The Role of Systemic Risk, Regulation and Efficiency within the Banking Competition and Financial Stability Relationship

Scott Ellis

A thesis submitted in partial fulfilment of the requirements of the University of Northumbria at Newcastle for the degree of Doctor of Philosophy

Northumbria University
NEWCASTLE

Accounting and Financial Management
Newcastle Business School
University of Northumbria
United Kingdom

May 2019

Supervisor: Dr Satish Sharma

'The recent crisis has reaffirmed an old lesson: good data and good analysis are the lifeblood of effective surveillance and policy responses at both the national and international levels'
(FSB, 2009a, P. 10)

The Role of Systemic Risk, Regulation and Efficiency within the Banking Competition and Financial Stability Relationship

Scott Ellis

Submitted for the degree of Doctor of Philosophy
May 2019

Abstract

This thesis provides empirical evidence of the banking competition-stability nexus from the Basel jurisdictions with a main focus on the United States (US) banking sector from 2000 to 2015. In order to assess this relationship, three papers in the format of journal articles were used to explore different theoretical concepts.

The first paper, is a systematic literature review of 4,859 abstracts to identify the different types of systemic risk measures and the challenges regulators face in addressing systemic risk. 56 measures of systemic risk developed post-2000 were identified and critically appraised to inform academics and regulators of the models' vulnerabilities. Additionally, a number of measures were calculated using US bank data. The findings of this paper suggests that the majority of these measures tend to focus on individual financial institutions' risk rather than the entire system stability. This directly reflects the current regulations, which aim to ensure individual institutions' soundness. As macro-prudential regulation evolves, policy-makers face the issues of understanding contagion and how such regulation should be implemented.

The second paper is an empirical analysis of banking cost efficiency, the aim of this paper is threefold, firstly to conduct an empirical literature review of banking sector efficiency over the last two decades, thereby identifying banking risk and regulatory variables used to access efficiency. Secondly, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) are applied to measure efficiency

within the Basel jurisdiction's banks. Thirdly, it aims to investigate the determinates of cost efficiency in the US banks by employing System Generalised Methods of Moments (GMM) regression analysis using panel data. This paper found the GMM analysis econometric measures of efficiency provided more statistically significant regression models than when using accounting based measures of efficiency. Also it was found that credit and liquidity risks are negatively associated with efficiency, and regulations designed to mitigate these risks have a negative impact on efficiency.

The final paper combines the literature and calculations from papers one and two, to examine the role of risk, regulation and efficiency within the banking competition and financial stability relationship. Using GMM regression, this paper found a neutral view of the competition-stability nexus within the US banking sector, where both competition and concentration fragility co-exist. In addition, a unique polynomial competition-fragility relationship was found. Interestingly using the Composite Index of Systemic Stress (CISS) as a measure of systemic risk, altered the competition-stability relationship to identify a concave relationship. This suggests that the competition-stability nexus within one country can differ at the microeconomic (financial stability) and macroeconomic (systemic risk) level. In regards to increased risk, credit, leverage, diversification and liquidity risk was found to be negatively associated with financial stability. Whilst increased capital requirements as proposed by Basel III enhanced stability, the Net Stable Funding Ratio (NSFR) was unexpectedly found to hinder stability, providing caution to regulators as this is currently implemented.

The findings within this thesis provide an incentive for further academic research in the area of liquidity & systemic risk, which would be relevant to practitioners and policy-makers to enhance their understanding of banking competition and financial stability.

Keywords:

Banking, Financial Stability, Systemic Risk, Regulation, Competition, Concentration, Efficiency, Financial Stability.

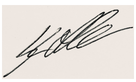
Declaration

The content of this doctoral dissertation is all my own work completed at Newcastle Business School, Northumbria University, UK. No material contained in the thesis has previously been submitted for an award in this or any other university.

Research ethical approval was sought and granted by the Faculty Ethics Committee on 12/06/2014

I declare the word count of this thesis as **77,969** words.

Name: Scott Ellis

Signature: 

Date: 07/05/2019

Acknowledgements

I would like to take this opportunity to acknowledge and appreciate the people who have help me dearly to conduct this research.

First of all, I would like to thank my supervisor and friend, Dr Satish Sharma. I consider myself to be very lucky to have him as my supervisor and I am especially appreciative of the time he has dedicated to me while guiding me through this research journey. Without his critical feedback, it would have been impossible for me to complete this research thesis.

Secondly, thank you to my colleagues, Prof. Janusz Brzeszczynski, Prof. Philip Shrives, Dr Binam Ghimire and Dr Pankaj Chandorkar who supported me professionally during this PhD journey.

Thirdly, a special thanks to all my Graduate Tutor and PhD peers, especially Bridgy, Merrel, Imanol, Lesley-Ann, Lisa, Paddy, Kate, Princess and Pablo who have supported me morally during this PhD journey and motivated me towards completion.

And last, but certainly not least, I would like to thank my mam and dad, Maxine and Peter Ellis, for their unconditional support.

Dissemination

Ellis, S. (2018, March). *Competition and Financial Stability in the US*. Findings discussion at the Ensuring Access to Capital: Banking models between the market and the state research seminar, Amsterdam University of Applied Sciences, Netherlands.

Ellis, S. (2017, July). *Determinants of Cost Efficiency in the US Banking Sector*. Paper presented at the Newcastle Business School Conference, Newcastle upon Tyne, UK.

Ellis, S. (2016, June). *Systemic Risk Measures and Data Requirements*. Paper presented at the INFINITI Conference on International Finance, Trinity College Dublin, Ireland.

Ellis, S. (2016, June). *Systemic Risk and the Challenges of Regulators*. Paper presented at The International Conference on Banking and Finance. London South Bank University, UK.

Ellis, S. (2015, July). *Recent Literature on Indicators of Systemic Risk a Critical Overview*. Paper presented at the Newcastle Business School Conference, Newcastle upon Tyne, UK.

Ellis, S. & Sharma, S. (2014, June). *Stability-Competition-Liquidity- The New Mantra for Banking Regulation*. Poster presented at the International Risk Management Conference, Warsaw, Poland.

Contents

List of Figures

List of Tables

List of Abbreviations

ASF	Available Stable Funding
BCBS	Basel Committee on Banking Supervision
BIS	Bank of International Settlements
CDS	Credit Default Swap
CISS	Composite Indicator of Systemic Stress
CFPB	Consumer Financial Protection Bureau (US)
CoVaR	Conditional Value at Risk
D-SIBs	Domestic Systemically Important Banks
DEA	Data Envelopment Analysis
DMU	Decision Making Units
EBA	European Banking Authority
ESA	European Supervisory Authority
ESFS	European System of Financial Supervision
ESP	Efficient Structure Paradigm
ESMA	European Security and Market Authority
ESRB	European Systemic Risk Board
EWS	Early Warning Systems
FDIC	The Federal Deposit Insurance Corporation (US)
FFL	Funding for Lending
FSB	Financial Stability Board
FSF	Financial Stability Forum
FSOC	Financial Stability Oversight Council (US)
HHI	Herfindahl-Hirschman Index
G7	Group of 7

G20	Group of 20
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
G-SIBs	Global Systemically Important Banks
IFRS	International Financial Reporting Standards
IOSCO	International Organization of Securities Commissions
LCR	Liquidity Coverage Ratio
LMI	Liquidity Mismatch Index
LRMES	Long-Run Marginal Expected Shortfall
LSAP	Large Scale Asset Purchases
LTD	Lower Tail Dependence
MES	Marginal Expected Shortfall
MPI	Malmquist Productivity Index
MPP	Market Power Paradigm
NCUA	The National Credit Union Administration (US)
NSFR	Net Stable Funding Ratio
OCC	The Office of the Comptroller of Currency (US)
OFR	The Office of Financial Research (US)
OMT	Outright Monetary Transactions
OTS	The Office of Thrift Supervision (US)
RAMSI	Risk Assessment Model for Systemic Institutions
RSF	Required Stable Funding
SFA	Stochastic Frontier Analysis
SIFI	Systemically Important Financial Institutions
SRL	Systemic Risk-Adjusted Liquidity
TARP	Troubled Asset Relief Program
TBTF	Too-Big-To-Fail
TLAC	Total Loss-Absorbing Capacity
QE	Quantitative Easing
QL	Quiet Life
VaR	Value at Risk

Chapter 1

Introduction

Over the last number of decades banking market structure and its impact on profitability and more recently stability has been debated by academics, practitioners and regulators alike (Beck, De Jonghe, & Schepens, 2013; Boyd & Nicoló, 2005; X. Fu, Lin, & Molyneux, 2014; IJtsma, Spierdijk, & Shaffer, 2017; Jayakumar, Pradhan, Dash, Maradana, & Gaurav, 2018; Keeley, 1990; OECD, 2010; Schaeck & Cihák, 2014, *inter alia*). Various factors have contributed towards enhancing integration and competition between financial institutions over the course of recent decades. Both the financial sides of the world economy and the real economy have become substantially more coordinated. Varying degrees of deregulation of the financial markets has taken place worldwide and financial institutions are less restricted on their activities and the areas they can operate. Up until the late 20th century bank competition, certainly in the western world, was restricted due to barriers to entry or geographical location. For example, in the USA individual states controlled banking licenses which allowed them to protect state banks from competition and foreign bank entry creating local monopolies. This created markets which contained a large number of smaller banks (low concentrations) with minimal competition. Protected monopolised banks were able to create larger profits, hence an incentive for the banks to want competition regulatory protections. However, this also created inefficiencies as well as potentially, restricting innovating, diminishing entrepreneurship, stalling growth and reducing the demand for labour. Following a succession of competition regulation change, consolidation and advances in technology transformed the banking landscape into what we know today. Innovative advances in the technology and telecommunication scectors have been far-reaching and thus, encouraged further specialised advances within financial institutions. These advances essentially diminished the expenses (cost) of financial activities. As a result, financial institutions have turned out to be more progressively coordinated in regards to their activities and across geographical borders (Wilcox, 2005). Economic theory suggests increased competition benefits consumers via additional choice and potentially cheaper services. It also benefits the financial institutions via increased income distribution (Beck, Levine, & Levkov, 2010), efficiency (Bertrand, Schoar, & Thesmar, 2007) and growth (Cetorelli & Gambera, 2001). However, increased competition may result in the unintended consequence of lowering profitability and increasing instability (Beck et al., 2013; Keeley, 1990). From a regulation point of view, fewer regulatory organisations have had to cope with increased financial activity, more diverse business models and innovative products and services. There is there is a plethora of literature regarding the level of competitions impact on banking performance, but less is known about its impact on overall financial stability (J. O. Wilson, Casu, Girardone, & Molyneux, 2010). The original academic interest between competition in the banking sector and financial stability was prompted by Keeley (1990), who empirically evidenced that increased competition within the US banking sector in the 1980s resulted in an increase in bank failures. Since the global financial crisis of 2007/08[1], academics have seek to investigate a range of risk management topics as well as re-open the debate regarding market structure (concentration and competition) and stability. This thesis will sort to contribute theoretically and empirically to this market concentration and competition, banking efficiency, profitability and stability nexus.

[1]Referred to as *the financial crisis* for the remainder of this thesis.

1.1 Motivation

The personal motivation for investigating this subject originated from my interest in the story of the collapsed UK bank, Northern Rock. When the Building Societies Act 1986 was passed this permitted societies to demutualise and become a limited company like other banks. Since then all ten building societies that demutualised (BSA, 2015) between 1989 and 2000 have either collapsed (e.g. Bradford & Bingley and Northern Rock) or have been acquired by larger banks (e.g. Abbey National, Halifax and Woolwich). They are all case studies of market competition pressures that have led to being acquired or to take excessive risk.

Following the financial crisis, research within risk management has sought to understand what happened, subsequently leading to a phase of identifying indicators for future possible financial crisis. J. O. Wilson et al. (2010, P.1) suggested "*Future research could also be directed to provide a better understanding between competition, capital, profitability, liquidity and risk*". The motivation of this thesis is to contribute to and support to this trend. The rescues of a number of the largest banks[2], the creation of larger banks by the absorption of failed ones[3] and national insolvencies[4] during the financial crisis re-opened the discussion of the negative externalitly of *too-big-to-fail* (TBTF)[5] policy (BOE, 2013; Haldane & May, 2011). An expectation from a larger (systemic) banks to receive a government or sovereign bailout in case of failure may reduce their incentives to exercise discipline and may increase risk-taking, ultimately increasing the sector's financial fragility. Such a scenario could also provide an incentive to smaller banks

[2]E.g. Fannie Mae and Freddie Mac in the USA, The Royal Bank of Scotland Group in the UK, UBS in Switzerland and Dexia by the Belgian, French and Luxembourg governments.

[3]E.g. JPMorgan's acquisition of Bear Stearns and Bank of America's acquisition of Merrill Lynch in the USA. Lloyds TSB's acquisition of Halifax Bank of Scotland (to form the Lloyds Banking Group) in the UK and France's BNP Paribas' acquisition of Fortis' Belgian and Luxembourg assets.

[4]E.g. Iceland in 2008, Ireland in 2010 and Cyprus in 2013 (Demirgüç-Kunt & Huizinga, 2013).

[5]Originally this term was universalised by Stewart McKinney during a 1984 U.S. Congressional hearing, discussing the Federal Deposit Insurance Corporation's (FDIC) intervention with Continental Illinois (Stern & Feldman, 2004).

to pursue an unsustainable growth strategy to enhance their size in order to be considered as TBTF. In addition, theoretical undercapitalised banks may have incentives to roll over loans to distressed borrowers (inefficient firms) instead of restructuring or liquidating them[6], effectively reducing credit supply to newer borrowers (potentially more efficient firms) hampering the economic recovery. Homar and van Wijnbergen (2017) analysed recapitalisation interventions during recessions following 69 banking crises during the period from 1980 to 2014, and provided positive and significant evidence in support of bailouts which enhanced the banks' probability of recovery (i.e. shortening recessions). There was no evidence that other interventions such as liquidity support or guarantees on bank liabilities enhance probability of recovery. Further, TBTF could lead to increased market concentration, restricting competition adding to the moral hazard incentives to take excess risk to generate higher levels of return and potential inefficiencies. Such a dilemma provides a cause for further investigation from a risk management, regulation and a market design perspective.

1.2 Aims and Objectives of the Research

The primary goal of this thesis is to enhance the understanding of the banking competition and financial-stability nexus across the Basel jurisdictions, with a focus on the United States banking sector. In order to achieve this, the papers within this thesis extend the understanding of financial stability, banking efficiency determinants and the competition and concentration relationship. Specifically, the aims and objectives of this study are:

1. To investigate the literature to gain a wider understanding of the concept of banking financial stability:
    - Provide a broad review of the various definitions;

[6] Write-offs may impact regulator capital requirement or trigger counterpart risk due to securitisation

- Conduct a systematic literature review in order to identify the models developed post 2000 to measure financial stability;
- Identify the data used to empirically test these models;
- Replicate a number of the sector level systemic risk measures using US data;
- Review the current regulations in place to address systemic risk and identify regulatory challenges from the literature.

2. To investigate the determinants of Banking Efficiency:
   - To employ Stochastic Frontier Analysis (SFA) to calculate bank level cost efficiency scores;
   - To employ Data Envelopment Analysis (DEA) to calculate bank level production efficiency scores;
   - To identify a number of determinants of banking efficiency such as credit risk, liquidity, regulatory ratios.

3. To evaluate the impact of efficiency, competition & concentration on banking financial stability:
   - To calculate various measures of banking competition within the Basel jurisdictions;
   - To calculate various measures of banking concentration within the Basel jurisdictions;
   - To analyse the determinants of financial stability such as credit risk, liquidity, regulatory ratios at a bank level;
   - To analyse the determinants of financial stability at a bank level with sector level variables of competition and concentration;
   - To analyse the role of systemic risk within the banking competition and stability relationship.

1.3 Organisation of this thesis

The thesis is organised in the format of research papers where chapters are designed in the format of journal articles. The structure of the thesis is as follows:

Chapter 1: Introduction

The introduction chapter will provide a brief background and the motivation for the topic as well as providing the thesis structure and summarising the notable elements and key findings of this thesis. This chapter will also discuss the epistemological stance of this thesis.

Chapter 2: Review of Related Literature

This chapter reviews the literature that will inform the rest of the thesis. The focus will be to outline the traditional market structure theories which will be tested within the later chapters and the banking regulatory environment which will be referred back to throughout the thesis. Note, this chapter is not in the format of a journal article.

Chapter 3: Financial Stability Measures and Regulation Challenges

This chapter provides a critical overview of the existing methodologies and regulations regarding systemic risk. Following a systematic literature review, this chapter aims to contribute by providing a transparent overview of the measures of systemic risk that have been developed post-2000. Furthermore, a number of the measures are evidenced using US data, such calculations will be used within later chapters.

Chapter 4: Banking Efficiency Determinants

This chapter surveys the banking efficiency literature and examines previous empirical evidence regarding banking efficiency determinants. In order to investigate the efficiency structure paradigm (ESP) in the following chapter, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) methodologies are used to generate bank level efficiency scores. Empirically within this chapter, US bank data is used to identify the determinants of cost efficiency pre and post the financial crisis.

Chapter 5: Banking Efficiency, Concentration and Competition and Financial Stability

This chapter combines knowledge and calculations from the previous chapters and empirically examines the relationship between banking efficiency, concentration, competition and financial stability. This chapter also provides evidence of the various market structure, risk and regulatory determinants of financial stability.

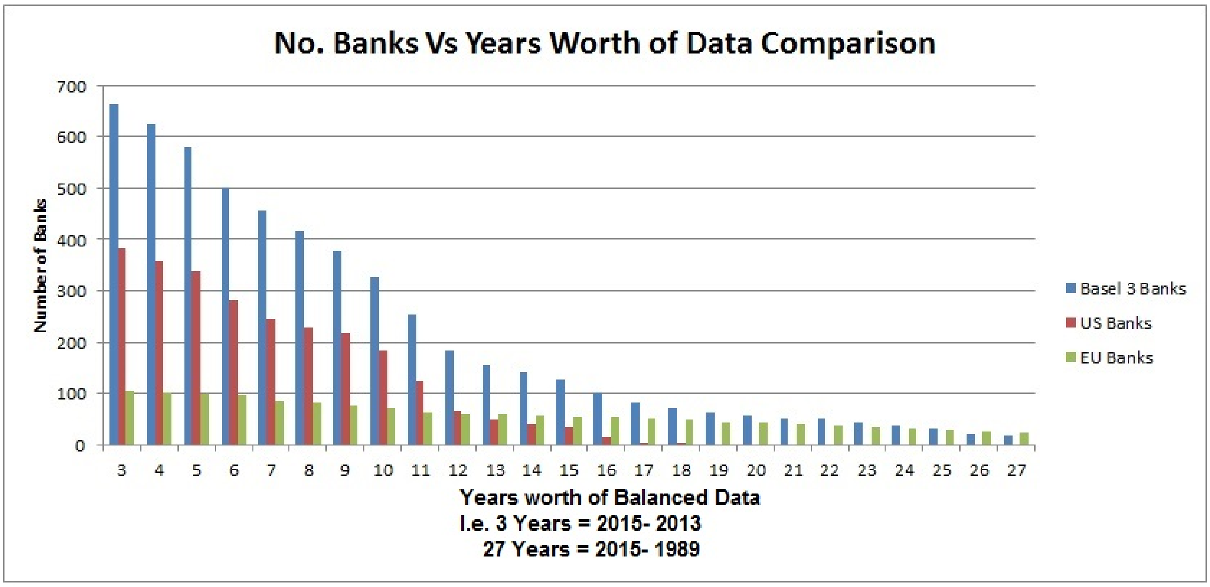
Chapter 6: Conclusion

This final chapter summarises the key findings from this research in order to articulate this thesis' contributions to theory and practice. This section also addresses the research limitations and provides suggestions for future research.

Chapters 3, 4 and 5 are in the form of an academic journal article which contains its own literature review, methodology section, finding and discussion and summary/conclusion. Although each paper is freestanding, in the sense they investigate the implications of bank efficiency and market competitions/concentration, yet all are related in the examination of the determinants of banking stability. Thus, the contribution of the thesis can be viewed as a collection of contributions of each paper. This thesis will focus on the 27 member jurisdictions subject to the Basel Accords[7] and Global Systemically Important Banks (G-SIBs) (see Table 2.2 in Section 2.4 for a list) given that they are subject to similar regulations. However, due to data limitations the majority of the empirical evidence will use US banking sector data. Due to this for consistency purposes when mining the data from Bloomberg Professional Service all nominal values for non–US banks were converted into USD for fair comparisons. According to Bloomberg (2019) the foreign exchange used to translate the values is the cross currency rate at the time of the annual report publication (or the translation rate declared in the annual report). The data used within this thesis will be discussed further in the relevant methodology sections of each paper. Figure 1.1 provides an indication of the data availability and will form the bases for investigate the BIS

[7]The 27 country jurisdictions include, Argentina, Australia, Belgium, Brazil, Canada, China, France, Germany, Hong Kong SAR, India, Indonesia, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, Russia, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States (BIS, 2016).

Figure 1.1: Balanced Panel Data Availability



Source: Bloomberg (2016)

Basel jurisdictions rather than just an individual country. It is worth noting that balanced data is not necessarily required. For example, in regression analysis, as long as the dependant variables are balanced the independent variables can be unbalanced[8]. As suggested by Baltagi (2008) and Hall (2005) all the panel data used was deflated by their corresponding years consumer price index (CPI) to the 2000 price levels to control for inflation effects. For empirical purposes within this thesis where dummy variables have been used to classify a systemic banking crisis such periods are defined following Laeven and Valencia (2013). Their classification is widely used within similar empirical studies (Acharya, Pedersen, Philippon, & Richardson, 2017; J. R. Barth, Caprio Jr, & Levine, 2013; C. Borio, 2014; Cerutti, Claessens, & Laeven, 2017; Sosa-Padilla, 2018).

The reason for adopting this structure rather than the traditional PhD thesis structure is that it offers a number of advantages. Firstly, each paper looks at the economic and risk management theories from different theoretical perspectives. Furthermore, each empirical paper will have its own empirical literature review to

[8]Statistical significance will determine if the unbalanced datasets are reliable, as well as other pre/post-regression diagnostics.

enhance the thesis comprehensiveness. Secondly, I have gained valuable experience in writing academic articles in a clear and concise manner, a skill which is necessary for my future academic career development. Thirdly, this structure results in a number of manuscripts for easier dissemination to academic journals. In addition, this thesis has been compiled using software called LaTeX, therefore the source code can be easily converting into the publishers' LaTeX templates. Finally, and importantly, organising the thesis in this format is simpler and is becoming increasing popular, certainly within mainland European universities. Given that this thesis structure is similar to a European thesis style that consists of essays/papers, producing a journal article from this is complementary (and vice versa).

1.4 Notable Elements and Key Findings of this Thesis

This research examines the relationship between banking competition and financial stability from a number of mutually supportive theoretical foundations. To understand the theory of financial stability, a systematic literature review was carried out to identify the techniques used to measure this concept. Also, to understand banking competition theory the concepts of efficiency and market concentration are empirically explored in relation to competition. In addition, while exploring these issues the current regulatory context is taken into account to understand how they also influence the competition-stability nexus.

The key findings of this research are as follows,

1. In Chapter 3, a systematic literature review is conducted to identify systemic risk measures developed post-2000. 56 different methods were obtained, which are categorised into five types depending on the area of risk they focus on. This grouping allows for a critical assessment of the techniques. A number of the methods were replicated to produce country level indicators which will be used in the later empirical papers. To date, only one other comprehensive systematic literature review on systemic risk has been

conducted, by Silva, da Silva Alexandre, and Tabak (2017). Their article mainly categorised systemic risk research and produced an author network, they did not critique or identify the techniques used to measure systemic risk, unlike this chapter. The main finding of this systematic literature review is that the majority of these measures tend to focus on individual financial institution's risk rather than the entire banking system stability. Also within this chapter, a table summarising the data requirements for each method was produced, and to the best of my knowledge, this is the first of its kind. This table identifies the data typically used to measure systemic risk and identifies the areas for future development. The most commonly used data is equity and fundamental data. One of the least used data types is from the foreign exchange market, despite the fact that when this type of data is used to measure systemic risk it usually yields interesting and significant results. Furthermore, the majority of data used is from developed countries therefore generalising elsewhere is difficult. Finally, this paper looked at macro potential regulation being developed to tackle systematic risk to identify a number of different regulatory challenges.

2. Within Chapter 4, SFA cost and DEA productivity efficiency is calculated for a number of countries' banks, however it was found that balanced panel data sets were required for statistically significant results. In addition, countries with small sample sizes resulted in insignificant model specifications. In analysing the determinants of efficiency using US panel data, the econometric measures of efficiency (SFA) within the GMM analysis provided more statistically significant regression models than the use of the accounting based measure of cost to income ratio[9]. Proxies for bank level credit and liquidity risk, were both found to negatively impact cost efficiency. This suggests that financial institutions that incur higher costs from non-performing loans (NPL) or from raising funds are more inefficient. In

[9]The alternative econometric measurement of efficiency DEA (calculated via linear programming), however, provided inconsistent results or insignificant model specifications.

addition, regulations designed to mitigate these risks, Basel's Tier 1 Capital Ratio (T1CR) and a proxy for the Net Stable Funding Ratio (NSFR) were also found to negatively affect cost efficiency. To the best of my knowledge this is the first time such regulatory ratios have been used in the study to determine efficiency. Typically, research in this area uses country level aggregates/index or dummy variables to assess regulatory impacts on efficiency. The findings of this paper using bank level variables contradicts previous findings, suggesting the use of bank level regulatory data may provide a more accurate picture[10]. These findings suggest an unintended consequence of the regulations, as their compliance costs (holding extra capital or purchasing further funding) hampers efficiency.

3. Chapter 5 investigates the competition-stability nexus using US Bank panel data. Empirical evidence found in this chapter supports a neutral view of competition versus stability where both competition and concentration fragility co-exist. This has not been found in previous empirical research using US data. In addition, this study investigates whether a non-linear relationship exists. By including a cubic function within the GMM regression analysis, evidence of a polynomial competition-fragility relationship was found. Existing literature suggests the possibility of non-linear relationships, with a number evidencing a concave/convex relationship via the inclusion of a quadratic function. However, no empirical study has introduced a cubic function before. Without the cubic function the evidence also supported a competition-fragility relationship, suggesting previous empirical literature which identified a linear relationship could have potentially investigated a monotonic/polynomial relationship. In addition, the measures of systemic risk which were calculated within Chapter 3 were introduced within the competition-stability nexus to identify whether this altered the relationship. The use of systemic risk measure within this empirical literature is rather limited, however this chapter found a contrasting view of the

[10] Assessing directly how institutions' regulatory ratios impact their cost efficiency.

competition-stability nexus, similar to Leroy and Lucotte (2017).

This chapter also investigated a number of risk and regulatory characteristics as determinants of financial stability. The majority of bank level characteristics were found to be statistically significant in line with the existing literature and theory. However, the inclusion of a proxy for the NSFR was found to hinder stability. This regulatory proxy for liquidity risk has not been used within this literature before. This negative association suggests that as financial institutions seek to enhance long-term stable funding, this could hinder profitability (similar to finding in Chapter 4) and subsequently stability.

1.5 Epistemological and Methodological Framework

Finance and economics, although belonging to the conventional soft or social sciences, more often than not are treated as though they are fields of hard sciences. Consequently, the research in these fields of social sciences has been dominated by a positivist ontology which relies on the assumption that there exists a single objective reality that can be achieved/perceived through controlled and structural approaches using statistics and mathematics.

Research within the competition-stability nexus field of finance tends to also be all 'positivist', in that the authors claim to give reliable and empirically sustainable answers to questions that policy-makers regard to be important. Empirical 'realists' determine whether a statement is true by comparing what is claimed with empirical evidence. This creates what is known as correspondence theory of truth. Positivists usually regard explanation as a process of discovering the necessary law-like generalisations that cover the singular instance to be explained. Positivism is regarded as rather out-of-date for some, although it has been particularly influential in the development of the disciplines of finance, economics and accounting (Ryan, Scapens, & Theobald, 2002).

Looking into positivism, positive is not always positive, it means you are

Table 1.1: Comte's view of positivism throughout the 19th century

Stage	Study	Explanation
Stage 1	Theological (Fictitious)	Religion without science
Stage 2	Metaphysical (Abstract)	An abstract power guides events in the world according to principles, scientific mind-set that believe a higher power/system. For example, ethics and aesthetics do not deal in facts and are therefore unverifiable
Stage 3	Positive (Observation & Experimentation)	Scientific method only, disregarding any metaphysical principles

Source: adapted from M. V. Wilson (1927) and Vincent (1995)

certain, not optimistic or pessimistic, just neutral (free from emotion), positive about knowing. Positivism is often credited to Auguste Comte (Crotty, 1998). Comte first used the word *positivism* in an essay written in 1848, then introduced it definitively as he developed his first major work (The Cours De Philosophie Positive) into a specific political theory of scientific religion (Vincent, 1995). Comte's views of the development of positivism is summarised in Table 1.1. In this research area and certainly within typical journal articles found within mainstream US literature, Comte's view that the only valid knowledge is knowledge gained through the scientific method is still prominent.

Therefore, from a philosophical perspective, this thesis is from a realist/objectivist stance and agrees with ontological materialism[11].

This thesis will observe what is already 'accepted knowledge' and is therefore in existence, can be viewed, read and discussed. The justification for the methodologies employed within this thesis is more important than its theoretical perspective. Notwithstanding (as Comte also warned) there are limitations of an

[11] Which is the belief that material things, such as particles, chemical processes and energy are more real for example than the human mind, and the belief that reality exists regardless of human observers.

over reliance of mathematical approaches (Gane, 2006). Even the 'perfect' method maybe rendered misleading if misused. Further, justification by using complex mathematical analysis and excessively lengthy, technical literature may betray illiterate audiences.

Within this epistemological and methodological framework, following any statistical analysis, the interpretion of findings will be based on fact (statistical significance) and all assumptions stated. Similarly, with other empirical studies in this area and following the principles set by Karl Popper (originally in 1959), this thesis cannot state that a theory is true, it can only provide evidence to support such a theory. Therefore, results can only falsify (reject) a theory (Popper, 2005).

1.6 Research Questions and Hypotheses

This section summarises the research questions and hypotheses that are investigated within this research. These questions are derived from the aims of this study as well as the identified gaps in the later literature reviews.

1. How does the academic literature define and measure systemic risk?
2. What are the determinants of banking efficiency in the Basel Jurisdictions?
3. How does banking competition impact financial stability in the Basel Jurisdictions?

For the second and third research question, following a positivist paradigm, a list of hypotheses was derived from the empirical literature review within the respective chapters. The purpose of stating the following hypotheses is to clarify exactly what is under investigation within each empirical chapter later. From the second research question the following five research hypotheses are tested in chapter 4:

Hypothesis 1: *The use of econometric calculations of efficiency is superior to traditional accounting measures.*

This hypothesis suggests that the use of SFA or DEA as a measure of efficiency within regression analysis is superior to using traditional accounting based measures of efficiency such as the Cost to Income Ratio.

Hypothesis 2: *Business model diversification has a negative impact on efficiency.*

This hypothesis suggests that as a financial institution increases its diversification (altering the intermediation process) this negatively affects cost efficiency. This hypothesis will be tested using US bank panel data, which to the best of my knowledge has not been addressed.

Hypothesis 3: *Increased credit risk has a negative impact on efficiency.*

This hypothesis suggests that as financial institutions face increased credit risk this negatively affects their cost efficiency due to the impact on outputs. This hypothesis will be tested using US bank panel data, which to the best of my knowledge has not been addressed.

Hypothesis 4: *Increased capital requirement regulations enhances efficiency.*

This hypothesis suggests that as financial institutions face increased pressure from regulators to reduce credit risk this positively affects their cost efficiency due to the impact on outputs. This hypothesis will be tested using US bank panel data, which to the best my of knowledge has not have been addressed before.

Simultaneous rejection of H3 and H4 would indicate that credit risk regulation may not been optimal given the detrimental impact on cost efficiency.

Hypothesis 5: *Increased liquidity has a negative impact on efficiency.*

This hypothesis suggests that as financial institutions increase their liquidity position, this hampers cost efficiency, due to the opportunity cost nature of holding more liquid reserves. This hypothesis will be tested using US bank panel data, which to the best my knowledge has not been addressed before.

From the third research question, the following seven research hypotheses are tested in Chapter 5:

Hypothesis 6: *The market power paradigm persists.*

This hypothesis suggests that the structure-conduct-performance paradigm (concentrate) and/or the relative market power paradigm (competition) exists, in the context of the US banking sector (See Figure 2.1).

Hypothesis 7: *The efficiency structure paradigm persists.*

This hypothesis suggests that the relative efficiency or scale efficiency paradigm exists in the context of the US banking sector (See Figure 2.1).

The simultaneous rejection of H6 and H7 would support the non-relationship, quiet life hypothesis.

Hypothesis 8: *Increased levels of competition negatively affects financial stability.*

In the context of the US banking sector, this hypothesis would support the competition-fragility view proposed by F. Allen and Gale (2004). The rejection of this hypothesis would support the competition-stability view proposed by Boyd and Nicoló (2005). Note that the rejection of hypothesis 6, would result in the inability to test this hypothesis.

Hypothesis 9: *Increased capital requirement regulation positively affects financial stability.*

This hypothesis suggests that increased capital requirements under the Basel III regulations have a positive impact on financial stability. These capital requirements are discussed further in Section 2.3.1. This hypothesis will be tested using US bank panel data.

Hypothesis 10: *Increased liquidity regulation positively affects financial stability.*

This hypothesis suggests that the newly imposed Basel III regulations for liquidity risk have a positive impact on financial stability. These liquidity requirements are discussed further in Section 2.3.1 and 3.4.3. This hypothesis will be tested using US bank panel data.

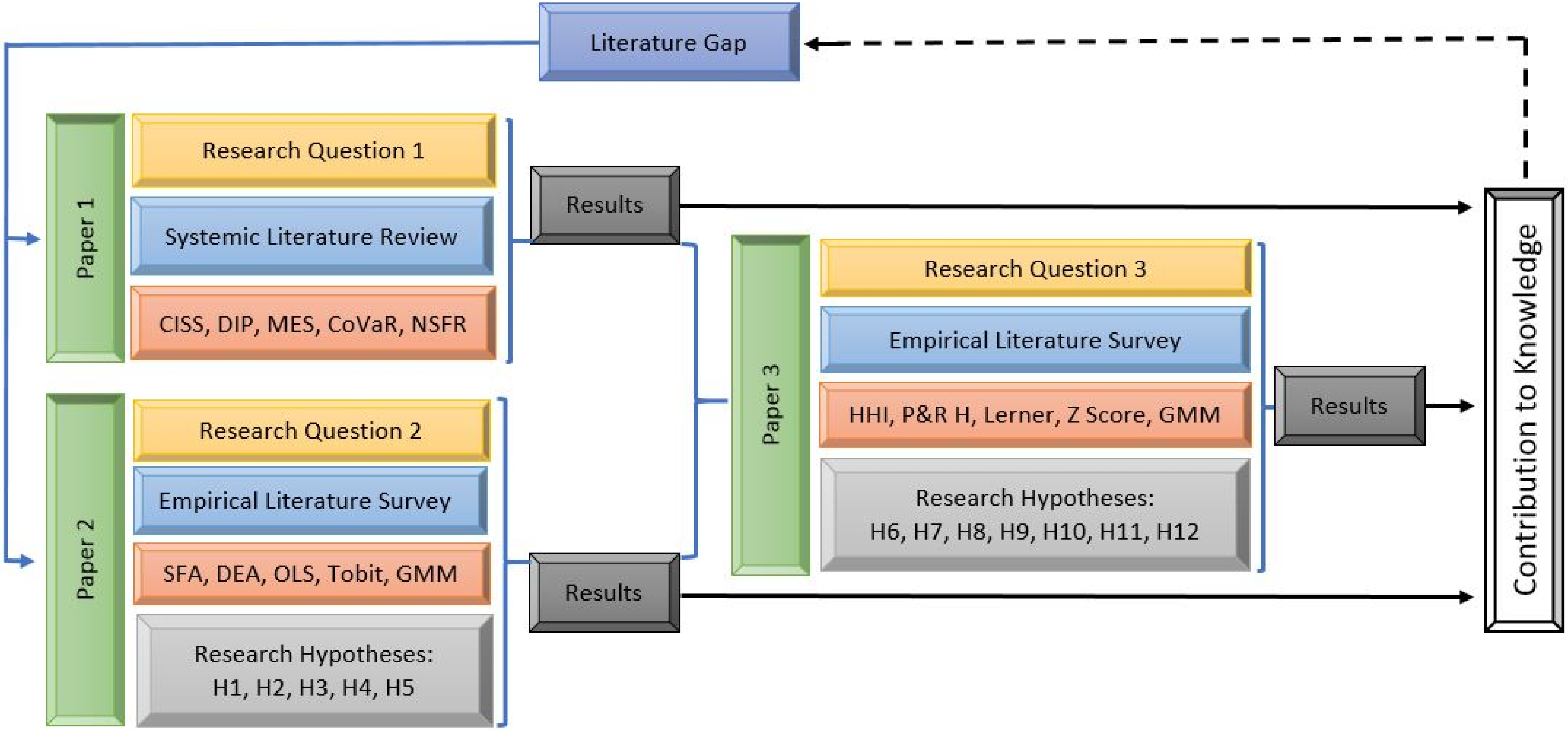
Hypothesis 11: *Being named as a SIFI or D-SIB positively affects the institutions financial stability.*

This hypothesis suggests that being a named a SIFI by the FSB or classed as a D-SIB by domestic regulators has a positive impact on an institution's financial stability. These classifications are discussed further in section 2.4. This hypothesis will be tested using US bank panel data.

Hypothesis 12: *The use of recently developed models to measure systemic risk* *provides contrasting results in the competition-stability nexus compared to traditional accounting measures of financial stability.*

This hypothesis suggests that the use of market level measures of systemic risk other than using traditional accounting based measures of stability (such as the Z-Score) alters the competition-stability relationship. Providing evidence to support this hypothesis would support similar findings by Abedifar, Giudici, and Hashem (2017) and Leroy and Lucotte (2017). This hypothesis will be tested using US bank panel data.

Figure 1.2: Design of the Quantitative Research



Chapter 2

Review of Related Literature

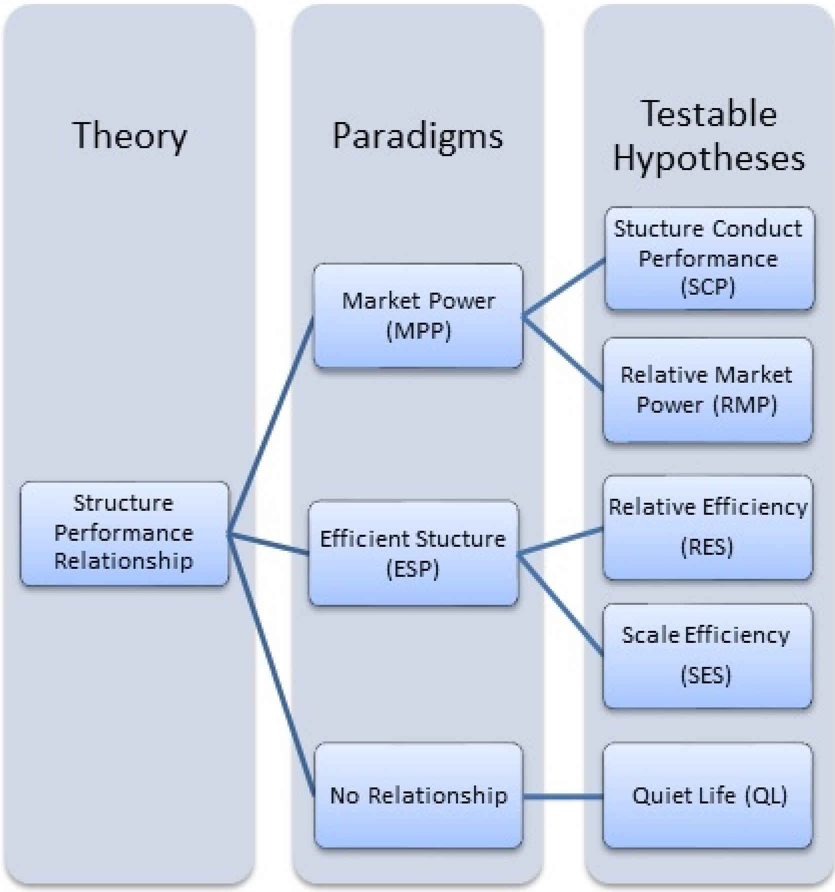
2.1 Introduction

The purpose of this section is to briefly review the literature of key concepts that will be covered within this thesis. Later, within each paper a further literature review, predominantly focused on empirical studies will be discussed prior to any methodology and analysis. Firstly, within this section the theoretical paradigms that will be later tested within this thesis are noted. Secondly, a review of the banking regulation literature will be presented with a focus on the US regulation. This is due to the majority of the analysis within this thesis being based on the US banking sector due to data availability. Further, the premise of systemic risk and macroprudential regulation will be discussed, ahead of the first paper (Chapter 3), which conducts a systematic literature review on this topic. Finally, this leads onto a discussion of the Systemically Important Financial Institutions (SIFI), a classification introduced by regulators, to identify institutions which require extra supervision (due to size and importance rather than incompetence). SIFI's will be included within Chapters 4 and 5's empirical analysis.

2.2 Banking Structure

The premise of this thesis is to evaluate the effects of banking competition on financial stability. The effects of market power on banking performance and stability has been a contentious debate amongst academics and policy-makers in recent years. This multifaceted relationship consists of concentration and efficiency *inter alia* leading to market power. Theoretically, the relationship between market structure and performance can be investigated by two debated paradigms, the Market Power Paradigm (MPP) and the Efficient Structure Paradigm (ESP). MPP suggests a positive relationship between the level of market share and individual performance whilst ESP argues the positive relationship between market concentration and performance is due to a firm's superior efficiency (Demsetz, 1973; Peltzman, 1977). The null hypothesis suggests there is no relationship between level of market share and performance. Figure 2.1 shows the paradigms and hypotheses within the Structure Performance Relationship Theory. Within MPP, a large proportion of this literature focuses on whether (or to what extent) market power/structure influences the firms ability to set prices. In theory, *ceteris paribus* the Structure-Conduct-Performance (SCP) paradigm advocates a higher market power in concentrated markets can allow an institution to influence/set prices (Bain, 1951). SCP however, only provides a current snapshot of the competitive environment, assessing this theory over a short timescale does not explain how the market has evolved or take into account future change. The selection of variables to test each SCP component, requires careful consideration. Structure is often measured in terms of market concentration, however there are a number of different possible measurement techniques emerging from the network theory literature. Further, the likes of firm conduct (C) can impact both the market structure (S) and firm performance (P), for example a firm could pursue a strategy of growth via integration (Tirole, 1988). Relative Market Power (RMP) takes this notion further and argues that only firms with a substantial market share and well-differentiated products can assert market power when pricing their products and earn enhanced profits (Shepherd, 1983). Distinguishing between the SCP and RMP paradigms can be challenging. This is due to the fact that the affects of both efficiency and market power could simultaneously exist within variables that represent market structure and/or could be notified by the level of market concentration (Zouari, 2010). Within ESP, Relative Efficiency (RES), which is also know as X-Efficiency (Leibenstein, 1966), proposes that firms with exceptional management or innovative technologies are able to lower their costs base to achieve higher profits. As a result such firm's are assumed to gain a larger market share which could result in high levels of market concentration, therefore gaining from a positive profit-structure relationship (Smirlock, 1985). Scale Efficiency (SES) argues similar in respect to management and technology, but argues the firms ability to produce more (increase production scale), can lower unit costs in order to achieve higher profit per unit, to ultimately enhance market share. Alternatively, the Quiet Life (QL) hypothesis (Hicks, 1935), advocates that a non-competitive market reduces institutions' managements effort to achieve operational efficiency. Without an incentive to maximise profit managers may spend resources, with the focus to achieve or maintain market power. Therefore inefficient managers/firms may still persist. In contrast, according to *Schumpeterian's* view on competition, a level of monopoly may be preferred compared to perfect competition, because monopolistic rents are an effective incentive to improve and innovate.

Figure 2.1: Structure Performance Relationship Theory



Source: Adaptation of Hannan (1991) and Smirlock (1985)

Bain (1951) was the first to test the impact of market share and concentration on individual performance (within the American manufacturing industry) and concluded that increased market concentration led to higher profit rates for individual companies. One of the earliest literature reviews of empirical evidence from the banking sector was conducted by Rhoades (1977), who concluded that out of 39 studies, 30 found a quantitatively small relationship between market structure and banking performance. Later Rhoades and Rutz (1982) conducted a large (for its time) empirical analysis in the US and concluded there was an overall inability to link market concentration and performance within the banking sector. Interestingly, they argue that the main driver in profitability is actually from the banks' ability to reduce risk. Rhoades and Rutz (1982) came from a standpoint that the QL hypothesis should apply in particular to the banking sector as they often avoided evidencing significant abnormal returns due to their fiduciary role within society and the nature of their regulated environment.

2.3 Regulation

Historically, J. R. Barth, Caprio Jr, and Levine (2008, 2013) noted there are significant cross-country variations in banking, regulation, supervision and information availability. Broadly, there are four main supervisory models: Functional; Institutional; Integrated; (Goodhart, Hartmann, Llewellyn, Rojas-Suarez, & Weisbrod, 1998) and Objectives (Cihák & Podpiera, 2006). The functional model is where there are a number of supervisors responsible for different business lines. For example, an institution licensed to engage in banking, insurance and market activity, will have to comply with multiple supervisors. The institution model is where an institution is assigned a supervisor depending on the main business/legal status of the institution. The supervisor will be responsible for overseeing both conduct and prudential activities. Even if the institution diversifies outside of that supervisors expertise, the supervisor would still remain. The integrated model (commonly know as single or consolidated model) is where one supervisor has the responsibility for all institutions and its functions. An attenuated version of this model would be where a supervisor is responsible for banking and insurance, but there is a separate authority for the market activity. The objectives model is where the supervisory responsibilities are distributed between a number of supervisors (typically two), one for prudential oversight and one for conduct oversight for example. The responsibility for macro-prudential oversight, however, may be located elsewhere or be non-existent.

Simon (2010) discusses two types of regulators, optimizers and managerialists, within the context of banking. The former tends to focus on resolution of isolated threats and uses tools such as mandating disclosure, reducing negative externalities with Pigouvian taxes (Carlton & Loury, 1980) or Calabresian liability rules (Attanasio, 1988). The latter learns from historical information and case studies to derive analytical indicators, for example stress-tests, to induce self-correction mechanisms. For example in the US, Acharya, Berger, and Roman (2018) found that institutions which are subject to regulatory stress-tests tend to reduce credit supply, particularly to relatively risky borrowers, e.g. large corporates which exhibit higher risk, in an attempt to decrease their credit risk. Table 2.1, adapted from Hannoun (2010), provides a synopsis of alternative regulatory toolsets available to contest financial stability.

