***	0.057***	0.054***	0.056***	0.053***	0.056***
	(0.018)	(0.020)	(0.018)	(0.019)	(0.018)	(0.019)
MNG_{it}	-0.005*	-0.004	-0.005*	-0.004	-0.005*	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$EARN_{it}$	0.083***	0.057***	0.084***	0.057***	0.084***	0.057***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
JCD_{it}	-0.001	0.007	-0.001	0.007	-0.001	0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$LOAN_{it}$	0.005	0.002	0.004	0.003	0.005	0.003
	(0.009)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)
$FEDF_{it}$	-0.058***	-0.040***	-0.057***	-0.040***	-0.058***	-0.040***
	(0.015)	(0.013)	(0.015)	(0.013)	(0.015)	(0.013)
$SIZE_{it}$	0.378***	0.255***	0.358***	0.247***	0.351***	0.247***
	(0.092)	(0.079)	(0.083)	(0.077)	(0.086)	(0.077)
AGE_{it}	0.090	0.035	0.099	0.037	0.093	0.039
	(0.099)	(0.088)	(0.098)	(0.088)	(0.099)	(0.088)
$HOLD_{it}$	-0.181	-0.251	-0.209	-0.260	-0.199	-0.261
	(0.273)	(0.246)	(0.273)	(0.247)	(0.272)	(0.247)
$TARP1_{it}$	-1.659***	-0.028				
	(0.601)	(0.238)				
$TARP2_{it}$			-1.735***	0.148		
			(0.646)	(0.230)		
$TARP3_{it}$					-1.559**	0.141
					(0.605)	(0.224)
$CONC_t$	0.010	0.009	0.010	0.009	0.009	0.009
	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)
HPI_t	0.010	-0.004	0.010	-0.006	0.009	-0.006
	(0.025)	(0.022)	(0.025)	(0.022)	(0.025)	(0.022)
UNE_t	0.179***	0.163***	0.182***	0.159***	0.177***	0.160***
	(0.067)	(0.056)	(0.067)	(0.056)	(0.067)	(0.056)
$INCO_t$	0.021	0.010	0.022	0.011	0.021	0.011
	(0.064)	(0.057)	(0.064)	(0.057)	(0.064)	(0.057)
Observations	42,038	41,666	42,038	41,666	42,038	41,666
# banks	2027	2027	2027	2027	2027	2027
# acquisitions	165	219	165	219	165	219
LLF	-691.0	-999.0	-691.0	-998.9	-692.2	-998.9
Pseudo R^2	0.439	0.387	0.439	0.387	0.438	0.387
Wald test	786.2	1031	770.3	1030	780.8	1030

All models are estimated by the Cox proportional hazard model with time varying covariates. Models I and II, III and IV, and V and VI employ TARP1, TARP2, and TARP3, respectively, as proxies for government bailout. LLF indicates log likelihood function. The pseudo R^2 evaluates the goodness of fit by comparing the log-likelihood of estimated models with the log-likelihood of constant-only model. The Wald test evaluates the overall significance of the estimated coefficients. Robust standard errors are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

efficiencies and better portfolio diversification in larger banks. However, higher likelihood of failure across larger banks in large bank sample may be attributed to higher agency costs and higher losses in complex mortgage-related products.

Coming to the real estate foreclosures, it appears that the estimated coefficient on real estate foreclosures is insignificant for large banks when regulatory closure is under consideration, while a rise in real estate foreclosures significantly increases the survival likelihood in small banks. Also, bank age appears to be insignificant in large bank models, while it significantly affects survival likelihood of small banks. This indicates that bank age plays a key role in credit rating and creditworthiness of small banks while large banks may rely more on their 'too-big-to-fail' guarantees. Another interesting finding of this chapter is that small banks are more sensitive to state-level banking concentration and house price fluctuations, while higher unemployment is associated with higher failure hazards in larger banks.

Furthermore, the empirical results show that the impact of capital infusions largely vary across small and large TARP recipients. While receiving TARP funds significantly reduces the probability of regulatory closure in large banks, regulators do not hesitate to close down 'small enough to fail' recipients in the event of technical insolvency. This may be partly because larger distressed recipients can benefit from 'too-big-too-fail' guarantee and better access to liquidity and external funding via capital markets whereas their smaller counterparts are either privately held or thinly traded and In general, results in Tables 4.8 and 4.9 suggest that larger banks are much better served by TARP capital infusions even though it does not effectively help them avoid technical insolvency.