Countries with efficient supervision and monitoring of financial institutions tend to react to banking system shocks better (Anginer & Demirguc-Kunt, 2014; Anginer, Demirgüç-Kunt, & Mare, 2018; Hoque, Andriosopoulos, Andriosopoulos, & Douady, 2015). Following the financial crisis, many countries reviewed their institutional structures of financial market supervision and regulation. Numerous changes took place, including the transfer of responsibilities between existing organisations, the amalgamation of stand-alone agencies into other organisations (typically central banks), and the establishment of new bodies, especially in the areas of macro-prudential system oversight. Additionally, there were changes to reinforce the institutional apparatus for the resolution of failing institutions.

The financial crisis highlighted a series of gaps that pervade, not only national regulatory regimes, but also the greater body of international financial law. International regulatory forums like the Basel Committee and International Organization of Securities Commissions (IOSCO) had neglected the likes of securitization, mortgage-related securities, derivatives, shadow banking or TBTF institutions that increasingly dominated the financial system of advanced economic countries (Brummer & Smallcomb, 2015).

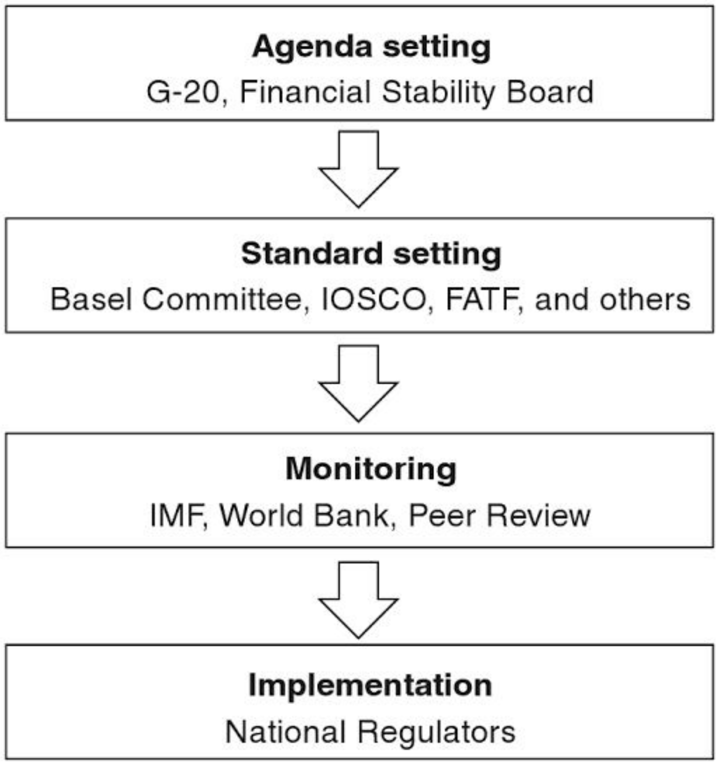
The Group of 20 (G20) was named the world's leading economic forum, fundamentally displacing the Group of 7 (G7). The Financial Stability Forum (FSF) was renamed the Financial Stability Board (FSB) with a mandate to co-ordinate standards setting activities of different regulation agencies and to ensures the complex interdisciplinary issues do not get neglected, if they fell outside the scope of different supervision mandates (FSB, 2009b). Figure 2.2 highlights the current regulatory implementation process.

Table 2.1: Potential Policies to Diminish Systemic Risk

Policy	Objective	Example Tools
Fiscal	Build fiscal safeguards	Reduce debt; pigouvian taxes
	Sector support when stressed	Capital injections; asset & liabilities guarantees
	Manage aggregate demand	Taxation; automatic stabilizers; discretionary countercyclical measures
Monetary	Price stability	Policy rate; standard repos
	Liquidity management	Collateral policies; interest on reserves; policy corridors
	Lean against financial imbalances	Increase policy rate; raise reserve requirements
	Provide support on downside	Decrease policy rate; lower reserve requirements; inject liquidity; quantitative and credit easing; emergency liquidity assistance
	Exit strategies	Legislation
	FX reserve buffers	Gold reserves
Prudential	Macro-prudential (system-wide)	Countercyclical capital charge; forward-looking provisioning; systemic capital charge; leverage ratio; LTV caps; robust infrastructure
	Microprudential (individual-institutions)	Quality/quantity of capital; leverage ratio; liquidity standards; counter-party credit risk; limits to bank activities; strengthened risk management

Source: Hannoun (2010, p.8)

Figure 2.2: The Vertically Integrated Regulatory Process



Source: Brummer (2014, p.108)

The current vertical integration process aims to provide consistency in regards to the quality and level of regulation across jurisdictions. The agenda setting process can be rather persuade politically given that it tends to be a negotiation amongst world leaders (e.g. the G-20), from various different stances. Organisations that develop the standards typically possess no enforcement mandate, rather they seek consultation with the industry participants before defining any rules. This consultation can attenuate the original proposal. For example, during the Basel III consultation process there was a compromise between Switzerland, the US and the UK, resulting in total regulatory capital being 8% rather than a higher original proposal (Howarth & Quaglia, 2016). Ultimately, the implementation of the rules comes down to the individual jurisdictions and their legislative process. Some jurisdictions are more efficient than others regarding this implementation. For example, in the adoption of Basel III, the Kingdom of Saudi Arabia has completed the adoption of the majority

Basel III in law, whilst the majority of standards are still currently being considered by legislators in the case of the European Union jurisdictions (BIS, 2018). Thus, the implementation process may also be subject to political motivation.

2.3.1 The Basel Accords

The Basel Accords were developed in the 1980s following the formation of the Basel Committee on Banking Supervision (BCBS) in 1974, to enhance international cooperation in banking supervision. Basel I was introduced in 1988, predominantly focusing on financial institutions' capital adequacy (in the event of unexpected loss). Generally financial institutions responded by moving higher risk assets off the balance sheet as Basel I failed to address the operational side and supervision of this capital adequacy (Mohanty, 2008). Basel II was issued in June 2004 with a revised framework focusing on minimal capital requirements, setting standards for institutions to develop their own internal capital adequacy models and enhancing disclosure. Prior to its implementation Rodríguez (2002) warned that it was not clear if Basel II could guarantee the soundness of the banking system and prevent moral hazard due to state deposit insurance schemes. Following the financial crisis Basel II was widely criticised (e.g. Acharya, 2009; Kaufman, 2009; Moosa, 2010; Tarullo, 2008). Caruana and Narain (2008) argued that Basel II failed to address all the regulatory issues that arose during the financial crisis which went beyond capital adequacy. As the capital requirements were based on a risk-adjusted measure of assets, financial institutions innovated to create securitised products to remove risky assets from their balance sheets to lower their capital requirements and increase counterparty risk and leverage (Acharya & Richardson, 2009a). Further, Basel II failed to take into account leverage and liquidity (Distinguin, Roulet, & Tarazi, 2013). Subsequently Basel III was introduced in July 2010, with enhanced capital requirements, risk coverage and containing leverage. The Pillar 1 capital requirements include:

- Quality and Level of Capital – This has an emphasis on common equity (4.5% of risk weighed assets).

- Capital Conservation Buffer – Which is common equity of 2.5% of risk weighed assets.
- Countercyclical Buffer – A discretionary range of common equity (0-2.5%) to be applied by individual jurisdictions, depending on the economic cycle/unacceptable build-up of risk.
- Capital Loss Absorption at Point of Non-Viability – Forcing institutions to reduce moral hazard and increase the private sectors contribution in resolving future crises.

It is argued that the enhanced levels of regulatory capital compared to Basel II would limit the availability of credit supply and reduce economic activity (B. Allen, Chan, Milne, & Thomas, 2012; Miles, Yang, & Marcheggiano, 2013). Also A. Barth and Seckinger (2018) warns that banking sectors with a higher degree of heterogeneity, face an exacerbated problem of allocating resources among individual financial institutions after an increase in the non risk-weighted capital adequacy requirements.

The risk coverage element stipulates that institutions must strengthen their capital treatment of securitised assets, maintain significantly higher capital for the trading book (derivative activity) and assess their counterparty credit risk network. In the event of exposure to qualifying central counterparties, a 2% risk weight exposure will require further capitalisation. Whilst the regulatory consensus has focused on increasing capital requirements, there is a continued debate around precisely what types of capital requirements are needed and how to structure them depending on country-specific factors (Anginer et al., 2018). Pillar 2, focuses on risk management and supervision, emphasising the need for a firm wide governance and risk management system. This system must now capture risk arising from off-balance-sheet exposures and securitisation activity. Pillar 3 covers market discipline, which further requires institutions' openness regarding the calculation of regulatory capital ratios, off-balance-sheet exposures and securitisation activity. All banks within the jurisdiction of Basel must comply with the pillar requirements. However, the Globally Systemically Important Financial

Institutions (G-SIFI) are subject to higher loss absorbing capacity, depending on their classification (See Section 2.4 and Table 2.2 for more details). Outside of these pillars Basel III stipulates the new Global Liquidity Standards and Supervision Monitoring regulation, comprising of a Liquidity Coverage Ratio (LCR), Net Stable Funding Ratio (NSFR) and the Principles of Sound Liquidity Risk Management and Supervision (See section 3.4.3 for a discussion).

2.3.2 EU Regulation

Within the EU following the financial crisis, regulation and supervisory oversight has become more concentrated at the EU level (rather than country level), under the European supervisory architecture, in order to achieve regulatory convergence and to centralise cross-border supervision (where appropriate). In 2010, the European Council and Parliament accepted the European Commission's proposals to increase micro-prudential supervision via the European System of Financial Supervision (ESFS) which includes the European Supervisory Authority (ESA) and establish a European Systemic Risk Board (ESRB)[1] to oversee macro-prudential regulation. Loipersberger (2018) conducted an event study which found that the European Central Bank announcements supported the notional that this type of single supervisory mechanism prevents banks from taking excessive risks and thereby stabilizes the financial sector. Further, The European Banking Authority (EBA)[2] is an independent EU Authority tasked with ensuring effective and consistent prudential regulation and supervision across the European banking sector. These changes were made to address supervisory inefficiencies highlighted in the Lamfalussy Report (Schaub, 2005), which critiqued the previous co-ordination of rule-making at the EU level and supervision at the member state level. Regarding the macro-prudential supervision by the ESRB, authors have

[1]The ESRB was set up as a body without legal personality or autonomous intervention power

[2]Interestingly, in November 2017, the EU announced that the EBA will relocate to Paris, Berninger, Kiesel, and Schiereck (2018) found this is associated with significant losses in the stock market valuation of French banks (the other seven bidding hosts' banking stocks were unaffected). The authors argued this is a natural experiment to test the effect of geographically close regulation.

critiqued the ability to make an efficient and effective decision in a situation of crisis (Ferran & Alexander, 2011; Haar, 2015). With *circa* 60 voting members, the main criticism is of the board's structure which may be unable to meet its objectives. Furthermore, the ESRB is meant to be an independent organisation, but it may appear (to observers) to be a coordinator amongst member states' central banks.

2.3.3 US Regulation

In the 1980s and 90s deregulation within the US banking sector was common, influencing levels of competition. Due to the growth in foreign banks operating in the US, the International Banking Act 1978 was passed in an attempt to reduce their competitive advantage[3]. In 1980, The Depository Institutions Deregulation and Monetary Contact Act was passed. This legislation was implemented as calls that regulated interest rates did not benefit both, banks and consumers. Allowing institutions to set their own interest rates, changed the dynamic of competition, giving consumers more choice. Part of this 1980 Act eliminated activity restrictions on thrift institutions[4] ultimately allowing them to issue consumer loans/credit cards and give them greater access to commercial customers, thus allowing them to be more competitive against other financial institutions. As US domestic banks sought to enhance their asset base, overseas lending became more significant, prompting the US Congress to introduce the International Lending Supervision Act in 1983. This required institutions to maintain capital gains against international loans, the first of its kind (Schooner & Taylor, 1998). Further, The Interstate Banking and Branching Efficiency Act 1994, repealed a number of interstate restrictions, ultimately allowing for cross state consolidation and allowing institutions open branches elsewhere, enhancing competition further.

Nowadays in the USA, multiple federation agencies are involved in financial regulation with each dedicated to regulate specific sectors of the financial system (e.g.

[3]Effectively imposing the same restrictions domestic banks have on foreign banks.

[4]These are financial institutions that have a simple business model of taking in deposits and originating mortgages.

Depository institutions, futures market and securities trading). State regulatory agencies also provided additional regulation for the same sectors as well as principal regulation of the insurance sector. Prior to the financial crisis, in the US, there were five different federal agencies in charge of regulating depository financial institutions, namely: (i) The Federal Reserve; (ii) The Federal Deposit Insurance Corporation (FDIC); (iii) The Office of the Comptroller of Currency (OCC); (iv) The National Credit Union Administration (NCUA); and (iv) The Office of Thrift Supervision (OTS). Depending on a financial institution's structure and their main functionality, it may be eligible for regulation by a number of federal agencies as well as numerous state regulators. For example, the OCC is an independent bureau (part of the US Treasury Department) with a number of roles, it charters, regulates and stress-tests national/state-wide banks. However, they also performs regular audits of national banks to ensure compliance with federal law and regulations. Further, the OCC regulated commercial banks as well as their subsidiaries, allowing them to have fewer activity restrictions, opening them up to newer products and services, altering market competition (Wilcox, 2005). On the other hand if the OCC was to find a deficiency within a financial institution, it can broadly administrate sanctions on violators.

In June 2007 the US Treasury Department announced they would restructure the US financial regulation system due to a number of concerns, firstly because the US regulation system was too complex. As above, many regulatory agencies at different federal or state level were regulating the same financial institution. Secondly, the lack of co-ordination between federal and state agencies often created a challenging enforcement environment. Thirdly, competition between regulatory agencies to exercise regulatory authority discouraged or hindered the development of new products and services. Finally, the regulatory system did not efficiently regulate the new financial conglomerates operating around the world.

Early 2008, as part of the restructure, the US Treasury Department proposed a blueprint that they would consolidate the Federal level regulatory agencies into three agencies with different objectives. These objectives are to oversee financial stability, prudential and conduct regulation. This plan advocated for:

- The Federal Reserve to be responsible for financial stability as well as implementing monetary policy supplying liquidity (if required) and exercising formal supervisory powers.

- A creation of a new Prudential Financial Regulatory agency which would have powers to ensure financial institutions are adequately capitalised and ensures that they have appropriate risk management controls. This regulator would also ensure that any financial institution that has government guarantees does not display moral hazard within the markets (taking excessive risk knowing that the government has already supported them).

- A new conduct of business regulatory agency. This agency would be responsible for overseeing business practices and setting standards regarding selling products and services.

This blueprint was never implemented due to opposition, other legislative priorities and political change.

Following a political change in 2009 (within the first 100 days of President Obama's Administration) the US Treasury Department introduced a white paper called *A New Foundation* (USTD, 2009). The main focus of this was to address financial stability and systematic risk oversight, with a focus on the G-SIBs. Furthermore this white paper made explicit reference to international regulatory standards and improving international co-operation particularly in connection with the Financial Stability Board (FSB).

The main white paper proposals which formed the basis of the Dodd-Frank Act 2010 include:

- The creation of a new Financial Stability Oversight Council (FSOC), with a mandate to identify systemic risk and advise the Federal Reserve on which institutions are systemically important. The FSOC acts as an umbrella agency which coordinates information sharing between the other regulatory agencies.

- The creation of The Office of Financial Research (OFR) which supports the FSOC via collection of institutional data and conducting analysis.

- The expansion of the Federal Reserve's mandate on supervising any financial firm that is classed as globally or domestically systemically important (not just banks).
- To combine the OCC, FDIC and the OTS, to form a new prudential regulator, the National Bank Supervisor[5].
- The formation of a new Consumer Financial Protection Agency. This is required as the previous prudential regulators did not provide adequate attention to consumer protection[6].

Compared to the previous administration's blueprint proposal of the three regulatory agencies approach[7], the Dodd-Frank Act was not a large reform process as it did not significantly reduce the number of federal agencies within the US.

In respect to competition in the US, the Federal Trade Commission's Bureau of Competition, is responsible for the anticipation and prevention of anti-competitive business practices. The Bureau is responsible for reviewing proposed mergers, investigating non-merger business practices that harm competition and has the enforcement power via antitrust laws (competition law). However, the US Government has given authority to examine financial institution mergers for approval to relevant supervisory bodies (Federal Reserve Board, FDIC and OCC). Nevertheless, the more authoritative Department of Justice's Antitrust Division must independently review all proposed mergers. This review must then be presented back to the supervisory body in charge. Following this review, if the Antitrust's analysis contrasts with the supervisor's analysis and the merger is still approved, the Antitrust Division can appeal the decision via the courts. Further, the banking laws enforce that supervisors must take into account the competition affects and not allow anti-competitive consolidation, unless it is in the public's

[5]This proposal was not included in the Dodd-Frank Act however, the OTS was disbanded and its responsibilities spread between the Federal Reserve, the OCC and the FDIC

[6]The Dodd-Frank Act formed the Consumer Financial Protection Bureau (CFPB) based on this proposal.

[7]A similar structures to the likes of Australia, Canada and Europe.

interest. During the financial crisis this exception was used a number of times in the effort to save a number of financial institutions from collapse.

In the US, regulators have a continuous physical presence at the largest financial institutions by conducting onsite examinations at least every 18 months, with poorly-rated institutions examined more frequently (Kupiec, 2016). Using the CAMELS ratings banks are rated from 1 to 5[8] (FDIC, 2016). Furthermore, at the micro level of supervision, using confidential supervisory CAMELS[9] ratings, Kupiec, Lee, and Rosenfeld (2017) found that a poor examination rating has a large negative impact on bank loan growth. This finding illustrates that the bank supervision process successfully constrains the lending activities of banks operating in an unsafe and unsound manner. They also found in the data, consistent with regulatory standards, a monotonic increase in the frequency of bank examinations as CAMELS ratings deteriorate.

2.3.4 Macroprudential Regulation

Thoraneenitiyan and Avkiran (2009) suggest that in dealing with future crises, local and international regulation should put more emphasis on macroeconomic policies rather than the likes of restructuring. Further, Longstaff (2010) argues that macroprudential regulation is needed as the likes of liquidity shock in a specific country's banking system result in contagion to all financial markets. Negative externalities resulting from individual bank behaviour and their financial interconnectedness are not taken into account by microprudential policies, which enhances calls for a more macroprudential regulation approach (Crockett, 2000; Knight, 2006). According to Barwell (2013) the term 'macroprudential regulation'

[8] 1 or 2 are judged to be healthy and well-managed, while banks with inadequacies receive 3 to 5. A rating of 5 is issued to banks with the most serious safety and soundness issues. If a bank is rated 3 or above they receive specific examiner guidance (Prompt Corrective Action guidelines) to improve. Failing to do this they will face remedial actions (LaFond & You, 2010).

[9] Which stand for Capital, Asset quality, Managerial skills, Earnings, Liquidity and Sensitivity to market risk. Aparicio, Duran, Lozano-Vivas, and Pastor (2018) provides proxies for CAMELS (p. 64) Papanikolaou (2018a) provides proxies for CAMELS (p. 82).

apparently dates back to the 1970s, but the term itself remains obscure. In a literature review of macroprudential policy Galati and Moessner (2013) noted that since 2008 usage of the term 'macroprudential' in speeches by central bankers had risen significantly. In both advanced and emerging economies macroprudential policies have been more actively applied since the crisis. Usually these regulations were changed alongside other bank capital flow restrictions, capital/liqudity reserve requirements, and monetary policy (Akinci & Olmstead-Rumsey, 2018).

Macroprudential regulation is designed to contribute towards the preservation of financial stability. Macroprudential supervision refers to the observation of the whole financial system which commonly comprises of tasks including (i) risk identification, (ii) risk assessment, (iii) policy assessment, (iv) implementation and (v) monitoring/follow-up (Sarlin, 2016). This task for regulators is challenging given the sizeable, complex, interconnected, highly diverse, and constantly changing nature of the financial system (Flood, Jagadish, & Raschid, 2016). A macroprudential policy system should not adopt a *one-size-fits-all* (Lombardi & Siklos, 2016). In order to identify effective macroprudential policy, regulators will have to enhance their current understanding and observe its usefulness within specific contexts via empirical back-testing or a natural experiment (following a real world crisis). Furthermore, any framework should be dynamically adjusted over time as knowledge is gained and experience is acquired.

Recently there have been a number of attempts to quantify macroprudential policy frameworks (Cerutti et al., 2017; Lim, Krznar, Lipinsky, Otani, & Wu, 2013; Lombardi & Siklos, 2016). Lim et al. (2013) ranked 39 countries' institutional systems based on the individual roles of governments and central banks in macroprudential regulation. Using 2010 IMF data on financial stability and macroprudential policy they produced three different non-mutually exclusive scales (from 1 to 4). The authors found a negative correlation between the central bank's involvement in the macroprudential policy framework and policy response. For example, if the central bank is involved, policy response time tends to be longer. Descriptively they generalised that smaller open economies, with the central bank ordinarily the authority tended to have a more integrated approach, while more complex economies allocate a larger authority role to the government. Cerutti et al. (2017) created an effectiveness indicator of 12 timeseries macroprudential instruments developed to suppress credit cycles for 119 countries. Generally macroprudential tools were effective at reducing credit growth, but the effectiveness varied depending on the instrument applied and the timing during the state of the credit cycle. Lombardi and Siklos (2016) found similar evidence when they developed an index for 46 economies of their capacity to deploy macroprudential policies. Their index compares the existing macroprudential frameworks with meeting the objectives set by the G20 and the FSB. Interestingly, they found that the economies which were the mostly affected by the financial crisis are the ones had already built up their macroprudential capacity. But, it is currently difficult to evaluate how effectively macroprudential regulations frameworks are likely to maintain financial stability as this will only be possible when they have been in place for a considerable period of time and potentially faced some sort of exogenous or endogenous shock (Lombardi & Siklos, 2016; Masciandaro & Volpicella, 2016). However, in a recent assessment of the effectiveness of macroprudential policies in 57 countries using a dynamic panel data model (GMM), Akinci and Olmstead-Rumsey (2018) found that the likes of targeted policies (e.g. limiting house price appreciation) seem to be more effective than macroprudential policy. In the US S. Kim, Plosser, and Santos (2018) found that macroprudential policies targeting leveraged lending were effective at reducing banks' leveraged lending activity[10]. However, from the authors evidence it is less clear whether such policy has addressed its broader goal of reducing the risk that these loans pose to overall financial stability.

[10]Predominately it was the largest, and most scrutinised, banks that cut their leveraged lending activity significantly.

2.3.5 Systemic Risk and Regulation

Holistically following the recent financial crisis[11], policy-makers aimed to address institutional and system wide risk with a range of regulatory tools. To contest institutions' contribution towards systemic risk, their policies are aimed at curbing moral hazard as well as mitigating contagion effects such as the formation of the macroprudential Financial Stability Board in 2009 and the Dodd-Frank Act of 2010. Policies to reduce participation in financial crisis include, for example, capital and liquidity buffers as well as encouraging diverse business models and risk management techniques (such as the Bank of International Settlements (BIS) Basel III Accords).

There have also been advances in the regulatory framework to address the issue of countercyclical buffers to counteract the overdrawn market movements arising from both negative and positive financial spillovers (Basel III, Solvency II). B. Allen et al. (2012) stated that the requirements under the Basel III accord result in structural adjustments that might affect the supply of credit in the economy.

Persaud (2013) argues that financial regulation is based on the premise that regulators can make the system safer by ensuring that individual institutions are more secure. Eder and Keiler (2015, p.306) also advocates this approach stating that "*historically financial regulation has concentrated on ensuring the stability of each individual* [financial institution] *and neglected the risk stemming from the financial system as a whole*". Yet Baker (2013) argues that privileged market participants with their own agendas have been efficacious in thinning such policy content. Furthermore, they claim that regulators are inclined to proceed cautiously when making policy decisions which are founded on empirical evidence[12]. This is compounded by the gradual process of conceptualising a macroprudential policy that then needs testing. Hence, an implementation of effective macroprudential regulation transformation could take decades. De Chiara, Livio, and Ponce (2018)

[11]Programmes developed to mitigate the affected of financial crises: In the US, the Troubled Asset Relief Program (TARP) and Large Scale Asset Purchases (LSAP); In Europe by the European Central Bank, quantitative easing (QE) and Outright Monetary Transactions (OMT); and in the UK the Funding for Lending FFL.

[12]This is because empirical evidence can take time to reach an overall consensus and be accrued.

argues that flexible supervision (banks select regulation that has been designed for their level of risk) would enable the regulator to obtain the same quality of information about the banks' risk, while significantly reducing welfare costs. i.e more stable financial institutions would be willing to enhance capital and become more transparent in exchange for less stringent intervention by supervisors. In addition, Haber and Perotti (2008) argue that some financial institutions could benefit from having close ties with governments and regulators to have a stronger influence in policy making.

2.3.6 Shadow Banking

The shadow banking sector's roles in the financial crisis has been investigated by comparing its impact with the more traditional banking system's impact (Hsu & Moroz, 2009; Meeks, Nelson, & Alessandri, 2014). A. Barth and Seckinger (2018) argues that the introduction of Basel I & II, resulted in a considerable increase of investment volume towards the shadow banking sector. The term shadow banking system has numerous different meanings; from a regulatory standpoint the FSB (2011b) loosely describes it as the system of credit intermediates that are involved in activities outside the regular banking system. Furthermore, the shadow banking system increased systemic risk due to range of activties such as maturity, liquidity and leverage transformation. Similarly within the literature, Claessens and Ratnovski (2015) defined shadow banking as all financial activities outside of the traditional banking system, that requires a private or public backstop to operate. Additionally the shadow banking system is a network of dedicated financial institutions that intermediate via securisation and secured funding (Adrian & Ashcraft, 2016). Pozsar, Adrian, Ashcraft, and Boesky (2012) classified the shadow banking system into two categories: the *internal shadow banking* sector which consists of banking activities that are conducted by subsidiaries of traditional financial institutions[13]; an *external shadow banking* sector which

[13]For example, a bank which has its own wealth management unit or provides funding to other institutions which are part of the shadow banking system. Furthermore, typically the largest non-

consists of regulated institutions and independents that engage in banking activities, which does not represent their primary business. This includes companies such as independent wealth management institutions, broker-dealers and credit hedge funds. These categories could also be classed as *independent shadow banking*, companies which specialise in trading the likes of collateralised debt obligation and structured investment vehicle or *government sponsored shadow banking* which are government-sponsored enterprises, for example, Freddie Mac and Fannie Mae of the US.

2.3.7 Accounting Issues

Prior to the financial crisis, 'mark to market' or 'fair value' accounting practices were increasingly adopted under the assumption that efficient capital market theory implies that asset prices in such markets are more reliable than the use of a cost based approach or expert judgment. This placed the emphasis on current asset prices when producing institutions' balance sheets. The ramifications of this could be felt in the event of liquidation, where asset prices can significantly drop. This would have a detrimental effect on institutions short term balance sheet. Mügge and Stellinga (2015) argue that regulators face a trade-off when adopting this type of accounting practice. They claim that up-to-date information on banks' financial positions is crucial for market supervision. Nevertheless, regulators cannot support standards that are over transparent which allow the market to identify stressed banks as this could exacerbate a problematic situation. Historical or cost accounting practices have become a poor guide to the health of a bank due to their complexity. Hitherto, regulators have allowed institutions to switch between accounting rules in the name of financial stability (Mügge & Stellinga, 2015).

The combination of fair value accounting and the use of Value-at-Risk models (advocated in Basel II) in the determination of minimum capital requirement ultimately was too parochial and misleading. Post-crisis it was acknowledged by

bank subsidiaries of banking groups are their wealth management unit, broker-dealers business, or market based funds.

the UK's Financial Services Authority's Turner Review (FSA, 2009, p.22) that sophisticated mathematical modelling techniques such as VaR, "*ended up not containing risk, but providing false assurance that other prima facie indicators of increasing risk (i.e. credit extension and balance sheet growth) could be safely ignored*". A lack of consistency in accounting practices can have direct implications for systemic risk evaluation. For example, under Basel III, the capital adequacy is calculated using total assets which is derived from risk-weighting formulas specified by the Basel Accord, not the International Financial Reporting Standards (IFRS)[14]. Yet, the majority of the systemic risk measures and bank fundamentals are in general calculated according to IFRS. Furthermore, the ability to use more creative accounting techniques by switching standards, or the use of shadow banking, was entrenched in a number of historical financial scandals and crises.

2.4 Systemically Important Financial Institutions (SIFI)

Following years of being rather implicit regarding which institutions were significant, in November 2011, the Financial Stability Board (BIS, 2011b) published the first list of Global Systemically Important Financial Institutions (G-SIFIs). See Table 2.2 for a list of the SIFI's and how this has changed over the past seven years. The allocation of financial institutions into the buckets (1 to 5) in Table 2.2 is defined by BIS (2013b). Each bucket requires a different level of additional common equity loss absorbency as a percentage of risk-weighted assets[15]. Notably, this list was dominated by the large western banks (mainly from the US and UK) with JP Morgan Chase constantly being in the second highest bucket (4). However, in recent years there has been an emergence of the four

[14] see Mügge and Stellinga (2015) for an overview of the most important accounting standard negotiations and modifications.

[15] Bucket 1 requires 1.0%, Bucket 2 requires 1.5%, Bucket 3 requires 2.0%, Bucket 4 requires 2.5%, Bucket 5 requires 3.5% (no financial institutions has been allocated into bucket 5 as yet).

largest Chinese banks, with two being promoted to higher buckets. Being named as a SIFI results in the institution being subject to further regulation namely: (i) higher requirements regarding the loss absorbency capacity (depending on which bucket); (ii) higher leverage ratios; (iii) more intense supervision; and (iv) a defined process in the event of a restructuring or orderly wind-down (process explained in FSB (2011a)). As well as the G-SIFI, a number of countries have produced lists of Domestic Systemically Important Banks (D-SIBs) for institutions that do not classify as a SIFI, but are considered as institutions that could damage country level banking systems in the event of failure. Often these institutions are subject to additional capital requirements, more stringent stress tests and extra scrutiny from domestic regulators. Since 2009, the US has identified 22 institutions, whilst nine EEA member states identified their D-SIBs in 2013. Elsewhere, Australia, Canada, China, Hong Kong, India, Japan and Switzerland have also identified their D-SIBs. Initially, it would be assumed that this is a positive status, branding them amongst the most important institutions in the world. However, an event study by Kleinow, Nell, Rogler, and Horsch (2014) noted that negative sentiment prevailed. Further, equity movement prior to the SIFI announcements suggested that the market participants had anticipated such news. The negative sentiment could be explained as the market participants' expectations of lower earnings due to stricter supervision and higher capital requirement *ceteris paribus*, resulting in lower equity prices. On the contrary, in the event of moral hazard and/or bankruptcy, market participants may assume these institutions are more likely to attract government assistance[16] raising equity prices.

As an example of how being classified as a SIFI can impact the balance sheet, Figures 2.3 and 2.4 demonstrate noticeable changes in leverage following the financial crisis. Due to Basel III, financial institution are expected to maintain a leverage ratio in excess of 3%, however the SIFIs are expected to maintain up to 6%. As demonstrated in Figures 2.3a and 2.4a there is a high correlation between the change in total assets and change in debt for the SIFI banks. Balance sheet expansions and

[16]Further, potential creditors and shareholders may be more inclined to deal with institutions for this reason, enhancing the banks' profitability opportunity *ceteris paribus*.

Table 2.2: Current List of Global Systemically Important Banks (G-SIBs)

G-SIB Name	**Country**	**Bucket**							
		2011†	2012	2013	2014	2015	2016	2017	2018
Agricultural Bank of China	China				1	1	1	1	1
Banco Bilbao Vizcaya Argentaria	Spain		1	1	1				
Bank of America	United States	✓	2	2	2	2	3	3	2
Bank of China	China	✓	1	1	1	1	1	2	2
Bank of New York Mellon	United States	✓	2	1	1	1	1	1	1
Banque Populaire CE	France	✓	1	1	1	1	1		
Barclays	United Kingdom	✓	3	3	3	3	2	2	2
BNP Paribas	France	✓	3	3	3	3	3	2	2
China Construction Bank	China					1	1	2	1
Citigroup	United States	✓	4	3	3	3	4	3	3
Commerzbank	Germany	✓							
Credit Suisse	Switzerland	✓	2	2	2	2	2	1	1
Deutsche Bank	Germany	✓	4	3	3	3	3	3	3
Dexia Group	Belgium	✓							
Goldman Sachs	United States	✓	2	2	2	2	2	2	2
Groupe BPCE	France								1
Groupe Crédit Agricole	France	✓	1	2	1	1	1	1	1
HSBC	United Kingdom	✓	4	4	4	4	3	3	3
ICBC	China			1	1	1	2	2	2
ING Bank	Netherlands	✓	1	1	1	1	1	1	1
JP Morgan Chase	United States	✓	4	4	4	4	4	4	4
Lloyds Banking Group	United Kingdom	✓							
Mitsubishi UFJ FG	Japan	✓	2	2	2	2	2	2	2
Mizuho FG	Japan	✓	1	1	1	1	1	1	1
Morgan Stanley	United States	✓	2	2	2	2	1	1	1
Nordea	Sweden	✓	1	1	1	1	1	1	
Royal Bank of Canada	Canada							1	1
Royal Bank of Scotland	United Kingdom	✓	2	2	2	1	1	1	
Santander	Spain	✓	1	1	1	1	1	1	1
Société Générale	France	✓	1	1	1	1	1	1	1
Standard Chartered	United Kingdom		1	1	1	1	1	1	1
State Street	United States	✓	1	1	1	1	1	1	1
Sumitomo Mitsui	Japan	✓	1	1	1	1	1	1	1
UBS	Switzerland	✓	2	2	1	1	1	1	1
Unicredit Group	Italy	✓	1	1	1	1	1	1	1
Wells Fargo	United States	✓	1	1	1	1	2	2	2

† In 2011 the financial institutions were not allocated into difference buckets (BIS, 2011b)

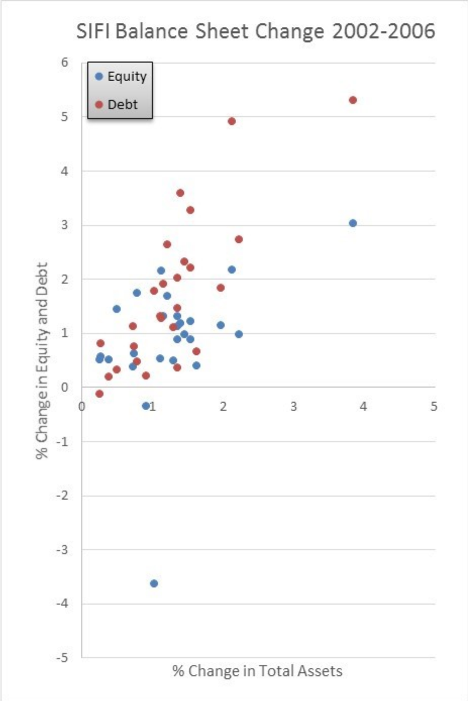
contractions (Figure 2.4a) tend to be conducted through changes in debt and not through changes in the book value equity. In nominal value terms (within the SIFI sample) on average, book debt is 5.392 times larger than book equity. Therefore a 1% change in debt will nominally be much greater than a 1% change in equity. Following the financial crisis the majority of the SIFI reduced their levels of debt while change in equity remained largely positive. This is very predominate from Figure 2.3b to Figure 2.4b which highlights the reduction in leverage.

2.5 Summary

This chapter provides the key theoretical foundations and regulatory framework which underpins the remaining chapters within this thesis. The banking structure paradigms and hypotheses discussed at the beginning of this chapter will be referred back to in Chapters 4 and 5, when these concepts are empirically tested. The regulations discussed within this chapter provide the regulatory context for the time-scales used within the later empirical chapters. Chapters 3, 4 and 5, will make reference to these regulations discussed. Also, this chapter discussed the creation of the Systematically Important Financial Institutions, within the empirical chapters (4 and 5) they will be included within the samples and their impact on the wider sample given their enhanced regulatory status will be discussed. Lastly, within the conclusion of this thesis (Chapter 6), the findings and contributions from the empirical chapters will be put into context using the topics discussed within this chapter.

Figure 2.3: SIFI Balance Sheet Change Before the Crisis

(a) Equity and Debt



(b) Leverage

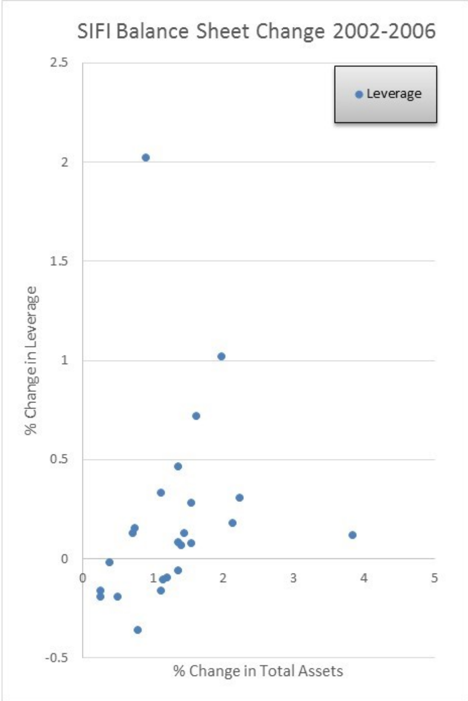
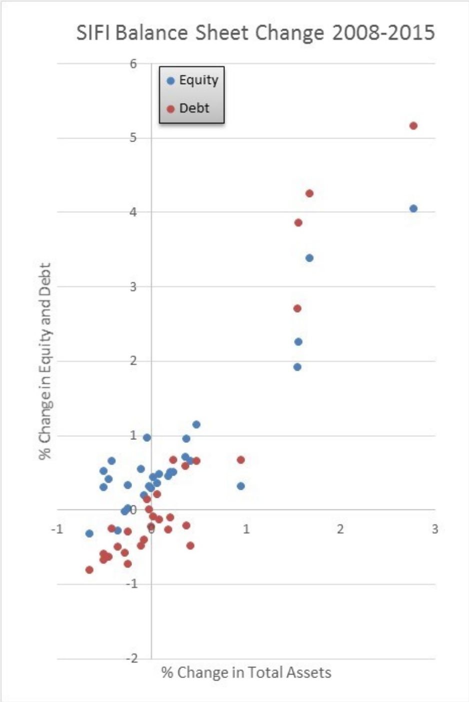
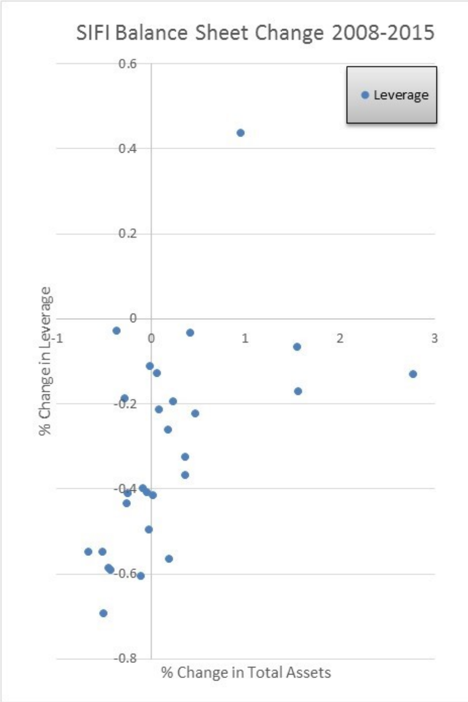


Figure 2.4: SIFI Balance Sheet Change After the Crisis

(a) Equity and Debt



(b) Leverage



Source: Adapted from Bloomberg (2017)

Chapter 3

Systemic Risk Measures and Regulatory Challenges

3.1 Abstract

This paper discusses the different definitions of systemic risk and identifies the challenges regulators face in addressing these phenomena. A systematic literature review of 4,859 abstracts was conducted to categorise the various methodologies developed to measure systemic risk. In total, 56 measures of systemic risk developed post-2000 are critically appraised to inform academics and regulators of the model's vulnerabilities. Additionally, a few measures are evidenced using US bank data. The findings of this review suggest that the majority of these methods tend to focus on individual financial institutions rather than the entire system stability. This directly reflects the current regulations which aim to ensure individual institution's soundness. As macro-prudential regulation evolves, policy-makers face the issues of understanding contagion and how such regulations should be implemented.

JEL Classification: G01, G15, G2, G28, C58, C6

3.2 Introduction

Recently, there has been a plethora of interest in systemic risk in the financial industry among academics (Anginer & Demirguc-Kunt, 2014; Bongini, Nieri, & Pelagatti, 2015; Ellis, Haldane, & Moshirian, 2014; J. O. Wilson et al., 2010) and regulators (BIS, 2009; N. A. Tarashev, Borio, & Tsatsaronis, 2009) alike. Over the last two decades, the financial markets have fundamentally changed and expanded globally, which has created numerous challenges for policy-makers. For example, in the US from the early 1990s until the financial crisis in 2007, deregulation had been one of the most influential changes within the banking sector (Beck et al., 2010). The process of removing regulatory barriers affected the dynamics of the market structure and significantly transformed the characteristics of risk that financial institutions face and have to manage, which potentially adds to the unintended consequences of systemic risk and financial instability.

The first main challenge regarding systemic risk assessment and measurement is that there is limited consensus on a widely accepted definition of this phenomenon. One of the first definitions from the BIS G10 stated that systemic risk is the risk of an event which can trigger a loss of economic value, or confidence in a substantial portion of the financial system, which is large enough to have significant adverse effects on the real economy and/or society (BIS, 2001). Alternative definitions of systemic risk include (but are not restricted to): (i) a failure of a significant part of financial institutions (Acharya, Pedersenn, Philipponn, & Richardson, 2011; De Bandt & Hartmann, 2000); (ii) The risk that a national, or the global, financial system will break down (Scott, 2010); (iii) An impairment of the financial system (Adrian & Brunnermeier, 2008); (iv) A correlation of defaults within the financial system over time (Billio, Getmansky, Lo, & Pelizzon, 2010); (v) A malfunctioning of the entire financial system (Bach & Nguyen, 2012; Rodríguez-Moreno & Peña, 2013); and (vi) loss of economic value or a widespread loss of confidence in the financial system (Cummins & Weiss, 2014). The need for a comprehensive approach to access the exposure of the financial sector to systemic risk was highlighted well before the recent financial crisis of 2007 (Eisenberg & Noe, 2001). There is a common view that systemic risk can be categorised by both cross sectional and time series dimensions

(Hartmann, De Bandt, & Peydro-Alcalde, 2014). Cross-sectional dimensions relate to the correlation of risk types throughout the system at given points in time. Time-series dimensions relate to changes of risk types or market conditions throughout, for example the economic cycle or the potential development of asset/liability bubbles. The likes of asset/liability price bubbles tend to be more dangerous when credit is involved (Anundsen, Gerdrup, Hansen, & Kragh-Sørensen, 2016; Jordà, Schularick, & Taylor, 2015; Virtanen, Tölö, Virén, & Taipalus, 2018). Risk within the financial sector can be either exogenous or endogenous, unexpected shocks from outside the system are exogenous, whilst interaction amongst market participants can develop endogenous financial risks (Danielsson & Shin, 2003).

For empirical purposes Laeven and Valencia (2013) classify a systemic banking crisis as a significant signal of financial distress in the banking system triggered by the likes of bank runs, excessive losses within the banking system and bank liquidations. There are a number of different crisis database/categories used within empirical studies which include; the ECB Heads of Research crisis dataset (Babecky̌ et al., 2012), the ESRB crisis definitions (Detken et al., 2014), and a newer database for financial crisis in European countries (Duca et al., 2017).

Individual financial institutions can impact systemic risk of the financial system in a range of different ways, they can be categorised as *contribution to* and *participation of* systemic risk. *Contribution to* systemic risk arises from an institution's actions having a knock-on effects on other institutions, which is also known as moral hazard. Examples of this behavior could be the liquidation of a financial institution's assets under fire sale and volatile market conditions (Coval & Stafford, 2007; Shleifer & Vishny, 1992). This type of action by one institution can lead to a situation where another institution is facing solvency issues due to depressed asset prices. *Participation of* systemic risk relates to the financial institution's susceptibility to amplifying systemic risk due to their inability to absorb shocks arising from other institutions or macroeconomic shocks.

Not every period of distress is classed as a financial crisis. For example the financial system can still functional in the event of an individual institution failing. Crisis *ex*-port can be categorised as banking, currency or sovereign crisis amongst others which is presented in Table 3.1. The rest of this paper is structured as follows. In Section 3.3 the systematic literature review methodology is explained. Section 3.4 critically appraises the 56 different methodologies developed to measure systemic risk. Also this section contains a number of real world examples of the measures using US data. Section 3.5 identifies the data required to measure systemic risk. Section 3.6 discusses the challenges faced by regulators in relation to systemic risk and section 3.7 concludes.

3.3 Literature Review Methodology

As the quality and quantity of research conducted and published within systemic risk literature has increased exponentially over recent years, the systematic review was conducted using a combination of scoping and keyword searches. The literature review was performed following key phases formalised by the Cochrane Collaboration[1] to ensure comprehensiveness and robustness (Jesson, Matheson, & Lacey, 2011). During the search phase various online databases and search engines were used[2], with a range of keyword and Boolean search terms[3]. Overall, the search identified 139,647 research articles, however the majority were rejected because of their title (e.g. literature relating to medical science and information technology) , they were duplicates, were pre-2000, and were non-English or due to non-availability. From the above identified research articles, 4,859 were related to systemic risk in banking. The abstracts of these 4,859 articles were reviewed and only 56 were selected as they proposed a source of systemic risk or new method of

[1]The key phases are: (i) mapping the field via a scoping review; (ii) a comprehensive search; (iii) quality assessment; (iv) data extraction; (v) synthesis; and (vi) write up.

[2]Databases searched included, ScienceDirect (10/12/16), Taylor & Francis Online (10/12/16), Business Source Premier (14/12/16), Emerald Insight (14/12/16), Scopus (15/12/16), Social Science Research Network (16/12/16) and Google Scholar (19/12/16). A further scoping search was conducted on 02/10/17 and 04/05/18 to identify more recent systemic risk measures.

[3]Search terms included 'measuring' AND 'systemic risk', 'estimating' AND 'systemic risk', 'modelling' AND 'systemic risk', 'indicators' AND 'systemic risk', 'contagion' AND 'systemic risk'. Additionally 'systemic risk' was used as a sweeping search.