In summary, the empirical results strongly support the hypothesis one that government bailout is not effective in preventing recipient banks from technical insolvency although larger recipients may avoid regulatory closure.

4.5.3. Acquisition hazard estimation

Next, it is investigated if the covariates affecting time-to-failure can also explain acquisition hazards of the U.S. commercial banks during the recent crisis. Table 4.9

presents the estimation results of time-to-acquisition model as specified in equation (2) with l=2. Again, the analysis of acquisition hazards differentiates among alternative TARP indicators as well as financial health of acquired institutions. While some acquisitions were related to banks facing imminent failure, other acquired institutions were financially healthy. Thus, within each pair of equations associated with a TARP indicator, two models are estimated. The first model includes all acquired banking institutions, whereas the second model only includes healthy acquired institutions. However, the results for healthy acquisition are expected to be very similar to that of all acquisitions as the number of acquired institutions with imminent failure is considerably smaller than number of acquired banks.

In general, the empirical results indicate that most CAMELS indicators significantly affect time-to-acquisition of the U.S. commercial banks. In particular, acquired institutions tend to be less efficient and less profitable banks, which is consistent with the positive relationship between lower managerial quality and acquisition hazard found by Hannan and Pilloff (2009). This indicates that poorly performing banks are attractive acquisition targets for other banking institutions, perhaps because acquiring institutions expect that there is room for improving the managerial quality of the target banks.

Consistent with the results found by Wheelock and Wilson (2000), it is found that acquired banks have lower real estate foreclosures in the asset portfolios. However, acquired institutions had significantly higher nonperforming loans to total assets and higher fraction of real estate loans in their loan portfolios. This may indicate that acquiring institutions were not optimistic about future house prices in the short run.

As regards the liquidity indicators, my empirical results reveal that acquisition targets were more liquid represented by lower loans in their asset portfolios, lower jumbo certificate of deposits, and lowed net Federal funds purchased in their asset portfolios. This may suggest that acquiring institutions were willing to take over liquid banks with relatively poor management quality in order to diversify their asset portfolios.

Table 4.9. Acquisition hazard estimation results for the U.S. commercial banks.

Variables	I Acquisition	II Healthy acquisition	III Acquisition	IV Healthy acquisition	V Acquisition	VI Healthy acquisition
CAP_{it}	-0.007	-0.006	-0.007	-0.006	-0.007	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
NPL_{it}	0.041***	0.040***	0.041***	0.040***	0.041***	0.040***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
ORE_{it}	-0.075**	-0.122***	-0.079**	-0.127***	-0.078**	-0.126***
	(0.031)	(0.031)	(0.032)	(0.032)	(0.032)	(0.032)
$COML_{it}$	-0.002	-0.002	-0.002	-0.003	-0.002	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
REL_{it}	0.010***	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
MNG_{it}	0.008**	0.008***	0.008**	0.008***	0.008**	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$EARN_{it}$	-0.036***	-0.037***	-0.035***	-0.036***	-0.036***	-0.036***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
JCD_{it}	-0.019***	-0.020***	-0.019***	-0.021***	-0.019***	-0.02`***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$LOAN_{it}$	-0.005*	-0.004	-0.004*	-0.003	-0.004*	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$FEDF_{it}$	-0.017***	-0.017***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$SIZE_{it}$	-0.099***	-0.096***	-0.088***	-0.086***	-0.088***	-0.086***
	(0.025)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
AGE_{it}	-0.125***	-0.123***	-0.125***	-0.124***	-0.127***	-0.125***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
$HOLD_{it}$	1.954***	1.966***	1.960***	1.971***	1.959***	1.971***
	(0.061)	(0.062)	(0.061)	(0.062)	(0.061)	(0.062)
$TARP1_{it}$	0.488***	0.497***				
	(0.098)	(0.099)				
$TARP2_{it}$			0.602***	0.619***		
			(0.101)	(0.102)		
$TARP3_{it}$					0.557***	0.572***
					(0.010)	(0.101)
$CONC_{t}$	0.011***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
HPI_{t}	0.025**	0.025**	0.026**	0.026**	0.026**	0.026**
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
UNE_{t}	-0.011	-0.014	-0.010	-0.012	-0.009	-0.011
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
$INCO_{t}$	-0.051***	-0.0483**	-0.051***	-0.048**	-0.051***	-0.048**
	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)
Observations	158,654	158,654	158,654	158,654	158,654	158,654
# banks	7405	7405	7405	7405	7405	7405
# acquisitions	1167	1147	1167	1147	1167	1147
LLF	-9613	-9440	-9609	-9435	-9611	-9437
Pseudo R^2	0.0647	0.0656	0.0651	0.0661	0.0649	0.0659
Wald test	1505	1515	1550	1561	1544	1557