Table 3.1: Criteria used to define types of crisis

Crisis	**Author**	**Criteria Applied**
Banking	Caprio and Klingebiel (1996)	The insolvency of important banks
	Demirgüç-Kunt and Detragiache (1998)	A sharp deterioration in the quality of assets; The involvement of the government (i)large scale nationalisation of banks (ii) high cost of the rescue packages (iii) the emergency measures enacted due to an extensive bank run
	Laeven and Valencia (2008, 2013)	Deposit runs represented by a monthly percentage decline in deposits in excess of 5%; Introduction of a deposit freeze or blanket guarantee; An extensive liquidity support or bank interventions defined as an extensive liquidity support involving claims from monetary authorities on deposit money banks to total deposits of at least 5% and at least double the ratio compared to the previous year
Sovereign	Schimmelpfennig, Roubini, and Manasse (2003)	Standard & Poors's classifies the country as being in default; The country receives a non-concessional IMF loan in excess of 100% of quota
	Laeven and Valencia (2008)	Soverign deafults to private lenders; Rescheduling the debt
Currency	Frankel and Rose (1996)	A nominal exchange rate depreciation of as least 25%; This depreciation also exceeds the previous years change by least 10%
	Kaminsky, Lizondo, and Reinhart (1998)	When their exchange market pressure index exceeds its mean by more than 3 standard deviation
	Andreou, Dufrénot, Sand-Zantman, and Zdzienicka-Durand (2009)	Applying Kaminsky et al. (1998) method to identify country specific thresholds

measuring it. Given that 56 articles which develop models to measures systemic risk were ascertained, this would suggest very little agreement amongst academics and regulators of what systemic risk is or how it is measured. Nevertheless, there are benefits of model diversity. For example, if regulators were to impose that institutions had to apply the same models, they may analyse potential shocks similarly. A potential consequence of this is that institutions could react in the same way and cause further problems. Also, if certain institutions were not obligated to use particular models, they could potentially use other models and gain a competitive advantage.

3.4 Models Proposed to Measure Systemic Risk

This sections provide a comprehensive review of the systemic risk models based on the 56 identified articles. The models are broken down into five categories: (i) early warning and credit default swap indexes (16 models); (ii) capital (12 models); (iii) liquidity (6 models); (iv) contagion (10 models) and (v) network (12 models).

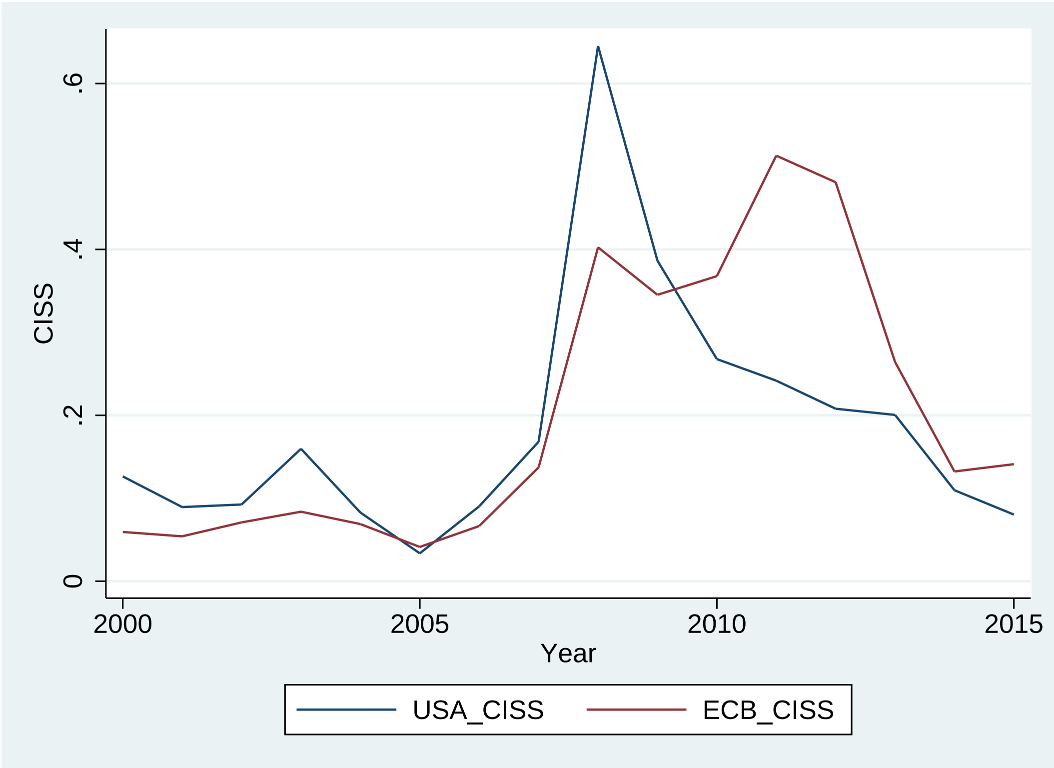
3.4.1 Systemic Risk Early Warning Systems (EWS) and Credit Default Swap (CDS) Indexes

There is a range of existing indexes which allow regulators to gauge the macro-economic health of a country and its financial industry. In the United States, for example, the St Louis and Kansas City Federal Reserve Bank have created the *Bank Financial Stress Index* and the *United States Financial Stress Index* respectively. The Bank of America and Merrill Lynch has created a *Global Financial Stress Index* which is a cross market measure of risk in the global financial system. Duca and Peltonen (2013) promote the benefits of their financial stress index which uses both global and domestic macroeconomic data. Their methodology takes into account policy-maker's preferences. Hollo, Kremer, and Lo Duca (2012)'s Composite Indicator of Systemic Stress (CISS) proposed new ways to determine critical levels during a crisis. Their index, based on portfolio theory, aggregates five market specific sub-indices, which includes indicators from the money, bond, equity and foreign exchange markets as well as financial institutions' book value to market price ratio. See Figure 3.1 for a graphical representation for CISS for the US and EU, Appendix 3.8 explains the data and methodology applied. Systemic risk indexes have their practical uses as a potential warning tool, however because a large element of systemic risk is centered on the economic cycle (Persaud, 2013), such EWS may only reflect this and have a limited scope in identifying specific indicators of systemic risk. Also Davis and Karim (2008) found in a comparative study of early warning systems that empirical results vary according to the dataset applied and the definition used for a financial crisis. Alessi et al. (2015) compared nine alternative early warning models, reporting both in-sample and out-of sample statistics for the exuberance indicators. The authors found that multivariate models, in their many forms (e.g. probit or logit models), have great potential and add value over simple signalling models. Virtanen et al. (2018) results from testing whether bubble theory can predict crisis corroborate previous findings in this early warning literature. The authors, with others, indicated that periods of accelerated growth in variables such as real estate[4], price-to-income, credit-to-GDP ratio, or debt service costs are linked strongly to financial crises.

Therefore, these EWS cannot offer precise predictions, however they are able to indicate heightened vulnerability. Alessi and Detken (2009, p. 35) concluded that "*central bankers on average tend to have a stronger preference for missing crisis than to act on noisy signals for various reasons*". The use of these measures assumes that the US financial system is a main indicator of the global financial conditions due to its far reaching impact. Outside of the US, regulators face a conundrum when developing an EWS. Do they pursue their own indicators, indicators which are used in the US or indicators developed from their larger trading partner? Depending on how they prioritise this could leave certain parts of their domestic policy isolated. Furthermore, EWS as with any statistical model (two- or three-dimensional) have their limitations when trying to encompass a

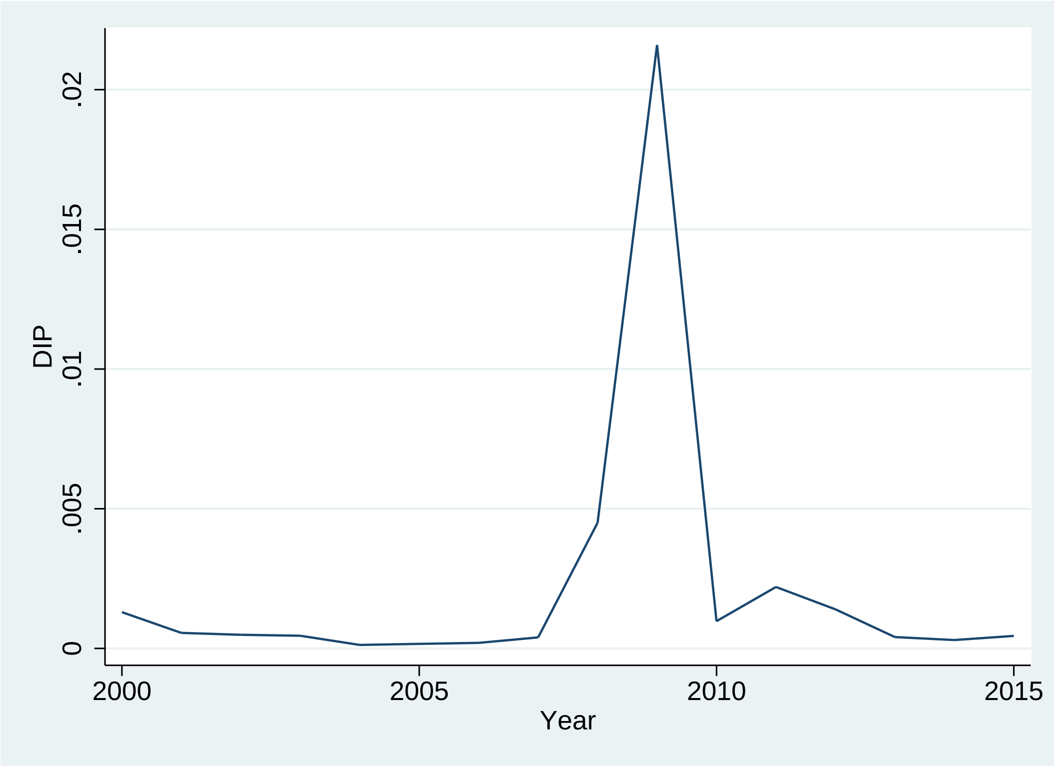
[4] Altunbas, Manganelli, and Marques-Ibanez (2017) also noted that exposure to real estate sector (or developments) seems to be a major driver of banking sector risk

Figure 3.1: US & Euro (ECB) Composite Indicator of Systemic Stress



chronological or cross-sectional dimension and having the ability to assess multiple countries over time. Constantin, Peltonen, and Sarlin (2018), advancing this literature, advocated for including estimated tail dependencies networks in EWS as they consistently outperformed models, which cover solely vulnerabilities coming from bank-specific, sector-level and macro-financial imbalances in order to predict bank distress events. Similar to systemic risk indexes, others have used the CDS indexes, premia and spreads to assess systemic risk of institutions or the industry. CDS premia are seen as a proxy indicator of how risky an institution is, as their CDS premia reflect market participants' view of the likelihood of default. Bhansali, Gingrich, and Longstaff (2008) quantify the relative magnitude of systemic risk embedded in the relatively liquid US (CDX) and European (iTraxx) credit derivative indices through a linear three-jump model. They concluded that systemic crises have become a much larger function of overall total credit risk. Trapp and Wewel (2013) also used CDS premia from the US and Europe to conclude that firms' exposure to the same common risk factors contributes to

Figure 3.2: US Distressed Insurance Premium



systemic risk. Their results imply that regulators should aim to address international bank dependencies arising from common risk factors. Alternatively, X. Huang, Zhou, and Zhu (2009) measured systemic risk of the financial system by the theoretical price of insurance against financial distress, Distressed Insurance Premium (DIP). They estimated the probability of default which was derived from the institution's CDS premia. See Figure 3.2 of graphical representation for DIP for the US, Appendix 3.8 explains the data and methodology applied. Table 3.2 presents an overview of the systemic risk indexes, EWS and CDS indexes proposed to measure systemic risk. The main advantage of using CDS premia instead of equity return is that CDS premium has a closer link to a firm's default. For example, the firm's equity price can trade at a non-zero price levels even after the firm has defaulted on debt payments. Similarly to equity prices, the CDS premia may reflect factors other than just the firm's default risk (e.g. investor sentiment and economic conditions). Rodríguez-Moreno and Peña (2013) tested high-frequency market-based indicators including equity price, interbank rates and

CDS premia. Their results suggest that CDS premium is a more accurate indicator of systemic risk than the others. The main disadvantage of using CDS premium as an indicator of systemic risk is that it is limited to the institutions that have traded CDS, which tend to be located in developed countries, thus limiting their application within countries that do not have developed CDS markets. Also, the CDS market may sometimes send wrong signals (Li & Tang, 2016) and ultimately provide inaccurate prices due to irrational exuberance or panics.

Therefore, the efficiency, transparency and quality of the CDS market becomes an issue of paramount importance. In addition, numerous studies, such as Giglio (2016); Trapp and Wewel (2013); Schneider, Sögner, and Veža (2010) *inter alia*, document that CDS premia are non-normally distributed, therefore future research should test for non-normality first or use non-parametric methods.

Table 3.2: Systemic Risk Indexes, Early Warning Systems and using Credit Default Swaps to Measure Systemic Risk

Author(s)	**Model**	**Methodology**	**Sample**	**Empirical Findings**
Bhansali et al. (2008)	Measure of systemic risk via indexes of CDS	Implementing a simple linear version of a three-jump model and calibrating it to assess market indexes and tranche spread levels.	A CDS index and tranches of investment grade US CDX and Europes iTraxx from March 2007 to December 2007.	They provided evidence to show that the information in credit derivatives about the market's expectations of systemic credit risk can be extracted.
X. Huang et al. (2009)	Distress Insurance Premium (DIP)	Systemic risk is measured by the price of insurance against financial distress (a situation in which at least 15% of total liabilities of the financial system are in default), via estimating the probability of default (from CDS spreads) and the equity return correlations.	Weekly CDS spreads and high frequency intra day, equity price data from 12 major US Banks between January 2000 and May 2008.	DIP was evidenced to be higher when the average actual failure rate increases or when the exposure to common factors in the system increases.

Table 3.2 Continued

Author	Model	Methodology	Sample	Empirical Findings
Alessi and Detken (2009)	Early warning indicator for asset price boom/bust cycles	This analyses various indicators (5 macroeconomic and 13 financial variables), relative performance of global versus domestic equity markets and money market versus credit based liquidity indicators. A warning signal is issued when an indicator exceeds a certain threshold.	Quarterly data from 18 OECD countries between 1970Q1 to 2007Q4.	The global measures of liquidity (private credit gap) is among the best performing indicators of systemic risk and displayed forecasting abilities. In addition, evidence suggested that the best indicators are global variables, this can be explained by the fact that asset price boom/bust cycles are largely an international phenomenon.
Gaganis, Pasiouras, Doumpos, and Zopounidis (2010)	A Stability Classification Model	A set of 11 indicators of; the macroeconomic, institutional, regulatory environment and characteristics of the banking sector within three multi criteria decision techniques, to classify banking stability.	114 countries' banking sectors during 2008.	Their model was capable of classifying, in line with the Economist's *Banking Sector Risk Rating*, between 75.60% and 79.81% of the observations correctly, which outperformed discriminant analysis and logistic regression methods.

Table 3.2 Continued

Author	Model	Methodology	Sample	Empirical Findings
Kritzman and Li (2010)	Mahalanobis Distance to measure financial turbulence	They obtain the average joint returns of securities then apply a tolerance boundary. Observations outside of that boundary are statistically unusual and are thus likely to be characterised as turbulent periods.	Monthly returns of six asset-class indices: U.S. Equities; non-U.S. Equities; U.S. bonds; non-U.S. bonds; commodities; and U.S. real estate from 1980 to 2009.	They provide evidence that their measure of financial turbulence coincides with well-known episodes of market turbulence.
Kritzman, Li, Page, and Rigobon (2011)	Measure of implied Systemic risk called the Absorption Ratio	They infer systemic risk from asset prices, defined as equal to the fraction of a set of assets' total variance explained (or absorbed) by a finite number of eigenvectors. A high value for the absorption ratio corresponds to a high level of systemic risk because it implies that the sources of risk are more unified.	Equity returns from 51 US industries in the MSCI USA index (1998 to 2010) and 14 US housing markets data, along with the Case-Shiller 10-City National Composite Index (1992 to 2010).	This measure predicted the most significant equity market declines and consolidations in the housing market. Also the absorption ratio systematically rose in advance of market volatility.
Hollo et al. (2012)	Composite Indicator of Systemic Stress (CISS)	Based on portfolio theory to aggregate five market-specific sub-indices which included 15 individual financial stress measures.	Based on European data from 1982 to 2011.	CISS identified the recent financial and economic crisis as well as the other stressed periods. This method can also determine crisis levels.

Table 3.2 Continued

Author	Model	Methodology	Sample	Empirical Findings
L. Allen, Bali, and Tang (2012)	Macroindex of systemic Risk ($CATFIN$)	$CATFIN$ is constructed using an average of three VaR and ES estimates: (i) a parametric extreme value method using estimates of the generalised pareto distribution; (ii) a parametric estimate of the skewed generalised error distribution ; and (iii) a non-parametric approach.	Out-of-sample tests were conducted using U.S., European, and Asian equity bank returns data from January 1973 to December 2009.	$CATFIN$ systemic risk measure was able to forecast macroeconomic downturns (measured by GDP, industrial production, the unemployment rate and an index of 85 existing monthly economic indicators) approximately six months before they occurred.
Duca and Peltonen (2013)	The Financial Stress Index (FSI)	A country-specific composite index, covering five segments of the financial market including: (i) Short-term interbank and government bill spreads; (ii) negative equity returns; (iii) volatility of the main equity index; (iv) realised volatility of the nominal effective exchange rate; (v) realised volatility of the yield on short-term government bills.	Based on 28 countries, both emerging and advanced economies using quarterly data from 1990 to 2009.	During known periods of crises indicators of domestic and global macro-financial vulnerabilities, significantly improved the model's ability to forecast a systemic financial crisis.

Table 3.2 Continued

Author	Model	Methodology	Sample	Empirical Findings
Trapp and Wewel (2013)	Measurement of systemic risk via CDS Premia	Applying a copula approach to focus on downside risk (extreme value theory). This method is used as previous studies have highlighted that CDS premia are non normally distributed.	Based on 550 US and European companies from nine industries, daily CDS bid quotes from 2004 to 2009.	They provided evidence that suggested banks are exposed to common risk factors which plays a significant role in systemic risk within the banking sector. Also, that the dependence between the banking sector and a wide range of real sectors is limited.
Bagliano and Morana (2014)	A US Summary Index of Financial Fragility	A country-specific composite index including: (i) Short-term interbank and government bill spreads as a measure of credit and liquidity risk; (ii) government agency long-term bond spreads; (iii) yield difference between BAA and AAA rating bonds; (iv) a range of global macroeconomic condition factors; (v) eight sources of US financial disturbances and fundamental imbalances; (vi) 10 oil market variables.	Based on US quarterly data from 1986 to 2010. The global macroeconomic factors is time series data from 50 different countries.	Fluctuations in the financial fragility index can be attributed to, global and domestic macroeconomic (20%), financial disturbances (40—50%) over both short- and long-term horizons, as well as to oil supply shocks in the long-term (25%).

Table 3.2 Continued

Author	Model	Methodology	Sample	Empirical Findings
Sensoy, Ozturk, and Hacihasanoglu (2014)	Financial Fragility Index (FIX)	A principal component analysis and dynamic conditional correlations of five variables which include: (i) stock market indexes; (ii) exchange rate against the US dollar and Euro; (iii) CDS quotes of the five year sovereign bond; (iv) overnight interbank rates; (v) two year bond yields.	Based on Turkish daily data covers the period from September 2006 to April 2014.	FIX is not an absolute measure of financial stress, but it does serve as a relative measure (due to dynamic weighting). They also evidenced that except for the overnight interest rate, all variables play almost equally important roles in determining the financial fragility of the system.
Eder and Keiler (2015)	A Spatial Econometric Approach	This method can decompose the variance of bank's CDS premiums into contagion, systematic and idiosyncratic risk components.	Five year monthly CDS spread data for 15 global systemically important financial institutions from 2004 to 2009.	Results indicate that contagion is important in the CDS market. Considerable risk of spill overs was due to the interconnectedness of the financial institutions.

Table 3.2 Continued

Author	Model	Methodology	Sample	Empirical Findings
Alessi and Detken (2018)	Random Forest Technique	An early warning system using binary classification trees to identify whether the financial system is particularly vulnerable owing to aggregate credit and asset price developments. Incorporating, macroeconomic indicators, property prices and interest rate market-based indicators.	Based on crisis timing from 28 EU members during 1970Q1 and 2012Q4.	The main advantages of this approach is that it takes into account the conditional relations between various indicators when setting early warning thresholds. It more accurately models the non-linear relationship between credit, asset prices and the occurrence of banking crises than standard linear regression models.
Gibson, Hall, and Tavlas (2018)	Systemic vulnerability for selected EU banking systems	This measure is based on the covariance of banks' performance (as measured by daily market value) via an univariate GARCH estimation.	57 Banks from nine European countries: Austria; France; Germany; Greece; Italy; Ireland; the Netherlands; Spain; and the United Kingdom. Data from 2000 to 2016.	The index often rises before stressful events (shocks) and captures elevated vulnerability levels prior to certain events.

Table 3.2 Continued

Author	Model	Methodology	Sample	Empirical Findings
Papanikolaou (2018a)	EWS of banking bankrupt and bailout	Regressing a range of bank level, macroeconomic and financial variables against distress scores or bailout dummies.	7,602 US banks of which 167 were bankrupt, 824 were bailed out, and 6,611 were non-distressed. Using quarterly data from 2003Q1 to 2009Q4.	Banks with inadequate capital, illiquid and risky assets, poor management, low levels of earnings and high sensitivity to market conditions have a higher bankruptcy probability. Neither the managerial expertise, nor the quality of assets is relevant to the probability of bailout.

Economic Indicators

Claessens, Dell'Ariccia, Igan, and Laeven (2010) *inter alia*, have attempted to empirically relate economic variables to the 2008 crisis. Commonly cited variables include the declines in real GDP, cross-border trade flows, sovereign debt credit ratings as well as the exchange rate overvaluation and central bank reserve losses (Frankel & Saravelos, 2012). Rose and Spiegel (2010, 2012) *inter alia*, have made comprehensive efforts to empirically explain the differences in the intensity of the crisis between countries. Having assessed the significance of almost 100 variables, it would be suggested that it is unrealistic to predict future crisis with the help of EWS indicators. McNelis and Yoshino (2016) provides evidence (using Japan as the example) that increasing money supply (QE) is effective in times of crisis (in terms of stabilising investment and the real exchange rate), relative to other fiscal instruments such as tax reform or negative interest rates. Furthermore they caution that QE policy is an emergency policy, to be used in times of prolonged crisis[5].

Generally, there appears to be no consensus on robust economic determinants of the crisis, or on the key indicators of its development. Empirical findings vary depending on the definition of crisis, methodology and time frame of the study (Jun, Ahn, & Kim, 2017). Further, L. Allen et al. (2012) provided evidence that micro-level systemic risk measures have no macroeconomic forecasting power.

3.4.2 Capital Measures of Systemic Risk

Prior to the financial crisis, banking regulation followed a microprudential approach in assessing the resilience of financial institutions. Thus, the original generation of stress testing models usually focused on individual banks' solvency risk[6] (Anand et al., 2018). Capital measures can identify the organisations that are

[5]They do not explore the impacts of QE policies in normal times (such as inflation and loss of credibility).

[6]For an empirical example Acharya et al. (2018) found that stress tests in the US generally resulted in safer banks in terms of capital ratios and risk-weighted asset ratios.

exposed to systemic risk and such tools are useful for regulators to identify institutions that could significantly be affected by market shocks. Table 3.3 presents an overview of the credit and capital risk measures of systemic risk. VaR models can be applied to measure financial stability as a simpler alternative to structural econometric models. VaR allows for dynamic interaction between a small number of variables with interaction driven by a set of exogenous shocks. Through simulations, a VaR analysis can generate a probability distribution of outcomes for the dependant variable, which can provide a measure of the probability of distress over the given time horizon. Aymanns, Caccioli, Farmer, and Tan (2016) suggests that the financial crisis could have been caused by the over reliance on VaR measurement techniques[7]. Adrian and Brunnermeier (2008) developed an aggregate Co-Risk approach based on Conditional VaR (CoVaR). This measure is directly fixated at individual institutions or minor cluster which cannot be combined as measure of system-wide risk. In other words, adding the CoVaRs of all the institutions in a system will not lead to the system-wide VaR. Their set of explanatory variables such as market to book, return on equity, the quick liquidity and maturity mismatch ratios were shown to be significant predictors of systemic risk.

VaR_q^i is implicitly defined as the $q\%$ quantile, i.e.,

$$Pr(X^i \leq VaR_q^i) = q\% \tag{3.4.1}$$

where X^i is the loss of institution i for which the VaR_q^i is defined. VaR_q^i is typically a positive number when $q > 50$, in line with the commonly used sign convention. Hence more risk corresponds to a greater VaR_q^i. X^i is defined as the return loss. Adrian and Brunnermeier (2008) denote $CoVaR_q^{X^j|\mathbb{C}(X^i)}$ the VaR of institution j (or the financial system) conditional on some event $\mathbb{C}(X^i)$ of institution i. That is, $CoVaR_q^{X^j|\mathbb{C}(X^i)}$ is implicitly defined by the $q\%$-quantile of the conditional probability

[7]Aymanns et al. (2016) suggested this measurement technique resulted in the institutions conducting similar risk management techniques followed the US housing bubble which may have triggered the crisis.

distribution:

$$Pr\left(X^j \mid \mathbb{C}(X^i) \leq CoVaR_q^{X^j|\mathbb{C}(X^i)}\right) = q\% \tag{3.4.2}$$

Institutions i's contribution to j is denoted by

$$\triangle CoVaR_q^{X^j|i} = CoVaR_q^{X^j|X^1=VaR_q^i} - CoVaR_q^{X^j|X^1=VaR_{50}^i} \tag{3.4.3}$$

Where $CoVaR_q^{X^j|X^1=VaR_{50}^i}$ denotes the VaR of j's asset returns when i's returns are at their median (i.e. 50th percentile).

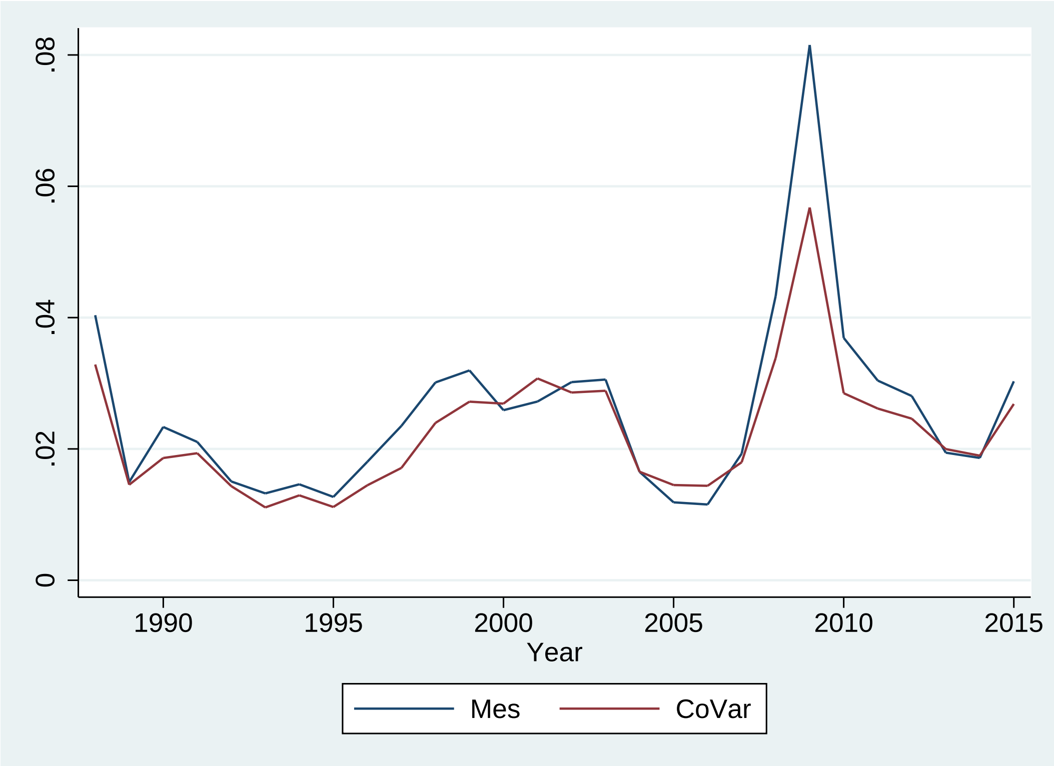
López-Espinosa, Moreno, Rubia, and Valderrama (2015) proposed an extension to CoVaR, which captures the asymmetric response of the banking system to both positive and negative shocks in the market-valued balance sheets of the individual financial institutions. They found that Adrian and Brunnermeier (2008)'s CoVaR assumption of a simple linear representation in which individual returns are proportional to system-wide returns is excessively restricted to larger banks. The empirical evidence in López-Espinosa et al. (2015) did suggest that CoVaR may provide a realistic approximation for smaller banks, however it can not capture the heteroscedasticity characteristic of financial assets which may severely underestimate systemic risk. Girardi and Ergün (2013) changes the definition of CoVaR, using another strand of literature which attempts to explore contagion by Generalized Autoregressive Conditional Heteroskedastic (GARCH) models[8] (Dimitriou, Kenourgios, & Simos, 2013; Mobarek, Muradoglu, Mollah, & Hou, 2016). Combining CoVaR with ADCC-GARCH models allows for possible changes over time in the linkage between individual markets and the global economy, which makes CoVaR more robust in assessing systemic risk and allowing for back testing as well.

Brownlees and Engle (2012) used the same explanatory variables as Adrian and Brunnermeier (2008) plus Marginal Expected Shortfall (MES) in developing the SRISK index, which measures the expected capital shortage of an institution conditional on a substantial market decline. MES is an estimate of the expected loss an equity investor of the institution would experience if the market was to

[8]This method alone ignores the extreme tail risks, which could lead to an underestimation of systemic risk (Girardi & Ergün, 2013)

decline substantially. This measure is useful for ranking firms according to their systemic risk level but, again, does not identify specific indicators of systemic risk. See Figure 3.3 for a graphical representation for CoVaR and MES for the US, appendix 3.8 explains the data and methodology applied. The MES concept has been known in the actuarial literature for quite some time under the name of conditional tail expectations (Tasche, 2002). Tasche (2002) introduced expected shortfall as an alternative measure of VaR, which builds on Acerbi, Nordio, and Sirtori (2001) work in response to VaR critics. For example, Heath, Delbaen, Eber, and Artzner (1999) comment that VaR cannot be considered as a sound methodology for allocating economic capital in financial institutions. Acharya, Pedersen, Philippon, and Richardson (2010); Acharya et al. (2017) provided evidence that capital based techniques could estimate the systemic risk contribution of institutions through their Systemic Expected Shortfall (SES) approach, which aims to measure the extent to which firms impose negative externalities on the system *via* increased leverage and MES. Closely related to MES, Weiß, Neumann, and Bostandzic (2014) propose a measure of extreme systemic risk, which captures the Lower Tail Dependence (LTD) of an individual institution with respect to the sector index. In other words, it captures the individual banks' and the sector's joint probability to crash together. However, this measure evaluates an institution's systemic relevance based on extreme events rather than moderate tail co-movements with the market. Pierret (2015) provides evidence that SRISK as a measure of capital shortfall outperforms CoVaR in determining how much short-term debt (liquidity) a financial institution can raise in a crisis period. SRISK unlike CoVaR is a function of size and leverage, which is relevant to regulators who want to measure solvency risk. Regulators employ capital ratios such as Tier 1 common capital and Tier 1 leverage to assess the solvency risk, however Pierret (2015) found that they do not appear to be related to either side of the financial institution's short-term balance sheet. $SRISK_{it}$ represents the expected capital shortfall of the financial institution i at time t in a crisis, which is when the respective equity market index falls by 40% over the next six month period. In such market conditions Acharya, Engle, and Richardson

Figure 3.3: US MES and CoVaR



(2012) state that $SRISK$ is based on an assumption that long-term book value debt D_{it} of the financial institution remains constant over the six month period while its market capitalisation MV_{it} decreases by its six month returns during a crisis, which is also know as long-run marginal expected shortfall ($LRMES$). Pierret (2015) defines the expected shortfall of capital in a crisis of financial institution i at time t by

$$\begin{aligned} SRISK_{it} &= E_t[k(D_{it+h} + MV_{it+h}) - MV_{it+h} \mid R_{mt+h} \leq -40\%] \\ &= kD_{it} - (1-k) * MV_{it} * (1 - LRMES_{it}) \end{aligned} \tag{3.4.4}$$

where R_{mt+h} is the return of the equity market index from period t to period $t+h$ ($h = 6$ months), k is the prudential capital ratio of the country, and $LRMES_{it} = -E_t(R_{it+h} \mid R_{mt+h} \leq -40\%)$.

Rather than focusing on relative losses in capital (equity or market capitalisation) in the way CoVaR, MES and $SRISK$ do Kreis and Leisen (2018) introduce Conditional Expected Default Frequency ($CEDF$) which focuses exclusively on default risk of the banking system, using equity return data. Kreis and Leisen (2018) back-tested their $CEDF$ measure as well as CoVaR and SRISK, during the two years beforehand and subsequently of the Lehman bankruptcy (September 2008); SRISK appeared to be a better EWS as it starts increasing from June 2007 and fairly smoothly trended upwards until July 2008 while CovaR only significantly reacted after the event. $CEDF$ however, was more volatile (during December 2007 – September 2009) with a number of peaks and troughs. This volatility could send mixed messages however, the original strong increase in December 2007 could have sent a strong signal of possible future threats in the financial system.

Kleinow, Moreira, Strobl, and Vähämaa (2017) examined four different systemic risk measures[9] using 122 US financial institutions' data (2005-2014) and concluded that the alternative measurement approaches produced heterogeneous estimates of systemic risk. Further, different metrics may lead to contradicting assessments regarding to riskiness of different financial institutions types (i.e. banks, non-depository financial institutions and insurance companies). Kleinow et al. (2017) findings suggest that assessing systemic risk based on a single risk metric should be approached with caution. MES appears intuitively most appealing (out of four credit risk based systemic risk measures) as it was able to accurately outlines the time line of the financial crisis via producing consistently high estimates of systemic risk for three different industry sectors.

The main challenge of these capital models is that a vast amount of data and computing is required. The majority of the information comes in the form of proxies and dummies from accounting data. It is common practice to judge the soundness of an institution by looking at its accounting data and most reports to regulatory agencies are based on this. However, it is worth observing that this approach is only as reliable as the accounting standard within that country as mentioned previously. The measures discussed within this section are all empirically tested using data from developed countries, therefore applying these measures to other countries with poor accounting standards may produce

[9]Four credit risk based measures, Co-dependence risk (Co-Risk), delta CoVaR , LTD and MES

unreliable results. Also, the effects of shadow banking can skew the data. For instance, prior to the recent crisis the financial institutions covertly increased leverage by moving risk onto the balance sheets of special-purpose vehicles that were ultimately backstopped by credit lines from the same institutions. Following the crisis, many institutions moved such shadow bank assets back onto their balance sheets (Adrian, 2015). After the recent crisis the regulators considered restricting the shadow banking system activity which was considered as a gap in the previous regulatory structure (Rixen, 2013). Regarding the computing power required, the number of minimum observations for verification of an internal risk management model is 250 (recommended by BIS (2010b)). Therefore, the ability to compute this number of observations largely depends on the feasibility on the operational capabilities of the institution. However, Kupiec (1995) states that even using 250 observations for testing often provides a low statistical power. Furthermore, C. E. Borio and Drehmann (2009) argue that the use of VaR models does not address the dynamics of distress, and they are unable to incorporate the likes of boom-bust economic cycles.

Table 3.3: Credit and Capital Measures of Systemic Risk

Author(s)	**Model**	**Methodology**	**Sample**	**Empirical Findings**
Bartram, Brown, and Hund (2007)	Presented three methods to quantify the risk of a systemic failure	The first approach examines equity returns of unexposed banks during financial crisis. The second is based on the likelihood of systemic failure based on a structural credit risk model (Merton, 1974). The third approach estimates bank default probabilities implied by equity option prices.	334 banks from 28 countries. The five global financial crises within the sample included the Mexican devaluation in 1994, Asian crisis in 1997/98, the Russian long-term capital Management default in 1998 and the Brazilian devaluation in 1999.	They interpret that small increases in estimated default probabilities of unexposed banks during crisis generated little risk of a systemic failure. They also provided possible explanations for this i.e the shocks might not be large enough and effective policy responses might have limited the risks or their approach might not be able to accurately measure of risk.
Adrian and Brunnermeier (2008)	Δ CoVaR, which is defined as the difference between the Conditional VaR of the financial system conditional on an institution being in distress.	They used panel quantile regression of equity prices and balance sheet fundamental data	15 US financial institutions using quarterly data from 1971Q1 to 2013Q2, and daily equity data over the same period.	Δ CoVaR estimates show that characteristics such as leverage, size, maturity mismatch and asset price booms significantly predict systemic risk contribution.

Table 3.3 Continued

Author	Model	Methodology	Sample	Empirical Findings
Segoviano Basurto and Goodhart (2009)	Joint Probability of Default (JPoD) and the Bank Stability Index (BSI)	JPoD represents the probability of all the banks in the system (as a portfolio) becoming distressed, i.e., the tail risk of the system. This uses an entropy-based copula approach that matches marginal default probability constraints from the CDS markets. The BSI reflects the expected number of banks becoming distressed given that at least one bank has become distressed.	Based on CDS data from 2005 up to October 2008 for major American and European banks, as well as sovereigns in Latin America, eastern Europe and Asia.	Their measures allow users to analyse (define) stability from three different, yet complementary perspectives using very limited datasets.
Acharya et al. (2010, 2017)	Each financial institution's contribution to systemic risk can be measured as its Systemic Expected Shortfall (SES)	Measures the extent to which an institution imposes negative externalities on the system. They calculate realised Marginal Expected Shortfall (MES) and SES on daily equity returns, volatility and Beta. They compare these with fundamental data such as leverage, assets and market value of equity.	102 US financial institutions using equity and CDS data from June 2005 to December 2008.	SES increases with the institution's leverage and with its expected loss in the tail of the system's loss distribution i.e. its tendency to be under-capitalised when the system as a whole is under-capitalised.

Table 3.3 Continued

Author	Model	Methodology	Sample	Empirical Findings
Khandani, Kim, and Lo (2010)	Consumer Credit Risk Measure	They apply a machine-learning techniques to construct non-linear, non-parametric forecasting models of consumer credit risk.	Customer transactions and credit bureau data from January 2005 to April 2009 for a sample of a major commercial bank's customers. The sample is a small percentage of the bank's total customer base (unique dataset).	Time-series patterns of estimated delinquency rates from this model of the 2007-08 financial crisis suggest that aggregated consumer credit-risk analytics may have important applications in forecasting systemic risk.
Brownlees and Engle (2012)	SRISK Index. The expected capital shortage of an institution conditional on a substantial market decline	SRISK is an index that is a function of fundamental data such as the degree of leverage, size, marginal expected shortfall (MES), equity returns, market capitalisation, liquidity ratios and book value.	94 U.S. financial institutions from July 2000 to June 2010.	Their results provided evidence that SRISK is useful for the ranking of systemically risky institutions at various stages of the financial crisis.

Table 3.3 Continued

Author	Model	Methodology	Sample	Empirical Findings
Puzanova and Düllmann (2013)	The financial sector is treated as a portfolio of debt represented by financial institutions' liabilities	They derive systemic risk capital contribution via a credit portfolio approach using a Gaussian factor model. Systemic risk is gauged by the tail risk of the portfolio loss distribution. This is based on book value of the bank's liabilities.	54 out of 86, of the world's major commercial banks from Europe, North America, South America, Africa, Japan and Asia & Pacific. Using monthly data from 1997 to 2010.	Their evidence suggests that macroprudential supervision should focus on a solid capital base throughout the financial cycle and the de-correlation of banks' asset values.
Girardi and Ergün (2013)	Multivariate GARCH estimation of CoVaR	This is a modification of Adrian and Brunnermeier (2008) *Delta* CoVaR by using it in conjunction with ADCC-GARCH models.	74 US financial institutions' data from June 2000 to February 2008.	This adaptation allows the *Delta* CoVaR model to consider more severe distress events (those beyond the institution's VaR and farther in the tail), to back-test and to improve consistency (monotonicity) with respect to the dependence parameter (Mainik & Schaanning, 2014).

Table 3.3 Continued

Author	Model	Methodology	Sample	Empirical Findings
Jobst and Gray (2013)	Systemic Contingent Claim Analysis	This measures systemic solvency risk, generated by aggregate estimates of the joint default risk of multiple institutions as a conditional tail expectation using multivariate extreme value theory. Based on equity prices and balance sheet data.	33 large US commercial and investment banks, insurance companies, and special purpose financial institutions using daily data between January 1, 2007 and January 2010.	This measure helps quantify the individual contributions to contingent liabilities and systemic risk of the financial sector during times of stress.
Avramidis and Pasiouras (2015)	They extend Puzanova and Düllmann (2013) model	They extend the previous Gaussian approach by proposing a model that accounts for extreme event dependence and they quantify the level of capital shortfall when this characteristic is ignored.	82 of the largest commercial banks in the world, data from January 2000 to December 2012.	This method is able to calculate systemic risk in the form of potential credit losses and can allocate total systemic risk to the financial system participants based on their contributions.

Table 3.3 Continued

Author	Model	Methodology	Sample	Empirical Findings
Kreis and Leisen (2018)	Conditional Expected Default Frequency ($CEDF$)	This structural model of the banking system assuming that defaults of individual banks are linked through correlated (changes in) asset values.	A core sample of 15 U.S. banks (largest by assets during 2004 and 2016) and an extended sample of an additional 15 U.S. Banks. Daily equity prices and quarterly asset values between 1980 and 2016 (extended sample from 1996).	Average asset loadings (correlation) considerably increased over the course of the last 36 years, while their heterogeneity decreased. Due to the limited focus, $CEDF$ will not be able to capture all dimensions of systemic risk in the banking system, but it proved to be a useful complement to existing systemic risk measures.

Impact of Leverage

Additional constraints on leverage arise from a number of regulatory policies. According to Aymanns et al. (2016), the following measures effectively impose a risk contingent leverage constraint: (i) if institutional investors trade collateralised loans they must maintain margin on its collateral; (ii) regulators such as the Basel Committee impose a risk contingent capital adequacy ratio[10]; and (iii) another possibility is that internal credit risk management procedures may adopt a VaR constraint[11] on leverage. High levels of leverage can exacerbate risk because in bear markets leverage increases when asset prices decease, and such drop in prices can then impact leverage constraints, which may force institutions to sell such assets into falling markets (quick fire-sales), thereby amplifying declines in prices further (see Figure 3.4). Due to the nature of the demand and supply curves they tend to be stronger when the leverage of the financial intermediary is pro-cyclical (when leverage is high during bull markets and low during bear markets). There are two main ways in which institutions can reduce their balance sheets leverage; by selling risky assets (potentially impacting profitability) or raise more capital (Sharma, Lavery, & Polyanskiy, 2010). Adrian and Shin (2008) found that in practice during and prior to the 2007 financial crisis, most institutions tended to do the former. A. Barth and Seckinger (2018) investigated the unintended consequences of more stringent leverage ratios, for example a binding leverage ratio might create an incentive for an originate-and-distribute strategy. They suggested that higher-quality institutions are not allowed to absorb the entire supply of debt if it is too costly to issue new equity. This can effectively enhance the market share of lower-quality institutions, raising interest in them from regulators and adding to the competition of higher-quality institutions.

[10]Financial instructions are expected to maintain a leverage ratio in excess of 3% under Basel III.

[11]In simple terms VaR is a measure of how much the bank could lose at a given probability, usually at the 95% confidence interval.

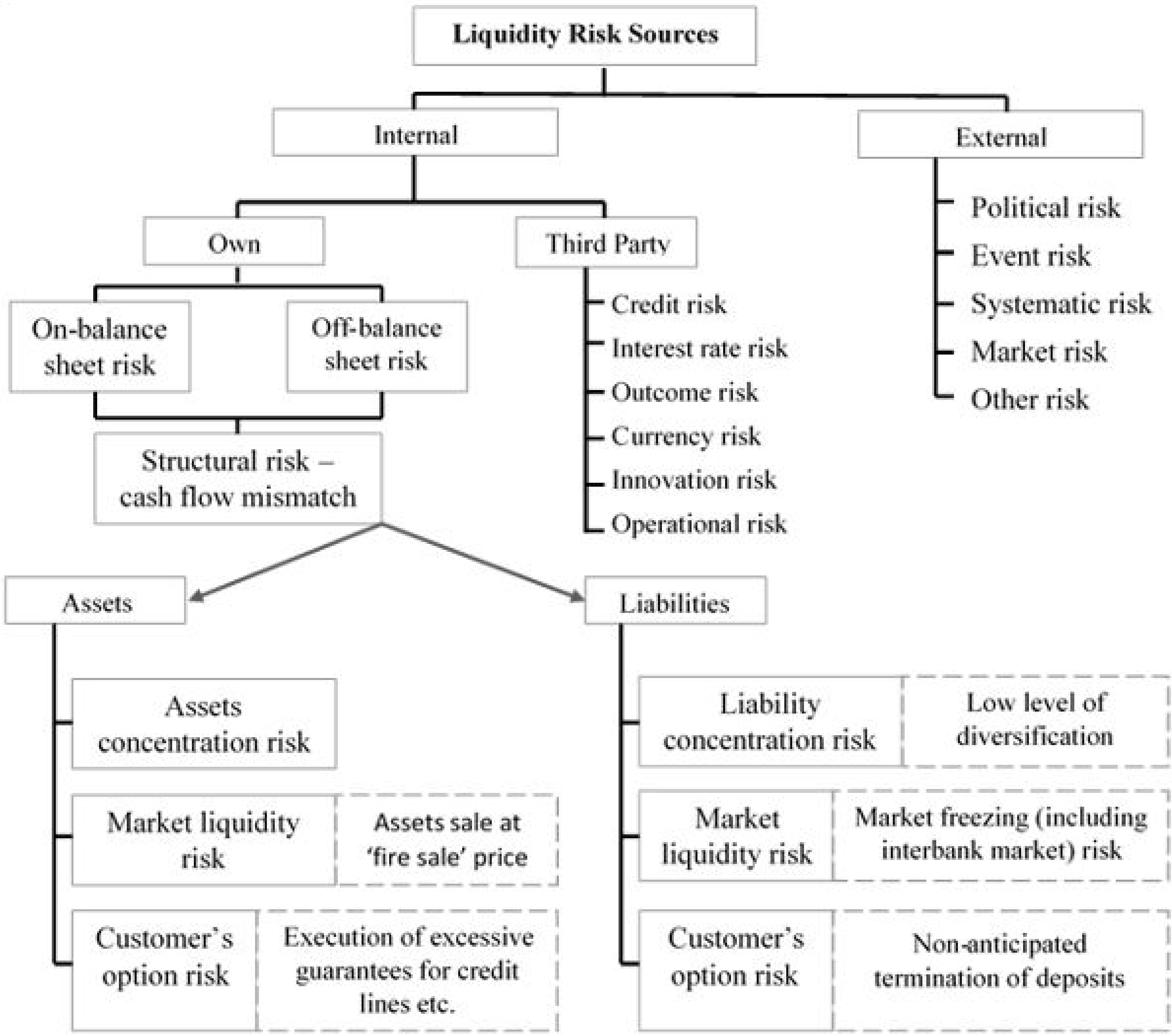
Figure 3.4: Leverage Price Amplification of Balance Sheet Change

Source: Adrian and Shin (2008, p. 5)

3.4.3 Liquidity Measures of Systemic Risk

Historically, until the recent financial crisis, liquidity risk was rarely viewed as a priority by most financial institutions and regulators (Vento & La Ganga, 2009). Recently, many authors have argued that in order to prevent another systemic crisis, liquidity requirements should be introduced to reduce the reliance on short-term refinancing and decrease the maturity mismatch between assets and liabilities (Acharya & Yorulmazer, 2008; Acharya, 2009; Acharya & Richardson, 2009b; Wagner, 2009). In addition, Cao and Illing (2010) proposed that if all institutions held extra liquidity the system on aggregate would be more resilient. The empirical findings of Distinguin et al. (2013) based on a sample of 781 US and European banks from 2000 to 2006 suggest that liquidity risk is a predictor of bank failure and to avoid such failures, liquidity risk should be minimized not just on an individual bank level but at a macro banking system level as well. See Figure 3.5 for a breakdown of liquidity risk sources within a financial institution.