All models are estimated by the Cox proportional hazard model with time varying covariates. The dependent variable in models I, III, and V is the acquisition dummy that equals 1 if a bank is acquired within one quarter. LLF indicates log likelihood function. The pseudo R^2 evaluates the goodness of fit by comparing the log-likelihood of estimated models with the log-likelihood of constant-only model. The Wald test evaluates the overall significance of the estimated coefficients. Robust standard errors are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Coming to the other covariates, the results show that smaller banks were more likely to be acquired, compared to larger banks. Also, acquisition probability was negatively associated with bank age. Not surprisingly, affiliates of MBHC are more likely to be acquired, supporting the contention that distressed MBHC may give up their inefficient subsidiaries in order to either survive during adverse macro-financial conditions or acquire better performing banks. Furthermore, my empirical results indicate that banks headquartered in States with falling house prices were less attractive targets while acquiring hazards were higher in States with more concentrated banking sectors. This indicates that local economic conditions and banking sectors play a key role in acquisition decisions.

More interesting, the empirical results show that receiving TARP capital assistance significantly increases probability of a recipient bank being acquired. This result is robust across all models. In particular, it indicates that recipient institutions are likely to be acquired when they hold TARP funds. This can be in part associated with a combination of factors, including public stigma, debt overhang problems, and restrictions on executive pay, which may encourage executive managers of recipient MBHCs to give up some of their subsidiaries to exit the program (see, e.g., Wilson and Wu, 2012; Cornett *et al.*, 2013). Also, some recipient MBHC may be willing to trade their less efficient subsidiaries with more efficient institutions.

Again, the sample was split into small and large banks using the $300 million demarcation threshold. The empirical results for time-to-acquisition of small and large banks are presented in Tables 4.10 and 4.11, respectively.

Broadly speaking, factors significantly affecting time-to-acquisition of small and large banks tend to be similar in many respects. In particular, higher nonperforming assets, lower profitability, lower net federal funds, higher real estate loans in the loan portfolios, and membership of multibank holding companies are common factors that significantly increase acquisition hazards in both small and large banks. Furthermore, the empirical results reveal that acquiring institutions are willing to take over small banks in less competitive markets, regardless of acquired bank size.

Table 4.10. Acquisition hazard estimation results for small banks.

Variables	I Acquisition	II Healthy acquisition	III Acquisition	IV Healthy acquisition	V Acquisition	VI Healthy acquisition
CAP_{it}	-0.020***	-0.019***	-0.020***	-0.018***	-0.020***	-0.018***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
NPL_{it}	0.044***	0.039**	0.044***	0.039**	0.043***	0.039**
	(0.016)	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)
ORE_{it}	-0.043	-0.092***	-0.045	-0.093***	-0.044	-0.093***
	(0.032)	(0.033)	(0.032)	(0.033)	(0.032)	(0.033)
$COML_{it}$	0.004	0.002	0.004	0.002	0.004	0.002
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
REL_{it}	0.010**	0.010**	0.010**	0.010**	0.010**	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
MNG_{it}	0.007	0.008*	0.007	0.008*	0.007	0.008*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$EARN_{it}$	-0.039***	-0.039***	-0.039***	-0.039***	-0.039***	-0.039***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
JCD_{it}	-0.019***	-0.022***	-0.019***	-0.022***	-0.019***	-0.022***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$LOAN_{it}$	-0.005	-0.003	-0.005	-0.003	-0.0053	-0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$FEDF_{it}$	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$SIZE_{it}$	-0.250***	-0.244***	-0.242***	-0.235***	-0.243***	-0.237***
	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
AGE_{it}	-0.173***	-0.170***	-0.173***	-0.170***	-0.175***	-0.172***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)
$HOLD_{it}$	1.912***	1.925***	1.919***	1.932***	1.918***	1.931***
	(0.072)	(0.073)	(0.072)	(0.073)	(0.072)	(0.073)
$TARP1_{it}$	0.605***	0.620***				
	(0.136)	(0.137)				
$TARP2_{it}$			0.631***	0.650***		
			(0.149)	(0.150)		
$TARP3_{it}$					0.602***	0.620***
					(0.146)	(0.147)
$CONC_t$	0.0101***	0.010***	0.010***	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
HPI_t	0.037***	0.036***	0.037***	0.036***	0.037***	0.037***
	(0.013)	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)
UNE_t	-0.016	-0.018	-0.013	-0.014	-0.012	-0.013
	(0.030)	(0.031)	(0.030)	(0.031)	(0.030)	(0.031)
$INCO_t$	-0.052**	-0.048**	-0.051**	-0.048**	-0.051**	-0.048**
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Observations	116,616	116,616	116,616	116,616	116,616	116,616
# banks	5378	5378	5378	5378	5378	5378
# acquisitions	820	802	820	802	820	802
LLF	-6511	-6365	-6512	-6365	-6513	-6366
Pseudo R^2	0.0652	0.0659	0.0651	0.0658	0.0651	0.0657
Wald test	1208	1204	1212	1207	1212	1208

The dependent variable in models II, IV, and VI is the healthy acquisition dummy that equals 1 if a healthy bank is acquired within one quarter. LLF indicates log likelihood function. The pseudo R^2 evaluates the goodness of fit by comparing the log-likelihood of estimated models with the log-likelihood of constant-only model. The Wald test evaluates the overall significance of the estimated coefficients. Robust standard errors are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Table 4.11. Acquisition hazard estimation results for large banks.

Variables	I Acquisition	II Healthy acquisition	III Acquisition	IV Healthy acquisition	V Acquisition	VI Healthy acquisition
CAP_{it}	0.022***	0.021***	0.023***	0.023***	0.023***	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
NPL_{it}	0.038*	0.039*	0.039*	0.040*	0.039*	0.040*
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
ORE_{it}	-0.182**	-0.206***	-0.213***	-0.238***	-0.203***	-0.228***
	(0.075)	(0.078)	(0.080)	(0.084)	(0.078)	(0.082)
$COML_{it}$	-0.013	-0.012	-0.015	-0.015	-0.015	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
REL_{it}	0.018***	0.018***	0.017***	0.017***	0.017***	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
MNG_{it}	0.007*	0.007*	0.007*	0.007*	0.0069*	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$EARN_{it}$	-0.040***	-0.040***	-0.038***	-0.038***	-0.039***	-0.038***
	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)
JCD_{it}	-0.012	-0.012	-0.014*	-0.013*	-0.014*	-0.013*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$LOAN_{it}$	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$FEDF_{it}$	-0.021***	-0.021***	-0.022***	-0.022***	-0.022***	-0.022***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$SIZE_{it}$	-0.008	-0.009	0.004	0.003	0.003	0.002
	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)
AGE_{it}	-0.040	-0.045	-0.038	-0.044	-0.042	-0.047
	(0.061)	(0.061)	(0.061)	(0.061)	(0.060)	(0.061)
$HOLD_{it}$	2.048***	2.052***	2.049***	2.052***	2.050***	2.053***
	(0.127)	(0.127)	(0.126)	(0.126)	(0.126)	(0.126)
$TARP1_{it}$	0.416***	0.404***				
	(0.154)	(0.155)				
$TARP2_{it}$			0.724***	0.715***		
			(0.151)	(0.152)		
$TARP3_{it}$					0.643***	0.634***
					(0.147)	(0.148)
$CONC_t$	0.009*	0.009*	0.009*	0.009*	0.009*	0.009*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
HPI_t	0.015	0.014	0.018	0.017	0.018	0.0167
	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.016)
UNE_t	0.027	0.027	0.0211	0.021	0.023	0.023
	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)	(0.043)
$INCO_t$	-0.058	-0.056	-0.059	-0.057	-0.059	-0.057
	(0.036)	(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Observations	42,038	42,038	42,038	42,038	42,038	42,038
# banks	2027	2027	2027	2027	2027	2027
# acquisitions	347	345	347	345	347	345
LLF	-2362	-2348	-2356	-2341	-2358	-2343
Pseudo R^2	0.0916	0.0919	0.0941	0.0944	0.0934	0.0938
Wald test	465.3	462.8	483.1	479.8	483.5	480.3