Figure 3.5: Liquidity Risk Sources



Source: Wójcik-Mazur and Szajt (2015, p. 28)

Berger and Bouwman (2009) using US bank data developed a number of liquidity creation measures which capture banks illiquidity by assessing the liquidity created for customers. They showed that larger banks (total assets $\geq$ \$1Bn) create over 80% of the sector's liquidity (despite accounting for a small percentage of all US banks). J. Bai, Krishnamurthy, and Weymuller (2018) using their Liquidity Mismatch Index (LMI) similarly found that the US banking sector's liquidity is largely determined by the top 50 banks.

The majority of measures regarding systemic liquidity risk focus on negative externalities caused by maturity mismatches (Table 3.5 provides an overview). For example, Brunnermeier and Pedersen (2009) proposed using the institution's CoVaR measure to calibrate charges for maturity mismatches to manage systemic liquidity risk. However, it is not clear whether this capital oriented measure can be applied for such a purpose. Also, based on financial institutions fundamentals, Pierret (2015) empirically investigated the link between solvency and liquidity in line with the bank run literature (F. Allen & Gale, 1998). Using the difference between short-term liabilities and short-term assets as a proxy for liquidity risk, Pierret (2015) provided evidence that financial institutions lose their access to short-term funding (liquidity) when markets expect that they will become insolvent. Perotti and Suarez (2011) proposed a mandatory liquidity insurance funded by taxation of short-term wholesale funding. This simple model requires institutions to pay different rates based on their contribution to negative externalities. However, institutions are funded by many different channels, so the assumption of short-term borrowing as the sole source of an institution's funding is oversimplifying the issue and makes it difficult to interpret the results in terms of regulatory recommendations. Also, Jobst (2014) argues that there is limited knowledge of how to empirically measure the systemic risk of wholesale funding. Jobst (2014) introduced a risk-adjusted liquidity measure which aims to assess the marginal contribution of each institution to total systemic liquidity risk. This approach is based on option pricing theory and it was acknowledged that this model can fail due to irrational market behaviour.

There has been progress with respects to developing regulation in this area. Basel Committee on Banking Supervision (BCBS) agreed the Basel III framework (BIS, 2011a) sets out a number of consistent liquidity monitoring tools, which are expected to capture information related to: cash flow issues; balance sheet structure; availability of encumbered collateral; market liquidity indicators and disclosure standards (Adalsteinsson, 2014). Further, BCBS's main approach to reduce funding concentration is to focus on the more significant[12] wholesale funding sources (both on counterparty and product basis). Basel III set out

[12]Their definition of a significant counterparty or product, is if it accounts for more than 1% of the bank's total balance sheet.

international liquidity requirements, including the introduction of the Liquidity Coverage Ratio (LCR)(BIS, 2013a)

$$LCR = \frac{\text{High Quality Liquid Assets}}{\text{Net Cash Outflows for 30 Day Period}} \times 100 \geq 100\% \tag{3.4.5}$$

and the Net Stable Funding Ratio (NSFR) (BIS, 2014)

$$NSFR = \frac{\text{Amount of Stable Funding}}{\text{Required Amount of Stable Funding}} \times 100 \geq 100\% \tag{3.4.6}$$

to be implemented by 2015 and 2018, respectively.

LCR focuses on financial institutions' short-term liquidity levels (over the next 30 days) in the event of shocks. In order to do this, it adds behavioural assumptions to the asset and liability categories, which makes it a more dynamic tool than alternative balance sheet ratios Adalsteinsson (2014). Where as the NSFR monitors the long-term funding stability (Ashraf, Rizwan, & L'Huillier, 2016) and identifies maturity mismatches which could impact funding risk (Schmitz & Hesse, 2014). Ultimately, both ratios are designed to encourage the use of more stable funding sources and ensure financial institutions have access to funding when required.

Within LCR, HQLA constitutes two liquidity groups: Level 1 are highly liquid assets which are not subject to haircuts such as cash, government debt and central bank reserves. Level 2 are market valued assets such as corporate debt and covered bonds. These assets are subject to a range of variable haircut (15% - 50%). Thus, the LCR numerator is given by

$$HQLA \equiv Level1 + min\left\{\sum_i (1 - haircut_i) \times Level2asset_i, \frac{2}{3} \times Level1\right\} \tag{3.4.7}$$

i.e. Financial institutions HQLA must be mainly Level 1 assets, level 2 assets are not allowed to cover over 2/3 of Level 1 assets. The LCR denominator is an estimation of cash inflow over the next 30 days minus cash outflows. Inflows must not cover any more then 75% of outflows, given by the following equation

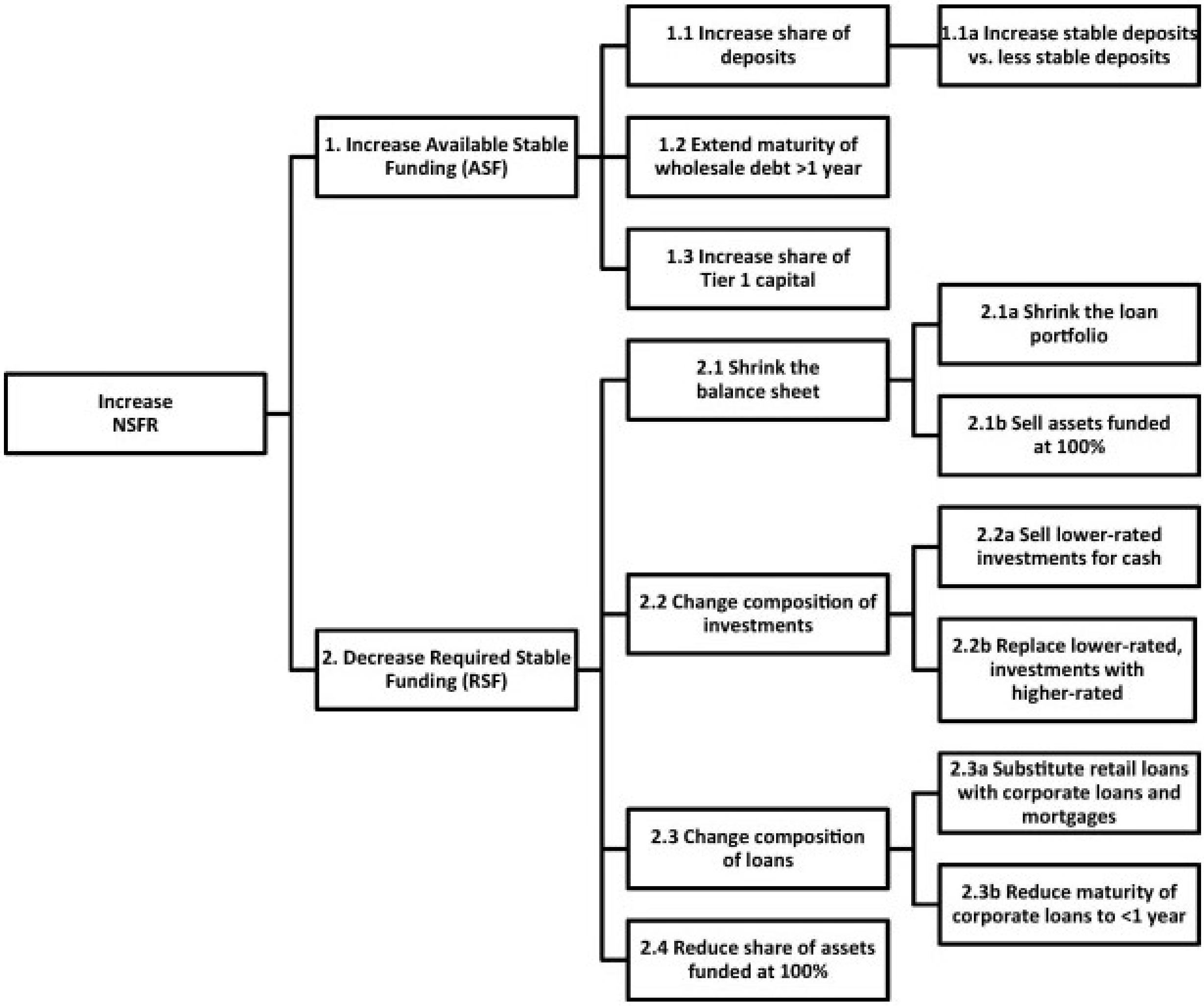
$$\text{Net Cash Outflows} \equiv Outflows - min\left\{0.75 \times Outflows, Inflows\right\} \tag{3.4.8}$$

Blundell-Wignall and Atkinson (2010) believe that the introduction of Basel III liquidity requirements will reduce systemic risk at times of liquidity tension and reduce a dependence on central banks for funding. Härle et al. (2010) evidenced that implementing the new liquidity requirement would lead to more capital and liquidity efficient business models and products. P. King and Tarbert (2011) also argue that the introduction of liquidity standards is the most important aspect of the new Basel III framework. In their view, the financial crisis was more a liquidity shock than a credit crisis, yet increased capital for credit risk remains the priority from the point of view of regulators. Pakravan (2014) supports P. King and Tarbert (2011) notion, suggesting that the new liquidity measures are an attempt to avoid a repeat future liquidity crisis. Chiaramonte and Casu (2017) empirically evidenced this as the NSFR was found to be a significant determinant of bank sector fragility using EU bank level data, thus supporting the need for such liquidity requirements.

A number of empirical studies have sought to assess the impact of the new liquidity regulations. These permanently focus on the NSFR due to the nature of LCR, for example, the complexity to derive proxies or assumptions to calculate the total net cash outflows over a 30-day period (Equation 3.4.8). Goodhart, Kashyap, Tsomocos, and Vardoulakis (2012) found the NSFR to be a good pre-emptive macro-prudential tool in comparison to cyclical variation in capital requirements or underwriting standards. M. R. King (2013) tested NSFR levels for larger financial institutions in 15 countries and, on average, representative banks in 10 out of 15 countries appear to have an NSFR below the minimum threshold at year-end 2009. Similarly, Dietrich, Hess, and Wanzenried (2014) explored the potential impact of the prescribed funding structures under Basel III on the performance of the banking industry in Western Europe with the sample of 921 banks during 1996 and 2010 to find that the majority of the banks have historically not fulfilled NSFR minimum requirements. Assessing US bank data prior to Basel III, DeYoung, Distinguin, and Tarazi (2018) found that on average, banks increased their NSFR following negative shocks to their risk-base regulatory capital ratios. There was no evidence to suggest banks increase their NSFR following negative shocks to their simple accounting (leverage) equity ratios. The authors argue that these results suggest that capital and liquidity have been historically treated as substitutes. Thus, implementing both capital and liquidity requirements will be a challenge to banks. Alternatively, Dietrich et al. (2014) reported that banks with higher capital ratios, lower loan growth, more interest-bearing business and branches operating in their native country have higher NSFRs. In other words, banks with traditional business models (based on deposit taking and lending) should have higher NSFR than banks with a high share of non-interest income.

A number of concerns have been raised regarding the liquidity requirements (König & Pothier, 2016), in relation to LCR, Keister and Bech (2012) suggest this requirement should increase demand for central bank funding impacting open market operations (e.g. use of the money markets). Also, Malherbe (2014) argues that cash hoarding to maintain a certain level of funding may actually reduce market liquidity. In relation to NSFR, Härle et al. (2010) suggest that banks with substantial capital markets and trading businesses will be impacted the most due to NSFR requirement, and this sentiment was also shared by M. R. King (2013) who argues that universal banks with diversified funding sources and high trading assets will be penalised the most. In addition, Blundell-Wignall and Atkinson (2010) proposed the idea that the liquidity requirements may significantly lower banks' returns. Also, Gideon, Petersen, Mukuddem-Petersen, and Hlatshwayo (2013) expects financial institutions to raise lending rates in order to keep their return on equity in line with market valuations and/or to reduce credit supply to lower the share of risky assets on the balance sheet. See Figure 3.6 for a breakdown of how financial institutions can enhance their NSFR. This diagram suggests a number of implications for the new longer-term liquidity requirement.

Figure 3.6: How banks can increase their NSFR



Source:M. R. King (2013, Pg 4147)

The consultation process and implementation of NSFR was also questioned as the calculation requires a highly-detailed classification of the funding, which banks do not disclose or even did not collect for their balance sheets (Gobat, Yanase, & Maloney, 2014; Härle et al., 2010). Analysts were unsure regarding the weights given to assets and liabilities in order to reflect appropriate liquidity risk assumptions (Gobat et al., 2014). Weighting changes will ultimately impact bank level risk. Wei, Gong, and Wu (2017) demonstrated that if short-term debt is given a sufficiently low weight as an example within the available stable funding, NSFR can lower the use of short-term debt and thus reduce banks' exposure to excess roll-over risk. Furthermore, the assumptions rather than empirical validation and the ratio will have little effect on bank failures (Dietrich et al., 2014; Hong, Huang, & Wu, 2014). See Table 3.4 for a summary of the Available Stable Funding (ASF) and Required Stable Funding (RSF) items weightings. Note the differences in weightings to the ASF factor for deposits. In addition, Schmitt and Schmaltz (2016) found that these revisions had significantly reduced both the number of non-compliant banks and the magnitude of shortfall. When NSFR is empirically tested, equation 3.4.9 is used as a proxy as financial institutions are not required to disclose this information as yet (Yan, Hall, & Turner, 2012; Chiaramonte & Casu, 2017).

$$NSFR = \frac{Equity + \substack{TotalLT \\ Funding} + \left(\substack{Term \\ Customer \\ Deposits} * 0.95 \right) + \left(\substack{Current \\ Customer \\ Deposits} * 0.9 \right) + \left(\substack{Other \\ Deposits \\ andST \\ Borrowing} * 0.5 \right)}{\substack{Other \\ Assets} + \left(\left(\substack{Government \\ Securities} + \substack{OBS \\ Items} \right) * 0.05 \right) + \left(\left(\substack{Other \\ Securities} + \substack{Loans \\ and \\ Advances \\ toBanks} \right) * 0.5 \right) + \left(\substack{Mortgage \\ Loans} * 0.65 \right) + \left(\substack{Retail \\ and \\ Corporate \\ Loans} * 0.85 \right)} \geq 100\% \tag{3.4.9}$$

Table 3.4: NSFR Calculation Breakdown

Assets Variables	RSF 2014 Factors	RSF 2010 Factors
Cash and equivalent due from banks	0%	0%
Off-balance-sheet items	5%	5%
Government securities	5%	5%
Loan and advances to banks	50%	0%
Other securities (total securities minus government securities and at-equity investment in associates)	50%	50%
Residential mortgage portfolio	65%	65%
Net loans (minus residential mortgage portfolio)	85%	85%
At-equity investment in associates	100%	100%
Fixed assets	100%	100%
Insurance assets	100%	100%
Investment in property	100%	100%
Other earning assets	100%	100%
Non-earning assets (Total assets minus total earning assets and cash and equivalent due from banks)	100%	100%
Reserves for non-performing loans	100%	100%
Liability & Equity Variables	**ASF 2014 Factors**	**ASF 2010 Factors**
Deposits from banks	0%	0%
Other deposits and short-term borrowings	50%	50%
Customer demand deposits	90%	80%
Customer term deposits	95%	90%
Customer savings deposits	95%	90%
Total equity	100%	100%
Total long-term funding	100%	100%

Source: BIS (2010a) and BIS (2014)

Despite the introduction of liquidity requirements in Basel III, according to Jobst (2014) systemic liquidity risk from a macro-prudential perspective remains largely unaddressed. Distinguin et al. (2013) argued that liquidity risk is a predictor of bank failure, and the previous regulations do not go far enough in the US and Europe as system level liquidity was not addressed. In an attempt to build a further liquidity buffer within the BCBS Global Systemically Important Banks (G-SIBs) (FSB, 2014a) the FSB announced the Total Loss-Absorbing Capacity (TLAC) (FSB, 2014b). This requires financial institutions to hold excess level of risk-weighted assets. TLAC is designed to minimize the *participation of* institutions in systemic risk from a liquidity perspective. This standards intention is to ensure that in the event of failure of a larger, interconnected and complex financial institution can be resolved in an orderly manner, without the need for public funded support. Following these initiatives, supervision authorities and central banks have been developing newer stress-testing models and tools that more rigorously take into account the interconnections between banks and the interactions between banks' liquidity and solvency risk. For example, the European Central Bank's *Stress-Test Analytics for Macroprudential Purposes in the Euro area (STAMP€)* (Dees, Henry, & Martin, 2017) comprises five different analytical assessments[13] and Bank of Canada's *Macro-Financial Risk Assessment Framework (MFRAF)* (Fique, 2017) with a focus on the country's D-SIBs.

[13](i) Dynamic dimension that takes into account banks' responses to a scenario, (ii) the interaction with the real economy, (iii) the interconnections between financial institutions, (iv) the integration of system-wide liquidity assessment and (v) the interaction with non-financial sectors.

Table 3.5: Liquidity Measures of Systemic Risk

Author(s)	Model	Methodology	Sample	Empirical Findings
Brunnermeier and Pedersen (2009)	A model that links an assets market liquidity and trader's funding liquidity	They define market asset liquidity as the difference between the transaction price and the fundamental value. They define funding liquidity as speculators' shadow cost of capital.	S&P 500 futures margins from 1982 to 2008. Funding requirement data from hedge funds, commercial & investment banks and market makers.	Their model predicts that market liquidity declines as fundamental volatility increased (negative correlation). They also provided evidence that, under certain conditions, margins are destabilised and that market and funding liquidity are mutually reinforcing, leading to liquidity spirals.
Aikman et al. (2009)	A Risk Assessment Model for Systemic Institutions (RAMSI)	RAMSI assesses the impact of macroeconomic and financial shocks on both individual banks as well as the banking system using Bayesian VAR (BVAR). They also regress bank fundamental data against credit rating.	The 10 largest UK banks from 1972Q2 to 2007Q4.	They demonstrate how rising funding costs and liquidity concerns can amplify other sources of risk.
Perotti and Suarez (2011)	A Pigovian Tax on short-term funding	They developed an analysis of the relative performance of realistic price-based and quantity-based approaches to the regulation of systemic externalities associated with bank's short-term funding strategy.		They provided evidence that a pigovian tax on short-term funding is efficient in containing risk and preserving credit quality, while quantity-based funding ratios are distortionary.

Table 3.5 Continued

Author	Model	Methodology	Sample	Empirical Findings
S. H. Lee (2013)	Systemic liquidity shortages due to interbank interconnectedness	A comparative analysis of six different types of network structures. Their models are described by several exogenous parameters such as reserve ratios, deposit shares, surplus funds and cross holdings.		They provide evidence that greater imbalances in liquidity positions across banks tends to aggravate the liquidity shortage of a deficit bank. Also banking systems becomes more vulnerable to liquidity shocks as its interbank networks becomes more ill-matched.
Hu, Pan, and Wang (2013)	Noise as Information for Illiquidity	Market-wide liquidity measure by exploiting the connection between the amount of arbitrage capital in the market and observed noise (deviations from a given pricing model) in U.S. Treasury bonds.	US daily cross-sections of end-of-day treasury bill and bond (one month to 10 year maturities) prices from 1987 to 2011. Total of 163 treasury bills and bonds.	Their noise measure captures episodes of liquidity crisis from different origins across the financial market, providing information beyond existing liquidity proxies.
Jobst (2014)	Systemic Risk-Adjusted Liquidity (SRL) Model	Using option price theory and institutions required and available stable funding ratios. This approach quantifies an individual institution's time-varying contribution to expected losses from system-wide liquidity shortfalls and insurance premia that provide incentives for banks' to internalise the social cost of their individual funding decisions.	13 largest US commercial and investment banks data from January 2005 to December 2010.	The SRL model provides a tractable framework for the assessment of system-wide valuation effects arising from joint liquidity risk.

3.4.4 Contagion Measures of Systemic Risk

The emergence of systemic risk in financial networks has also been receiving increasing attention in the literature (Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015a; F. Allen & Babus, 2009; Stiglitz, 2010) and among regulators (IMF, 2012; Yellen, 2013). Within the banking sector, financial institution interconnectedness can have wider implications in the event of financial shock. This is because exogenous or endogenous shocks can be intensified in various ways (Roukny, Battiston, & Stiglitz, 2018), for example, funding concentration can spread bank runs and capital flight (Diamond & Dybvig, 1983); similar asset portfolios (both indirect interconnectedness) can be exposed to supressed valuations via fire sales and deleverage (Caccioli, Shrestha, Moore, & Farmer, 2014); and intertwined balance sheets (via derivatives and loans) can results in cascading defaults (F. Allen & Gale, 2000). Further, Cai, Eidam, Saunders, and Steffen (2018) argues that syndication increases the overlap of bank loan portfolios and makes them more vulnerable to contagious effects. The likes of indirect interconnectedness could be limited by reducing the reliance on mark-to-market accounting or by promoting greater diversity in business strategies. Possible channels of contagion in the banking sectors can originate from a range of sources, both on the liability side (e.g. bank runs) and asset side (e.g. interbank lending, derivative exposure and settlement systems)[14]. Garriga (2017) argues that delays in revising banks' prudential regulation provide opportunities for banks to elude regulation and adopt risky behaviour. This effect increases a country's vulnerability to systemic banking crisis. The majority of systemic risk measures that relate to contagion are based on the assumption that the greater the correlation of indicators the greater the systemic risk. Table 3.6 presents an overview of the proposed contagion measures of systemic risk.

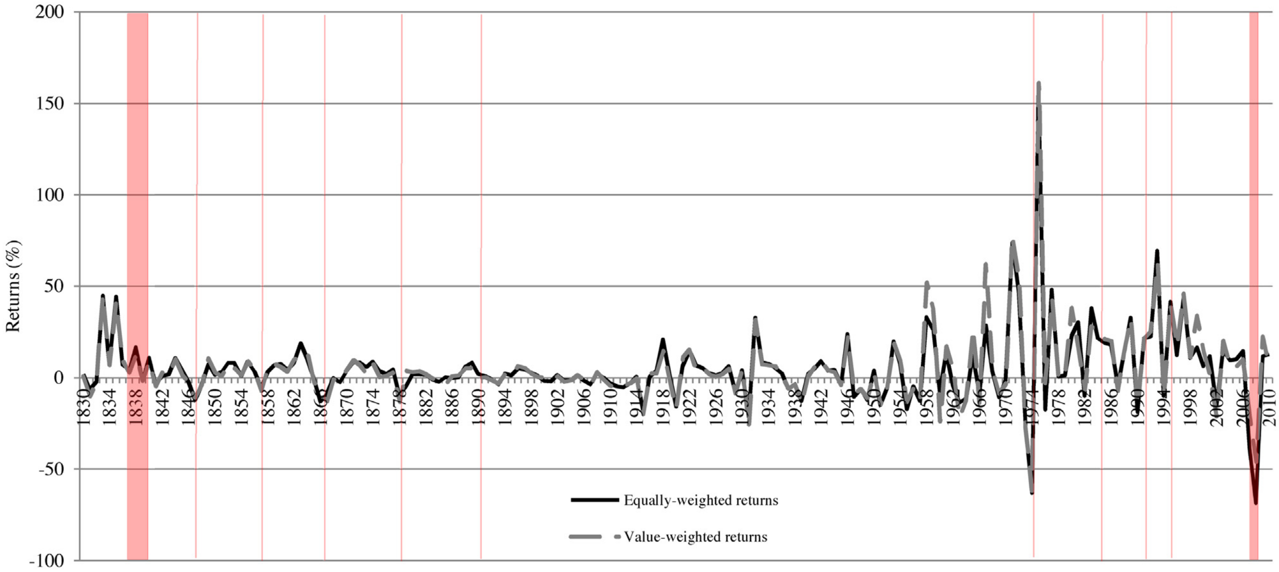
Nicoló and Kwast (2002) argue that institution's interdependencies provide an indication of systemic risk by using equity return correlations of large and complex

[14]See Table 1 and footnote 4 in Upper (2011) for a comprehensive list of references on the various channels of contagion.

US financial institutions. Their claim is based on the assumption that increased equity return correlation may signal an increase in the potential for a shock to become systemic. The use of equity returns does reflect market participants' collective evaluation of an institution. However, it is unclear to what extent this reflects the total impact of its interactions with other institutions, as this may be private information. Patro, Qi, and Sun (2013) also conducted a similar study and found that daily equity return correlation is a simple, robust, forward-looking, and timely systemic risk indicator.

Using Reinhart and Rogoff (2009) measurement of banking instability (equity pricing) and defined crisis periods in the UK over a 181-year period, Campbell, Coyle, and Turner (2016) made the following five observations (see Figure 3.7). First, on average two years prior to any crisis there tend to be substantial equity gains followed by considerable declines in the year of the crisis. Secondly, economic indicators (real interest rates, inflation and GDP growth) are higher than historical averages in the two years prior to a crisis, as economic activity tends to accelerate before a crisis. Thirdly, money supply is consistent with improved averages in the years before the crisis. Fourthly, proxies for commodities display negative growth two years prior to a crisis, however one year before and during a crisis, price growth is considerably above historical averages. Lastly, in the years leading up to a crisis, financial institutions lending and house price growth rates were above average, supporting the view that significant credit growth fuels a housing asset bubble in the lead up to financial crisis.

Figure 3.7: UK Bank Equity Returns 1830-2010



Source: Campbell et al. (2016, p. 77)

Lehar (2005) measures risk at the level of the banking system rather than at the level of individual institutions, by estimating the dynamics and correlations between institution asset portfolios following Merton (1973) method of equity as a call option of institution's assets. This does not attempt to capture systemic risk but the measure enables regulators to track and compare risk of the system. This method was extended by Allenspach and Monnin (2008) who assessed co-movement of banks assets to debt ratio as they believe that changes in the assets to debt ratio can be considered as a good summary of changes in the overall financial health of an institution. Allenspach and Monnin (2008) finding warns against viewing systemic risk as a pure correlation phenomenon and highlight the danger of high and volatile leverage at the individual institution level.

It is worth noting that the studies that use equity indices returns to assess the contagion across different markets do provide evidence consistent with studies that are focused on international diversification. For example, Ye, Luo, and Du (2014) used a Multivariate Conditional Autoregressive Value at Risk (MV-CAViaR) model to assess contagion from the US equity market to five other countries (China, Japan, UK, France and Germany) during a crisis period. They found that contagion from the US increased market risks of the other tested countries during the crisis except for China, however during the recovery period this contagion effect was reduced and varied. These findings were consistent with previously findings by Bae, Karolyi, and Stulz (2003). With the assumption that a crisis period reflects a bear equity market and the recovery period reflects a bull market, these findings are similar to You and Daigler (2010). Their study empirically investigated the theory of international diversification using dynamic correlation away from the US equity market during bull and bear periods. Their findings provided evidence that investors can get diversification benefits from Asian markets but limited benefits from European market. They also found that during bear periods (crisis periods) the indexes they tested became increasingly correlated and during bull periods the evidence was mixed. This phenomenon is not just isolated to equity prices. For example, Eder and Keiler (2015) found in European and US financial institutions CDS premia were strongly affected by financial contagion, whilst the Asian financial institutions were found to be rather independent.

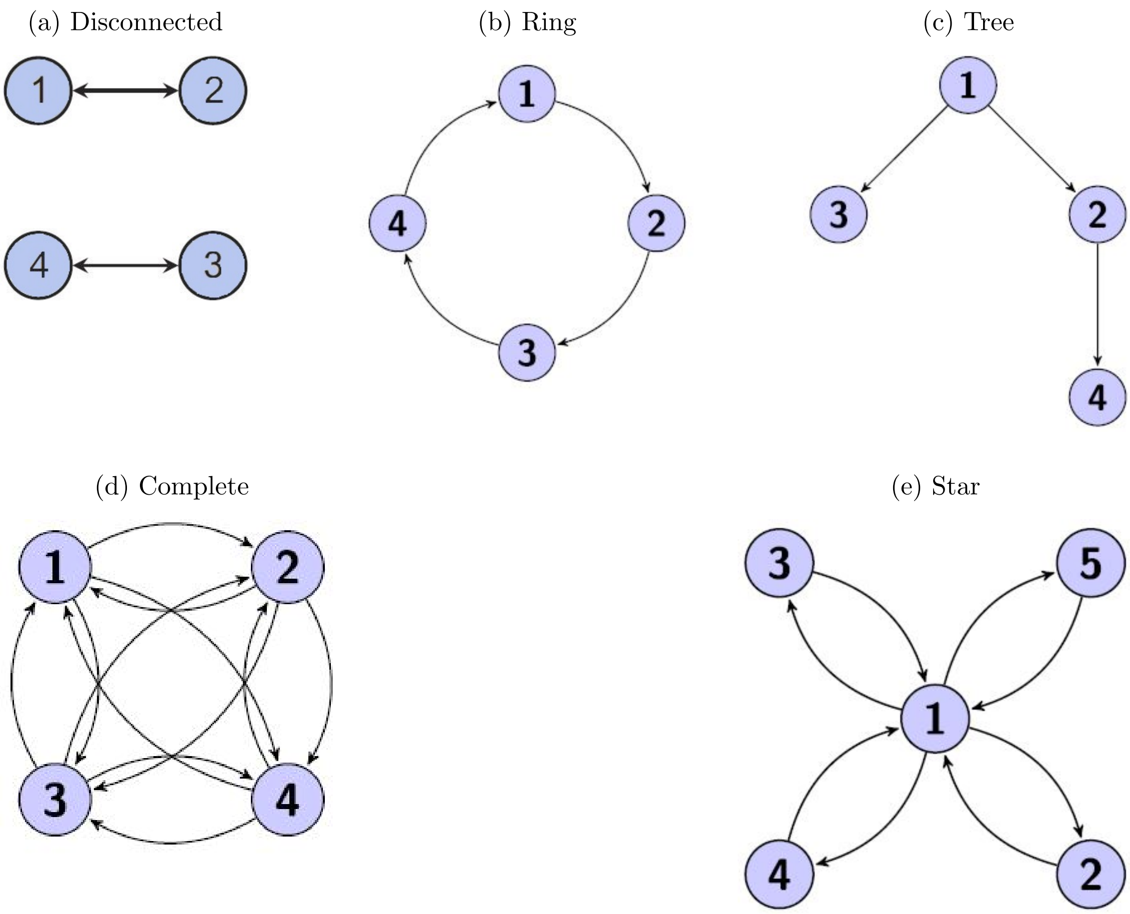
A more recent assessment of contagion at the industry level was conducted by Tonzer (2015), who used the BIS aggregate bilateral cross-border asset and liability positions reporting and macro-economic data regressed against industry bank risk (as measured by the Z-Score). He found that countries that are connected *via* foreign borrowing or lending positions to more stable banking systems overseas are significantly affected by positive spillovers. This implies that linkages in the banking system can be beneficial, however this may not be the case in a crisis period.

3.4.5 Network Measures of Systemic Risk

Network theory or simulation models of systemic risk emerged in the early 2000s and they seem to be homogeneous in nature, in particular, due to the type of parameters included such as connectivity, concentration and size of financial institutions. The majority of this research tends to focus on systemic risk through contagion effects following a shock. Generally, there are five types of network structures that can be tested (see Figure 3.8).

Simulations provide policy-makers with a rough indication of whether

Figure 3.8: Network Structures



Source: adaptation of S. H. Lee (2013) and Roukny et al. (2018)

contagion could become a possible consequence of endogenous or exogenous shocks. Thus, such methods can be used to identify potential financial institutions whose failure could potentially cause system contagion and/or other institutions to fail (e.g. node 1 in Figure 3.8e). Unlike other models, simulations can take into account simultaneous factors, such as balance sheet data and their interaction with interbank markets. However, the simulation studies tend to be based on similar strong underlying assumptions, which can lead to a range of different biases. Moreover, data availability is a serious issue with simulation methods. The simulation method may be sophisticated, however limited access to the data may make models redundant. Data on bilateral exposures within, for example, the interbank market is currently limited, especially for over the counter bilateral agreements. Therefore, some financial institutions' exposures are intrinsically unobservable. In time, as more bilateral agreements are conducted via central platforms, the data availability could improve. When creating a method of measuring systemic risk within networks it is common for them to be conceptual or theoretical without real data. Table 3.7 provides an overview of the current network measures of systemic risk. A more recent example by Roukny et al. (2018) introduces a conceptual model to compute the probability of default for individual financial institutions as well as systemic defaults within a network of banks connected via a credit contracts network. This model is designed to be applied using actual data with adjustable parameters depending on the data availability within the assets/credit portfolios and balance sheet. A main advantage of this technique is that it can be used by regulators to access both the level of (individual and systemic) risk and identify any uncertainty arising from the interconnectedness. Barroso, Silva, and de Souza (2018) proposed a method of identifying from systemic risk arising from insolvency contagion arising from aggregated cross-border debt exposure networks. Using BIS's Consolidated Banking Statistics database and aggregated capital buffer data, they found that the US and UK hold the most cross-border risk bearing with the potential to cause a shock/damage within a global network. Their approach is a useful tool for monitoring cross-border financial systems but does not attempt to identify interconnectedness among individual financial institutions.

Poledna, Molina-Borboa, Martínez-Jaramillo, van der Leij, and Thurner (2015) provide a robust example of this research area, using a unique dataset which covers four different types of exposure in the Mexican banking system. This dataset is only available to supervisors or for systemic risk research purposes. Uniquely they were able to provide evidence that focusing on a single layer network underestimates the total systemic risk by up to 90%. Their results demonstrated that the exposures related to the cross-holding of securities and from FX transactions (both of which are traded over-the-counter) are crucially important components of the systemic risk. However, it would be dangerous to generalise such findings to larger banking systems such as the one in the US. Recent work has shown how network research can be advanced. Aldasoro and Alves (2016) analysed multiplex network structure of 53 anonymous large European banks (as of year end 2011), presenting exposures partitioned (layered) according to maturity and instrument type. They found a high level of similarity between the different layers, a core-periphery structure which comprises of a large core and positively correlated multiplexity[15]. Similarly Berndsen, León, and Renneboog (2018) investigated coupling financial institutions' multiplex networks with financial market infrastructures' networks and found that central financial institutions tend to overlap across financial networks, thus their systemic importance may be even greater than envisaged. In both cases, the layout was similar to the star structure in Figure 3.8e, but with a number of central nodes which have similar exposures (instrument and maturity) from other smaller nodes. These methods can be used to evidence which institutions play an important role within a network and identify correlated channels of transmission. Their dataset of granular level data was compiled by two regulatory bodies for such a purpose, and is therefore not available publicly and difficult to criticise. Even if more interconnection data was available, practical issues such as the computing power required for larger banking

[15] Bliemel, McCarthy, and Maine (2014) defined multiplexity as interaction of exchanges within and across relationships.

systems would be substantial, for example in order to estimate loss distributions methods such as Monte Carlo simulation would be required.

Table 3.6: Contagion Measures of Systemic Risk

Author(s)	**Model**	**Methodology**	**Sample**	**Empirical Findings**
Nicoló and Kwast (2002)	Institution Interdependencies	For the dynamics of interdependencies they use equity return correlation. Then they relate the correlations to their consolidation activity by estimating measures of the consolidation elasticity of correlation through time and cross sectionally.	Major US Banks from 1988 to 1999, taking into account 22 consolidation events.	They provide evidence of a positive trend in equity return correlations net of diversification effects. This suggests that the systemic risk potential in the financial sector may have increased during the sample periods.
Bae et al. (2003)	Contagion captures the coincidence of extreme returns	They observe large positive and negative daily equity returns, then calibrate the joint occurrences of extreme returns using Monte Carlo simulation followed by multinomial logistic analysis against economic indicators.	Based on 17 Asian and Latin American markets from April 1992 to December 2000.	They found contagion is predictable and depends on regional interest rates, exchange rate changes, and conditional equity return volatility. In addition, contagion is stronger for extreme negative returns than for extreme positive returns, which is mixed.
Gropp and Moerman (2004)	Co-incidence of extreme shocks to bank's risk to examine contagion	Bank's risk is measured by the first difference of weekly distances to default and abnormal returns, applying Monte Carlo simulations to observed frequency of large shocks experienced by two or more banks simultaneously. This is consistent with the assumption of a multivariate normal or a student t-distribution.	67 of the largest EU banks from 1991 to 2003.	Their measure may be able to accurately measure contagion among any bank pair, as long as the probabilities of an idiosyncratic shock hitting the two banks are quite similar. Also their measure can be used to identify banks which have systemic importance within countries and across countries.

Table 3.6 Continued

Author	Model	Methodology	Sample	Empirical Findings
Lehar (2005)	Standard tools that regulators require banks to use for their internal risk management are applied at the level of the banking system to measure the risk of a regulator's portfolio	Estimate the dynamics and correlations between bank asset portfolios. Fundamental data included bank size, ROA, book value of equity over total assets, long term debt and regulatory capitalisation.	149 International Banks (50 US, 40 Europe, 45 Japan, 14 Other) from 1988 to 2002.	Within the sample period they showed that in line with market events the North American banking system gains stability while the Japanese banking sector becomes more fragile.
Rodriguez (2007)	A Copula approach to measure contagion	They used a Copula approach with time-varying parameters that change with the states of the variance to identify shifts in the dependence structure in times of crisis. This method can capture increases in tail dependence.	Five East Asian equity indices during the Asian crisis (1/1/96 to 30/6/98), and four Latin American equity indices during the Mexican crisis (1/1/93 to 31/12/95).	They provided evidence that the dependence structure between equity market returns of countries in Asia and Latin America changed during the crisis periods. They argue that structural breaks in tail dependence are an actual dimension of the contagion phenomenon.

Table 3.6 Continued

Author	Model	Methodology	Sample	Empirical Findings
Schwaab, Koopman, and Lucas (2011)	A coincident measure and an indicator for the likelihood of simultaneous failure	Using a dynamic factor framework based on state-space methods. The indicators of systemic risk are based on underlying macroeconomic (8 US and 8 European indicators) and credit risk components such as exposure and actual default count.	Dataset of 450 U.S. and 400 EU-27 area financial firms, compared with non-financial firms from 1984Q1 to 2010Q4.	They found that decoupling credit risk from macro-financial fundamentals may serve as an early warning signal of systemic risk.
Giesecke and Kim (2011)	Dynamic hazard model of failure	Their formulation attempts to capture the spill over effects channelled through a complex network of relationships in the economy. The model is based on actual failures rates as compared against macroeconomic and sector-specific risk factors.	US default timing data from 1987 to 2008.	Their evidence indicated that the model provides accurate out-of-sample forecasts of the term structure of systemic risk. Also the cause of systemic distress is the correlated failure of institutions to meet obligations to creditors, customers, and trading partners.
Billio, Getmansky, Lo, and Pelizzon (2012)	Econometric measures of connectedness	Several econometric measures of connectedness based on principal-component analysis and Granger-causality networks.	Monthly returns of US value weighted indexes of hedge funds, banks, broker/dealers and insurance companies' data from 1994 to 2008.	Their evidence suggests that the four sectors have become highly interrelated over the sample period, likely increasing the level of systemic risk in the finance and insurance industries.

Table 3.6 Continued

Author	Model	Methodology	Sample	Empirical Findings
Ye et al. (2014)	MVMQ-CAViaR Method	They use Multivariate Conditional Autoregressive Value at Risk (MV-CAViaR) models to analyse the variation of market risk among diffident countries at different stages of the crisis period. This is based on the equity index daily return data.	Equity market indices include, the S&P 500 (US), CSI300 (China), Nikkei 225 (Japan), FTSE-100 (UK), CAC-40 (France) and DAX (Germany). Over number of periods including: Pre-crisis (January 2006 to December 2007); Crisis Period (January 2008 to June 2009); and the Recovery phase (July 2009 to July 2013).	Their evidence shows that their estimated coefficients became more significant or that the market risks of the tested countries increase during the crisis except for China. Also their model demonstrated the changes in market risk where consistent with market events.

Table 3.6 Continued

Author	Model	Methodology	Sample	Empirical Findings
Tonzer (2015)	Linkages in interbank markets affect the stability of interconnected banking systems (not individual banks)	They used a spatial modelling approach to test for spillovers in cross-border interbank markets, using the banking system's international balance sheet positions data, i.e total cross-border positions disaggregated from the BIS bilateral cross-border asset and liability positions data. They also used a range of macroeconomic data with dependant variables bringing the industry Z-Score as a measure of Bank Risk.	Data from the US, 15 European countries, Canada and Japan from 1994 to 2012.	The results suggest that foreign exposures in banking play a significant role in channelling banking risk. Countries that are linked through foreign borrowing or lending positions to more stable banking systems abroad are significantly affected by positive spillover effects. This implies that in stable times, linkages in the banking system can be beneficial, while they have to be taken with caution in times of financial turmoil affecting the whole system.

Table 3.7: Network Measures of Systemic Risk

Author	Model	Methodology	Sample	Empirical Findings
Eisenberg and Noe (2001)	A network approach to introduce a single clearing mechanism that produces the number of defaults required to induce a firm to fail	They developed an algorithm that both clears the financial system in a computationally efficient fashion and provides information on the systemic risk faced by the individual system firms.		They provided comparative statics which imply that, in contrast to single-firm results, even unsystematic, non-dissipative shocks to the system will lower the total value of the system.
Elsinger, Lehar, and Summer (2006)	To assess two sources of systematic risk by analysing the market and credit portfolios of all banks simultaneously	They extend Eisenberg and Noe (2001) model to include indirect linkages through correlation	Austrian interbank lending exposure cross-sectional data (881 reporting banks) for September 2002 (plus three additional times periods for robustness).	Correlation in bank's asset portfolios dominates contagion as the main source of systemic risk. They also computed the VaR for a lender of last resort and find that the funds necessary to prevent contagion were unpredictably low.
Chen and Wang (2009)	CDS market network model to study systemic risk	They developed an algorithm in which a bilateral connection matrix is generated stochastically in order to simulate a plausible CDS network reflecting the real market. The node links are the bilateral obligations from the CDS market.	FDIC data and market share data of 26 banks to create a U.S. CDS market with the incorporation of 'non-U.S. bank' nodes.	The network model of the CDS market shows how certain parameters of a network can affect the expected loss of the system relative to the initial loss caused by a default.

Table 3.7 Continued

Author(s)	Model	Methodology	Sample	Empirical Findings
Canedo and Jaramillo (2009)	Systemic Risk Network Model (SyRNet)	A network model to analyse systemic risk in the banking system that seeks to obtain the probability distribution of losses for the financial system resulting from the shock/contagion process.	Mexican interbank exposure data (25 banks) from January 2004 to December 2006 (unique dataset).	Their model allows them to perform stress tests along both the bank default probabilities and the interbank exposures and is used to assess the risk of the system.
Martínez-Jaramillo, Pérez, Embriz, and Dey (2010)	Model systemic risk via random shocks that weakens one or more financial institutions and a transmission mechanism which transmits such effects to the rest of the system	They enhance Canedo and Jaramillo (2009) model to make it more robust by incorporating CVaR in order to evaluate if the system is become more or less fragile.	Mexican Interbank exposure data (27 banks) from December 2007 to June 2009 (unique dataset).	Their results suggest that the probability distributions of the initial shock, the size of the losses and the correlations, play a key role in the determination of the robustness or fragility of a financial system.

Table 3.7 Continued

Author(s)	Model	Methodology	Sample	Empirical Findings
Bluhm and Krahnen (2014)	A macroprudential risk management approach building on a system wide value at risk (SVaR)	This model incorporates multiple sources of systemic risk including: size of financial institutions; direct exposure from interbank lending; asset fire sales using a Shapley value-type measure; and fundamental data (Assets such as liquid, non-liquid assets and interbank lending. Liabilities such as deposits, interbank borrowing and equity).		Using SVaR they provide evidence that a fair systemic risk charge which is proportional to a bank's individual contribution to systemic risk, diverges from the optimal macroprudential capitalisation of the banks. Also that bank's size and interconnections in the form of interbank lendings, and fire sale spirals are driven by a mark-to-market mechanism.
Poledna et al. (2015)	Quantify the daily contributions to systemic risk from four network layers	The four network layers include deposits & loans, security cross-holdings, derivatives (swaps, forwards, options, and repo transactions) and foreign exchange (FX) transactions.	Applying Mexican banking system data 2007 to 2013. A unique dataset (confidential to regulators and supervisors).	They provide evidence to show that focusing on a single layer network underestimates the total systemic risk by up to 90%. Their results demonstrate that the exposures related to the cross-holding of securities and the exposures arising from FX transactions are crucially important components of the systemic risk.