The dependent variable in models II, IV, and VI is the healthy acquisition dummy that equals 1 if a healthy bank is acquired within one quarter. LLF indicates log likelihood function. The pseudo R^2 evaluates the goodness of fit by comparing the log-likelihood of estimated models with the log-likelihood of constant-only model. The Wald test evaluates the overall significance of the estimated coefficients. Robust standard errors are reported in parentheses. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

Despite these similarities, there are some key differences between factors affecting acquisition hazards of small and large banks. Notably, while larger banks with lower foreclosed real estate and less efficiency are more attractive targets, acquisition hazards of small banks are significantly and negatively associated with bank size, bank age and the fraction of jumbo certificate of deposits in their asset portfolios. Furthermore, although no robust relationship is found between local economic conditions and acquisition hazards, the results indicate that falling house prices and rising personal income significantly reduced likelihood of acquisition for small banks.

In addition, one of the most striking findings of this study is the asymmetric impact of capital ratio on time-to-acquisition of small and large banks: large acquired institutions tend to have higher equity to asset ratio, while small acquisition targets had significantly lower capital ratios and closer to failure. Hannan and Pilloff (2009) argue that, on one hand, lower capitalization reflects lower income in the past and signals lower efficiency, which may increase the attractiveness of the target. On the other hand, higher capitalization may indicate inefficient capital allocation and therefore a well-capitalised bank can be a very attractive target for acquiring institutions.

Finally, the results indicate that receiving capital assistance significantly increases probability of being acquired across both small and large banks, although the impact is slightly higher across small banks. These results are robust across alternative TARP indicators and strongly support the second hypothesis of this chapter.

To summarize, the empirical findings strongly support hypothesis two, which postulates that recipient banks are very attractive acquisition targets, regardless of their size and financial health, particularly before the repayment of the bailout funds.

4.6. CONCLUSIONS

The collapse of real estate bubble in the U.S. triggered severe liquidity shortages in many financial institutions exposed to real estate and mortgage backed securities, which eventually culminated in a series of unprecedented events in September 2008. As a comprehensive response to rapidly deteriorating financial system, the U.S. government created the Troubled Asset Relief Program (TARP) to bailout the US financial system and restart the economy. Under the TARP, the US Treasury purchased preferred stock and equity warrants from qualified institutions to help them survive and stimulate lending activities. Using a panel of the U.S. commercial banks over the period 2007Q1 to 2012Q4, the Cox proportional hazard model is estimated to investigate the impact of receiving capital assistance on two different types of bank exits; exit due to regulatory closure and exit due to acquisition.

The empirical results indicate that providing capital assistance enhances survival likelihood of large banks, while smaller banks are less likely to avoid regulatory closure. Also, capital infusions do not reduce probability of technical insolvency among recipient banks, regardless of their size. These results suggest that governmental capital assistance serves larger banks much better than their smaller counterparts. Furthermore, the empirical results reveal that receiving capital assistance significantly increases acquisition likelihood of recipient banks, regardless of their size and financial health. In general, these findings suggest that capital infusions do not improve financial stability of recipient banks.

The findings of this chapter have important policy implications for policymakers and financial regulators: first, success of likewise programs require more transparency in selection of qualified institutions. Qualifying distressed institutions questions financial health of other participants and results in market stigmatisation which limits their access to liquidity and external funding. Second, government authorities must ensure that government funds will be used in the manner they were intended in order to avoid creating huge moral hazard incentives as well as opportunistic behaviour among recipient institutions. Finally, government bailout of smaller banks does not effectively help out of a distressed period unless enough capital is injected before they become stressed. One of the main reasons that smaller recipient did not perform well is that smaller banks waited much longer and received much less compared to their larger counterparts.

APPENDIX A4

Table A4.1. Geographical distribution of US commercial banks as of March 31, 2007, along with distribution of closed and acquired banks during 2007Q1-2013Q1.

Name	Banks	Closed	Acquired	Name	Banks	Closed	Acquired
Alaska	5	0	1	Montana	76	0	14
Alabama	152	5	25	North Carolina	80	5	23
Arkansas	144	2	25	North Dakota	93	0	7
Arizona	50	11	19	Nebraska	240	2	37
California	279	32	52	New Hampshire	10	0	5
Colorado	149	8	52	New Jersey	69	4	14
Connecticut	24	0	8	New Mexico	48	2	3
District of Colombia	5	0	1	Nevada	36	10	7
Delaware	24	0	8	New York	139	4	21
Florida	270	54	58	Ohio	177	2	30
Georgia	332	82	57	Oklahoma	256	5	23
Hawaii	7	0	0	Oregon	38	6	6
Iowa	383	1	55	Pennsylvania	168	2	36
Idaho	15	0	2	Rhode Island	6	0	1
Illinois	588	50	65	South Carolina	76	5	16
Indiana	126	2	24	South Dakota	85	1	12
Kansas	342	8	51	Tennessee	193	3	21
Kentucky	197	0	26	Texas	607	7	97
Louisiana	142	2	16	Utah	58	6	4
Massachusetts	51	0	10	Virginia	109	2	22
Maryland	70	4	19	Vermont	14	0	4
Maine	12	0	4	Washington	83	17	13
Michigan	154	10	31	Wisconsin	265	6	31
Minnesota	426	20	52	West Virginia	64	0	7
Missouri	334	15	36	Wyoming	42	1	9
Mississippi	92	2	7	***Total***	8449	452	1074

CHAPTER FIVE

CONCLUDING REMARKS

Throughout history, banking systems around the world have faced a wide range of difficult challenges including banking crises. In response to these distressing events, banking literature substantially extended to (*i*) identify major contributors to banking distress at both country-level (see Laeven and Valencia, 2008; Reinhart and Rogoff, 2009) and bank-level (see Wheelock and Wilson, 2000; DeYoung, 2003), (*ii*) provide policy implications to limit riskiness of banks and banking system by designing early warning systems (see Martin, 1977; Demirgüc-Kunt and Detragiache, 2005; Kaminsky and Reinhart, 1999), and (*iii*) design appropriate policy tools to resolve banking crises (see Diamond and Rajan, 2002, 2005). Parallel to the banking literature, banking regulations also evolved enormously to ensure stability and soundness of banking systems. Notably, the Basel Committee on Banking Supervision (BCBS) established the most comprehensive international regulatory framework to address major risk components, including market risk and credit risk, in banking institutions.

In spite of all these advances in banking literature and regulations, in late 2000s, the United States faced subprime mortgage crisis, which rapidly spread throughout the globalised and interconnected world. The main implication of this crisis was that the complex banking regulations failed to identify and limit riskiness of the banking systems at both domestic and international levels. It is therefore not surprising that a tremendous number of studies have focused on the causes (see Demyanyk and Van Hemert, 2011; Acharya *et al.*, 2009), consequences of contagion effects (see Mian and Sufi, 2009; Longstaff, 2010), and remedies of the recent crisis (see Diamond and Rajan, 2009; Freedman *et al.*, 2010).

Nevertheless, there remains substantial uncertainty on how reliable quantitative models are in measuring risk, how systematic factors such as house prices undermine the stability of banking system, and how effectively government bailout programs can combat the banking crisis. This thesis contributes to this literature and includes three empirical studies to address the abovementioned questions. Notably, forecasting performance of alternative value at risk (VaR) models, the linkage between house price fluctuations and evolution of nonperforming loans (NPL), and the impact of capital infusions on stability of recipient banks are evaluated in this study. In essence, the last three chapters can be considered as an empirical investigation of market risk, credit risk, and liquidity risk in the U.S. banking institutions. Throughout this thesis, various econometric approaches are used. These models include univariate and multivariate time series analysis, dynamic panel data models, and survival analysis. Below an outline of the thesis is given.