Table 3.7 Continued

Author(s)	Model	Methodology	Sample	Empirical Findings
Hautsch, Schaumburg, and Schienle (2015)	A systemic risk beta as a measure of financial companies' contribution to systemic risk, given the network interdependence between firms' tail risk exposures	They define the realised systemic risk beta as the total time-varying marginal effect of a firm's Value-at-risk (VaR) on the system's VaR. They use a wide range of publicly accessible macroeconomic market, equity return and fundamental data.	59 US Financial institutions from 2000 to 2008	They provide evidence to highlight how interconnected the US financial system is and clearly marked channels of relevant potential spillovers. In particular, this method can classify companies into major risk producers, transmitters or recipients within the system.
Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015b)	A theoretical framework for the study of the economic forces shaping the relationship between the structure of the financial network and systemic risk	They focus on an economy consisting of banks (simulating different network structures), which lasts for three time periods. At the initial date, banks borrow funds from one another to invest in projects that yield returns both in the intermediate and final date. The liability structure that emerges from such interbank loans determines the financial network, capturing the pairwise counterparty relationships between different institutions.		They found that highly interconnected complete financial network is the configuration least prone to contagion. This is because losses of a distressed bank are passed to a larger number of counterparties, guaranteeing a more efficient use of the excess liquidity. Ring networks tend to be the most fragile. However they provided evidence that in the case of larger shocks, networks do not aid the system.

Table 3.7 Continued

Author(s)	Model	Methodology	Sample	Empirical Findings
Constantin et al. (2018)	Estimated network linkages into an EWS model to predict bank distress	The approach estimates tail-dependence networks via equity returns and combines them with a bank-level early-warning model (mainly focused on the CAMELS variables).	EWS was produced using 171 European banks' data from 1999Q1 to 2012Q3. The wider sample includes 243 European banks	The EWS including estimated tail dependencies consistently outperform the EWSs which cover solely vulnerabilities coming from bank-specific, sector-level and macro-financial imbalances in order to predict bank distress events.
Roukny et al. (2018)	A theoretical model to compute the individual and systemic probability of default	Using a theoretical financial network of over-the-counter (OTC) credit contracts the authors compute the individual and systemic probability of default in a system of banks connected in a generic interbank network.		Their main contribution shows that multiple equilibria can arise from the presence of closed chains of debt within the network. If the default conditions of a set of banks are mutually dependent along cycles of credit contracts, there exists a range of external shocks such that the equilibrium where all those banks default and the equilibrium where none of them defaults co-exist.
Barroso et al. (2018)	Insolvency contagion within Financial Networks	This method decomposed drivers of systemic risk from insolvency contagion. Assessing the drivers of systemic risk from financial institutions debt network exposures and capital buffers.	Quarterly data on cross-border debt exposures and aggregated tier 1 capital buffers from 26 countries during 2005 to 2014.	Their findings suggest that network debt topology explains most of the volatility of contagion risk and that capital buffers are effective at reducing contagion risk.

3.5 Data Requirements

This section provides an overview of the different types of data required to compute and empirically test the measures proposed to calculate systemic risk which is summarised in Table 3.8[16]. The most common indicators are equity prices (55% of models) and financial institution fundamental data (45% of models). This data is readily available to the public via stock exchanges or a range of subscription databases (e.g. Thomson Reuters Datastream and Bloomberg Professional Service). As mentioned previously, these have their limitations which are widely acknowledged in the literature. For example, the use of equity prices tends to come with the assumption of rational markets which is not always the case, especially in the times of crisis. From an empirical perspective, Zhang, Vallascas, Keasey, and Cai (2015) questioned whether purely equity based measures capture systemic risk adequately. As equities become more correlated globally (Roll, 2013; You & Daigler, 2010) this could impact the models reliability and/or statistical significance. As an example from using bank equities, Born, Ehrmann, and Fratzscher (2014) conducted an event study focusing on how central bank's dissemination, the likes of a Financial Stability Report publication (and ad hoc speeches/interviews) affect equity markets by further increasing correlation in returns and reducing market volatility. As a number of EWS (e.g. FSI and CISS) use correlation and realised volatility, such models may also be indirectly affected by such announcements.

In many papers that use fundamental data from financial institutions' balance sheets, items or a combination of items are used as proxies for risk and in some cases there is limited consistency (e.g. the decision to use the natural log function or not). Also, some methodologies require interpolation, extrapolation or disaggregating from yearly to quarterly or monthly data. Given the operational nature of the financial institutions this technique could provide misleading observations. Section 2.3.7 briefly outlines the issues surrounding accounting

[16]Within this table, 50 models are presented, six models from the previous discussion are not included as they are theoretical and were not empirically tested with real world data.

standards. Macroeconomic data is used in 27% of the models. Again this data is widely available within the public domain. However, similarly to fundamental data the frequency and time of publication varies across different countries, often impacting comparability.

The contagion and network methods of measuring systemic risk tend to require unique datasets (for example, Poledna et al. (2015) used data only available from the Mexican central bank and Khandani et al. (2010) who had access to customer transactions and credit bureau data from a sample of major US commercial banks) and interbank market data (Canedo & Jaramillo, 2009; Elsinger et al., 2006; Tonzer, 2015). Such studies provide an insight into specific cases using data which is not readily available in the public domain and they tend to provide interesting and important findings, thus providing an argument for more data transparency and availability. Previous literature (Aldasoro & Alves, 2016, *inter alia*) has argued the need to use more granular data by noting that banks interconnectedness can range differently in different layers (different asset or liability types) and thereby the focus on a single layer may be misleading (Poledna et al., 2015). Still important information can be obtained from one layer dataset, in particular if one is able to decompose global systemic importance, then regulators can identify institutions to investigate them further. Nevertheless, without unique/granular level data Aldasoro and Alves (2016) provided evidence that simple network measures can be an inferior alternative.

Foreign exchange data is rarely used in the systemic risk models. This data tends to be in the form of an index or a currency pair price. As foreign exchange transactions are over the counter, such indexes/prices tend to aggregate averages of the bid/offer prices. In attempts to capture inter-day volatility, the spot price is often compared to the previous price 30 minutes ago or the futures price. Interestingly, despite the rare use of foreign exchange market data, when it is employed it tends to be in studies covering the emerging economies and is found to be a statistically significant indicator of systemic risk (Bae et al., 2003; Poledna et al., 2015; Sensoy et al., 2014, *inter alia*). As noted by Laeven and Valencia (2013), the majority of financial crises within developing economies originally develops from either sovereign default and/or the depreciation of their currency. Therefore, in future development of systemic risk models the incorporation of foreign exchange data may provide valuable insight.

Table 3.8: Data Requirements

Author(s) and Year of Publication	Credit Default Swaps	Equity	Macroeconomic	Fundamental	Bond Market	Interbank Market	Commodities Market	Foreign Exchange Market	Real Estate	Hedge Fund	Regulation Environment	Futures Margins	Credit Rating/Default Timing	Consolidation Timing	Unique/Granular Dataset
Nicoló and Kwast (2002)		x												x	
Bae et al. (2003)		x	x					x						x	
Gropp and Moerman (2004)		x		x											
Lehar (2005)				x											
Elsinger et al. (2006)						x									x
N. Chan, Getmansky, Haas, and Lo (2006)										x					
Bartram et al. (2007)		x													
Rodriguez (2007)		x													
Bhansali et al. (2008)	x														
Adrian and Brunnermeier (2008)		x		x											
X. Huang et al. (2009)	x	x		x											
Alessi and Detken (2009)			x	x											
Segoviano Basurto and Goodhart (2009)	x														
Brunnermeier and Pedersen (2009)												x			
Aikman et al. (2009)		x	x	x									x		
Canedo and Jaramillo (2009)						x									x
Chen and Wang (2009)	x														
Gaganis et al. (2010)			x	x							x				
Kritzman and Li (2010)		x			x		x		x						
Acharya et al. (2010, 2017)	x	x		x											
Khandani et al. (2010)													x		x
Martínez-Jaramillo et al. (2010)						x									x
Kritzman et al. (2011)		x								x					
Schwaab et al. (2011)			x										x		
Giesecke and Kim (2011)		x	x			x							x		
L. Allen et al. (2012)		x	x												
Hollo et al. (2012)		x		x	x	x		x							
Brownlees and Engle (2012)		x		x											
Billio et al. (2012)										x					
Duca and Peltonen (2013)		x		x	x	x	x								
Trapp and Wewel (2013)	x														
Girardi and Ergün (2013)		x		x											
Puzanova and Düllmann (2013)		x		x											
Jobst and Gray (2013)		x		x											
Hu et al. (2013)					x	x									
Sensoy et al. (2014)	x	x			x	x		x							
Jobst (2014)				x											
Ye et al. (2014)		x													
Avramidis and Pasiouras (2015)		x		x									x		
Poledna et al. (2015)															x
Hautsch et al. (2015)		x	x	x											
Tonzer (2015)			x	x		x									
Eder and Keiler (2015)	x	x	x	x	x	x									
Aldasoro and Alves (2016)															x
Kreis and Leisen (2018)		x		x											
Alessi and Detken (2018)			x		x				x						
Constantin et al. (2018)		x	x	x											
Gibson et al. (2018)		x													
Papanikolaou (2018a)			x	x							x		x		
Barroso et al. (2018)				x											x

3.6 Challenges for Regulation and Systemic Risk Measurement

This section highlights the key challenges that policy-makers face in terms of choice and implementation of systemic risk measures.

Firstly, the term macroprudential regulation can be interpreted in a number of ways. From a systemic risk perspective, it means controlling financial instability inherent to financial markets and institutions using a top-down approach. However, macro-prudential regulation is often considered to be an activity that focuses on mapping and managing the economic cycle while sceptics treat it as meaningless. Therefore, a consensus on the precise definition of macroprudential regulation would be desirable[17]. As previously discussed, there is a wide range of systemic risk measures, which when coupled with a plethora of proposed policy instruments to address the individual type of risk leaves policy-makers facing a conundrum. The main problem is deciding on a universally accepted regulatory instrument (or a combination of instruments) that would be cost-effective[18] in mitigating systemic risk.

Secondly, as a policy response to systemic risk being a global issue, a macroprudential approach would need to be led by a co-ordinated partnership of central banks, regulators and governments with a harmonised supervisory style. Separation of the mandates without coordination between policy-makers is an inferior arrangement regardless of the type of shock (Lazopoulos & Gabriel, 2019). Following the financial crisis, there were repeated calls to strengthen the co-operation between national regulators as part of the policy response (Arner, 2009). There has been a number of proposals to develop cross-border regulations (mainly focused on the G-SIB)[19], including proposals by the WTO, BIS and IMF

[17] See Clement (2010) for a discussion of term *macroprudential*

[18] Cost-effective in the sense that the new regulation has a minimal effect on banking efficiency, productivity and innovation. This would have to be based on empirical simulations which would be a subjective and time-consuming process.

[19] Away from the G-SIB's, The European Union has an example of an international supervisor, the European Security and Market Authority (ESMA). Beginning its operations in January 2011,

(Arner & Taylor, 2009), however this harmonised supervisory style idea currently is a long way off. For example, Carretta, Farina, Fiordelisi, Schwizer, and Lopes (2015) found that among the European banks there is a substantial number of different supervisory cultures. Further, they showed that a collectivism-oriented supervision culture[20] improves the banks' distance to default (as measured by the Z-Score) and that a power-distance-oriented culture[21] diminishes banking stability. Also, Clark and Jokung (2015) found that regulators with a higher level of risk aversion are associated with tighter regulations and regular intervention, whilst low levels of risk aversion are associated with lighter regulation and infrequent interventions. Hence, a consistent supervisory approach is desirable. This harmonisation challenge was recently highlighted by Masciandaro and Volpicella (2016), who investigated the economic and political drivers of the policy-makers' decision to assign macro-supervisory powers to central banks. They found that governments tend to be cautious when placing too much power in the hands of independent and/or discretionary central banks.

Thirdly, when deciding what type of regulation to implement the policy-makers face the challenge of which banks need further regulation or whether the 'one size fits all' approach is sufficient. Empirical evidence can help answer this question. For example,Vazquez and Federico (2015) found that smaller and larger banks (in the US and Europe) were susceptible to failure for different reasons, i.e. smaller banks due to liquidity problems and large banks due to insufficient capital buffers. For larger banks, Demirguc-Kunt, Detragiache, and Merrouche (2013) found that stronger capital reserves were linked with better equity price performance and Chiaramonte and Casu (2017) found that for the G-SIBs, the Basel III capital and

it assesses risk to investors and financial institutions by promoting supervisory convergence and directly supervising European credit rating agencies.

[20]Supervisors that are oriented towards collective outcomes, e.g., focusing on the overall stability of the banking system, with the aim of preventing any social costs for stakeholders (Hofstede, Hofstede, & Minkov, 2010).

[21]This culture is based on a strict supervision with authoritative empowerment of the regulation and no flexibility without looking for a general consensus toward banking regulation(Hofstede et al., 2010).

liquidity standards have proven to be important in reducing a bank's probability of default.

Fourthly, another relevant issue is whether regulators should target banks as *contributors to* (reducing moral hazard) or as *participants of* (making individual banks safer) systemic risk. Finally, to enhance the effectiveness of measuring systemic risk, there is a need for improved data availability and quality as discussed previously.

In summary, continued progress is needed for policy-makers to improve their understanding of macro-prudential regulation. They need to move towards a more harmonised approach, improve identification of which financial institutions to target with regulation and enhance data availability and quality.

3.7 Summary

In this paper, a systematic literature review was conducted to identify pre-2000 measures of systemic risk, with the intention to obtain a better understanding of systemic risk, how it is measured and regulated. Since 2000, and more so following the 2007 financial crisis, there has been an over-abundance of different definitions, sources and measures of systemic risk. The main challenge regarding measuring systemic risk, is that there is no single definition and the wide range of measures developed provides no consistency in understanding systemic risk. In other words, the definition of systemic risk changes depending on what the proposed method to measure systemic risk actually captures. Ultimately, these measures only address specific aspects of systemic risk. The more recent measures are moving in the right direction to create more holistic measure of the institutions and market by incorporating a range of idiosyncratic and market indicators. Without macro-prudential regulation, policy-makers will continue to focus on individual institutions which are incapable of withstanding shocks or which fail to address issues arising from contagion. However, further research into which indicators are the most reliable in a global context would be of obvious benefit.

3.8 Chapter Appendix

For all the author calculations within chapter 3, the top 20 US (and European in the case of CISS) banks was derived from the exchanged listed banks based on market capitalisation as of the 2nd January 2007. This is prior to the financial crisis which caused significant changes to the market capitalisation of the banks in the sample. The observation period is between 1988 and 2015.

In order to estimate CISS for both the US and Europe, a portfolio of indexes was created within Bloomberg Professional Service PORT function (and their historic simulation capability) applying a similar data and method to Hollo et al. (2012). The following data was all obtained from Bloomberg Professional Service:

- Bond Market data
  - Realised volatility of the US and German 10-year benchmark government bond index. Germany was selected as this countries bond was used by Hollo et al. (2012)
  - Yield spread between the above government bonds and the A-rated non-financial corporations within that country (10-year maturity)
  - 10-year interest rate swap spreads bracket
- Equity Market data
  - Realised volatility of the S&P500 and Euronext 100, non-financial sector stock market index
- Financial Intermediaries data
  - Yield spread between A-rated financial and non-financial corporations (10-year maturity)
  - Realised volatility of the idiosyncratic equity return of the US and European bank sector index over the respective market indexes (S&P500 and Euronext 100)

- Foreign Exchange Market data
  - Realised volatility of the Euro exchange rate vis-à-vis the US dollar
- Money Market data
  - Realised volatility of the 3-month Euribor rate and 3-month Fed Funds rate
  - Interest rate spread between 3-month Euribor and 3-month French T-bills rate (Europe CISS). France was selected as this countries T-bill was used by Hollo et al. (2012)
  - Interest rate spread between 3-month Fed Funds rate and 3-month US Government T-bill rate (US CISS)

In order to estimate DIP (Figure 3.2), a similar methodology to X. Huang et al. (2009) was applied using MatLab15a code obtained from Bisias, Flood, Lo, and Valavanis (2012). The method to estimate DIP is two fold, firstly a probability of default is required and secondly a forward looking correlation metrics. For the probability of default data rather than using the method explained in X. Huang et al. (2009), this was obtained using Bloomberg Professional Services DRSK function. See Leeney (2015) for the methodology, this data has been used by a number of authors such as Cetina and Loudis (2016); Cetina, Paddrik, and Rajan (2017); Laurent, Sestier, and Thomas (2016); Nirei, Sushko, and Caballero (2016) *inter alia*. This default likelihood model is based on the Merton distance-to-default (DD) measure (Merton, 1974), along with additional economically and statistically relevant factors. To produce the forward looking correlation metrics X. Huang et al. (2009)'s method was applied using the geometric return for the top 20 US banks in Stata12. Then both were combined in MatLab15a to obtain DIP.

MES (in Figure 3.3) is defined as the average return of its equity (R_i) during the worst 5% of days of an overall market return (R_m), where the market is proxied by the S&P500 index. The following equation is applied:

$$MES_b = \frac{1}{Numberofdays} \sum_T R_{it}$$

Where T is the system is in its 5% tail. Weekly geometric return of the banks as a portfolio and the S&P500 were used. Equation 3.8 was calculated using Stata12.

In estimations CoVaR (see Figure 3.3) weekly bank (as a portfolio) equity returns were used as well as the following US Country level data:

- 3 Month Repurchase Agreement Rate
- 3 Month Treasury Bill Rate
- Weekly return in the 10 year and 3 month Treasury Bill spread
- Weekly return in the Chicago Board Options Exchange SPX Volatility Index (VIX)
- Weekly return in the S&P500

Note all returns were geometric, all data was collected from Bloomberg Professional Service. CoVaR was calculated following the methodology discussed earlier (see equation 3.4.3) using the Econometrics Toolbox within MatLab15a.

Chapter 4

Banking Efficiency Determinants

Abstract

The aim of this paper is threefold, firstly to conduct an empirical literature review on the banking sector efficiency over the last two decades, thereby identifying banking level risk and regulatory variables used to assess cost efficiency. Secondly, apply Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to measure efficiency within the Basel jurisdictions banks. Thirdly, to investigate the cost efficiency of United States banking sector by employing System Generalised Methods of Moments (GMM) regression analysis on a panel data of 233 commercial banks over the period of 2000 to 2015. This paper found that: (i) within the GMM analysis econometric measures of efficiency provided more statistically significant regression models than when using accounting based measures of efficiency; (ii) credit and liquidity risk is negatively associated with cost efficiency; and that (iii) regulations designed to mitigate these risks also negatively affect efficiency.

JEL Classification: G21, D24, N20

4.1 Introduction

As financial institutions have changed over the decades from the traditional transformation business model to a more contemporary and diverse model the comparison of productive performance has become more difficult. Further the regulation landscape across the banking sector has transformed at both transnational and domestic levels, changing the market structure via the likes of consolidation and opening new markets to foreign banks. This provided new challenges to academics and regulators, to answer what factors are key to growth and productivity of banks. It may not always be possible for a financial institution to ever become fully efficient, because several of the inputs may not be under full control of management. With special reference to the US banking sector[1], this study examines the determinants of cost and productivity efficiency[2] among US bank holding companies (BHCs). Applying the two most commonly used measures, the non-parametric, Data Envelopment Analysis (DEA) and the parametric, Stochastic Frontier Analysis (SFA).

The rest of this paper is organised as follows: Section 4.2 provides on overview of the theoretical concept of banking efficiency and covers a broad range of empirical findings. Section 4.3 outlines this paper's research hypotheses derived from the gaps or inconclusive evidence highlighted in the empirical literature review. Section 4.4 contains two steps, first of all, it provides a discussion of the main parametric and non-parametric methods of calculating efficiency, as well as applying these approaches to the data. Then, step two discusses the generalized method of moments (GMM) regression methodology and the variables used to identify the determinants of bank efficiency. Section 4.5 discusses the main findings in the context of the US Banks. Finally, Section 4.6 summarises this paper's findings.

[1]This is due to data availability amongst the full Basel jurisdictions sample, efficiency scores were also calculated for Japanese, Indonesian and French Banks.

[2]These types of efficiency are chosen over profit efficiency due to the assumption that banks need to enhance cost efficiency to survive. Further not all financial institutions types are motivated by profitability.

4.2 Theoretical and Empirical Framework

According to the organisational literature, market competition is considered to improve a firm's efficiency (Tirole, 1988). Historically, the literature on banking efficiency is extensive dating back to Hicks (1935) seminal article which proposed the quiet life hypothesis. This argues that under monopolistic competition, senior management tend to relax and become increasingly wasteful of economic profit via discretional expenses. Leibenstein (1966) in proposing the liquidation hypothesis claimed that as competition increases (moves away from monopolistic) management face pressure to increase efficiency. In contrast to these hypotheses Demsetz (1973) introduced the relative market power hypothesis which advocates that the banks' market power (reduced competition) has a positive influence on efficiency. Haber and Perotti (2008) noted that weaker institutions impede bank efficiency negatively due to restrictions that prevent them from attracting funds in the cheapest way or allocate them to the more profitable investment projects.

4.2.1 Empirical Literature

There has been a plethora of empirical research conducted within the banking efficiency area over the past decades. Berger and Humphrey (1997) identified 130 studies that applied frontier efficient analysis to financial institutions from 21 countries. They were unable to reach a consensus, due to the various efficiency methods used producing contrasting results. This seminal paper paved the way for further research to improve banking efficiency theory and empirical research, consistency, accuracy and usefulness. Earlier studies tended to focus on frontier efficiency techniques, however since then research within banking efficiency has tended to focus on methodology advances and what factors influence efficiency scores. Recently, Bhatia, Basu, Mitra, and Dash (2018) conducted a similar exercise to Berger and Humphrey (1997) and identified 11 different broad themes from 103 studies spanning 19 years (1998-2017). The remainder of this section highlights a range of empirical findings covering a number of themes relevant to this study[3]. This empirical literature review does not address efficiency within the Islamic banking sectors, for a comprehensive review of this literature see Hassan and Aliyu (2018).

Efficiency and Market Consolidation/Structure

Banking consolidation can impact efficiency in numerous ways, generally management seek consolidation to enhance the bank's current position. There are numerous motivations to engage in merger and acquisition (M&A) activity for example, access to new markets, increase market share, benefit from economies of scale and rescue a failing institution.

Caiazza, Pozzolo, and Trovato (2016) asserted that banks with higher cost to income ratios (lower efficiency) engage in domestic M&A while efficient banks measured by SFA engage in cross-border M&A. Al-Sharkas, Hassan, and Lawrence (2008) applied for both DEA & SFA (for cost and profit efficiency) to a sample of 440 US bank mergers (between 1986-2002). Their empirical evidence indicated that merged banks lowered their costs due of technical efficiency[4] and allocative efficiency (mergers lowered the inputs into the efficiency models). Thus, providing economic rationale for mergers to take place. Further, following the merger the efficient bank was able to help improve the input efficiency of the weaker bank, which is further economic rationale as stability of the weaker bank was enhanced. Du and Sim (2016) found similar results in a panel of six emerging countries, the M&A led to cost efficiency improvements (measured by DEA) but the target banks tended to be more efficient after an M&A but no efficiency improvements were found for the acquiring banks. Alternatively, in evidence from the Greek banking industry, Halkos and Tzeremes (2013) found that M&A between efficient banks does not necessarily result in an overall more efficient bank.

Subsequently consolidation alters the shape of the market and the size of the

[3]Using similar classifications as Bhatia et al. (2018) which have sought to identify determinants of banking efficiency.

[4]A DEA Malmquist Index was produced to observe trends, these results concluded merged banks experience greater productivity growth.

financial institutions. For example, Thoraneenitiyan and Avkiran (2009) found that in Asian countries, country-specific conditions such as market concentration appeared to have unfavourable influences on efficiency. As the size and diversity of an institution increases this will add extra challenges to managers to enhance efficiency. Rossi, Schwaiger, and Winkler (2009) found that diversification negatively affects SFA cost efficiency in Austrian banks, however it does enhance profit efficiency and reduces bank risk. In the context of Australian banks (1995-2002) Kirkwood and Nahm (2006) found cost efficiency via DEA Malmquist index has improved over time in major banks however smaller/regional banks experience little improvement. Further, it could be observed that efficiency scores are reflective of equity returns. Paul and Kourouche (2008) assessing a different time (1997-2005) found alternatively that medium-size Australian banks outperformed both smaller and larger banks in terms of efficiency improvement (smaller banks' efficiency mainly deteriorated). Further their results suggested the mergers between large banks may reduce overall efficiency, however they advocated for smaller banks to increase consolidation to improve their declining efficiency scores. Similar evidence was found by Ariff and Luc (2008) in the Chinese banking system as medium-sized institutions were significantly more efficient than smaller and larger banks. Contrastingly, earlier in China X. Zhao (2000) found that larger and smaller banks were more efficient. Within transitional European Union countries, Stavarek (2006) investigated whether the degree of economic integration and development increased banking efficiency (via DEA), finding that large banks were largely inefficient. Using a similar sample Bonin, Hasan, and Wachtel (2005) found that foreign owned banks were more cost efficient via SFA. Also Kyj and Isik (2008) applied DEA to a panel of 150 Ukraine banks and concluded that larger banks dominated via managerial efficiency however smaller banks increasingly improved efficiency throughout the observation period (1998-2003). Given, that the Ukraine is a transitional economy they suggested that the consolidation of smaller banks could enhance efficiency (by benefiting from economies of scale) and attract foreign owned joint-venture to further improve efficiency. These findings indicates that just focusing on size does not fully explain efficiency differences.

Efficiency and Ownership

Ownership type plays a significant role in explaining bank efficiency (T.-T. Fu, Juo, Chiang, Yu, & Huang, 2016). Ownership structure, which influences management can result in different levels of banks efficiency. For example, institutions under state intervention/ownership could tend to be less efficient (Berger, Hasan, & Zhou, 2009). Reasons for this include: (i) state owned institutions tend to be overstaffed, this was very common within communist regimes (Abarbanell & Meyendorff, 1997; Kyj & Isik, 2008); (ii) the institutions motivation may not be to increase profitability but to provide a public service; (iii) also state intervention may be in reaction to bank failure. The majority of studies that investigate ownership structure and efficiency tend to be conducted in Asia due to the varied ownership styles and tend to be dominated by state-ownership. Berger, Hasan, and Zhou (2009) found that the reduction in stated ownership of banks in China during their reforms increased the role of foreign ownership and was strongly favourable to both cost and profit efficiency. Also the authors found that the big four Chinese banks[5] were the least profit efficient due to poor revenue performance and high levels of non-performing loans (NPLs). This was also evidenced by Ariff and Luc (2008) who applied a nonparametric measure of cost and profit efficiency to 28 Chinese banks. After applying Tobit regression, their findings suggested that joint-owned banks (national and city-based) on average appeared to be more cost and profit efficient than state-owned banks. Laurenceson and Qin (2008) also found this relationship using DEA cost efficiency in 65 Chinese banks between 2001-06, albeit not statistically significant.

Contrastingly, Xiaogang, Skully, and Brown (2005) also applied DEA (to 43 Chinese banks) but found that state banks showed a relatively higher efficiency score than joint equity and foreign investment banks. Further, they advocated that technical efficiency tends to dominate over allocative efficiency in China. This implies that banks need to enhance their ability to choose cost minimisation

[5]Namely, The China Construction Bank, The Bank of China, The Industrial and Commercial Bank of China and The Agricultural Bank of China.

inputs. Within Asian banks, Thoraneenitiyan and Avkiran (2009) noted that it is not just ownership, but management background which impacts efficiency. Applying a combined approach of DEA and SFA methodology the authors found that bank restructuring does not necessarily enhance efficiency. In general, domestic managers appear to have a positive impact on efficiency, suggesting that domestic banks are more likely to have local advantage over foreign banks, despite relaxed regulations encouraging foreign bank penetration at the time of the Asian crisis.

In the context of India, Sahoo and Tone (2009) found that following the Indian reforms in the late 1990s, increased competition generated higher banking sector efficiency (via DEA) and that private banks outperformed nationalised banks in cost minimisation behaviours. Also, Jaffry, Ghulam, and Cox (2013) asserted that over an 18 year time frame that sector average DEA efficiency improved throughout the Indian reforms, advocating the benefits of opening the market to foreign owned banks or foreign direct investment in the banking sector. Investigating of efficiency in India by applying DEA, Kumar and Gulati (2008) found that the exposure to off-balance-sheet items, employee productivity, market share/size were major explanatory factors of this efficiency measure. However, this study was conducted on a small sample of 27 banks over two years later. Kumar and Gulati (2009a) analysed a larger timescale (1992 to 2006) and compared before and after the banking reforms; similarly to their previous research they found technical efficiency was enhanced[6] due to staff productivity and increased off-balance-sheet activity, however this time, recovery of non-performing loans was significant. Building on this further[7] Kumar and Gulati (2009b) found that size, profitability and off-balance-sheet activity were the most influential determinants of technical efficiency, also noting no significant differences between public and private sector efficiency. Similarly Fujii, Managi, and Matousek (2014) found that efficiency does vary between different ownership types in Indian banks. Elsewhere,

[6]T. Zhao, Casu, and Ferrari (2010) found similar regarding technological progress in India following the reforms, however this did not translate into efficiency gains.

[7]Analysed 51 Indian domestic banks in 2006/7.

in the context of Malaysia, Sufian (2007) found that domestic Islamic banks were marginally more efficient than their foreign counterparts. Also, In the context of Indonesia, Shaban and James (2018) found that state-owned banks tend to be less profitable and more exposed to risk than private and foreign banks. In the event of consolidation, domestic investors tend to select the best performers for acquisition, which results in an overall reduction in both cost and profit efficiency of the acquired bank.

Where ownership is via majority publicly listed, numerous studies have sought to assess the impact of efficiency on shareholder value. Using DEA for cost efficiency Beccalli, Casu, and Girardone (2006) found that the more cost efficient banks equity-price performance tended to outperform their inefficient counterparts, in the Western European market. However, such a trend was not as clear when SFA efficiency was used. Further, explanatory variables such as size, risk and profitability did not significantly increase their models' power. In contrast, again using Western European data, Fiordelisi (2008) found that profit efficiency was better at explaining variations in shareholder value than cost efficiency. Further, SFA cost efficiency estimations performed better than DEA estimations at explaining shareholder value. Banks' ownership structures that differ depending on country was found to be more statistically significant in explaining shareholder value rather than efficiency (irrespective of SFA or DEA calculation). Guzman and Reverte (2008) also applied the DEA Malmquist index technique to a small sample of Spanish banks to find that the banks with higher efficiency and productivity change have greater shareholder value (even after controlling for conditional performance measures such as ROA).

Efficiency and Risk

Within the efficiency literature, banking risk is an emerging theme (Bhatia et al., 2018) with several studies investigating the interplay of risk and bank efficiency.

Diallo (2018) advocated that during crisis periods[8] efficient banks are more resilient to credit shocks within a cross country sample, and stressed the importance of efficiency to improve the financial sector. Earlier, Uchida and Satake (2009) evidenced that banks with higher deposit bases in Japan were more SFA cost efficient, suggesting that deposit does have a significant role to play within ensuring bank management discipline. The Moral Hazard hypothesis (Jeitschko & Jeung, 2005) suggests banks with higher capital adequacy have lower motivation to engage in more risky practices. Therefore, if the probability of default (PD) or NPL losses is lowered then in turn this leads to higher efficiency. Chiu, Jan, Shen, and Wang (2008) found using Taiwanese banks that on average efficiency scores were higher for banks with higher capital adequacy, implying that banks with better financial status and lower relative risk operate more efficiently. Similarly, Wang and Huang (2007) found that an increase in non-performing loans to total loans reduces bank efficiency in Taiwan banks. However, within the Taiwanese and Chinese banking systems other environmental factors (e.g. GDP and inflation) should be explored (M.-Y. Huang & Fu, 2013). Sun and Chang (2011), using Asian bank panel data, found that different measures of risk (credit, operational and market risk) lead to significant changes to SFA cost efficiency, both level and variability. Similarly, Inanoglu, Jacobs, Liu, and Sickles (2016), using a frontier efficiency estimation for US TBTF banks between 1994 to 2013, found that credit, liquidity and market risks hampers cost efficiency. Further, effects vary across countries and time. Moving this research area forward Silva, Guerra, Tabak, and de Castro Miranda (2016) relate network measures (see Section 3.4.4 for a discussion) from interbank activities[9] to banking SFA profit and cost efficiency as well as risk. Their found that the core—periphery structure contributes to better cost efficiency levels, however, they did not find any significant evidence regarding affects to profit efficiency.

[8]Typically, literature usually identifies the influence of crisis on bank efficiency by introducing the dummy variables into their model (Diallo, 2018; Luo, Tanna, & De Vita, 2016).

[9]In particular how compliant is the financial network to a core–periphery (similar to Figure 3.8e) structure.

Financial innovation was seen as one of the numerous factors that changed traditional business banking models in the lead up to the financial crisis (Beck, Chen, Lin, & Song, 2016) influencing bank risks as well as banking efficiency. Limited empirical studies have been conducted regarding the influence of innovation on efficiency, typically making extensive use of subjective proxies for innovation[10]. Using a unique data set, Duygun, Sena, and Shaban (2013) provided an interesting insight into this relationship, they found that product innovation (using trademarks registrations as a proxy) in the UK, resulted in reducing SFA cost and profit efficiency. Suggesting that innovation in the short-term can be a costly process, however they then found that if trademark intensity increases (increased competition) in the sector banks react by improving their own efficiencies. Developing on this work, Duygun, Sena, and Shaban (2014) clarified that banks that participate in trademarking appear to be more profit efficient than banks that do not, whilst there was no significant difference between cost efficiency scores. Applying the Malmquist productivity efficiency measure, Duygun, Sena, and Shaban (2016) found a positive relationship between innovation and productivity efficiency, however, the financial crisis altered this relationship which still persisted until 2016.

Efficiency and Regulation

As well as internal factors, external factors outside of management control, such as economic influences (typical cycles and times of crisis) and regulation change will also influence banking efficiency levels. For example, M.-Y. Huang and Fu (2013) warned in the context of Taiwan that environmental factors play a significant role in explaining bank cost frontier efficiency. Further, external influences like regulation may have a long implementation timetable therefore effects may take a while to be fully felt at bank level. Within the context of Germany and Austria, Hauner (2005) found that cost efficiency and productivity on average did not improve following a period of deregulation and bank mergers, suggesting it takes a considerable amount

[10]Typically diversification indicators are used as a proxy for innovation (Rossi et al., 2009).

of time for efficiency gains to materialise. Similar results were found using US data post the de-regulations period by Mukherjee, Ray, and Miller (2001).

Table 4.1 highlights the differing empirical findings regarding how efficiency scores are affected by different types of regulation increase. In summary, although many countries have followed the Basel guidelines, existing evidence on the impact of Basel Accords on bank efficiency is mixed. Gaganis and Pasiouras (2013) found that bank efficiency is affected by level of oversight from one supervisor. The authors found that profit efficiency is reduced when their central bank is required to supervise more financial sectors. Further, if the central bank is independent this also results in reduced bank profit efficiency. The quality of the regulating body has also been shown to impact banking efficiency. Applying SFA to a panel of *circa* 8000 banks from 136 countries, Lensink and Meesters (2014) evidenced that banks operating in countries with a better regulatory environment apply more cost-reducing technologies and can use existing technology more efficiently.

Contrastingly to Table 4.1, applying DEA efficiency to a sample of 715 banks from 95 countries in 2003[11], Pasiouras (2008) found no robust impact of regulation on efficiency, however, noting that several countries, specific characteristics were sufficiently related to efficiency[12]. The authors results did support the introduction of the Basel II regulations as in most cases it enhanced the banking system under all three pillars.

[11]The authors claimed data limitations for not allowing them to use time series or panel data, previously J. R. Barth, Caprio Jr, and Levine (2004) claimed this was a major issue for cross country empirical research.

[12]Market capitalisation to GDP, bank claims to GDP, branches and ATMs relative to population, ownership and market concentration.

Table 4.1: Regulations impact on efficiency

Author	Method	Supervision Power	Capital Requirements	Activity Restrictions	Market Discipline	Transparency
Pasiouras, Tanna, and Zopounidis (2009)	Using SFA on 615 commercial banks from 74 countries	Profit & Cost Efficiency $\Uparrow$	Cost Efficiency $\Uparrow$	Profit & Cost Efficiency $\Uparrow$	Profit & Cost Efficiency $\Uparrow$	
Lozano-Vivas and Pasiouras (2010)	Using SFA on 752 commercial banks from 87 counties	Profit & Cost Efficiency $\Uparrow$		Profit & Cost Efficiency $\Uparrow$		
Chortareas, Girardone, and Ventouri (2012)	Using DEA on 5227 commercial banks from 22 EU countries	Productivity Efficiency $\Downarrow$	Productivity Efficiency $\Uparrow$	Productivity Efficiency $\Downarrow$		
J. R. Barth, Lin, Ma, Seade, and Song (2013)	Using DEA on 4050 banks in 72 countries	Cost Efficiency $\Uparrow$	Cost Efficiency $\Uparrow$	Cost Efficiency $\Downarrow$		Cost Efficiency $\Uparrow$
T.-H. Lee and Chih (2013)	Using DEA on 242 commercial banks in China		Profit Efficiency $\Downarrow$			
Manlagnit (2015)	Using SFA on 17 commercial banks in the Philippines	Cost Efficiency $\Downarrow$	Cost Efficiency $\Uparrow$		Not significant in explaining Cost Efficiency	

A number of authors have investigated the opposite, how increased financial openness (deregulation) influences efficiency. Chortareas, Girardone, and Ventouri (2013) using a sample of EU countries found that banks within countries that have higher degrees of financial freedom have higher overall efficiency and benefit from cost advantages. Further, this is more prevalent in countries with freer political systems and enhanced governance. Hermes and Meesters (2015) found similar results from a wider multi-country analysis (61 countries), where overall their results showed that financial liberalisation programmes are positively correlated with increased bank efficiency (measured by SFA). However, this positive relationship is conditional on the quality of bank regulation and supervision. Suggesting that if countries liberalise their financial markets without putting in place strong institution level regulation, liberalization could decrease efficiency. Also Luo et al. (2016) warned that financial openness increases bank risk, without mediation from profit efficiency channels, thus profit efficiency may be enhanced but other factors still enhance bank risk levels. Due to the recent financial crisis Chortareas, Girardone, and Ventouri (2011) warns that the existing approach to identify the impact of regulation and supervision on bank efficiency may not be useful due to its interaction with the outputs. From a practical point of view as previously noted, the level of regulation (e.g. capital requirements) or supervision scrutiny impact the levels of both deposits and total loans.

4.3 Research Hypotheses

This section outlines the research hypotheses that will be under consideration in this paper, bearing in mind identified gaps and inclusive evidence noted in the empirical literature and the aims of this paper.

Hypothesis 1: *The use of econometric calculations of efficiency is superior to traditional accounting measures.*

This hypothesis suggests that the use of SFA or DEA as a measure of efficiency within regression analysis is superior to using traditional accounting based measures of efficiency such as the Cost to Income Ratio.

Hypothesis 2: *Business model diversification has a negative impact on efficiency.*

This hypothesis suggests that as a financial institution increases its diversification (altering the intermediation process) this negatively affects cost efficiency. This hypothesis will be tested using US bank panel data, which to the best of my knowledge has not been addressed.

Hypothesis 3: *Increased credit risk has a negative impact on efficiency.*

This hypothesis suggests that as financial institutions face increased credit risk this negatively affects their cost efficiency due to the impact on outputs. This hypothesis will be tested using US bank panel data, which to the best of my knowledge has not been addressed.

Hypothesis 4: *Increased capital requirement regulation enhances efficiency.*

This hypothesis suggests that as financial institutions face increased pressure from regulators to reduce credit risk this positively affects their cost efficiency due to the impact on outputs. This hypothesis will be tested using US bank panel data, which to the best my of knowledge has not have been addressed before.

Simultaneous rejection of H3 and H4 would indicate that credit risk regulation may not be optimal given the detrimental impact on cost efficiency.

Hypothesis 5: *Increased liquidity has a negative impact on efficiency.*

This hypothesis suggests that as financial institutions increase their liquidity position, this hampers cost efficiency, due to the opportunity cost nature of holding more liquid reserves. This hypothesis will be tested using US bank panel data, which to the best my knowledge has not been addressed before.

4.4 Methodology and Data

Holistically, there are three main widely accepted approaches to examining efficiency within the banking sector; production, profitability and intermediation (Eskelinen & Kuosmanen, 2013). The input and output units under assessment differ between approaches[13], namely, the production approach uses input units such as labour and capital, to generate output services of deposits and loans. The profitability approach examines how efficiently its cost factors are in creating revenues and the intermediation approach considers the units as an in-between that accumulates funds for loans and other income activities. This paper follows the intermediation approach, suggested by Sealey and Lindley (1977), to define the input and output variables. The input and the output variables considered for observation are not only those commonly found in the banking efficiency empirical literature, in this case similar to Košak and Zajc (2006) *inter alia*. This approach treats a bank as an intermediary, which receive funds from depositor or savers and transforms those funds into profitable assets (loans and other earning assets). Accordingly, the input consists of total costs, which consists of personnel expenses, other administrative expenses and other operating expenses. Following the estimation model proposed by Kuosmanen (2012) the outputs consist of (i) Other Earning Assets, (ii) Total Loans and (iii) Total Deposits (see Table 4.2 for details). Further the choice of such output variables came from the value-added approach (Berger, Hanweck, & Humphrey, 1987). In order to control for the bank's heterogeneity and their operating environments several contextual variables are included within the cost function.

Despite the large amount of research within this area the definitions of the banks' input and output are still controversial, especially the ongoing debate to whether deposits should be treated as an input or output (Degl'Innocenti, Kourtzidis, Sevic, & Tzeremes, 2017). Typically, deposits are classed as an input during intermediation approach and an output for production approach[14] (An, Chen, Wu, & Liang, 2015; Holod & Lewis, 2011). However, similar to Kuosmanen (2012) and Molyneux and Williams (2013) *inter alia* this paper takes the position that customers' deposits are an output because customers purchase deposit accounts from financial institutions for the service they provide (i.e. storage and payment

[13]Input and output selection is important as different selections can produce contrasting efficiency scores (Das & Ghosh, 2006).

[14]Sealey and Lindley (1977) provide the traditional theoretical discussion of both approaches.

Table 4.2: Efficiency Calculation Variables

Symbol	Variable Name	Description
TC	Total Cost	The total sum of personnel expenses, other administrative expenses and other operating expenses (S. Kasman & Kasman, 2015)
OEA	Other Earning Assets	The total sum of marketable securities, short-term investments, interbank assets, long-term investments and long-term receivables
TLOAN	Total Loans	The total sum of loans including, commercial loans, consumer loans and other loans
Deposits	Total Deposits	Total deposits (including term deposits) received from customers

mechanism) and that incur costs in maintaining deposits. Furthermore, as this paper tests determinants within the US banking sector, it is common for US customers to pay a fee to have a deposit account. The above input and output will be used to calulate cost efficiency which this study focuses on rather than profit efficiency. As García-Cestona and Surroca (2008) warned the assumptions that banks are only focused on profit maximisation is one amongst several goals, the widespread use of profit efficiency measures as the only comparative performance may prove to be insufficient in certain contexts. Further, the argument that banks need to enhance cost efficiency in order to generate profit or ultimately survive is plausible. Also, Ariff and Luc (2008) found that within previous literature profit efficiency levels tend to be well below cost efficiency levels, therefore suggesting profit efficiency is subject to wider factors outside of managements control. Further, Pasiouras et al. (2009) noted that cost efficient banks are not necessarily profit efficient. A downside to selecting cost efficiency is that it tends to neglect banks' operating revenues and loan losses implications (Berger, Hasan, & Zhou, 2009). In contrast, Guevara and Maudos (2002) argue that analysis of cost efficiency alone would offer only a partial view of bank efficiency and it is important to analyse profit efficiency as well.

There are many different approaches to evaluate intermediation efficiency within banks. Traditional approaches included the analysis of financial indicators or accounting ratios such as costs to income ratio[15]. Cost to Income Ratio (CIR) also known as the Efficiency Ratio is an approximation for managerial quality. The CIR ratio is a key financial measure, particularly important in valuing banks. It shows a company's costs in relation to its income. To calculate the ratio, divide the operating costs (administrative and fixed costs, such as salaries and property expenses, but not bad debts that have been written off) by operating income. The ratio gives investors an indication of how efficiently the firm is being run. A lower CIR value indicates better managerial quality. Changes in the ratio can also highlight potential problems: if the ratio rises from one period to the next, it means that costs are rising at a higher rate than income, which could suggest that the company has taken its eye off the ball in the drive to attract more business. The modern approaches focus on economic efficiency analysis calculation via parametric, non-parametric or hybrid techniques. Abuzayed, Molyneux, and Al-Fayoumi (2009) suggested information regarding the banks' efficiency calculated via econometric analysis, rather than traditional financial statement information, can help close the gap between book value and market valuations. The inefficiency of a bank is measured in terms of that banks deviation from a best practice (frontier) within the industry. This study will use the two most commonly used measures as highlighted in Section 4.2, the non-parametric, DEA and the parametric SFA. In a brief summary, the main advantages of SFA over DEA are that (i) it distinguishes between inefficient and other stochastic shocks in the estimation of efficiency scores (Yildirim & Philippatos, 2007) and (ii) this approach uses estimated averages parameter values, thus, it is not sensitive to large data changes at the firm level. The two main limitations of SFA are the need for assumptions regarding efficiency distribution and the functional form of the frontier, which are not necessary in DEA. Previous studies have found a relationship between SFA and DEA scores but a lack of robustness between the

[15] Typically financial institutions focused on reducing their cost to income ratio as a proxy of cost efficiency (Beccalli et al., 2006).

parametric and non-parametric approaches[16] (Al-Sharkas et al., 2008; Fiordelisi, 2008; Weill, 2004), therefore studies should compare efficiency scores from both techniques. In evaluating the SFA & DEA scores persistence Eisenbeis, Ferrier, and Kwan (1999) and Wang and Huang (2007) found scores were statistically stable over time.

4.4.1 Stochastic Frontier Analysis (SFA)

The parametric SFA approach originated from two innovative papers by Meeusen and Van den Broeck (1977) and Aigner, Lovell, and Schmidt (1977) who sought to captures best practice to gauge inefficiency purely by observation of best practise within the sample of banks tested. This approach however does not necessarily represent a best-possible practice (Berger & Mester, 1997) depending on the sample size or selection bias. This empirical methodolgy was later operationalised by Battese, Rao, and O'Donnell (2004) and O'Donnell, Rao, and Battese (2008). SFA is a form of regression which separates the influence of exogenous factors on the dependent variable, from the measurement error (noise) and firm inefficiency is captured in the error term. The error term in SFA, consists of two components, one is a two-sided random error that represents noise, the other is a one-sided error representing inefficiency. The noise is assumed to be normally distributed with a zero mean and for cost inefficiency the error is assumed to be positively half-distributed. As this is a structural approach the selection of the environment and bank characteristic variables to determine best practice is particularly important (Mester, 2008). To ensure SFA is appropriate the structural form imposed on the analysis also has to reflect the firms' behaviour. Theoretically within a panel data framework (Feng & Serletis, 2009), the cost frontier model can be written as:

$$C_{it} = f(\mathbf{X}_{it}, \boldsymbol{\rho})\tau_{it}\zeta_{it}, \quad i = 1, \ldots, I, \quad t = 1, \ldots T \qquad (4.4.1)$$

[16] On the contrary Olgu and Weyman-Jones (2008) evidence suggested consistency between parametric and non-parametric for 10 old EU countries and 12 new EU countries' banking systems (164 Banks).

This model decomposes the observed total cost (C_{it}) for firm i at time t, into three elements. Firstly is the actual frontier $f(\mathbf{X}_{it}, \boldsymbol{\rho})$, dependent on $\mathbf{X}_{it}$, which is the vector of, input prices and output quantities (exogenous variables), and $\boldsymbol{\rho}$, which is a vector of parameters, that represents the minimum possible cost of producing a given level of output for a certain input. Secondly a non-negative term $\tau_{it} \geq 1$[17], measures firm-specific inefficiency. Lastly the random error ζ_{it}, captures the statistical noise. The deterministic kernel of the cost frontier is $f(\mathbf{X}_{it}, \boldsymbol{\rho})$, and the stochastic cost frontier is $f(\mathbf{X}_{it}, \boldsymbol{\rho})\zeta_{it}$. As required by microeconomic theory, $f(\mathbf{X}_{it}, \boldsymbol{\rho})$ is a linearly homogeneous and concave function in prices and also non-decreasing in both input prices and outputs. Following common practice in this literature it is assumed that $f(\mathbf{X}_{it}, \boldsymbol{\rho})$ is a log-linear function form. The stochastic cost function in (4.4.1) can be rewritten as:

$$c_{it} = \alpha + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + \varepsilon_{it} \tag{4.4.2}$$

where $c_{it} = \ln C_{it}$ and $\alpha + \mathbf{x}_{it}^{'}\boldsymbol{\beta} = \ln f(\mathbf{X}_{it}, \boldsymbol{\rho})$. The composite error term $\varepsilon_{it} = u_{it} + \upsilon_{it}$ consists of two parts, ν_{it} is a two-sided normal disturbance term with zero mean and variance σ_{ν}^2 and represents the effects of statistical noise; the inefficiency term υ_{it} is assumed to be half-normally distributed. Thus, $u_{it} = \ln \tau_{it} \geq 0$ and $\upsilon_{it} = \ln \zeta_{it}$. Further in equation 4.4.2 $\mathbf{x}_{it}$ is the counterpart of $\mathbf{X}_{it}$ with the input prices and output quantities transformed to logarithms, $\boldsymbol{\beta}$ is a $\mathbf{K} \times 1$ vector of parameters and α is the intercept. Following the most commonly used functional form in the bank efficiency literature to identify a frontier, a transcendental logarithmic (translog) form is applied. The empirical cost frontier model is as follows:

$$\begin{aligned}
lnTC_{i,t} = \alpha &+ \sum_m \beta_m y_{imt} + \sum_j \gamma_j w_{ijt} + \frac{1}{2}\sum_m \sum_n \beta_{mn} y_{im} y_{in} + \frac{1}{2}\sum_j \sum_k \beta_{jk} y_{ijt} y_{ikt} \\
&+ \sum_m \sum_j \psi_{mt} \ln y_{imt} \ln w_{ijt} + \varphi_1 \ln E_{it} + \frac{1}{2}\varphi_2 \ln E_{it}^2 + \sum_m \lambda_m \ln y_{imt} \ln E_{it} \\
&+ \sum_j \xi_j \ln w_{ijt} \ln E_{it} + \theta_1 T + \theta_2 T^2 + \sum_m \kappa_m \ln y_{imt} T + \sum_j \rho_j \ln w_{ijt} T \\
&+ \eta \ln E_{it} T + \ln OEA + \ln TLOAN + \ln Deposits + \upsilon_{it} + \nu_{it}
\end{aligned} \tag{4.4.3}$$

[17]The cost efficiency is defined as $CE_{it} = 1/exp(u)$ and takes a value between 0 and 1.

Where the dependent variable $lnTC_{i,t}$ is the observed total costs (personnel expenses, other administrative expenses and other operating expenses) of bank i at time t. y_i and w_i are vectors of output and inputs for the ith bank[18]. E_i is the total equity of a bank (which is treated as a quasi-fixed input)[19]; T is the time trend used to capture technological changes; and $\ln OEA$, $\ln TLOAN$ & $\ln Deposits$ is the natural logarithm of Other Earning Assets, Total Loans and Total Deposits respectively. As previously stated, ν_{it} is a two-sided normal disturbance term with zero mean and variance σ_ν^2 and represents the effects of statistical noise; the inefficiency term υ_{it} is assumed to be half-normally distributed[20]. $\alpha, \beta, \gamma, \psi, \varphi, \lambda, \xi, \theta, \kappa, \rho$ and η are coefficients to be estimated. Furthermore, the standard symmetry restrictions, $\beta_{nm} = \beta_{mn}$ and $\gamma_{jk} = \gamma_{kj}$, are applied.

4.4.2 Data Envelopment Analysis (DEA)

DEA was formed in Farrell (1957) seminal work and built on by Charnes, Cooper, and Rhodes (1978), the non-parametric methodology applies linear programming to measure the distance of individual firms (refered to as Desision Making Units (DMU)) from the efficient or best practice frontier. In other words, DMUs are compared to other identified best practice DMUs (Cook & Seiford, 2009). DEA identifies the inefficiency in firms by comparing it to efficient firms. This is as oppose to relating a firm's performance with statistical averages which may not be relevant to that firm. Also, DEA does not assume any functional structure imposed on the data in determining efficient firms. DEA allows for multiple inputs and outputs which are readily available via published financial accounts. Input

[18] $lnTC$ and input price terms are normalised by the last input price, in order to impose linear homogeneity of degree one on the input prices.

[19] Equity capital is treat without any associated price as quasi-fixed in the frontier model this is because equity levels is more difficult to alter in the short-term (compared to the outputs). Furthermore, it is used to control for insolvency risk and the different risk preferences of banks.

[20] Hence in stata12 the true fixed-effects model (Greene, 2005) half-normal distribution for the inefficiency term method was applied.

and output weights are endogenously derived, thus avoiding subjective weights or externally imposed weights from other samples. They are used to produce a parsimonious scalar estimate where multidimensional interactions are simultaneously captured (Avkiran, 2013). Mathematical programming eliminates the impact of market prices and other exogenous components affecting actual bank performance, as is thus superior over accounting ratios. Wang and Huang (2007) argue that typical financial ratios from annual reports such as ROA and cost to revenue are often compounded with other effects irrespective of the managers performance. Halkos and Salamouris (2004) also advocate that frontier efficiency estimation via DEA is superior to simple ratio analysis. Most early empirical studies showed that using DEA to estimate the efficient frontier yielded robust results (Seiford & Thrall, 1990).

However, DEA does not assume statistical noise and that the data is free of any measurement errors, which can allow the error term to be attributed to inefficiency. This is due to DEA assuming random variants to cancel each other. Further, as the inputs and outputs indicators are relative to the sample, results can be influenced by idiosyncratic risk such as regional price differences and extreme observations. Therefore, it is common practice to scrutinise the data for outliers to reduce the impact of measurement error. Distributions of parameter estimates are known asymptotically and statistical significance tests such as the T-test can be designed, however DEA makes no distribution assumption. Horsky and Nelson (2006) acknowledged this in developing statistical significance tests for linear programming methods. Further, Asmild and Zhu (2016) warn that traditional DEA may potentially be biased during crisis period as it does not control for extreme weights. For example, during the recent financial crisis a number of institutions, (i) relied on wholesale funding rather than retail funding (skewing input, price of deposits) (ii) and/or relied on risky asset portfolios via exposure to the property sector (skewing outputs). In such cases it would be inappropriate to class these banks as efficient, for the given level of risk. Following a meta-analysis of the global microfinance efficiency, Fall, Akim, and Wassongma

(2018) argued that use of SFA should be increased over DEA because it suffers from inherent weaknesses such as being highly sensitive to the data and sample size which may lead to biased estimates if there are measurement errors or outliers. Earlier Staat (2001) also evidenced how DEA efficiency scores can be affected by various sample sizes.

The DEA production technology constitutes a convex relationship, which is determined by using piecewise combinations of all efficient banks. Similar to Koetter and Meesters (2013) a formal program to obtain this set is given by:

$$\begin{aligned}
&\min_{\Theta,\lambda} \mathbf{\Theta} \\
&\textit{subject to} \\
&-\mathbf{y}_i + \mathbf{Y}\lambda \geq 0, \\
&\mathbf{\Theta}\mathbf{x}_i - \mathbf{X}\lambda \geq 0, \\
&\lambda \geq 0
\end{aligned} \tag{4.4.4}$$

$\mathbf{\Theta}$ is the component that reflects the efficiency of the DMUi, which is minimized. Accordingly, the production function is put as far as possible to the outside. $\mathbf{y}_i$ and $\mathbf{x}_i$ are vectors of outputs produced and inputs consumed respectively (the same output and inputs used in 4.4.1). $\mathbf{Y}$ and $\mathbf{X}$ are matrices with all the output and inputs of all DMUs respectively. λ is a weighted vector, which uses the linear combination of producers corresponding to the lowest $\mathbf{\Theta}$. It therefore represents the vector that measures which DMUs outperforms DMUi[21]. Fukuyama and Weber (2009) pointed out that when the optimal solution to the cost function using DEA allows for slack in the constraints that define the technology efficiency it is possible to increase at least one output without increasing costs. This may result in two banks being deemed equally cost efficient even though one may produce more of at least one output.

[21]The constant returns to scale assumptions in equation 4.4.4 can be relaxed by factors of the variables return to scale assumption by adding a convexity constraint (i.e. the sum of the elements of λ should be equal to 1) (Coelli, Rao, O'Donnell, & Battese, 2005).

Malmquist Productivity Index using DEA Frontier

Using DEA and the cost efficiency input and outputs highlighted previously (similar to Al-Sharkas et al. (2008); Duygun et al. (2016); Guzman and Reverte (2008); Kirkwood and Nahm (2006); Tortosa-Ausina, Grifell-Tatjé, Armero, and Conesa (2008) *inter alia*) the Malmquist productivity index (MPI) (Malmquist, 1953) will be used to calculated DEA using the panel data which requires bivariate density estimation, which was performed via kernel smoothing. The MPI measures the productivity changes along with time variations and can be decomposed DEA into changes in efficiency and taking into account of time variants of technology (Färe, Grosskopf, Norris, & Zhang, 1994). The input oriented geometric mean of MPI change (similar to Total Factor Productivity change, (TFPCH)), can be decomposed using the concept of input oriented technical change (TECHCH) and input oriented efficiency change (EFFCH); while the technical efficiency change can be further decomposed into scale efficiency change (SECH) and pure technical efficiency change (PECH) components. Park and Weber (2006) following Chambers' (2002) Luenberger productivity indicator, combining EFFCH and TECHCH obtains a proxy from Productivity growth (ProdGrowth). Boussemart, Briec, Kerstens, and Poutineau (2003) showed that the Malmquist index is a linear approximation of the Luenberger indicator of productivity growth, but they did not discuss their exact relationship. Later Balk, Färe, Grosskopf, and Margaritis (2008) provided this relationship.

4.4.3 Data

It has been argued that efficiency is better studied and modelled with panels (Coelli et al., 2005). Panel data provides more degrees of freedom in estimations of parameters over cross-sectional data. On a practical level panel data allows for time variations in efficiency scores, internally, this could account for the possibility that management may learn from previous experiences. Externally, environmental and regulatory factors can affect banks efficiency overtime. The bank level panel data for which consolidated financial statements were available, were obtained via

Bloomberg Professional Service[22]. The classification of a bank is based on the industry classification benchmark (Russel, 2018). All individual bank level data was converted to US dollars for consistency purposes. The Bloomberg Professional Service applies the foreign exchange rate at the time of the original annual report publication date. This list of banks was derived from the exchanged listed banks based on market capitalisation as of the 2nd January 2007. This date is at the midpoint of the 16 year observation period between 2000 and 2015 and prior to the financial crisis which caused significant changes to the market capitalisation of the banks in the sample. The purpose of this time-scale is to capture the determinants of bank efficiency since the implementation of Basel II (first proposed in June 1999).

The wider panel dataset contains banks from all the 27 Basel jurisdictions. However, to calculate SFA and DEAs MPI for each individual bank, balanced datasets were required. Balanced data was required for the input and output, namely Total Cost (TC), Other Earning Assets (OEA), Total Loans (TLOAN) and Total Deposit (Deposits). This exercise was conducted on all the banks within the wider panel, following this SFA was first applied to all jurisdictions balanced data. Due to sample size and the statistical significance, the 16 years' worth of efficiency scores were only calculated for the USA (233 banks), Japan (69), Indonesia (13) and France (11). See Table 4.3 for a data summary of inputs. Large variations (large standard deviations) can be seen within these summary tables, however it reflects 16 years' worth of data, in which time the banking sectors have grown substantially. As both techniques compare how each institution performs at converting inputs to outputs, year on year, to identify best practice each year, the differences in size do not skew this. Further, the natural log of each variable is used within the calculations. This approach also aids the suggestion that before calculating DEA the data should be scrutinised to remove extreme outliers.

[22]Similar to Altunbas et al. (2017) and other authurs who used Bloomberg data, this research considers only commercial or universal banks. Hence foreign subsidiaries, investment banks, and non-bank financial institutions are not included in the sample.

Table 4.3: Banks level SFA/DEA summary statistics per country

US Banks

Variable	Mean	Std. Dev.	Min	Max
TC ($m)	1200.106	7820.207	2.713	135260
OEA ($m)	8733.598	69294.11	5.564	1020543
TLOAN ($m)	14405.98	79149.43	12.407	975498
Deposits($m)	15604.21	88871.45	22.538	1223312
Observations= 3728, t=16, n=233				

Japanese Banks

Variable	Mean	Std. Dev.	Min	Max
TC ($m)	536.011	503.935	51.573	5238.336
OEA ($m)	11290.09	22287.27	395.612	285141.9
TLOAN ($m)	20177.77	16764.61	1887.376	108623
Deposits ($m)	29101.73	28380.97	2456.61	261356.4
Observations= 1104, t=16, n=69				

Indonesian Banks

Variable	Mean	Std. Dev.	Min	Max
TC ($m)	841.115	1047.291	3.817	4367.603
OEA ($m)	3817.488	5165.555	5.122	19677.92
TLOAN ($m)	6510.826	9947.407	12.432	43926.27
Deposits ($m)	9139.352	12642.11	1.651	51197.27
Observations= 208, t=16, n=13				

French Banks

Variable	Mean	Std. Dev.	Min	Max
TC ($m)	12862.4	22500.22	224.926	104303.7
OEA ($m)	239252	468947.2	298.922	2019302
TLOAN ($m)	113546.9	214733.6	22.293	1036581
Deposits ($m)	102522.1	201951.3	676.831	776467.9
Observations= 176, t=16, n=11				

4.4.4 Efficiency Calculations

The SFA regression using Stata12 (xtfrontier command) was applied to all 27 jurisdictions balanced data individually. The only models with significant efficiency (ν) were the USA, Japan, Indonesia, and France. Elsewhere, the regression output was incomplete therefore the coefficients $\alpha, \beta, \gamma, \psi, \varphi, \lambda, \xi, \theta, \kappa, \rho$ and η could not be estimated in the cost frontier model (Equation 4.4.3). Table 4.4 contains the SFA outputs per country. In the case of the USA and Japan as expected the inefficiency term υ_{it} was significant to 1% and negative. However, Indonesia was significant to 5% with France's significance being greater than 10% with a high standard error. Also at the 10% significance level the frontier distribution for France would be rejected given the χ^2 statistic. LnTLOAN as an output for France was not statistically significant. A potential reason behind this is the limited sample size of only 11 banks (however the Indonesia frontier was significant with only 13 banks) and on inspection there are wide variations (standard deviations) within the French bank sample. Because of this the SFA efficiency scores produced for individual banks within France are not considered to be reliable.

Table 4.4: SFA Estimation Results per Country

	USA Frontier		**Japan Frontier**		**Indonesia Frontier**		**France Frontier**	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
lnOEA	0.099***	(0.011)	-0.077***	(0.027)	0.175***	(0.033)	0.200***	(0.045)
lnTLOAN	0.720***	(0.027)	0.554***	(0.059)	0.214***	(0.030)	0.014	(0.023)
lnDeposits	-0.167***	(0.033)	0.148**	(0.068)	0.372***	(0.031)	0.298***	(0.055)
υ Usigma	-12.579***	(0.066)	-13.200***	(0.088)	-13.650**	(0.611)	-21.552	(36.916)
ν Vsigma	-3.290***	(0.023)	-3.920***	(0.043)	-3.090***	(0.098)	-3.416***	(0.107)
N	3728		1104		208		176	
Log-likelihood	841.863		597.419		26.196		50.838	
$\chi^2_{(3)}$	8394.342***		965.528**		2230.15***		329.816	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Figures 4.1a to 4.1d present the average yearly bank SFA scores per country. As warned by Stavarek (2006) large efficiency variations within countries skewed the country's averages. Figure 4.1e suggests that the USA overall has the least efficient banks, however, this is not necessarily the case, as the sample size is larger compared to the other countries[23]. Further, Figure 4.1d suggests that France is the most efficient on average, however as previously establish the SFA scores for France cannot be considered as reliable. Also given the high average, almost 1 (efficient), on a scale of 0 to 1, this further suggests the data is unreliable.

Looking specifically at the USA (Figure 4.1a), this suggests that on average cost efficiency rose in the years towards the financial crisis and then subsequently declined following. The rationale to explain this trend, focuses on the variable LnTLOANS which has the highest coefficient. As an output, prior to the financial crisis the number of loans on the balance sheets expanded considerably, relative to total costs. Therefore, outputs enhanced relative to input, increasing efficiency. Following the crisis the opposite trend took effect as institutions decreased their loans books (previously illustrated in Figure 2.4 of Chapter 2). Also, declines in cost efficiency can be attributed to a number of reasons. For example (i) financial institutions may have incurred more costs than their counterparts in dealing with higher levels of non-performing loans; and (ii) they may devote more resources to strengthening capitalisation in order to achieve compliance with regulatory requirements such as Basel III (Feng & Wang, 2018). The decline in cost efficiency was more gradual than the rise prior to the financial crisis, as institutions sought to increase their customer deposits (another output) base. Thus, it is important to investigate the interaction between efficiency and risk (also implications from regulation). The SFA scores suggest the banks became more efficient, however this score does not take into account how the institutions acted (taking excess risk) in this intermediary approach. Japan followed a similar trend (Figure 4.1b) subject to slight delay given the financial crisis impacted the US first. Indonesia's (Figure 4.1c) average SFA score was more volatile due to the small sample size.

[23]This variation is noted later within Table 4.6, with the SFAEFF in the US banks having a wide spread of 0.406

Figure 4.1: Mean Cost Efficiency via SFA

Figure 4.2: Mean Productivity Growth Efficiency via DEA

(a) USA

(b) Japan

(c) Indonesia

(d) France

(e) Combined

Productivity Growth calculated for DEA using Stata was subsequently calculated for the same countries for comparative purposes. Given that DEA is a linear programming process, DEA could have been calculated for the other Basel jurisdictions subject to balance data sample size. Figure 4.2e demonstrates consistency between the average DEA scores, with an element of a delay to the change of the efficiency trend following the financial crisis. Generally, the USA and Indonesia trends resemble the corresponding SFA scores, with more volatility. Such, volatility in the scores around the crisis period is consistent with the findings of Asmild and Zhu (2016).

4.4.5 Variable Selection and Regressions

As previously noted the dependant variables will be the parametric SFA and non-parametric DEA. In order to compare with an accounting based efficiency ratio the cost to income ratio (CIR) will be used. The ratio is calculated by dividing the operating costs (administrative and fixed costs, such as salaries and property expenses, but not non-performing loans) by operating income. According to Chiaramonte, Croci, and Poli (2015) managerial quality is approximated by CIR, a low value indicates better managerial quality as they are able to keep costs down (or stable) whilst increasing income. The following independent variables will examine the impact of banking risk characteristics and regulatory variables on cost (in)efficiency while controlling for profitability and size. See Table 4.5 for a descriptive summary of the variables uses within this study[24] and Table 4.6 for a statistical summary. As this paper focuses on the USA banking industry only, other country-specific characteristics are not required as controls. Such variables would be required if this was a cross-country study.

A proxy for Diversification (DIV) is the magnitude of non-interest income to operating income, which greatly reflects bank participation in financial markets

[24] All the data used was deflated by their corresponding years consumer price index (CPI) to the year 2000 price levels to control for inflation effects, a similar approach to Abuzayed et al. (2009); Gardener, Molyneux, and Nguyen-Linh (2011); Molyneux and Williams (2013) *inter alia*.

such as securities trading, asset management services, to name a few. The expected relationship with efficiency is uncertain. On the one hand, a negative relationship would suggest that diversification leads to excess risk and therefore lower cost efficiency. Otherwise, the sign may be positive if diversification is seen as a way for financial institutions to increase income streams more than it costs to achieve this extra income.

To account for banks' asset quality the variable CreditRisk is used. Financial institutions which provide more loans, especially in the context of pre-crisis, are expected to incur higher credit risk. This variable is expected to have an inverse relationship with cost efficiency, as higher credit risk would theoretically increase costs (via write off and the redress process) and lower profitably. A similar relationship is expected for Leverage (FLVRG) as another proxy for credit risk.

The Tier One Capital Ratio (T1CR) is a regulatory variable that could have a positive or negative effect on cost efficiency. It could possibly enhance cost efficiency as banking regulations enhance market discipline (Pasiouras et al., 2009) which makes the institutions safer. On the contrary having to hold extra capital could be seen as costly, as capital affects costs through its use as a source of funding (Berger & Mester, 1997). Within Table 4.1 on regulation impact on efficiency, all authors found that capital requirement had a positive impact on cost efficiency. Typically previous studies have applied dummy variables or capital requirement indexes rather than the individual bank level measures.

A liquidity (LIQ) variable similar to Williams and Nguyen (2005) can also be positive or negative in relation to efficiency. If increased loans helps banks to diversify their credit risk and/or enhance interest income, a positive relationship might be expected. However, if this enhances credit risk (due to non-performing loans) and increases the asset/liabilities gaps this could negatively impact cost efficiency due to the need to source extra funds.

The Net Stable Funding Ratio (NSFR) is another regulatory variable with an unknown relationship with cost efficiency. This variable to the best of my knowledge has not been tested in relation to efficiency before. This ratio as discussed in section 3.4.3 is required to be above 100% to demonstrate the financial institution has sufficient access to longer term funding in the event of a liquidity shortage. This is approximated using equation 4.4.5 (Chiaramonte & Casu, 2017).

$$NSFR = \frac{Equity + \substack{TotalLT \\ Funding} + \left(\substack{Term \\ Customer \\ Deposits} * 0.95 \right) + \left(\substack{Current \\ Customer \\ Deposits} * 0.9 \right) + \left(\substack{Other \\ Deposits \\ andST \\ Borrowing} * 0.5 \right)}{\substack{Other \\ Assets} + \left(\left(\substack{Government \\ Securities} + \substack{OBS \\ Items} \right) * 0.05 \right) + \left(\left(\substack{Other \\ Securities} + \substack{Loans \\ and \\ Advances \\ toBanks} \right) * 0.5 \right) + \left(\substack{Mortgage \\ Loans} * 0.65 \right) + \left(\substack{Retail \\ and \\ Corporate \\ Loans} * 0.85 \right)} \geq 100\% \tag{4.4.5}$$

If this ratio is seen as a onus on the institutions to hold/source more funding this would increase cost negativity affecting cost efficiency. However, as with LIQ if it helps banks to diversify other risks and makes them safer (bringing funding costs down) this will enhance cost efficiency.

As a control variable for profitability, Return on Assets (ROA) is expected to have a positive relationship with cost efficiency, with the assumption that profitable institutions are more efficient at transforming inputs into outputs. In the event of profitability due to higher credit risk, this could result in lower cost efficiency.

To investigate the role of size (and indirectly enhanced regulation) on cost efficiency, the dummy variable to indicated whether a financial institution is classed as a SIFI or G-SIB. $SIFI$ is included as another control variable (only applicable from 2011). This variable to the best of my knowledge has not been tested in relation to efficiency before. Due to mixed previous empirical results regarding size, no *a priori* expectation is expected.

Year effects (year dummies, excluding the first year) capture the influence of aggregate (time-series) trends. It allows to control for the exogenous increase in the dependent variable which is not explained by the other variables. For example, the likes of an external shock where it's impact is restricted to a given time-period, affecting all panel units that are not controlled by other explanatory variables.

In the first instance this study applies OLS (Tobit in the case of SFA) regression, followed by Generalized Method of Moments (GMM) regression to study the relationship between banking variables and cost efficiency. The cost efficiency scores (as the explained variable) calculated via SFA are limited to values between 0 and 1. Thus, this dependent variable cannot be expected to have a normal distribution. If ordinary least squares (OLS) regression was applied in

Table 4.5: Individual Bank Explanatory Variables

Symbol	Variable Name	Description	Expected Sign	Authors
DIV	Diversification	Proxy for a bank's business model calculated by net non-interest income to net operating income.	+/−	Beck et al. (2016)
CreditRisk	Credit Risk	Ratio of Non-performing loans divided by total loans. The higher the ratio, the lower the quality of the loan portfolio.	−	Ariff and Luc (2008); Luo et al. (2016)
FLVRG	Leverage	Financial Leverage is defined as the ratio of total assets to total common equity. A lower figure represents less leverage	−	Färe, Grosskopf, and Weber (2004)
T1CR	Tier 1 Capital Ratio	The ratio of Tier 1 capital to risk-weighted assets.	+/−	N/A
LIQ	Liquidity	Liquidity is measured by the ratio of net loans to deposits and short term funding. Lower figure represents higher liquidity	+/−	Williams and Nguyen (2005)
NSFR	Net Stable Funding Ratio	A regulatory ratio to measure long-term funding	+/−	N/A
ROA	Return on assets (control variable)	Indicator of how profitable a company is relative to its total assets, as a percentage. Provides an idea of how efficient management is at using its assets to generate earnings	+	Berger and Mester (2003); Ariff and Luc (2008)
SIFI	SIFI Bank (control variable)	A dummy variable 1= classified as a systemically important institution or a domestically important institution, otherwise 0	+/−	N/A
Year	Time (control variable)	Time dummy variable		

Table 4.6: US Bank Efficiency Determinants Statistics Summary

Variable	Obs	Mean	Std. Dev.	Min	Max
SFAEFF	3728	.751	.085	.548	.954
ProdGrowth	3495	2.144	.261	.89	4.366
CIR	10400	68.345	24.623	-9.565	580.645
DIV	10370	.862	3.899	-81.368	89.286
CreditRisk	6359	.019	.209	0	16.562
FLVRG	9353	11.818	16.229	1.142	1043.228
T1CR	9326	13.243	7.72	-4.15	438.98
LIQ	7718	.815	.197	.001	6.468
NSFR	4675	.938	.057	.646	1.787
ROA	9372	.167	53.059	-5133.206	16.126

this case the result may be biased and/or produce inconsistent parameter estimates (Greene, 1981). Typically, the empirical literature applies the Tobit estimation (Tobin, 1958) to avoid this issue (Ariff & Luc, 2008; J. R. Barth, Lin, et al., 2013; Delis & Papanikolaou, 2009; S. H. Lee, 2013), using the Stata12 command xttobit for the following model:

$$y_{it} = \alpha_i + \beta_n X_{it} + \varepsilon_{it}, \quad \varepsilon_{it} \sim N(0, \sigma_t^2) \tag{4.4.6}$$

where α_i is the firm-specific constant effect, X_{it} is a $1 \times L$ vector of bank level financial explanatory variable which are time-varying, β_n are the corresponding vector parameters to be estimated, finally the error term, ε_{it}, which is assumed to be normally distributed. Also, the technique of bootstrapping will be applied to assess whether this alters the explanatory power of the variables. Simar and Wilson (2007) first advocated the use of single and double bootstrapping as it enhanced the statistics significance of efficiency in their empirical evidence from the US banking sector. Further, Delis and Papanikolaou (2009) found that when a bootstrapping technique is applied the explanatory power of certain variables was enhanced. Tortosa-Ausina et al. (2008) also found that bootstrapping allows for more careful analysis at firm level[25]. In the context of this study the model 4.4.7 outlines the equation to determine bank efficiency.

[25]Out of their panel of Spanish savings banks circa 90% of banks efficiency grows following

$$EFF_{it} = \alpha_i + \beta_1 DIV_{it} + \beta_2 CreditRisk_{it} + \beta_3 FLVRG_{it} + \beta_4 T1CR_{it} \\ + \beta_5 LIQ_{it} + \beta_6 NSFR_{it} + \beta_7 ROA_{it} + \beta_8 SIFI_{it} + Year + \varepsilon_{it} \quad (4.4.7)$$

where EFF_{it} will be SFA, ProdGrowth and CIR. Following the application of Tobit and OLS regression, GMM regression is applied to the same explanatory variables. The purpose of applying GMM is to incorporate the lag dependant variable to test whether the previous efficiency level significantly impacts future efficiency scores.

$$y_{it} = \alpha_i + \beta_1 y_{it-1} + \beta_n X_{it} + u_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots T \quad (4.4.8)$$

where α_i is the firm-specific constant effect, y_{it-1} is an endogenous lagged dependant variable, X_{it} is a $1 \times L$ vector of bank level financial explanatory variable (see Table 4.5 for more details) which are time-varying and not strictly exogenous, β_n are the vector parameters to be estimated, finally the error term, u_{it}, assumes a mean of zero and is probably serially correlated. Daraio and Simar (2005) acknowledged possible serial correlation as a shortcoming of multistage DEA and SFA analysis among estimated coefficients.

Due to y_{it-1} being an endogenous explanatory variable (with respect to both α_i and u_{it}). The conventional covariance estimators of equation 4.4.8 are no longer consistent[26]. Endogeneity can arise by: (i) omitted variables (correlation with errors); (ii) measurement error in the independent variable (e.g. the efficiency or market power calculations); and (iii) reversed causality (from the lag or selection bias) (Hall, 2005). This provides justification for adopting GMM to obtain consistent estimates (Arellano, 2003). Further, due to the use of panel data the GMM estimations are mostly valid for data with small T and large N. This is the case within this paper's sample, thus the GMM method proposed by Ahn and

bootstrapping, However, not every banks Malmquist productivity index was significantly different from the original value before bootstrapping.

[26]as noted and examples by Anderson and Hsiao (1981); Arellano (2003); Hsiao (2003).

Sickles (2000) is used. Using Stata12, a two-step system dynamic GMM approach was applied with windmeijer-corrected standard errors (Windmeijer, 2005) to control for potential instances of endogeneity (Blundell & Bond, 1998) and for the downward bias in the estimated asymptotic standard errors. The issue of endogeneity arises due to the possibility of reverse causality that certain bank characteristics may be determined by performance (efficiency and asset quality) or that such characteristics may be derived by underlying unobservable factors that impact performance. To ensure the GMM models fit correctly it is expected that AR(1) is statistically significant due to the way it is constructed and statistically insignificant AR(2). Therefore the output requires the p-values of AR(2) and Hansen tests to be greater than 0.1 (10% significance) (Dovonon & Hall, 2018). The Hansen J-statistics of over identifying restrictions should be statistically insignificant as this indicates that the instruments are valid in the two-step system GMM estimation. If the previous holds this implies that the models fit correctly with statistically insignificant test statistics of second-order autocorrelation in second differences (AR(2)) and the Hansen J-statistics (Matousek, Nguyen, & Stewart, 2016).

4.5 Finding and Discussion

This section will present the finding from the regression outlined previously using US bank panel data, then discuss the robustness strategies. Firstly, in the pairwise correlation matrix for the full sample (table 4.8), all of the variables display low correlation scores, which reduces the likelihood of multicollinearity within the regressions. The highest relationship is between all the variables of CIR and ROA (Control variable) at -0.507 (moderately negatively correlated). During the regressions this relationship will be tested for multicollinearity[27]. Table 4.9 showing the pairwise correlation within the sample prior to the crisis demonstrates similar results, however there is a moderately negatively relationship between cost efficiency (SFAEFF) and productivity growth (ProdGrowth). The post crisis table

[27]Stata12 omits any independent variables that causes multicollinearity.

(4.10), evidences generally higher correlation between the variables however none raised above 0.5 (or lower that -0.5). Within all three pairwise correlation matrices, the variables of DIV and CreditRisk, display correlation scores, with other variables, which have low statistical significance. However, non-significant correlation does not imply no association. To ensure that multicollinearity does not exist amongst the independent variables the variable inflation factor (VIF) test was conducted. The results are presented in Table 4.7. As suggested by Asteriou and Hall (2015) a VIF less than 10 is acceptable. The highest VIF was 3.70, therefore within this paper's regressions there is a low level of multicollinearity. Even with the inclusion of the lagged dependent variables multicollinearity was not an issue. Noticeably the models with the econometric measures of efficiency as the dependency variable had lower VIF means then the accounting based model. Interestingly the highest VIF values were the dummy time variables surrounding the financial crisis (year06-year09). This highlights that during this time period variables may have become more correlated by an unpredictable exogenous shock (the financial crisis).

Table 4.7: US Bank Efficiency VIF Test

Variable	SFAEFF		ProdGrowth		CIR	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
$SFAEFF_{y-1}$	1.84	0.542				
$ProdGrowth_{y-1}$			2.66	0.375		
CIR_{y-1}					1.19	0.840
DIV	1.01	0.987	1.01	0.987	1.01	0.995
CreditRisk	1.93	0.517	1.92	0.521	1.81	0.551
FLVRG	1.20	0.833	1.19	0.839	1.17	0.853
T1CR	1.27	0.785	1.27	0.789	1.17	0.857
LIQ	1.13	0.886	1.13	0.888	1.06	0.943
NSFR	1.10	0.899	1.11	0.900	1.04	0.966
ROA	1.60	0.624	1.60	0.625	1.65	0.606
SIFI	1.28	0.779	1.29	0.783	1.16	0.865
Year01	2.01	0.496	2.01	0.499	2.02	0.495
Year02	2.05	0.488	2.03	0.492	2.05	0.489
Year03	2.10	0.476	2.07	0.483	2.13	0.470
Year04	2.23	0.448	2.21	0.453	2.49	0.407
Year05	2.32	0.431	2.31	0.433	3.01	0.332
Year06	2.39	0.419	2.36	0.423	3.20	0.312
Year07	2.48	0.402	2.45	0.408	3.54	0.282
Year08	2.60	0.386	2.46	0.407	3.70	0.271
Year09	2.57	0.390	2.37	0.421	3.35	0.298
Year10	2.39	0.418	2.22	0.450	3.14	0.318
Year11	2.21	0.452	2.06	0.486	2.88	0.347
Year12	2.22	0.450	2.09	0.479	2.83	0.353
Year13	2.09	0.479	1.97	0.506	2.55	0.393
Year14	2.00	0.501	1.99	0.512	2.36	0.424
Year15	1.93	0.518	1.84	0.543	2.27	0.441
Mean VIF	1.91		1.90		2.20	

Table 4.8: US Bank Efficiency Determinants Cross-correlation

Variables	SFAEFF	ProdGrowth	CIR	DIV	CreditRisk	FLVRG	T1CR	LIQ	NSFR	ROA
SFAEFF	1.000									
ProdGrowth	-0.127	1.000								
	(0.000)									
CIR	0.162	-0.075	1.000							
	(0.000)	(0.000)								
DIV	-0.039	0.012	0.014	1.000						
	(0.018)	(0.493)	(0.209)							
CreditRisk	0.004	0.017	0.042	0.001	1.000					
	(0.817)	(0.328)	(0.001)	(0.930)						
FLVRG	0.052	-0.007	0.088	-0.026	0.017	1.000				
	(0.001)	(0.701)	(0.000)	(0.022)	(0.185)					
T1CR	-0.160	-0.067	0.104	-0.011	-0.009	-0.147	1.000			
	(0.000)	(0.000)	(0.000)	(0.323)	(0.489)	(0.000)				
LIQ	-0.012	0.108	-0.068	-0.012	-0.018	-0.040	0.014	1.000		
	(0.521)	(0.000)	(0.000)	(0.369)	(0.216)	(0.003)	(0.294)			
NSFR	-0.003	0.070	0.013	-0.020	0.013	-0.021	-0.102	0.537	1.000	
	(0.879)	(0.001)	(0.358)	(0.178)	(0.404)	(0.163)	(0.000)	(0.000)		
ROA	-0.251	-0.114	-0.507	0.031	-0.041	-0.065	0.052	0.002	-0.046	1.000
	(0.000)	(0.000)	(0.000)	(0.007)	(0.002)	(0.000)	(0.000)	(0.883)	(0.002)	

Table 4.9: US Bank Efficiency Determinants Cross-correlation (Pre-Crisis)

Variables	SFAEFF	ProdGrowth	CIR	DIV	CreditRisk	FLVRG	T1CR	LIQ	NSFR	ROA
SFAEFF	1.000									
ProdGrowth	-0.492	1.000								
	(0.000)									
CIR	0.075	-0.024	1.000							
	(0.001)	(0.327)								
DIV	0.017	0.007	0.031	1.000						
	(0.472)	(0.770)	(0.057)							
CreditRisk	-0.013	0.032	0.005	0.001	1.000					
	(0.620)	(0.232)	(0.810)	(0.967)						
FLVRG	0.056	0.026	0.058	-0.031	0.022	1.000				
	(0.016)	(0.291)	(0.001)	(0.064)	(0.287)					
T1CR	-0.028	0.021	0.228	-0.036	-0.003	-0.280	1.000			
	(0.233)	(0.396)	(0.000)	(0.028)	(0.896)	(0.000)				
LIQ	-0.046	-0.126	-0.082	-0.002	-0.052	-0.094	0.101	1.000		
	(0.057)	(0.000)	(0.000)	(0.900)	(0.016)	(0.000)	(0.000)			
NSFR	-0.007	-0.088	0.010	-0.042	-0.055	-0.058	-0.083	0.599	1.000	
	(0.811)	(0.002)	(0.620)	(0.034)	(0.022)	(0.004)	(0.000)	(0.000)		
ROA	-0.119	0.041	-0.586	0.017	-0.006	0.003	-0.096	0.080	-0.045	1.000
	(0.000)	(0.098)	(0.000)	(0.303)	(0.759)	(0.843)	(0.000)	(0.000)	(0.027)	

Table 4.10: US Bank Efficiency Determinants Cross-correlation (Post-Crisis)

Variables	SFAEFF	ProdGrowth	CIR	DIV	CreditRisk	FLVRG	T1CR	LIQ	NSFR	ROA
SFAEFF	1.000									
ProdGrowth	0.131	1.000								
	(0.000)									
CIR	0.334	-0.176	1.000							
	(0.000)	(0.000)								
DIV	-0.062	0.007	0.000	1.000						
	(0.007)	(0.774)	(0.994)							
CreditRisk	0.367	0.026	0.390	0.004	1.000					
	(0.000)	(0.269)	(0.000)	(0.816)						
FLVRG	0.078	-0.017	0.106	-0.027	0.134	1.000				
	(0.001)	(0.474)	(0.000)	(0.088)	(0.000)					
T1CR	-0.220	-0.220	-0.074	0.000	-0.144	-0.148	1.000			
	(0.000)	(0.000)	(0.000)	(0.996)	(0.000)	(0.000)				
LIQ	0.029	0.291	-0.041	-0.020	0.006	-0.032	-0.151	1.000		
	(0.294)	(0.000)	(0.040)	(0.311)	(0.773)	(0.109)	(0.000)			
NSFR	0.006	0.158	0.015	-0.008	0.020	-0.015	-0.125	0.474	1.000	
	(0.838)	(0.000)	(0.469)	(0.707)	(0.359)	(0.500)	(0.000)	(0.000)		
ROA	-0.462	-0.079	-0.411	0.054	-0.345	-0.120	0.225	-0.072	-0.048	1.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)	

Table 4.11: Tobit/OLS Bank Efficiency Determinants (2000-2015)

	(1a) SFA (Tobit RE)		(1b) SFA Boot (Tobit RE)		(2a) DEA (OLS FE)		(2b) DEA Boot (OLS FE)	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
DIV	-0.031***	(0.003)	-0.031	(0.003)	0.002	(0.001)	0.002*	(0.001)
CreditRisk	-0.467***	(0.095)	0.467***	(0.095)	-2.431***	(0.437)	2.431***	(0.661)
FLVRG	-0.022	(0.002)	-0.023	(0.002)	-0.002*	(0.003)	-0.002**	(0.001)
T1CR	0.001***	(0.003)	0.001***	(0.003)	-0.002	(0.002)	-0.002	(0.002)
LIQ	0.019***	(0.007)	0.019**	(0.009)	0.182***	(0.035)	0.182***	(0.039)
NSFR	0.026*	(0.100)	0.026	(0.159)	0.137***	(0.051)	0.137**	(0.068)
ROA	-0.0174***	(0.002)	-0.0174***	(0.002)	-0.036**	(0.015)	-0.036***	(0.007)
SIFI	-0.521*	(0.440)	-0.521*	(0.312)	-0.084	(0.573)	-0.084	(0.501)
Intercept	0.946***	(0.056)	0.946***	(0.063)	1.968***	(0.033)	1.269***	(0.028)
Year Dummies	Yes		Yes		Yes		Yes	
N	2723		2723		2590		2590	
Log-likelihood	16387.116		16387.116					
$\chi^2_{(7)}$	511.25***		408.63***					
$F_{(250,2339)}$					180.452*		202.211**	
Pseudo R^2	0.395		0.395					
R^2					0.234		0.234	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 4.12: OLS US Bank Efficiency Determinants (2000-2015)

	(3a) CIR (OLS FE)		(3b) CIR Boot (OLS FE)	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
DIV	0.040	(0.041)	0.040	(0.043)
CreditRisk	-45.757***	(13.570)	-45.757	(33.444)
FLVRG	-0.124***	(0.022)	-0.124	(0.120)
T1CR	0.212***	(0.063)	0.212	(0.122)
LIQ	5.876***	(1.711)	5.876	(5.381)
NSFR	-1.528	(2.494)	-1.528	(2.491)
ROA	-6.714***	(0.223)	-6.714	(1.235)
SIFI	-2.302*	(0.598)	-2.302	(4.031)
Intercept	69.657***	(1.818)	69.657	(4.600)
Year Dummies	Yes		Yes	
N	4462		4462	
R^2	0.324		0.324	
$F_{(579,3882)}$	6.60***		88.733	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

For the determinants of SFA (Table 4.11) model 1a and 1b were used to witness the random effects tobit regression[28], as the variable value is between 0 and 1. For the determinants of DEA productivity growth (Table 4.11) model 2a and 2b and CIR (Table 4.12) model 3a and 3b, OLS fixed effects regression was used. For all four models the Hausman test was conducted to ensure that fixed affects was the appropriate method (over random affects). Notability only models 1a, 1b and 3a were significant to 1%, the models for productivity growth, 2a & 2b were significant to only 10% and 5% respectively, whereas model 3b was non-significant. The use of the bootstrap technique was effective for the determinants of SFA and DEA by enhancing the explanatory power of a number of variables, although this technique was detrimental to the accounting based measure of efficiency of CIR as model 3b was non-significant. The results from these tables provide statistical significance for the majority of the explanatory variables, therefore warranting further analysis with the inclusion of the dependent lag variables.

[28]Tobit is a non-linear function and the likelihood estimator for fixed affects is biased and inconsistent.

Table 4.13: SFA, DEA & CIR GMM of US Bank Efficiency Determinants (2000-2015)

	(1) SFAEFF		**(2) DEA (ProdGrowth)**		**(3) CIR**	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
SFAEFF_{y-1}	0.236***	(0.004)				
ProdGrowth_{y-1}			-0.251*	(0.037)		
CIR_{y-1}					0.271***	(0.009)
DIV	-0.0113***	(0.003)	0.028***	(0.001)	0.131	(0.012)
CreditRisk	-0.0285***	(0.004)	-2.395**	(0.309)	24.017*	(12.431)
FLVRG	-0.038	(0.082)	-0.003*	(0.003)	-0.150**	(0.011)
T1CR	-0.0053***	(0.002)	0.015	(0.001)	0.249	(0.041)
LIQ	-0.0777***	(0.005)	0.377	(0.034)	6.895***	(1.299)
NSFR	-0.135***	(0.021)	0.428***	(0.009)	-0.539	(1.664)
ROA	0.0456**	(0.006)	-0.220*	(0.008)	-7.061**	(0.285)
SIFI	-0.542*	(0.534)	-0.135	(0.821)	-2.209	(1.023)
Intercept	0.309***	(0.004)	31.476***	(1.017)	52.644***	(1.397)
Year Dummies	Yes		Yes		Yes	
N	2590		2440		4460	
Group	231		231		559	
Instruments	171		174		210	
AR(1) (p-value)	0.000		0.000		0.000	
AR(2) (p-value)	0.437		0.062		0.318	
Hansen (p-value)	0.988		0.288		0.652	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

In the full sample table 4.13 model 1 (SFAEFF) and 3 (CIR) both the Arellano-Bond and Sargan/Hansen tests reported to confirm the validity of instruments underlying the GMM estimation and the absence of serial correlation in the first difference residuals respectively. In comparing models 1 and 3, model 1 is marginally more fitting with the higher AR(2) (0.437) and Hansen value (0.988). However, in model 2 for DEA productivity growth, the autoregressive two (AR(2)) was only significant to 10%. Thus, the null hypothesis, of no autocorrelation at the 5% significance level, cannot be rejected. Given the AR(2) of 0.062, this model (2) for the determinants of DEA at the 5% confidence level can not be considered as reliable. As the dependant lag (ProdGrowth_{y-1}) was only significant at 10% this helps explain the > 0 AR(2). In order to achieve second-order serial correlation in differences (make AR(2) closer to 0.000), further lags of the dependent variable (i.e. ProdGrowth_{y-2} or ProdGrowth_{y-3}) could be used. However, Roodman (2009a) suggests this could weaken the Hansen test (due to missing observations). Furthermore, suggesting that the productivity growth of two or three years ago influences this year's productivity growth may theoretically be unfounded. In all three models the results confirm the persistence of the dependent variables' own effect (lagged) on efficiency, which advocates their inclusion in efficiency determinant models, this is similar to Luo et al. (2016) findings.