Chapter 2 contributes to the existing literature by investigating the performance of alternative value at risk (VaR) models in measuring riskiness of international equity portfolios. Many large banking institutions have become highly involved in market-based activities (see Laeven *et al.*, 2014). In addition, over the last two decades and due to deregulations, technological advances, and globalisations of financial markets, many large banks have expanded their market-based activities across the world to benefit from portfolio diversifications and potentially higher rates of return. Mismanagement and miscalculation of market risk of international equity portfolios in such banks can pose severe threat to the existence of the bank and stability of the global financial system. In general, an international equity portfolio is composed of two main risk components: equity risk and foreign exchange rate risk. Accordingly, two alternative approaches can be used to estimate VaR threshold of international equity portfolios: (*i*) applying univariate VaR models on portfolio returns, and (*ii*) applying multivariate VaR models on portfolio's risk components.

In Chapter 2, a variety of GARCH type models are employed to model conditional volatilities in both univariate and multivariate frameworks while constant conditional correlation (CCC), dynamic conditional correlation (DCC), and asymmetric dynamic conditional correlation (ADCC) are applied to model conditional correlations in multivariate framework. Using these alternative approaches, international portfolio VaR thresholds are calculated in eight countries and during both pre-crisis period, from January 2003 to December 2006, and crisis period, from January 2007 to December 2010. Once VaR thresholds are measured, various backtesting criteria are applied to evaluate the performance of alternative VaR models from both regulatory and risk management perspectives.

From regulatory perspective, the empirical findings of Chapter 2 reveal that most parametric VaR models have satisfactory performance with low number of violations during pre-crisis period, while the number of violations, mean deviation of violations, and maximum deviation of violations dramatically increase during crisis period. More importantly, most VaR models fail to pass BCBS criteria during crisis period, indicating that parametric VaR models are not very reliable during financial crises. Another interesting finding of this chapter is that performance of alternative VaR models widely vary across countries and no benchmark model can be selected as a superior VaR model across all countries. However, portfolio VaR models incur lower number of violations compared to univariate VaR models, while DCC and ADCC models perform better than CCC models during crisis period. Furthermore, applying Student-t distribution as distributional assumption for VaR models leads to more accurate and conservative VaR estimations over both sub-sample periods. While regulators are mainly interested in the number of violations of internal VaR models, risk managers are primarily concerned about goodness of fit and capital requirements of VaR models. From risk management perspective, it is found that portfolio models produce slightly higher regulatory capital requirement and weaker goodness of fit across most sample countries, while most univariate models fail to pass the BCBS criteria during crisis period. Furthermore, mixed empirical evidence is found on the performance of alternative portfolio models across sample countries.

The findings of Chapter 2 have several important implications for regulators and risk managers. First and foremost, the empirical results reveal that existent parametric VaR models are not reliable during crisis periods. This in turn indicates that despite all advances in volatility and VaR modelling over the last three decades, further investigations are of paramount importance to develop better performing models during crisis periods. Moreover, in response to weak performance of VaR models, the BCBS (2009) revised its market risk framework by adding stressed VaR to capital requirements to ensure stability of large international banks. However, the revised framework significantly increases the capital requirements imposes excessive capital requirements for banks, which eventually leads to inefficient capital allocation in banks (see Rossignolo *et al.*, 2012). Therefore, further research is required to design a more appropriate capital requirement framework before stressed VaR is officially incorporated into regulations. Future works might also focus on designing a more comprehensive backtesting framework to overcome current issues with existent backtesting models. Finally, the empirical study presented in Chapter 2 can be developed by considering larger international portfolios containing more assets and risk components.

Chapter 3 puts under econometric scrutiny the linkage between house price fluctuations and evolution of nonperforming loans (NPL) in the U.S. banking institutions. The recent subprime mortgage crisis in the U.S. was originated with the collapse of house price bubble. The U.S. banking institutions dramatically suffered from falling house prices while they were the primary contributors to the creation of the housing bubble through their lending policies in pre-crisis period. This indicates that house price fluctuations can be considered as a key indicator that can systematically undermine the stability of individual banks and thereby the stability of the whole banking system. The performance of banks' Loan portfolios are expected to be tightly associated with house price fluctuations as (*i*) real estate loans often form a large portion of loan portfolios, and (*ii*) real estate is widely used as collateral for other types of loans (see Goodhart and Hofmann, 2008; Davis and Zhu, 2009). Nonetheless, previous studies, including Reinhart and Rogoff (2009), and Barrell *et al.* (2010), have mainly focused on the linkage between house prices and stability of the banking systems while far less is known about how house price fluctuations affect quality of loan portfolios in individual banks. Using a large panel of the insured banking institutions in the United States, dynamic panel data models are applied in Chapter 3 to investigate the linkage between house price fluctuations and evolution of nonperforming loans over three periods; the pre-crisis period of 1999-2005, the crisis period of 2006-2012, and full sample period of 1999-2012. This study is further developed by investigating this relationship across different loan categories, different types of banks, different bank size.

The empirical findings of Chapter 3 reveal that NPL dynamics across U.S. banks can be explained by a mixture of idiosyncratic and systematic factors. In particular, it is found that evolution of NPL is highly associated with the swings in house prices, while the impact of house price fluctuations on NPL is stronger during crisis period. Furthermore, there is strong empirical evidence that the impact of house price fluctuations widely vary across different loan categories, with real estate loans being the most responsive loan category. Moreover, different loan categories respond differently to idiosyncratic factors. In other words, while real estate NPL is most sensitive to loan portfolio concentration, commercial NPL and consumer NPL are highly responsive to bank size. The empirical results also show that sensitivity of loan portfolios to house price fluctuations and other NPL determinants varies across savings institutions and commercial banks. Finally, it is found that falling house prices have greater impact on the evolution of NPL in large banks during crisis period, while large banks are also more sensitive to business cycle fluctuations.

The empirical work presented in Chapter 3 is among first studies on the linkage between house prices and stability of individual banks and further analyses are no doubt needed. Future works might assess the impact of house prices on the quality of capital in banks. It is also interesting to evaluate the impact of house price fluctuations and funding resources of banks on their riskiness and lending behaviour. Furthermore, one of the main findings of Chapter 3 is the asymmetric linkage between house prices and quality of loan portfolios. Therefore, further research is required to investigate the potential nonlinear relationship between house prices and NPL. This in turn requires developing a dynamic threshold framework, which is beyond the scope of this thesis. Finally, the impact of house price fluctuations on the quality of loan portfolios can be investigated at loan-level, which has been largely neglected due to data constraints.

Chapter 4 examines how effectively government bailout programs can combat the banking crisis. The U.S. financial system faced an unprecedented liquidity crisis in September 2008 when a series of distressing events occurred in various key industries. As a comprehensive response, the U.S. government applied a wide range of policy tolls to combat the crisis. In particular, the U.S. government created the troubled asset relief program (TARP) to stem the panic and restore confidence in the U.S. financial system, with special focus given to the banking system. The capital purchase program (CPP) was then launched as an initial program under TARP to purchase preferred stock and equity warrants from qualified institutions to help them survive and stimulate lending activities. However, the success of capital infusion programs has been challenged by many pundits and researchers (see Diamond and Rajan, 2005; Farruggio *et al.*, 2013). Using a panel of the US commercial banks over the period 2007Q1 to 2012Q4, the Cox proportional hazard model is applied in Chapter 4 to investigate the impact of receiving capital assistance on two different types of bank exits; exit due to regulatory closure and exit due to acquisition.

The empirical results of this study indicate that providing governmental capital assistance to banks during periods of banking crisis do not enhance the probability of avoiding technical insolvency. However, larger recipient banks might avoid regulatory closure, perhaps due to better regulatory and political connections. This in turn indicates that governmental capital assistance serves larger banks much better than their smaller counterparts. It is also found that recipient banks are more attractive acquisition targets, regardless of their size and financial health. Overall, the empirical findings of Chapter 4 reveal that capital infusions do not enhance financial stability of the recipient banks.

Considering the key role that government policy tools play in restoring stability during periods of banking crisis, further research is needed in this line of literature beyond any doubt. Future works can be developed in several directions. First, it is essential to design a framework for the selection of qualified institutions in capital injection programs. Second, better instruments of intervention are essential for smaller banking institutions as their credit rating adjustment process might be very slow, while they are vulnerable to public stigma. Third, new guidelines are required to monitor risk taking behaviour of the recipient banks to reduce moral hazard incentives and to ensure that government funds are used in the manner they are intended to. In addition, empirical studies can evaluate indirect effects of capital infusion programs on the stability of the banking system. In particular, special focus can be given to competition distortion in the banking system due to implementation of government bailout programs and its impact on risk taking behaviour of individual banks.

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