In relation to CIR, comparing Table 4.12 model 3a with Table 4.13 model 3, this suggests that the introduction of the lag dependent variable (CIR_{y-1}) alternates the signage and significantly reduces the explanatory power of the majority of other independent variables[29]. This suggests that for the accounting based efficiency measure, the previous year's efficiency level heavily influences the next. However, theoretically this is unclear as CIR is a non-dynamic ratio from the income statement of operating costs to operating income. Further, the positive sign on the lag in model 3 suggests this would increase following years' CIR (i.e. lower efficiency). Given these inconsistencies, interpreting results of CIR efficiency determinants with the lagged effect included maybe misleading.

[29]Achen (2001) explains why lag dependent variables can significantly impact independent variables.

Thus, the following interpretation relates to the determinants of SFA efficiency (Table 4.13, model 1) as all the model specifications for this dependent variable are appropriate and constant. First of all, the lagged effect of the dependent variable as expected positively influences the subsequent years' efficiency. As SFA is a measure that compares institutions against best practice year on year, it would be expected that institutions that ranked highly one year would maintain this the next, unless that institution faced an idosyncratic shock to either their inputs or outputs.

Similar to Rossi et al. (2009) findings, diversification (DIV) is negative and statistically significant which implies that the more diverse a bank's business model it negatively impacts cost efficiency. A potential reason for this is that diversification reduces the traditional outputs used to measure SFA cost efficiency. This could also be due to diversifications impacts on credit risk (which in model 1 is also negative and statistically significant). This association of credit risk to cost efficiency implies that higher credit risk (associated with increased provisions for NPLs) contributes to lower cost efficiency, similar to findings by Inanoglu et al. (2016); Sun and Chang (2011). Such findings advocate that banks should restrict their banking activities to their more traditional area of competence (Inanoglu et al., 2016). The negative sign for leverage would further confirm this, however FLVRG was non-significant. In order to reduce the impact of credit risk and leverage banks under the Basel III regulations are required to hold further capital. Within this regression, enhanced capital requirement ratios was also found to negatively impact cost efficiency. T1CR's negative relationship could be explained by two reasons. Firstly, as suggested by Berger and Di Patti (2006), higher capital requirements forces institutions to hold more capital, thus increasing institutions' premia on potentially costly risk management activities. Secondly, higher capital requirements increase the cost of raising bank capital (Berger & Mester, 1997), however this may be slightly offset by the fact that this capital does not bear any interest payments. This negative relationship between capital requirements and cost efficiency contrast the cross-country results of J. R. Barth, Lin, et al. (2013); Pasiouras et al. (2009). As previous studies in this area tend to use country level measures of capital requirements, this papers finding suggests the use of a bank level measure should also be considered to observe a more complete picture.

As financial institutions become less liquid (higher LIQ) this negatively impacts cost efficiency given the role of deposits within LIQ ratio. If customer deposits reduce, this increases LIQ, also this negatively affects SFA cost efficiency as deposits is an output. Less liquid institutions, could have higher credit risk, resulting in them facing higher funding costs to enhance liquidity. Furthermore, NSFR is negative and statistically significant, which implies that institutions who are seeking/holding extra funds face lower cost efficiency. Again, this could be a result of institutions facing higher funding costs as they aim to meet this new statutory requirement.

The use of time dummies (2000 and 2015 were omitted) was to identify any years that may have influenced the dependent variable. Without the time dummies the majority of model specifications were not reliable (significant AR(2) and/or Hansen). In Table 4.13, model 1, the years of 2007, 2008 and 2011 were statistically significant to 1%, 1% and 5% respectively. Understandably the timing of the financial crisis impacted the cost efficiency of banks, due to significant changes in outputs such as total loans and deposits. Given this influence, the following models test the same independent variables pre-and post crisis. The literature highlights a number of possible positive implications stemming from the exit of inefficient banks (Spokeviciute, Keasey, & Vallascas, 2019). By accelerating the exit of these banks, crises could not only be a cause of social and economic costs but also a source of longer-term benefits for the banking industry and the whole economy. For instance, the value of the investments of failed banks might be captured by surviving banks via spillovers (Knott & Posen, 2005).

Table 4.14: SFA & DEA GMM of Bank Efficiency Determinants Pre and Post Crisis

Variable	(1a) SFAEFF Pre Crisis Coefficient	(1a) SFAEFF Pre Crisis (Std. Err.)	(1b) SFAEFF Post Crisis Coefficient	(1b) SFAEFF Post Crisis (Std. Err.)	(2a) DEA Pre Crisis Coefficient	(2a) DEA Pre Crisis (Std. Err.)	(2b) DEA Post Crisis Coefficient	(2b) DEA Post Crisis (Std. Err.)
$SFAEFF_{y-1}$	0.657***	(0.025)	0.592***					
$ProdGrowth_{y-1}$					-0.129***	(0.038)	-0.137***	(0.020)
DIV	-0.059***	(0.009)	-0.026***	(0.003)	0.005***	(0.001)	0.005***	(0.001)
CreditRisk	-0.022***	(0.080)	-0.017**	(0.078)	0.007	(0.301)	-0.985***	(0.365)
FLVRG	-0.046**	(0.143)	-0.055***	(0.011)	-0.004	(0.003)	0.003***	(0.001)
T1CR	-0.436	(0.506)	-0.287***	(0.003)	-0.001	(0.002)	0.011***	(0.002)
LIQ	0.004***	(0.009)	-0.007***	(0.001)	0.040	(0.054)	0.252***	(0.030)
NSFR	0.054***	(0.013)	-0.051***	(0.075)	0.054	(0.368)	0.739***	(0.084)
ROA	-0.153	(0.064)	0.203***	(0.008)	-0.003	(0.006)	0.008*	(0.004)
SIFI			-0.725**	(0.138)			-0.545	(0.452)
Intercept	0.292***	(0.021)	0.348***	(0.013)	0.045***	(0.028)	1.792***	(0.054)
Year Dummies	Yes		Yes		Yes		Yes	
N	1281		1530		1131		1309	
Group	229		229		229		225	
Instruments	81		119		70		106	
AR(1) (p-value)	0.000		0.000		0.000		0.000	
AR(2) (p-value)	0.245		0.754		0.318		0.058	
Hansen (p-value)	0.587		0.457		0.189		0.908	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Both models 1a and 1b for SFA in Table 4.14 statistically fit, allowing for comparison. Noticeably, a number of the independent variable effects are consistent with the SFA models in Tables 4.11 and 4.13. In comparing pre and post crisis, there were a few discrepancies. Prior to the crisis, LIQ increases (less liquid) was positively related with cost efficiency. This could be explained by the increased levels of loans acting as diversifying credit risk or enhancing interest income. Also, prior to the crisis, the likes of perceived high credit ratings and securitisation enhanced institutions' access to cheaper liquidity. This may also explain why the NSFR, prior to the crisis, had a positive impact on cost efficiency, given the availability of cheaper funding. Post-crisis the opposite affects of liquidity on cost efficiency took over, as total loans decreased and funding costs increased for institutions that relied on wholesale funding. Another discrepancy between pre-and post crisis related to the control variable of profitability (ROA), prior to the crisis profitability negatively impacted cost efficiency albeit non-significantly. Then following the crisis profitability is positively associated with cost efficiency. This can be explained as institutions who sought to reduce total costs (e.g. redundancy and restructuring) following the crisis in order to return to profitability. In relation to SIFI, the full sample demonstrated a negative relationship with cost efficiency, though only significant at 10%, but in the post crisis regression the same relationship was evidenced with a higher significance, suggesting that larger banks have a lower cost efficiency. This finding is consistent with Ariff and Luc (2008); Berger, Hasan, and Zhou (2009); Stavarek (2006). Further, as these institutions are subject to extra regulatory requirements this could also explain the negative relationship to cost efficiency further. Such finding is similar to Spokeviciute et al. (2019) who showed that financial crises do not necessarily produce meaningful cleansing effects in the banking industry and are indeed detrimental to the post-crisis efficiency of the sector. This finding has two implications. First, the purpose of mitigating the short-term effect of a crisis does not appear to go against the long-term efficiency of the banking sector. Second, the prudential regulation aimed at strengthening bank resilience in good times might also contribute to mitigating the effects of crisis on the longer-term efficiency of the banking sector. To enhance cost efficiency, large banks could either consolidate the input base (which is harder to operationalise) or make progress in utilisation of its outputs. For example, the closure of branches (reduce inputs) is highly unlikely because of competition from medium-size banking retail market and impact of on market share. Further, bank consolidation via mergers or acquisition is unlikely due to the regulator's mandate in preventing *too big to fail*. Thus, the adequate approach to improve efficiency is by better use of existing inputs in the financial intermediation process.

In Table 4.14, model 2b for DEA after the crisis was only significant to 10% (AR(2) of 0.058), therefore considered unreliable. Prior to the crisis (model 2a) for DEA, the only statistically significant variables were the lag effect (negative) and diversification which is inconsistent from the DEA models in Tables 4.11 and 4.13.

Table 4.15: CIR GMM of US Bank Efficiency Determinants Pre and Post Crisis

	(3a) CIR Pre Crisis		**(3b) CIR Post Crisis**	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
CIR_{y-1}	0.274	(0.169)	0.289**	(0.023)
DIV	0.198***	(0.015)	0.184	(0.129)
CreditRisk	335.846**	(16.036)	-14.610	(25.006)
FLVRG	0.225**	(0.055)	0.197***	(0.018)
T1CR	0.091	(0.085)	0.469***	(0.095)
LIQ	-0.362	(1.920)	1.881	(4.227)
NSFR	-2.793	(3.182)	5.405	(4.326)
ROA	-10.250***	(0.372)	-6.806***	(0.533)
SIFI			-2.584*	(0.305)
Intercept	50.342***	(2.396)	44.425***	(4.985)
Year Dummies	Yes		Yes	
N	2076		2384	
Group	447		506	
Instruments	106		106	
AR(1) (p-value)	0.091		0.000	
AR(2) (p-value)	0.705		0.368	
Hansen (p-value)	0.377		0.596	

Significance levels : * : 10% ** : 5% *** : 1%

Furthermore, as noted from Table 4.13, model 3 and Table 4.15 models 3a and 3b for CIR, there were a number of inconsistencies amongst the independent variables.

The lagged affect in model 3a, before the crisis, was non-significant, hence the AR(1) only being significant to 10%, rendering this model unreliable.

4.5.1 Robustness Checks

To address the possible endogeneity concerns extra control variables are added to the baseline specification for SFA for the full period, to observe any changes. Overall result within Table 4.16 are quantitatively similar. The additional control variables are to further capture banks' profitability (ROE & TobinQ), ownership structure[30] (Foreign), size (LogASize & LogLSize) and macroeconomic variables (GDP & Inf).

The first strategy applied was to incorporate further profitability ratios, Return on Equity (ROE) and TobinQ, to see if the interaction between profitability and cost efficiency, outweighs the impact of the other dependent variables. Within model 2, the introduction of the further profitability variables mainly affected the credit risk variable making it change sign albeit non-significant and enhancing leverage's significance slightly. Thus, profitability (which may have resulted from extra credit risk) and credit risks interaction should both be explored in determining cost efficiency.

The second strategy was to introduce a dummy variable indicating foreign ownership. Within the empirical literature review numerous authors highlighted the influences of different ownership structures on efficiency (T.-T. Fu et al., 2016; Thoraneenitiyan & Avkiran, 2009). Thus, any significant change from the baseline specification would suggest the need for dividing the sample to avoid endogeneity. Further, two extra variables, relating to institution size were incorporated within model 3. Generally model 3 was consistent with model 1, with slight differences in significance levels. Size via total assets was consistent with the SIFI dummy albeit non-significant. The negative relationship with the foreign ownership dummy suggests that domestic banks are more cost efficient than foreign owned institutions. Similar findings to Du and Sim (2016); Xiaogang et al. (2005) and

[30]The degree of foreign ownership is measured by bank assets that are 50% or more foreign owned (B. N. Jeon, Olivero, & Wu, 2011).

contrasting Ariff and Luc (2008); Berger, Hasan, and Zhou (2009) results. The results may have some bearing on the debate over why most cross-border studies of bank efficiency found that foreign affiliates, on average, are less efficient than the domestic banks in the same nation (Berger & DeYoung, 2001).

Another strategy was to incorporate the economic variables of GDP and inflation to determine whether macroeconomic effects (which indirectly affect all variables) alter the baseline, which was found not to be the case. In model 4, both variables were significant and as expected GDP growth is positively associated with efficiency while inflation erodes cost efficiency. Finally, all additional control variables were added to the baseline specification (model 5). Ultimately the coefficients signage and significance remained largely the same, thus this paper's findings remain robust given the introduction of further control variables.

Table 4.16: SFA GMM of US Bank Efficiency Determinants (2000-2015) Robustness

	(1) SFAEFF		**(2) Profitability**		**(3) Ownership and Size**		**(4)Macroeconomic**		**(5)All**	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
$SFAEFF_{y-1}$	0.236***	(0.004)	0.615***	(0.003)	0.649***	(0.007)	0.652***	(0.006)	0.661***	(0.007)
DIV	-0.0113***	(0.003)	-0.064*	(0.095)	-0.071***	(0.003)	-0.096***	(0.035)	-0.060**	(0.039)
CreditRisk	-0.0285***	(0.004)	0.064	(0.521)	-0.001**	(0.029)	-0.009**	(0.029)	-0.056	(0.354)
FLVRG	-0.038	(0.082)	-0.165*	(0.020)	-0.242	(0.051)	-0.285	(0.049)	-0.167*	(0.002)
T1CR	-0.0053***	(0.002)	-0.019***	(0.084)	-0.194**	(0.057)	-0.021***	(0.016)	-0.173**	(0.050)
LIQ	-0.0777***	(0.005)	-0.268***	(0.001)	-0.393***	(0.006)	-0.516***	(0.004)	-0.332***	(0.006)
NSFR	-0.135***	(0.021)	-0.013**	(0.049)	-0.112***	(0.020)	-0.244***	(0.018)	-0.098***	(0.005)
ROA	0.0456**	(0.006)	0.063*	(0.033)	0.107***	(0.036)	0.107***	(0.004)	0.973***	(0.064)
SIFI	-0.542*	(0.534)	-0.256*	(0.256)	-0.425**	(0.247)	-0.498*	(0.199)	-0.226**	(0.125)
ROE			0.938***	(0.078)					0.114***	(0.021)
TobinsQ			0.555*	(0.085)					0.453*	(0.045)
Foreign					-0.477***	(0.022)			0.802***	(0.045)
LogASize					-0.221	(0.959)			-0.279	(0.474)
LogLSize					0.728	(0.882)			0.223	(0.485)
GDP							0.027***	(0.057)	-0.264***	(0.061)
Inf							-0.329***	(0.069)	0.321***	(0.001)
Intercept	0.309***	(0.004)	0.327***	(0.003)	0.478***	(0.001)	0.225***	(0.008)	0.336***	(0.002)
Year Dummies	Yes		Yes		Yes		Yes		Yes	
N	2590		2588		2590		2590		2588	
Group	231		231		231		231		321	
Instruments	171		188		189		187		190	
AR(1) (p-value)	0.000		0.000		0.000		0.000		0.000	
AR(2) (p-value)	0.437		0.533		0.233		0.437		0.464	
Hansen (p-value)	0.988		0.414		0.359		0.375		0.609	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

4.6 Conclusion

It seemed likely that the US banking industry would have sought to improved cost efficiency to survive after the recent financial crisis, however evidence in this paper based on econometric measurement of efficiency does not conform. This paper examines the determinants of cost efficiency and productivity growth in the US banking sector, pre and post financial crisis. To briefly summarise, this paper found, in determining cost efficiency the use of SFA as a measure of efficiency within the regression analysis provided more constant and robust results than DEA productivity growth and the accounting based cost to income ratio, providing evidence to support hypothesis one[31]. With reference to SFA cost efficiency and business model diversity, hypothesis two is accepted as in all models DIV was negatively associated with cost efficiency, suggesting as finance institutions deviate from the traditional intermediation process this reduces cost efficiency. Enhanced credit risk and leverage was found to be negatively associated with cost efficiency, accepting hypothesis three. However, capital requirement regulation implemented to mitigate the impact of credit risk, was also found to negatively impact cost efficiency therefore rejecting hypothesis four. Finally, this paper's results accepted hypothesis five by providing evidence that increased liquidity negatively impacts cost efficiency (except from the sample prior to the crisis).

This paper has both policy implications and also evaluates various econometric techniques as potentially valuable analytical tools for supervisors. First, the results both overall and pre/post crisis highlight the importance of the prudential supervisory role in controlling the level of risk in the banking sector, as the elevation in risk measures coupled with the growth of the sector has resulted in declining measures of efficiency, a result that is robust to several econometric specifications (using both econometric and accounting based measures). The policy implication is that regulators may want better capitalised banks and somewhat smaller or less diverse banking systems, as this is likely to imply a more

[31] The hypothesis was overall rejected because the use of DEA as an econometric measure was not consistent within the regression analysis.

efficiently functioning banking industry. However, this is not necessarily the case with the rejection of hypothesis four. Thus, regulators should focus on ensuring banks' business models do not diversify too much (increasing the level of credit risk and leverage) rather than the sole emphasis being on capital requirements to enhance banking cost efficiency.

Chapter 5

Banking Efficiency, Concentration, Competition and Financial Stability

5.1 Abstract

This paper examines the role of risk, regulation and efficiency within the banking competition and financial stability relationship in the US banking sector. Using System Generalised Methods of Moments (GMM) regression on panel data from 2000 to 2015, this paper finds a neutral view of the competition-stability nexus, where both competition and concentration fragility co-exist. In addition, a unique polynomial competition-fragility relationship was also found. Interestingly when using the Composite Index of Systemic Stress (CISS) as a measure of systemic risk, this altered the competition-stability relationship to identify a concave relationship. Both relationships ruled out the efficiency structure paradigm. In regards to risk, increased credit, leverage, diversification and liquidity risk was found to be negatively associated with financial stability. Whilst increased capital requirements enhance stability, unexpectedly, the Net Stable Funding Ratio (NSFR) was found to hinder stability, providing caution to regulators as this is implemented under Basel III.

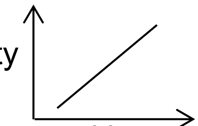
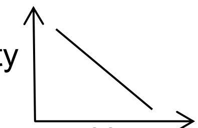
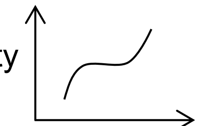
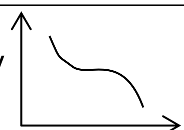
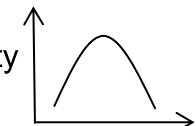
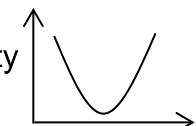
JEL Classification: G21, G23, G28, L1

5.2 Introduction

Historically, institutions have changed via demutualisation (Tayler, 2003) geographical diversification (Ibragimov, Jaffee, & Walden, 2011), financial innovation (Tufano, 2003), mergers with the objective to further enhance scale (Vallascas & Hagendorff, 2011), domestic competition policy and diversifying revenue streams (Fecht, Grüner, & Hartmann, 2012), which ultimately transformed the market structure and the characteristics of risk financial institutions have to manage (Cornett, McNutt, Strahan, & Tehranian, 2011). Despite such changes, J. O. Wilson et al. (2010) suggest there are confines to the extent in which banks can deviate from their traditional business model in the effort to enhance profitability and gain further market share. Generally in most industry sectors, competition also leads to positive change via innovation, product quality and efficiency, the banking sector is no exception (Andrievskaya & Semenova, 2016). However, the level of banking competition can affect (i) the instability of the financial system (see 5.3 for an empirical review), (ii) the significance of relationship lending (Simkovic, 2013), (iii) credit risk (lending quality standards) (Ruckes, 2004) (iv) the tendency of lenders to exclude certain borrowers (Favara & Giannetti, 2017; Gormley, Gupta, & Jha, 2018), and the (v) allocation of labour, impeding efficiency (J. J. Bai, Carvalho, & Phillips, 2017). Following the recent financial crisis important questions have been highlighted by policy-makers regarding whether limits should be placed on the bank size, complexity and efficiency growth. Such questions are ultimately trying to end institutions that are 'too-big-to-fail'. This doctrine can be somewhat misleading as such institutions in the past have been allowed to fail, although the likes of their depositors have been protected against losses through bailouts by governments (Mishkin, 1999; Mishkin, Stern, & Feldman, 2006). Empirically according to Tan and Floros (2018) there are limited studies testing the interrelationships among risk, competition, and efficiency combined within the banking sector. As the financial market has changed, four opposing views have arisen on how competition and market concentration affects systemic risk. Firstly, the *competition-fragility* view argues that more bank competition erodes market power, decreases profit margins and results in reduced franchise value that encourages bank risk taking (F. Allen & Gale, 2004; Carletti, 2008). Secondly, the *competition-stability* view argues that more market power (i.e. less competition) in loan market may result in higher institutional risk as higher interest rates can be charged to loan customers make it harder to repay and exacerbate moral hazard and adverse selection problems (Boyd & Nicoló, 2005). Therefore, it could be argued that more competition leads to stability. Also Schaeck, Cihak, and Wolfe (2009) and Schaeck and Cihak (2012) found that banks have a tendency to hold increased capital when they operate in a more competitive market, hence being more stable. But Berger, Hasan, and Zhou (2009) noted that those two literature streams need not pose opposing views due to risk-mitigating techniques. Figure 5.1 provides an illustration of the competition-stability relationship. Thirdly, the *concentration-fragility* view suggests that larger financial institutions consider themselves to be *too-big-to-fail* and rely on government intervention or subsidies which raise the issue of moral hazard within the system (Uhde & Heimeshoff, 2009) Finally, the *concentration-stability* view proposes that larger financial institutions within a concentrated market may enhance profitability and thus reduce financial instability by higher capital reserves that protect them against external macroeconomic and liquidity shocks (Nicoló, Boyd, & Smith, 2004). Also F. Allen and Gale (2000) argues that a more concentrated banking industry may be easier to regulate. Hence, supervision could be more effective and the risk of a system-wide contagion should be reduced.

In order to investigate this competition-stability nexus this paper will examine US banking sector panel data from 2000-2015. In addition, a number of efficiency, risk and regulator factors will be incorporated within this relationship, given its complex nature. This timescale includes the financial crisis, which potentially affected the structure of the banking market. In a crisis, the number of distressed financial institutions tends to increase, and this, in turn, leads to an upsurge in the volume of banking bankruptcies, liquidations, and forced consolidations. Consequently, the shape of the industry (number of banks) and the level of competition could drastically change (Papanikolaou, 2018b). The rest of this paper

Figure 5.1: Relationship between Competition and Stability

	Type	Graph
Linear relationship	Positive relationship (competition-stability)	Stability  Competition
	Negative relationship (competition-fragility)	Stability  Competition
Non-linear relationship	Monotonic (competition-stability)	Stability  Competition
	Monotonic (competition-fragility)	Stability  Competition
	Concave relationship (n-shaped relationship)	Stability  Competition
	Convex relationship (u-shaped relationship)	Stability  Competition

is organised as follows: Section 5.3 provides on overview of the broad range of empirical evidence investigating the banking competition-stability nexus. Section 5.4 outlines the research hypotheses developed from the inconclusive evidence highlighted in the empirical literature review. Section 5.5 discusses the methodology of this paper. Firstly this section, discusses the need for the GMM regression, secondly explains the calculations of competition, concentration and stability, and finally the extra explanatory and control variables are identified. Section 5.6 discusses the main findings in the context of the US banking sector then briefly summarises findings from other Basel jurisdictions. The final section 5.7 summarises this paper's findings in relation to the research hypotheses.

5.3 Literature Review on Banking Competition and Financial Stability

Generally, empirical studies within the competition-stability nexus advanced from studies evaluating the effects of banking competition on profitability. According to economic competition theory, increased competition erodes excessive returns due to new entrants or forced operational improvement costs (Berger, Bonime, Covitz, & Hancock, 2000; Goddard, Liu, Molyneux, & Wilson, 2011; Hung, Jiang, Liu, & Tu, 2018). For example, within the European Union banking sector, both market concentration and competition as well as credit and liquidity risk management, efficiency, business model diversification all positively influence profitability (Petria, Capraru, & Ihnatov, 2015). Thus, such variables can then be tested to find the subsequent impact on financial stability.

Empirical evidence tends to be in the form of regression testing, typically OLS (if lags are not included) or GMM due to autocorrelation. In addition, granger causality testing, using dynamic panel data, is becoming more popular (Casu & Girardone, 2009; Fiordelisi & Mare, 2014; A. Kasman & Carvallo, 2014; Tan & Floros, 2018). Originally, granger causality was designed for variable pairs within time-series or to cross-sectional analysis, however, it has been modified to incorporate panel dynamics (Greene, 2018). Granger causality identifies gross statistical associations between two variables but does not prove economic causation. When this technique is applied via GMM, often authors (Fiordelisi & Mare, 2014; Tan & Floros, 2018) interpret models that fail autocorrelation stage one or two diagnostic testing, which have to be treated with caution.

The first investigation into the relationship between competition and stability within the banking sector was conducted by Keeley (1990) who found that the US bank failures in the 1980s were a consequence of increased competition. The author suggested that as competition increased the benefits of having a monopoly (monopolistic rents) erode. One consequence of higher competition within the banking sector may be an increase of lower creditworthy loan application approvals as institutions compete for market share, thus deteriorating the quality of banks assets, ultimately increasing fragility. Later, Saunders and Wilson (1996) using similar data provided support to this finding. Contrastingly, using publicly listed thrift (similar to credit unions or mutual savings banks), Brewer and Saidenberg (1996) were the first to find a negative relationship between banking competition and risk (measured by equity volatility) in the US.

5.3.1 Competition-Fragility

The competition-fragility view argues that in more competitive markets banks cannot benefit from monopolistic rents such as more stable deposits and price setting, thus taking excess risk to attract new customers or lower profit margins affecting stability. Leon (2015) suggested this was the case in the context of developing countries as increased competition led to increased loan approval decisions and reduced borrower confidence. Using the H-Statistic to measure of competition, Yeyati and Micco (2007) found that in the 1990's increased bank competition enhanced eight Latin American countries' banks risks (indirectly reducing stability). Also, in the context of developing economies, Turk-Ariss (2010) results show that an increased market power (less competition) leads to higher stability due to enhanced profit efficiency, despite significant cost efficiency losses. Turk-Ariss (2010) also included a quadratic function of the Lerner Index to test for a non-linear relationship, however these results were insignificant.

In a large sample of European listed banks from 2004-2013, Leroy and Lucotte (2017) found using the Lerner index an inverse relationship between competition and stability. They then uniquely, using SRISK (discussed in Section 3.4.2) as a proxy of systemic risk, found the opposite, competition enhances stability due to reduced systemic risk. This finding was due to increased correlation in risk-taking behaviour in less competitive markets (Acharya & Yorulmazer, 2007). Also, within Europe, ownership was seen to interfere with this relationship as Brzoza-Brzezina, Kolasa, and Makarski (2018) showed in a series of experiments that foreign ownership amplifies the impact of shocks on the domestic economy.

Elsewhere, Azar, Raina, and Schmalz (2016) argued that the main driver of competition within the US banking sector arises from the banks owners. It is argued that the larger institutions are all majority owned by the large hedge funds and each other. Figure 5.2 broadly supports this notion, with a number of investment management companies having ownership in all four of the largest US Banks. Further, the banks also have equity stakes in their competitors. Azar et al. (2016) found that within US states where common ownership increased (amongst banks) on average the fees charged by banks for deposit accounts increased and interest rates on savings accounts decreased. Further, the decrease in competition also reduced the banks productivity (lowering efficiency) incentive.

5.3.2 Competition-Stability

This view advocates that increased competition enhances stability. This argument is on the premise that less competitive markets (monopoly/oligopoly) leads to excess risk taking. Institutions within this type of market could be deemed too-big-too-fail, exert moral hazard and/or charge higher loan rates in the expectation of government safety nets if they fail (Mishkin, 1999). Also, Boyd and Nicoló (2005) argue that more competition lowers borrowing rates and government subsidies, promoting better banking risk management and thus increasing stability. In addition, banks tend to invest less in loan applicants screening technology when competition is eroded (Papanikolaou, 2018b).

Within the US mortgage market, Müller and Noth (2018) found that banks

Figure 5.2: The Top 10 Owners of the Top 4 US Banks (2018 Quarter 1)

JPMORGAN CHASE & CO	% Own
Vanguard Group Inc/The	7.57
BlackRock Inc	6.79
State Street Corp	4.68
Capital Group Cos Inc/The	3.34
FMR LLC	2.6
T Rowe Price Group Inc	2.17
Wellington Management Group LLP	1.71
JPMorgan Chase & Co	1.53
Bank of America Corp	1.51
Northern Trust Corp	1.41

BANK OF AMERICA CORP	% Own
Berkshire Hathaway Inc	7.01
Vanguard Group Inc/The	6.72
BlackRock Inc	6.63
State Street Corp	4.21
FMR LLC	3.43
Wellington Management Group LLP	2.11
JPMorgan Chase & Co	1.85
Bank of America Corp	1.55
Dodge & Cox	1.36
Norges Bank	1.12

WELLS FARGO & CO	% Own
Berkshire Hathaway Inc	10.03
Vanguard Group Inc/The	6.72
BlackRock Inc	6
Capital Group Cos Inc/The	5.66
Wells Fargo & Co	4.08
State Street Corp	4.02
FMR LLC	2.75
Dodge & Cox	1.61
T Rowe Price Group Inc	1.36
Franklin Resources Inc	1.25

CITIGROUP INC	% Own
BlackRock Inc	7.35
Vanguard Group Inc/The	7.19
State Street Corp	4.56
FMR LLC	4.19
JPMorgan Chase & Co	1.89
Bank of New York Mellon Corp	1.77
Invesco Ltd	1.66
Harris Associates LP	1.61
Sun Life Financial Inc	1.3
Bank of America Corp	1.28

Source: Adapted from Bloomberg (2018)

with more market power significantly reduced Loan-to-Income ratios which is an indication for safer business[1]. Using a panel of 8,412 commercial banks from a single-state Metropolitan statistical area in the US, Goetz (2018) findings suggest that competition, increases stability, as well as improves bank profitability and asset quality.

In the context of European cooperative banks between 1998 and 2009 using Granger causality testing, Fiordelisi and Mare (2014) found a positive relationship between competition and stability. This relationship was more prominent in homogenous markets. However, evidence regarding concentration and stability was ambiguous. Also within Europe, more cost efficient banks were reported to exhibit higher market power (Delis & Tsionas, 2009). Using a MES and CoVaR as a measure of systemic risk rather than a measure of financial stability, Silva-Buston (2019) results also supported the view that competition increases stability in European banking sector.

In a cross-country study, using the Panzar and Rosse H-Statistic as a measure of competition in 45 countries from 1980 to 2003, Schaeck et al. (2009) found that more competitive banking systems are less prone to instability. Radić, Fiordelisi, Girardone, et al. (2011) investigated 10 developed countries' investment banking sector during 2001 to 2008 and found that the competition-stability paradigm holds and broadly supported that capital requirements reduce risk. In regards to efficiency they found that in general, cost efficiency increases temporally precede increased insolvency risk. Similarly, in the context of Latin American A. Kasman and Carvallo (2014) found higher competition leads to greater stability, however, higher efficiency is associated with increased market power (less competition). From a liquidity risk perspective using commercial bank data from 25 OECD countries during the period 2000 – 2010, J. Kim (2018), found that prior to the financial crisis banks took higher liquidity risks[2] with the aim to enhance market power, thus implying

[1]Higher market power protects their charter value, evidence to support Keeley (1990) charter value paradigm.

[2]Banks transformed towards a more contemporary business model which was more reliant on short-term funding.

competition benefits stability. Liu, Molyneux, and Nguyen (2012) findings from the South East Asian commercial banking sector, suggested that competition does not increase risk-taking, thus supporting the competition-stability view. Further, the authors found that more concentrated markets are safer. Interestingly their regulation variable, an index including, bank activity restrictions, banking entry requirements and diversification opportunities suggested more regulation increased risk taking. Recently, using system GMM on Southeast Asian panel data, Noman, Gee, and Isa (2018) found similarly that competition is associated with greater financial stability due to lower credit risk. In the context of China, Tan and Floros (2018) found that greater competition decreases credit risk and insolvency risk, but increases liquidity risk. Further, Hou, Wang, and Zhang (2014) asserts that intense market competition compels Chinese commercial banks to enhance technical efficiency.

Elsewhere, Fungáčová, Solanko, and Weill (2010) supported the competition-fragility view within Russia during the period 2001 – 2006 and found that the determinants of market power include the role of market concentration and risk. In the Commonwealth Independent States Clark, Radić, and Sharipova (2018) also found that competition enhanced stability (using both NPL and Z-Score). They tried to incorporate a quadratic function of the Lerner index within their main model although the authors do not discuss this quadratic function in their findings, which did suggest a concave relationship at a 10% confidence level.

5.3.3 Non-Linear Relationships

Following a meta-analysis of the bank competition-financial nexus literature, Zigraiova and Havranek (2016) stressed the importance of testing for potential non-linearities which has generally been limited. Martinez-Miera and Repullo (2010) were the first to claim that the relationship between competition and financial stability could be non-linear, because competition can simultaneously cause excess risk taking but also achieve higher capital buffers from larger profit margins. The non-linear relationships tested so far include; a concave (n-shaped) a convex (u-shaped) and a monotonic (positive and negative) relationship, see Figure

5.1 for illustration. A convex relationship suggests that the banking system is stable due to less competition then stability reduces, initially by increased competition, but then returns to stable when competition increases to a certain degree. On the contrary, a concave relationship suggests when competition is low, stability is low (i.e. potentially due to inefficient risk management) and stability is enhanced by increased competition, but in a highly competitive environment stability falls. These relationships could be caused by the banking system taking time to adjust to a new competitive environment (e.g. regulation change to allow foreign banks to enter the market). Another example includes, in a highly competitive banking system, the risk-shifting or spreading effects amongst banks can result in reducing the probability of default and increases bank stability. However, the margin effects of increased competition could lead to reduced loan rates (as well as relaxed credit risk management) therefore lowering revenues and profitability, in turn decreasing stability. Such dynamics/trade-offs can lead to a non-linear relationship between bank competition and stability.

Martinez-Miera and Repullo (2010) evidenced that a non-linear (convex) relationship theoretically exists between the risk of bank failure and market competition. Their model identified that risk-shifting effects (identified by Boyd and Nicoló (2005)) dominate in monopolistic markets whilst marginal effects account for fewer defaults when loan rates decrease in more competitive markets. N. Tarashev, Borio, and Tsatsaronis (2010) argued that there are several factors that contribute to financial institutions' system wide risk, e.g. bank size, institutions' specific probability of default and various risk factors that interact in non-linear fashion. Contrary to other sectors, banks are funded by demand deposits and this motivates several mechanisms of regulatory and legal environments that influence the bank's incentive for efficiency and risk-taking. Using the Spanish banking sector data, Jiménez, Lopez, and Saurina (2013) found a non-linear relationship between market concentration and fragility, but when using the Lerner index as the measure of competition their evidence supported a linear competition-stability view. In Turkey, S. Kasman and Kasman (2015) introduced a quadratic efficiency adjusted competition function into their robustness tests and found that a concave relationship exists for NPL as the dependant variable, however with the Z-Score as the dependent variable the competition-fragility view was found. In a cross-country study of 8,235 banks operating in 23 different developed countries, Berger, Klapper, and Turk-Ariss (2009) included quadratic function of the Lerner index to account for the possible non-linearity competition-stability relationship. Initially they found a concave relationship between competition and stability however, further analysis with the effect of competition on bank capitalisation resulted in no-relationship. Thus, the authors concluded they found support for both the competition-fragility and competition-stability hypotheses.

5.3.4 Relationship between Competition and Concentration

Concentration can also influence stability, it is believed that competition and concentration can co-exist and can cause fragility and stability simultaneously (Berger, Hasan, & Zhou, 2009; Jiménez et al., 2013; Liu, Molyneux, & Wilson, 2013; Martínez-Jaramillo et al., 2010). In investigating this phenomenon Martínez-Jaramillo et al. (2010) found that the risk-shifting effect is more expected in highly concentrated markets, while the margin effect tends to surface in competitive markets. Determining banking system concentration and its significance on a range of factors has been of interest to academics, economist and regulators alike, because it has implications on numerus areas of economics. For example, greater concentration within the banking sector has been associated with: (i) increased barriers to entry for newer organisations and innovative companies (i.e. FinTech) which may undesirably affect economic growth (Canales & Nanda, 2012; Cetorelli & Strahan, 2006; Love & Martínez Pería, 2014); (ii) lower innovation and the adoption of new technologies, (J. Allen, Clark, & Houde, 2008); (iii) it can impede the transmission of monetary policy (Drechsler, Savov, & Schnabl, 2017); (iv) increase social imbalances and criminal active (Beck et al., 2010; Garmaise & Moskowitz, 2006); (v) and adversely affect consumers, via lower savings rates and higher interest rates on consumer loans (Kahn, Pennacchi, & Sopranzetti, 2005).

Literature has sought to understand the relationship between competition and concentration but with conflicting results depending on what methodology was applied. For example, in Europe Bikker and Haaf (2002) found an inverse relationship, i.e. the higher the concentration the lower the competition. Casu and Girardone (2006) concluded that there is no statistical relationship between concentration and competition. Also, according to Hagendorff, Casu, and Girardone (2009) and Claessens and Laeven (2004)[3] concentration is a poor proxy for competition, because they argue concentrated banking systems are not necessarily less competitive than their un-concentrated equivalents. Shaffer (2004) also noted that concentration is a weak proxy for competitive behaviour. Berger, Demirgüç-Kunt, Levine, and Haubrich (2004) identified that market structure cannot accurately explain competition levels. Similarly, Beck, Demirgüç-Kunt, and Levine (2006) study into competition and concentration on stability found that both concentration and competitiveness of the banking system is positively related to stability. This suggests that concentration is an insufficient measure of competitiveness. Bremus (2015) theoretically and empirically, argues that different modes of cross-border banking impact bank concentration and market power differently. Using panel dataset of 18 OECD countries, foreign lending and foreign bank ownership coincides with lower concentration whilst its impact on competition is mixed.

5.3.5 Concentration-Fragility

The concentration-fragility view argues that banking sectors which are dominated by a few larger banks are more prone to instability. Similar to competition-fragility argument this is due to the too-large-too-fail problem. In the US, Dick (2006) noted that banking branch deregulation, which increased concentration at the regional level, increased loan losses hampering stability. Within the EU, Căpraru

[3] Claessens and Laeven (2004) originally provided evidence of a positive and significant relationship between bank concentration CR_5 and competition $P\&RH$, however their robustness analysis proved the opposite, thus the rejection.

and Andrieş (2015) applied GMM to analyse the impact of concentration on stability[4] of 923 commercial banks during the period of 2001 to 2009. Depending on the measure of concentration and group of countries, they found contrasting results. Using CR_5 they found that increased concentration had a negative impact on stability for all Euro zone countries (except for new member states). When using HHI, the concentration-stability view was found for countries outside of the Euro zone and new member states. In another, cross-country analysis De Nicoló, Jalal, and Boyd (2006) found that concentrated banking markets (as measured by HHI) are associated with greater risk of bank failures. They divided their sample into two, (i) a cross section of *circa* 2500 small US banks and (ii) a panel data set of *circa* 2700 banks from 134 non-Western countries. Both samples provided evidence of concentration-fragility. In addition, De Nicoló and Loukoianova (2007) using similar data found this relationship becomes stronger when controlling for bank ownership. In the context of the Asia Pacific region, X. Fu et al. (2014) found that greater concentration fosters financial instability due to low pricing power, which enhances risk-taking exposure, although S.-G. Chan, Koh, Zainir, and Yong (2015) noted that higher bank concentration in Asia reduces commercial banks' efficiency. When comparing systemic resilience of different market structures (Islamic, conventional and conventional with Islamic windows) in six GCC countries via MES, SRISK and CoVaR, Abedifar et al. (2017) identified conventional with Islamic banks as the least resilient due to market synchronicity and interconnectedness. This type of interconnectedness network, hampers stability.

5.3.6 Concentration-Stability

The concentration-stability view argues that more saturated markets spread risk around banks and increase interbank lending networks. Donaldson and Micheler (2018) found that prior to the financial crisis more concentrated credit market

[4]This study claims to investigate the competition stability relationship using concentration measure as a proxy for competition.

networks lead to increased borrowing via non-resaleable debt (a fivefold increase in repo borrowing) enhancing market instability. Beck et al. (2006) examined the effect of market concentration on financial stability using data from 69 countries and provided empirical evidence that increased concentration does not result in increased financial instability within the market, thus confirming the concentration-stability view. In addition, they question the appropriateness of using the three firm concentration ratio ($CR - 3$) as a proxy of competitiveness. Mirzaei, Moore, and Liu (2013) empirically investigated the effect of market structure on both profit and stability which they claimed was a first. They concluded that banking profits in developed countries are generally biased towards the relative market power (RMP) hypothesis, but there was not enough evidence to support this effect in the emerging economies. This bias towards RMP appeared to achieve a systematic stabilising effect within the financial markets. However, they also found a positive correlation between increased market concentration and increased systemic risk in the advanced economies, thus confirming on the contrary the concentration-fragility view. Uhde and Heimeshoff (2009) also confirmed this view using a dataset of more than 2600 credit institutions from 25 EU countries noting more concentrated banking markets also appear to have lower levels of risk. Samad (2008) using a similar OLS methodology to Smirlock (1985) and Lloyd-Williams, Molyneux, and Thornton (1994) for Bangladesh bank data rejected the structure conduct performance (SCP) hypothesis and supports the relative efficiency (ER) hypotheses (concepts discussed in Section 2.2). However, bank specific factors were more consistent in explaining bank performance. The higher the capital and reserves as a percentage of total assets the lower the risk for the bank. Similarly, the higher the amount of loans as a percentage of deposits the higher the risk for the bank. Also in the context of India, Das and Kumbhakar (2016) found that higher levels of concentration allowed larger banks to impose higher prices benefiting from significant market power, in turn being more profitable.

5.3.7 Quiet-Life

Relatively limited studies have sought to identify the quiet-life (QL) hypothesis proposed by Hicks (1935). Such empirical studies aim to identify other risk explanatory variables that impact stability more than competition or market structure. In the context of the US, Berger and Hannan (1998) testing the QL identified welfare losses with banks were more due to ineffciencies relative to those due to market power. In the context of Europe, Maudos and de Guevara (2007) attempted to test the QL hypothesis in line with the approach from Berger and Hannan (1998), however their results showed the existence of a positive relationship between market power and cost X-efficiency. An important contribution within this study was to highlight the requirement to obtain both competition and efficiency measures simultaneously. Recently, using EU data from 1998 to 2014 at both country and bank level, IJtsma et al. (2017) found that concentration hardly affects stability which had not been previously established within this literature, suggesting that both market-driven or regulatory forced consolidation are not likely to alter financial stability. This finding further suggests that neither supervisory restructuring, nor normal market-driven mergers, are likely to be substantially harmful to financial stability. In addition, in the Eurozone, Aparicio et al. (2018) assessed whether charter value is aligned with supervision, they provided additional support for the idea that the relation between risk and charter value is complex, and the relationship is not homogeneous, regardless of the type and level of risk or the period.

5.4 Research Hypotheses

This section outlines the research hypotheses that will be under consideration in this paper. Bearing in mind the identified gaps and inconclusive evidence noted in the empirical literature and the aims of this paper, the aim is to test the following hypotheses:

Hypothesis 6: *The market power paradigm persists.*

This hypothesis suggests that the structure-conduct-performance paradigm (concentrate) and/or the relative market power paradigm (competition) exists, in the context of the US banking sector (See Figure 2.1).

Hypothesis 7: *The efficiency structure paradigm persists.*

This hypothesis suggests that the relative efficiency or scale efficiency paradigm exists in the context of the US banking sector (See Figure 2.1).

The simultaneous rejection of H6 and H7 would support the non-relationship, quiet life hypothesis.

Hypothesis 8: *Increased levels of competition negatively affects financial stability.*

In the context of the US banking sector, this hypothesis would support the competition-fragility view proposed by F. Allen and Gale (2004). The rejection of this hypothesis would support the competition-stability view proposed by Boyd and Nicoló (2005). Note that the rejection of hypothesis 6, would result in the inability to test this hypothesis.

Hypothesis 9: *Increased capital requirement regulation positively affects financial stability.*

This hypothesis suggests that increased capital requirements under the Basel III regulations have a positive impact on financial stability. These capital requirements are discussed further in Section 2.3.1. This hypothesis will be tested using US bank panel data.

Hypothesis 10: *Increased liquidity regulation positively affects financial stability.*

This hypothesis suggests that the newly imposed Basel III regulations for liquidity risk have a positive impact on financial stability. These liquidity requirements are discussed further in Section 2.3.1 and 3.4.3. This hypothesis will be tested using US bank panel data.

Hypothesis 11: *Being named as a SIFI or D-SIB positively affects the institution's financial stability.*

This hypothesis suggests that being a named a SIFI by the FSB or classed as a D-SIB by domestic regulators has a positive impact on an institutions' financial stability. These classifications are discussed further in Section 2.4. This hypothesis will be tested using US bank panel data.

Hypothesis 12: *The use of recently developed models to measure systemic risk provides contrasting results in the competition-stability nexus compared to traditional accounting measures of financial stability.*

This hypothesis suggests that the use of market level measures of systemic risk other than using traditional accounting based measures of stability (such as the Z-Score) alters the competition-stability relationship. Providing evidence to support this hypothesis would support similar findings by Abedifar et al. (2017) and Leroy and Lucotte (2017). This hypothesis will be tested using US bank panel data.

5.5 Methodology

To examine the relationship between banking efficiency, competition, concentration and financial stability, this study uses the following general dynamic regression model:

$$\begin{aligned} Stab_{it} &= \alpha + \beta_1 Stab_{it-1} + \beta_2 Comp_t + \beta_3 Conc_t + \beta_4 EFF_{it} \\ &\quad + \beta_5 BANK_{it} + \delta_1 Profit_{it} + \delta_2 Macro_t + \delta_3 Year_t + \mu_{i,t} \end{aligned} \tag{5.5.1}$$

In equation 5.5.1, β are parameters to be estimated and δ are control variables/parameters to be estimated whilst i and t refers to the individual banks and time in years respectively. $Stab_{it}$ is the dependent variable denoting financial stability for bank i at time t. Following numerous studies (Clark et al., 2018; Noman et al., 2018; Tan & Floros, 2018, *inter alia*), $Stab_{it-1}$, the lagged dependent variable is incorporated to capture the persistence of financial stability. $Comp_t$ and $Conc_t$ are the measured of sector level competition and concentration respectively as discussed in section 5.5.1. EFF_{it} is a vector of efficiency explanatory variables as calculated previously in Section 4.4. $BANK_{it}$ is a vector of bank level variables outlined in Section 5.5.3, this vector incorporates accounting based ratios for risk and regulatory requirements[5]. Most empirical studies that investigated the impact of competition on risk mainly focus on credit risk (Tan & Floros, 2018). Thus, this study will included other types of risk such as diversification and liquidity. Unlike J. R. Barth et al. (2004) and Noman et al. (2018) lagged regulation variables are not used, this is because in this study the regulatory variables are bank level ratios rather than country level dummies or indicators (i.e. new regulations are not felt by institutions until years after implementation). At the bank level the amount of capital held one year will impact the same year's risk level. $Profit_{it}$ is a bank level profitability control variable. $Marco_t$ is a vector of country level macroeconomic control variable and $Year_t$ is a time dummy variable, to capture the effects amongst variables. Further, $\mu_{i,t} = \lambda_i + \varepsilon_{i,t}$, where λ_i is the unobservable individual effects whist $\varepsilon_{i,t}$ is the error term.

In order to identify and capture any non-linear relationships between financial stability and banking competition (Figure 5.1), $(Comp_t)^2$ is incorporated (similar to Berger, Klapper, and Turk-Ariss (2009) and Turk-Ariss (2010)), the cubed effect $(Comp_t)^3$ will also be tested in the case of a monotonic or polynomial relationship, using the following equations:

$$\begin{aligned} Stab_{it} = \alpha + \beta_1 Stab_{it-1} + \beta_2 Comp_t + \beta_3 (Comp_t)^2 + \beta_4 Conc_t \\ + \beta_5 EFF_{it} + \beta_6 BANK_{it} + \delta_1 Profit_{it} + \delta_2 Macro_t + \delta_3 Year_t + \mu_{i,t} \end{aligned} \tag{5.5.2}$$

$$\begin{aligned} Stab_{it} = \alpha + \beta_1 Stab_{it-1} + \beta_2 Comp_t + \beta_3 (Comp_t)^2 + \beta_4 (Comp_t)^3 + \beta_5 Conc_t \\ + \beta_6 EFF_{it} + \beta_7 BANK_{it} + \delta_1 Profit_{it} + \delta_2 Macro_t + \delta_3 Year_t + \mu_{i,t} \end{aligned} \tag{5.5.3}$$

As studies have shown (Berger, Hasan, & Zhou, 2009; Fiordelisi & Mare, 2014; Jiménez et al., 2013; Liu et al., 2012, *inter alia*), the interaction term of competition and concentration ($Comp_t \times Conc_t$) should be included to identify any moderation effects, using the following equation:

[5] According to Pasiouras et al. (2009) regulations must take account of interactions between competition, efficiency and financial stability.

$$Stab_{it} = \alpha + \beta_1 Stab_{it-1} + \beta_2 Comp_t + \beta_3 Conc_t + \beta_4(Comp_t \times Conc_t) + \beta_5 EFF_{it} + \beta_6 BANK_{it} + \delta_1 Profit_{it} + \delta_2 Macro_t + \delta_3 Year_t + \mu_{i,t} \quad (5.5.4)$$

Having a lagged dependent variable ($y_{i,t-1}$) within the equation can be an issue when applying Ordinary Least Squares, as it may be correlated with the fixed effect error term, leading to dynamic panel bias (Nickell, 1981). As an example, if a bank was to experience a large negative unexpected shock to its balance sheet capital (e.g. capital losses from operational risk), say in 2010, that shock would appear in the error term. All else being equal, the apparent fixed effect for that bank for the whole period (the deviation of its average unexplained capital from the sample average) will appear to be lower. In the following substantial years the lags for 2011/12 capital and the fixed effects with both be lower. This positive correlation between a regressor and the error violates the Gauss-Markov (Consistency) assumption for OLS. Thus, the estimates are obtained using the Arellano–Bond (AB) System–GMM method which treats all the explanatory variables as endogenous, following the same rationale and methodology as Section 4.4.5. GMM is preferred in this research area over OLS and 2SLS because it is more efficient at taking account of heteroskedasticity (X. Fu et al., 2014; Hall, 2005). In addition, to allow for non-linear variables to be added to the regression, linear technigues like OLS would be inappropriate, GMM does not assume a linear model as it compares the population moment conditions to the sample moment conditions, thus it does not have to assume linearity (Hall, 2005).

5.5.1 Competition and Concentration Measures

The methodologies to measure the level of competition can be generally divided into two different groups: the structured and non-structured approaches (Liu et al., 2012). The non-structured approach relies on specific bank behaviour and conduct that can influence its peers' competitiveness. The structured approach focuses on the number and size of the banks by way of concentration. Based on the assumption that a small number of larger banks behave in the same way, they therefore become less competitive.

Within the banking competition literature, competition is not directly observed (Tabak, Fazio, & Cajueiro, 2012) it is calculated econometrically. Commonly used techniques include the Lerner Index, adjusted-Lerner Index, Panzar and Rosse H-Statistic and the Boone Index. Alternatively, market concentration can be directly observed by using a Herfindahl-Hirschman Index (HHI) or Concentration Ratio's (Commonly 3 and 5 firm). This section will discuss these measurements and where appropriate will demonstrate their application, starting with the competition measures.

The Lerner index has been widely used by economists since the mid-1930s (Jayakumar et al., 2018) as a measure of competition however, due to the difficulty of measuring marginal cost, it has only been used in banking literature relatively recently. The Lerner index as calculated by following Fernandez de Guevara, Maudos, and Perez (2005) and Fiordelisi and Mare (2014), is defined as the difference between the marginal price and marginal cost divided by the marginal price, as follows:

$$Lerner_{i,t} = \frac{P_{i,t} - mc_{i,t}}{P_{i,t}} \tag{5.5.5}$$

where P is i's price of the output at year t and mc is marginal cost. The increase in the Lerner index indicates a deterioration of the competition. This index takes a value between 0 and 1, where 0 indicated perfect competition and 1 is a monopoly (X. Fu et al., 2014). The price of output TA is calculated as total revenue (interest and non-interest income) divided by total assets:

$$\begin{aligned} lnTC_{i,t} = {} & \alpha_0 + \alpha_1 lnTA + \frac{\alpha_2}{2} lnTA^2 \\ & + \sum_{j=1}^{3} \beta_j lnP_j + \frac{1}{2}\sum_{j=1}^{3}\sum_{k=1}^{3} \delta_{jk} lnP_j lnP_k + \frac{1}{2}\sum_{k=1}^{3} \gamma_j lnTAlnP_j + \tau_1 t + \frac{\tau_2}{2} t^2 \\ & + \tau_3 t \times lnTA + \sum_{k=1}^{3} \psi_j t lnP_j + \varepsilon_{it} \end{aligned} \tag{5.5.6}$$

where $TC_{i,t}$ is the bank's total costs (personnel expenses, other administrative expenses and other operating expenses). As a measure of production (output proxy) total assets (TA) is used. The prices of the production factors (outputs) are as follows: P_1 Price of labour: Personnel expenses/total assets[6]. P_2 Price of capital: Operating costs (except personnel costs)/fixed assets. P_3 Price of deposits: interest expenses/total deposits and money-market funding. t is a time trend capturing the dynamics of the cost function over time, and $\alpha\beta\gamma\delta\tau$ and ψ are coefficients to be estimated. ε_{it} is the error term which comprises of two-components: $\varepsilon_{it} = \upsilon_{it} + \nu_{it}$, ν_{it} is a two-sided error term, and υ_{it} is a one-sided disturbance term representing inefficiency. Marginal cost can be derived from equation 5.5.6 as follows:

$$MC_{i,t} = \frac{TC_{i,t}}{TA_{i,t}}\left[\alpha_1 + \alpha_2 lnTA + \sum_{j=1}^{3}\gamma_j lnP_j + \tau_3 t\right] \tag{5.5.7}$$

$MC_{i,t}$ is substituted into the previous equation to calculate the Lerner index for bank i at time t, thereby providing the dynamic change in market power across banks over time. This measure is based on readily available accounting data and can be interpreted easily. However, this measure does not capture the risk premia within prices of institutions' products and services, thus its positive relationship with the size of monopoly (Berger, Klapper, & Turk-Ariss, 2009). Further, using the translog function (similar to the measure of efficiency, see Section 4.4) the Lerner index assumes both cost and profit efficiency. Koetter, Kolari, and Spierdijk (2012) suggested the estimation of the price-cost margin may be a biased measure and does not correctly measure the true extent of market power, thus advocating an adjusted-Lerner index. They propose a correction in the form of the efficiency-adjusted Lerner index:

$$AdjustedLerner_i = \frac{\pi_i + TC_i - q_i mc_i}{\pi_i + TC_i} \tag{5.5.8}$$

where π is the profit of bank i, TC is the total cost, mc is marginal cost (as previous) and q is the total output.

As efficiency will be an independent variable, the adjusted Lerner Index will not be used within this research to avoid multicollinearity. In order to calculate the Lerner Index for each jurisdiction of Basel, Tables 5.11 and 5.10 in the appedix provide a statistical summary of the data used. There are jurisdictions that do not

[6] Total assets is used an an alternative to the number of employees due to data availability.

appear within this table[7] due to limited data availability. When attempting to calculate their Lerner Index the models were not statistically significant. For the calculation of the Lerner Index of the full sample (including the missing jurisdictions), country dummies were included in order to identify whether they significantly changed the outputs. This may have been expected given the proportion of data coming solely from the US banking sector. This approach was also taken in the calculation of Europe's Lerner Index. Noticeably for many countries the Price of Labour lacked data (especially in Japan) due to the availability of personal expenses data. The timescales were determined based on data availability when calculating the translog cost function for marginal cost. From Table 5.12 and Figure 5.3, it is noticeable that the majority of countries are closer to perfect competition (index of zero) than monopoly. The financial crisis caused a slight reduction in competition (higher Lerner index) in many countries, except from Russia. This may be explained by following the financial crisis and the subsequent drop in oil price and a large number of Russian banks failures (bankruptcy or forced merge) (Zhivaikina & Peresetsky, 2017) ultimately affecting competition levels.

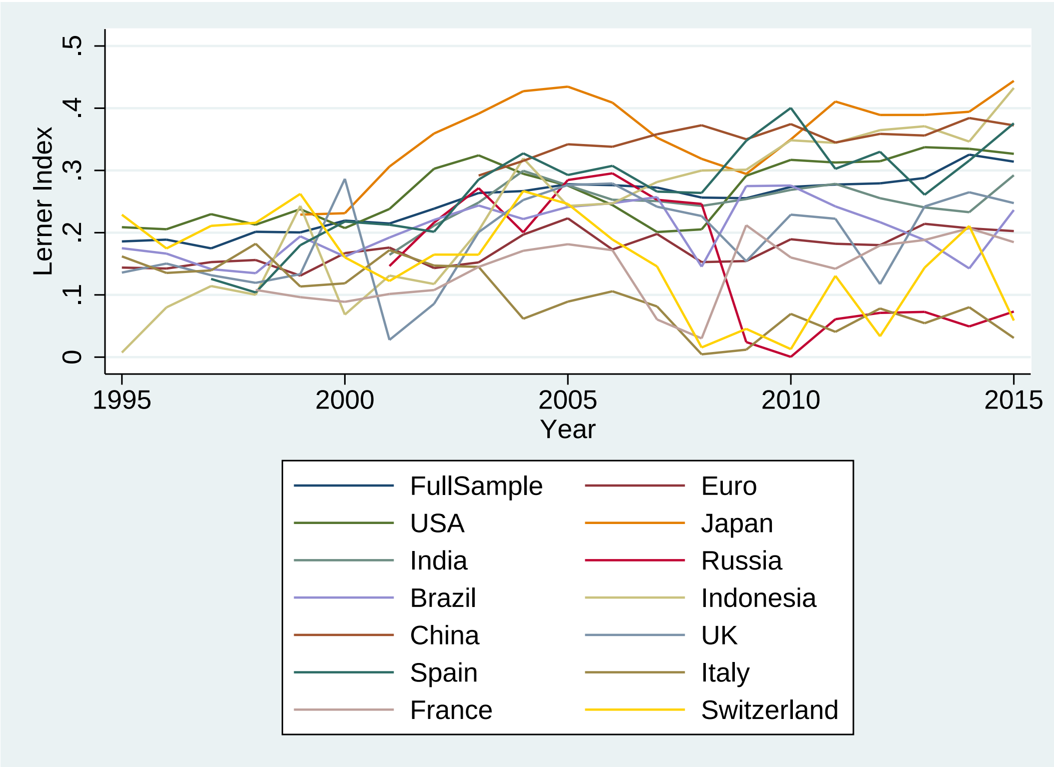
An alternative measure of competition is the Panzar and Rosse (1987) H-Statistic which infers the different degrees of competition within a sector. This measures the sum of the elasticities of institutions revenue with respect to input prices. This reduced-form revenue equation is calculated via

$$H = \sum_{k=1}^{m} \frac{\partial R_i^*}{\partial w_{ki}} \frac{w_{ki}}{R_i^*} \tag{5.5.9}$$

where R_i refers to revenues of bank i (* indicates equilibrium values) and w_i is a vector of m factor input prices of bank i. Market power is measured by the extent to which a change in factor input ∂w_{ki} is reflected in the equilibrium revenues ∂R_i^* earned by bank i. The main drawback of this Herfindahl index is the econometric identification and interpretation, as sometimes higher values does not necessarily

[7] Argentina, Australia, Belgium, Canada, Germany, Hong Kong, Luxembourg, Mexico, Netherlands, Saudi Arabia, Singapore, South Africa, South Korea, Sweden and Turkey.

Figure 5.3: Lerner Index Per Country



imply low market power (Claessens & Laeven, 2004) and that the range of $-\infty < x > 1$ indicates a degree of uncertainty (Van Leuvensteijn, Bikker, Van Rixtel, & Sørensen, 2011). A critical feature of this approach is that it must be conducted in long-run equilibrium (X. Fu et al., 2014) which is not always true due to market entries and exits. A non-structural extension of the H-Statistic in order to include lagged dependent variables (the disequilibrium approach) was proposed by Matousek et al. (2016) following this empirical form:

$$\begin{aligned} lnROA_{i,t} = \beta_0 + \beta_1 lnROA_{i,t-1} + \beta_2 lnPL_{i,t-1} + \beta_3 lnPFC_{i,t-1} \\ + \beta_4 lnPPC_{i,t-1} + \beta_5 lnETA_{i,t} + \beta_6 lnLTD_{i,t} + \beta_7 Year + \varepsilon_{it} \end{aligned} \tag{5.5.10}$$

where the dependant variable $lnROA_{i,t}$ is bank i's revenue in period t, which can be replaced by two further variables, (i) the natural logarithm of revenue $lnREV_{i,t}$ and (ii) the natural logarithm of interest income $lnINT_{i,t}$. Similar to Claessens and Laeven (2004); Gelos and Roldós (2004); Nathan and Neave (1989), $lnROA_{i,t-1}$ is the lagged dependant variable, $lnPL_{i,t-1}$ is the lagged natural log of the price of labour, $lnPFC_{i,t-1}$ is the lagged natural log of the price of financial capital, $lnPPC_{i,t-1}$ is the lagged natural log of the price of physical capital. The following are control variables of size and time, $lnETA_{i,t}$ is the natural log of equity to assets, $lnLTD_{i,t}$ is the natural log of total loans to deposit and $Year$ is the year time dummy. Based upon the disequilibrium approach the H-Statistic that is used to determine the degree of competition is calculated from equation 5.5.10 uses:

$$H = \frac{\beta_2 + \beta_3 + \beta_4}{1 - \beta_1} \tag{5.5.11}$$

where, $H < 0$ indicates a collusive oligopoly or monopoly, in which an increase in costs causes outputs to fall and prices to increase. If firms aim to profit-maximize they must be operating on the price elastic portion of its demand function, if not, total revenue will fall. $H > 1$ indicates perfect competition, in which an increase in costs causes some firm to exit, prices to increase and the revenue of the survivors to increase at the same rate as the increase in costs. $0 < H < 1$ indicates the intermediate case of monopolistic competition in which an increase in costs causes revenues to increase at a rate slower than the rate of increase in cost.

To apply this disequilibrium approach, US banking sector data was employed. Following the approach by Matousek et al. (2016) both different (D) and system (S), One-step (1) and two-step (2) GMM regression was applied (See Tables 5.15 and 5.16 in the appendix). First of all, with any form of regression analysis, Table 5.14 presents the variables correlation matrix. As expected total return and net interest income are highly positively correlated (0.992), but these are both dependent variables and will not feature in the same regression analysis. The independent variables, Price of Labour and Price of Capital are also highly positively correlated (0.979) therefore will be monitored for omissions (by Stata12) during the regressions and the variable inflation factor (VIF) test will be conducted, to assess whether both variables are needed. Table 5.15 contains the GMM H-Statistic output using return on assets (ROA) as the dependent variable, whilst Table 5.16 contains the output when using total return (TR) and net interest income (INT) as the dependent variable. In all cases of the preferred system-GMM[8], model specification did not fit as the number of instruments was greater than number of groups (Roodman, 2009b). Further, in all instances the year 2000 dummy was dropped due to collinearity. For the dependent variables INT both 1D & 2D models were rejected due to the Hansen J statistic being significant at 10% (non-significance, > 0.100, is required). The distance GMM models for both ROA and TR fit, in this case the preferred model is the one which has the lowest standard error on the dependent lag (Matousek et al., 2016), which is ROA (Table 5.15). Further, following the VIF post regression diagnostic testing[9], in the models of TR the VIF for the lagged Price of Labour equalled 19.64 (above 10 therefore should be removed from the model). Thus, the highlighted column in Table 5.15, ROA two-step distance GMM, is the approach is used to calculate the H-Statistic. The H-Statistic value of 0.7613 suggests that over the whole period from 2000 to 2015 the United States banking industry was under monopolistic competition. Figure 5.4 shows the H-Statistic at a yearly level, fluctuates between perfect competition (greater than 1) to monopolistic competition, generally in line with the Lerner Index previously calculated for the US.

The Boone Index (Boone, 2008b) estimates the level of competition by assessing the efficiency and performance relationship, based on the assumption that as industries become more competitive, efficient firms are rewarded whilst inefficient firms are punished (Boone, 2008a). This measures estimates a percentage decrease in profit resulting from a 1% increase in marginal cost. This is determined by the parameter $\left(\vartheta = \dfrac{\vartheta ln\pi_i}{\vartheta lnmc_i}\right)$, given by the following equation:

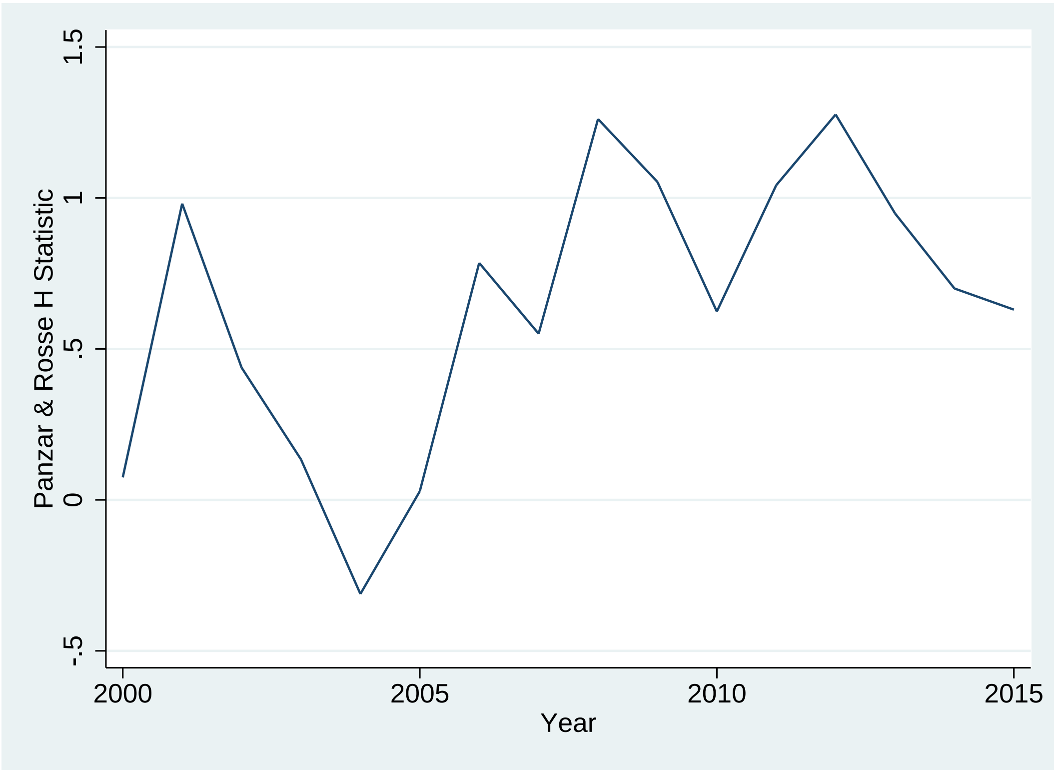
$$ln\pi_i = \alpha + \vartheta lnmc_i \tag{5.5.12}$$

where π is the profit of bank i and mc is marginal cost. The estimated coefficient of ϑ is interpreted as the banks' profit elasticity which is mainly negative, under the assumption that institutions with greater marginal costs lose market share (Boone,

[8]Distance GMM often suffers from weak instruments (Roodman, 2009b).

[9]ROA's average VIF was 5.21 with highest value being 8.4 (for L.lnPL), TR's average VIF was 6.22 with highest value being 19.64 (for L.lnPL) and INT's average VIF was 5.76 with highest value being 9.02 (for L.lnPL).

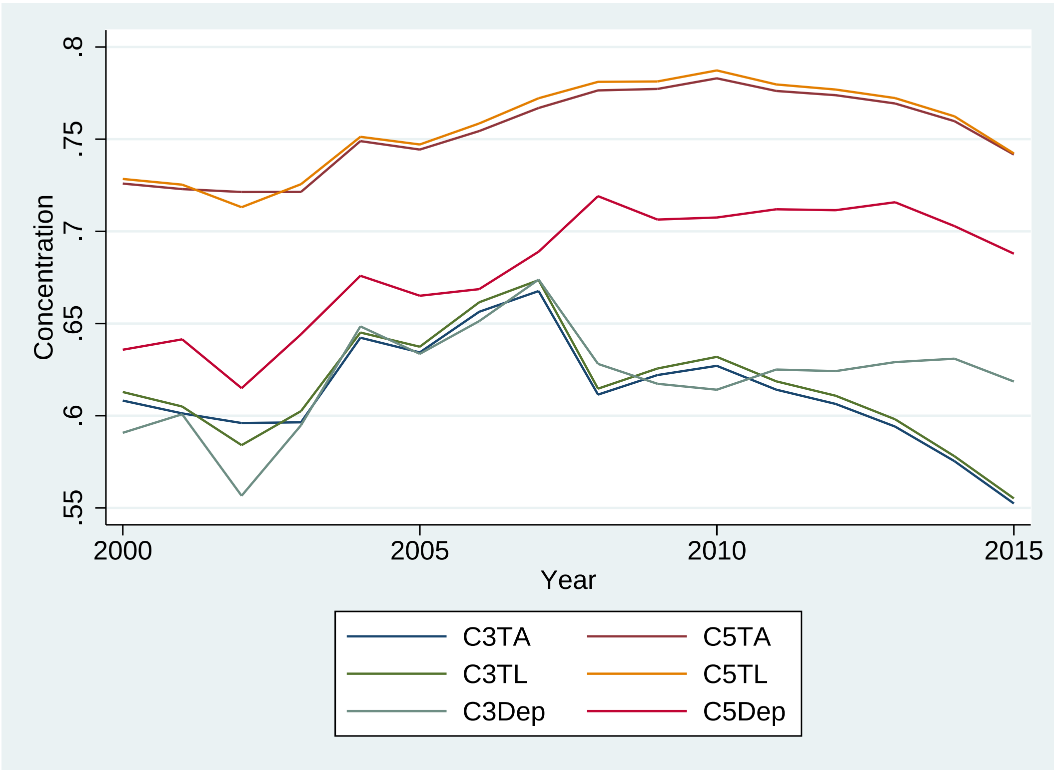
Figure 5.4: US Panzar & Rosse H-Statistic



2008a). Higher competition in the sector results in the value of ϑ becoming more negative (Clerides, Delis, & Kokas, 2015). A positive ϑ suggests that higher marginal costs result in gaining market share, A. Kasman and Carvallo (2014) suggests this would arise in the event of high levels of collusion or banks competing on quality. Unlike the H-Statistic, the Boone indexes are typically monotonically related to competition (Jayakumar et al., 2018) because the association between banking costs and profits are both constant and monotonic. The main drawback of this approach is that its only focus is on one relationship that is exaggerated by levels of competition, thus ignoring other microeconomic or macroeconomic features (J. Q. Jeon & Lim, 2013; Tabak et al., 2012). Similar to the adjusted-Lerner Index, this study will not use this measure due to inclusion of efficiency individuals variables within the regression models. As the Boone Index incorporates efficiency within its calculation and assumptions this could cause moderation effects with the efficiency variable.

To measure the degree of concentration the most commonly used variables are the Herfindahl-Hirschman Index (HHI) and the three or five-bank concentration

Figure 5.5: US Concentration Ratios



ratio (CR_3 and CR_5 respectively). The concentration ratio's are defined as the combined market share in term of assets/loans/deposits (depending on the study) of the three or five largest banks operating within a country. Thus, more concentrated markets are indicated by higher values. This straightforward approach is based on an arbitrary choice of large banks (3 or 5) in respect to the other banks, which ignores the market share of all other banks within that country. Theoretically, Bikker (2004) suggests this may result in two very different market structures having the same concentration ratio.

Figure 5.5 demonstrates the concentration ratios based on US data[10] for three (C3) and five (C5) largest banks based on total assets (TA), total loans (TL) and total deposits (*Deposits*). As expected there is a high correlation between the TA and TL ratio as total loans is a large proportion of assets. Thus, in later analysis

[10]In order to calculate these measures of concentration for the US banking sector a balanced dataset of the 385 banks was obtained from Bloomberg Professional Service. The top 3 and 5 banks were based on market capitalisation as of the 2nd January 2007.

only one of these variables should be used. The first notable element is that all C5's are bigger than C3's indicating that the proportion of assets/loans/deposits is distributed amongst more of the larger banks within the sector. Secondly, the C5's trend is smoother than the C3's, indicating that the former captures a large proportion of the valuable under assessment within the sector. Thus, C5 ratios will be used within later analysis. Finally the concentration of TA/TL is higher than deposits within the US, suggesting that the larger banks, have less deposit relative to loans and that deposits are more distributed across a range of banks within the sector. This would concur with the previous literature regarding leverage and the liquidity risk.

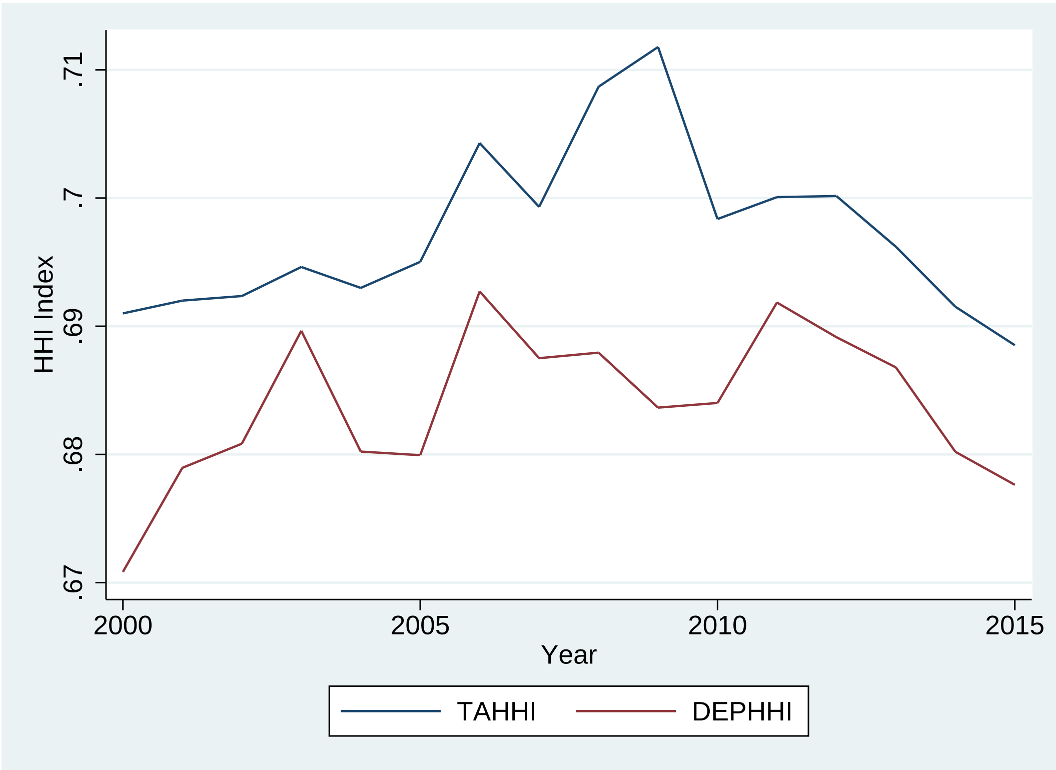
An alternative measure of concentrationis the HHI Index, which does not suffer from an arbitrary cut-off point and is the most commonly used concentration measure in literature and by regulators (Căpraru & Andrieş, 2015; Fiordelisi & Mare, 2014; IJtsma et al., 2017). It is defined as the sum of the squared market share:

$$HHI_t = \sum_{i=1}^{n} MarketShare_{it}^2 \tag{5.5.13}$$

When n is the number of banks in the market and $MarketShare_{it}^2$ is the squared market share of bank i at time t. Again, higher values equal more concentrated markets, however, this measures can be sensitive in the event of increased entries from smaller banks within a short period (Rhoades, 1995). Using the same data as the concentration ratios for the US, Figure 5.6 shows the calculated HHI for total deposits ($Deposits$) and total assets (TA). Compared to the concentration ratios the HHI is a broader measure of concentration as the scores are slightly lower but generally follow the same trend, with increased concentration prior to the crisis then noticeably subsequently drops after 2010. Further, confirming the concentration ratios, HHI index of assets is higher than deposits.

In this paper to measure banking competition, the Lerner index is preferred because it allows for the measurement of each year (rather than pooled) therefore it can be matched with the other country and bank-specific (efficiency and risk) variables within the panel data. Also, as seen with the calculation of P&R H-

Figure 5.6: US Herfindahl-Hirschman Index



Statistic this used Distance-GMM (which can suffer from weak instuments) rather than the preferred System-GMM (Luo et al., 2016; Matousek et al., 2016; Noman et al., 2018). However, P&R H-Statistic will be used for robustness checks as Bolt and Humphrey (2015) warn that measures of competition within the banking sector tend to be uncorrelated, and therefore advocates the use of more than one measure within analysis. Bikker, Shaffer, and Spierdijk (2012) advocated the use of Both HHI and CR_5 (for assets) because each technique slightly differs in approach. HHI results mainly from differences in the number of banks operating in the market whilst CR_5 is determined by the skewness of the size distribution of banks (IJtsma et al., 2017).

5.5.2 Measures of Financial Stability

Within the competition-stability nexus literature the most commonly used accounting based indicator to measure of individual institutions stability is Altman's (1968) Z-Score which was the first multivariate bankruptcy prediction model (A. Kasman & Carvallo, 2014; Laeven & Levine, 2009; Liu et al., 2013;

Mirzaei et al., 2013, *inter alia*). The fundamentals required for this model to be applicable for financial institutions are constructed using proxies, therefore authors have to be conscious of this. Elsewhere in literature following a review of 33 papers, since 2000 on the application of the Z-score, Iwanicz-Drozdowska, Altman, Laitinen, and Suvas (2014) concluded it has been directly applied 16 times, modified 14 times and used three times as a robustness check. Z-Score is calculated using the following equation:

$$Z_{it} = \frac{ROA_{it} + ETA_{it}}{\sigma_{ROA}} \tag{5.5.14}$$

where ROA is return on assets (proxy for performance), ETA denotes the equity to asset ratio (proxy for capitalisation/risk aversion) and σROA is the standard deviation of return on assets. A 3 year rolling time window for σROA is used to allow for variation in the denominator of the Z-score. This variation captures volatility in risk over the last 3 years. This approach avoids that the Z-scores are exclusively driven by variation in the levels of capital and profitability. z is expressed in units of σROA which shows the extent to which earnings can be depleted until the bank has insufficient equity to absorb further losses. Therefore, the lower value of Z implies a greater probability of bankruptcy (Molyneux & Williams, 2013) providing a more direct measure of soundness compared to other measures of risk (Jayakumar et al., 2018). Chiaramonte et al. (2015) investigated the accuracy of the Z-score, as a proxy of bank soundness, on a sample of financial institutions from 12 European countries over the period of 2001 to 2011. Their results indicated that the Z-score performs as well as the CAMELS[11] variables, but it has the advantage of being more parsimonious than the CAMELS models, because it demands less accounting and questionable data (i.e. the covariates to be used in CAMELS related analyses).

The main disadvantage of the Z-Score is that by its nature it does not capture the correlation between other financial institutions as it is purely based on accounting data. On a practical implementation note both Houston, Lin, Lin, and Ma (2010)

[11]This stands for, Capital adequacy, Asset quality, Management, Earnings, Liquidity and Sensitivity to Market Risk.

and Laeven and Levine (2009) support the use of the natural log of the Z-Score over the absolute value due to the latter's skewed distribution. Lepetit and Strobel (2015) tested for this using OECD commercial, cooperative and savings banks data and found that the log Z-Score skewness was much lower than the simple Z-Scores[12]. Alternative accounting based measures for stability include, non-performing loans (NPL) (Berger, Hasan, & Zhou, 2009; Deli, Delis, Hasan, & Liu, 2019; Gadanecz & Jayaram, 2008; Jiménez et al., 2013; Noman et al., 2018). NPL is a proxy as higher NPLs negatively impact profitability and directly relate to the problem of debt extension. However, NPL is only confined to one aspect of the bank's balance sheet and does not fully capture stability (Schaeck & Cihak, 2012). Another alternative is to include the loan loss provisions (LLP). However, both Cummings and Durrani (2016) and Fonseca and Gonzalez (2008) found that the increasing use of LLP data being used in loss modelling resulted in the non-transparent management of loss reserves and income smoothing within financial institutions. In an attempt to prevent this practice in 2014 the International Accounting Standards Board and in 2016 the Financial Accounting Standards Board decided to replace the existing LLP standards to incorporate a more forward looking approach based on expected losses of financial instruments[13] (Krüger, Rösch, & Scheule, 2018). Thus, the use of this variable may provide a mis-leading view of loan quality prior to 2014. Lastly, the use of country level dummy variables representing either bank failure or an outbreak of a systemic banking crisis (Beck et al., 2006; Fungáčová & Weill, 2013) have been used. As these studies makes use of bank level independent data the use of this type of independent variable would not be appropriate for comparison purposes[14].

Table 5.1 is a correlation matrix providing pairwise correlation coefficients of Z-Score versus NPL, LLP and country level measures of systemic risk (calculated

[12]The authors did note that the Z-Score skewness was not an issue in itself, however it could affect regression analysis interpretation.

[13]The International Financial Reporting Standards 9 (IFRS 9) and Generally Accepted Accounting Principles Topic 326 (GAAP 326) thereby contribute to a more adequate recognition of economic values.

[14]The use of time dummies within the GMM regressions will identify whether the crisis periods, had a significant impact on the independent variables.

in Section 3.4) based on US data. This table highlights the disparity between the commonly used measure of financial stability (Z-Score) and the measures of systemic risk. The Z-Score comparison versus aggregated country level systemic risk scores suggest no correlation[15], thus competition levels may influence financial stability and systemic risk differently. Leroy and Lucotte (2017) used the Z-Score and SRISK (another measure of systemic risk) exploring this phenomenon within the competition-stability nexus and noted that having these two different dimensions of risk can provide conflicting results. Noticeably, the Z-Score is also not correlated (also no statistical significance) with NPL and LLP (which are highly correlated with each other). A potential reason for this is that the Z-Scores focus on profitability led stability rather than credit risk and the Z-Score captures three rolling years of data rather than one.

Table 5.1: US Z-Score Cross-correlation with Country Measures of Systemic Risk

Variables	ZScore	NPL	LLP	CISS	Mes	CoVar	DIP	Crisis
ZScore	1.000							
NPL	-0.014	1.000						
	(0.294)							
LLP	-0.014	0.874	1.000					
	(0.225)	(0.000)						
CISS	-0.082	0.039	0.059	1.000				
	(0.000)	(0.002)	(0.000)					
Mes	-0.080	0.055	0.072	0.646	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)				
CoVar	-0.077	0.054	0.067	0.581	0.966	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
DIP	-0.055	0.045	0.063	0.524	0.910	0.864	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Crisis	-0.073	0.032	0.067	0.711	0.629	0.566	0.524	1.000
	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

[15]The signage is negative because lower Z-Score indicates increased default probability whilst higher CoVar, MES, CISS and DIP means higher probability of systemic risk.

5.5.3 Other Bank Level Explanitory Variables

The following independent variables will examine the impact of banking risk characteristics and regulatory variables on financial stability while controlling for profitability and size. See Table 5.2 for a descriptive summary of the variables[16] and table 5.17 in the appendix for a year on year statistical summary.

To assess whether cost efficiency is positively associated with financial stability the variable SFAEFF is included (as calculated in Section 4.4.1). It is assumed that institutions become more cost efficient as a matter of survival, thus being positively related to stability. It may be possible that inefficient banks in certain market structures with low competition are able to survive. In this case the signage would be negative. As an alternative measure of efficiency, ProdGrowth, calculated by DEA (see Section 4.4.2) is also included with an expectation of a positive relationship with stability.

A proxy for diversification (DIV) is the magnitude of non-interest income to operating income, which greatly reflects bank participation to financial markets such as securities trading, asset management services, to name a few. The expected relationship with stability is uncertain. A negative sign may suggest that diversification leads to risk reduction due to increased revenues steams, potentially enhancing profitability thus lower probability of instability. Alternatively, the sign may be positive since a higher dependence from market related income may increase the different types of risk the bank faces, ultimately threatening stability in the event of market downturns. In highlighting the uncertainty regarding the influence of diversification on stability using US bank data, Ly, Liu, and Opong (2018) evidenced that multi-bank holding companies benefited from internal capital markets (diversification) compared to single bank holding companies. However, at the subsidiary level these banks faced higher insolvency risk, the authors suggested this was due to the level of risk taking with the premise of the

[16] All the data used was deflated by their corresponding year's consumer price index (CPI) to the 2000 price levels to control for inflation effects, a similar approach to X. Fu et al. (2014); Hung et al. (2018); Liu et al. (2013); Noman et al. (2018) *inter alia*.

parent's ability to diversify income. Further, diversification can influence liquidity as diversification at the parent holding company level enhances the bank's ability to increase its sourcing of external funds, therefore increasing the ability of the parent company to withstand any liquidity shocks (Khanna & Yafeh, 2005, 2007). Thus, in the regression analysis the interaction between DIV and LIQ will be tested for multicollinearity and moderation effects.

To account for banks asset quality the variable CreditRisk is used. Financial institutions which provide more loans especially in the context of pre-crisis, are expected to incur higher credit risk. For example, Altunbas et al. (2017) identified banks which following aggressive credit expansion policies, with unstable funding in the years before the crisis experienced excessive credit risk during and preceding the crisis. This variable is expected to have an inverse relationship with stability, as higher credit risk would reduce profitability and increase the probability of instability. A similar relationship is expected for leverage (FLVRG) as another proxy for credit risk. As banks become more leveraged in the event of a crisis, such institutions with greater assets than equity could face liquidity and credit risk issues.

The Tier One Capital Ratio (T1CR) is a regulatory variable that is expected to have a positive relationship with stability. As discussed in Section 2.3.1 the Basel regulatory requirements were originally introduced to enhance financial institutions' capital to mitigate the risk of increased non-performing loans or write-downs. For example, Anginer et al. (2018) found that greater capital reduces system-wide fragility as measured by CoVaR and MES (see Section 3.4.2) in their sample of 1735 publicly listed banks from 61 countries. In addition, Berger and Bouwman (2013) suggested that increased capital increased the banks' incentive to engage in more relationship lending which would reduce moral hazard and default probability. In the event of a negative relationship, if increased capital reduced stability, this would suggest that this type of regulation may not be fit for purpose. Also, Northcott (2004) argued that the amount of capital required may prevent new entrants, thus protecting the market power of existing banks, allowing them to benefit from monopolistic rents. However, Hakenes and Schnabel (2011) suggest that the stabilising effect of capital regulation benefits both competitive and non-competitive markets.

A similar regulatory variable included within the regressions is the Tier 1 leverage ratio (T1LVGR) which was introduced by Basel III. This ratio represents the relationship between a bank's tier 1 capital and its total assets. Thus, the ratio uses the bank's core capital to judge how leveraged it is in relation to consolidated assets. Higher ratios increase the likelihood of banks stability during times of stress, therefore the ratio is expected to be positively associated with stability. This regulatory variable to the best of my knowledge has not been tested within the competition and stability nexus literature.

The relationship between financial stability and LIQ is expected to be positive (negative signage). Banks that follow the traditional banking intermediation business model (mainly funding their loan portfolio with its deposits) would be less likely to face stability issues in the event of increase defaults. On the other hand banks relying on short-term funding (i.e. from the money markets) to finance longer-term loans are more exposed to refinancing problems in adverse macroeconomic scenarios. In such circumstances, banks may find difficulty in raising wholesale short-term funds thus increasing probability of instability.

The Net Stable Funding Ratio (NSFR) is regulatory variable which is designed to enhance institutions access to longer term funding in the event of a crisis. The relationship is expected to be positive as institutions' that are able to access funds in times of crisis, should be less likely to suffer instability issues. This variable to the best of my knowledge has not been tested within the competition and stability nexus literature. This ratio as discussed in Section 2.3.1 and 3.4.3 is required to be above 100% to demonstrate the financial institution has sufficient access to longer term funding in the event of a liquidity shortage. NSFR is approximated using equation 5.5.15 (Chiaramonte & Casu, 2017).

$$NSFR = \frac{Equity + \substack{TotalLT \\ Funding} + \left(\substack{Term \\ Customer \\ Deposits} * 0.95\right) + \left(\substack{Current \\ Customer \\ Deposits} * 0.9\right) + \left(\substack{Other \\ Deposits \\ andST \\ Borrowing} * 0.5\right)}{\substack{Other \\ Assets} + \left(\left(\substack{Government \\ Securities} + \substack{OBS \\ Items}\right) * 0.05\right) + \left(\left(\substack{Other \\ Securities} + \substack{Loans \\ and \\ Advances \\ toBanks}\right) * 0.5\right) + \left(\substack{Mortgage \\ Loans} * 0.65\right) + \left(\substack{Retail \\ and \\ Corporate \\ Loans} * 0.85\right)} \geq 100\% \tag{5.5.15}$$

On the contrary, if the NSFR is seen as a burden and requires banks to hold/source more funding which results in lowering profitability this could have unintended consequence on stability.

As a control variable for profitability (ROA) is expected to have a positive relationship with stability given the role of ROA in the calculation of Z-Score. In the event of profitability due to higher credit risk, this could result in lowering stability.

To investigate the role of size (and indirectly enhanced regulation) on stability, the dummy variable SIFI is included as another control variable (only applicable from 2011). This variable to the best of my knowledge has not been tested within the competition and stability nexus literature. As SIFI and D-SIBS are subject to extra regulation (discussed in section 2.4) this variable is expected to have a positive relationship with stability.

Year effects (year dummies, excluding the first year) capture the influence of aggregate (time-series) trends. It allows to control for the exogenous increase in the dependent variable which is not explained by the other variables. For example, the likes of an external shock where its impact is restricted to a given time-period, affecting all panel units that are not controlled by other explanatory variables.

The inclusion of macroeconomic control variables, GDP growth (GDPc) and the inflation rate (INF) is to take into account macro level effects on stability. X. Fu et al. (2014) and C.-C. Lee and Hsieh (2014) suggest the inclusion of GDPc as changes in economics activities (business cycle fluctuations) ultimately affect the performance of financial institutions. Cubillas and González (2014) advocated for the inclusion of INF as measured by the consumer price index as a proxy of macroeconomic instability given its inverse effect on the real economy.

5.6 Financial Stability Findings and Discussion

Table 5.3 is a pairwise correlation matrix of all the US, country and bank level explanatory and control variables. The lagged affect of the dependent variable has a highly positive correlation (0.611) as expected, advocating the use of GMM

Table 5.2: Country Level and Bank Level Exploratory Variables

Symbol	Variable Name	Description	Expected Sign	Authors
Explanatory Variable: measure of competition				
LernerIndex	Lerner Index	Measure of competition	+/−	Berger, Klapper, and Turk-Ariss (2009); Clark et al. (2018); Deli et al. (2019); Fiordelisi and Mare (2014); X. Fu et al. (2014); Jiménez et al. (2013); Silva-Buston (2019)
Explanatory Variable: measure of concentration				
HHiTA	Herfindahl-Hirschman Index	Measure of concentration based on total assets	+/−	De Nicoló et al. (2006); Fiordelisi and Mare (2014); IJtsma et al. (2017); Jiménez et al. (2013)
Explanatory Variable: measures of efficiency				
SFAEFF	Cost Efficiency	Parametric measure of efficiency via Stochastic Frontier analysis (see section 4.4.1)	+	
ProdGrowth	Productivity Growth Efficiency	Non-Parametric measure of efficiency via Data Envelopment Analysis (see section 4.4.2)	+	Tan and Floros (2018)
Bank Level Explanatory Variables				
DIV	Diversification	Proxy for a banks' business model calculated by net non-interest income to net operating income.	−	Amidu and Wolfe (2013)
CreditRisk	Credit Risk	Ratio of Non-performing loans divided by total loans. The higher the ratio, the lower the quality of the loan portfolio.	−	
T1CR	Tier 1 Capital Ratio	The ratio of Tier 1 capital to risk-weighted assets.	+	Berger, Klapper, and Turk-Ariss (2009)
FLVRG	Leverage	Financial Leverage is defined as the ratio of total assets to total common equity. A lower figure represents less leverage	−	
T1FLVRG	Tier 1 Leverage Ratio		+	N/A
LIQ	Liquidity	Liquidity is measured by the ratio of net loans to deposits and short term funding. Lower figure represents higher liquidity	−	Leroy and Lucotte (2017); J. Kim (2018); Liu et al. (2012)
NSFR	Net Stable Funding Ratio	A regulatory ratio to measure long-term funding	+	N/A
Bank Level Control Variables				
ROA	Return on assets	Indicator of how profitable a company is relative to its total assets, as a percentage. Provides an idea how efficient management is at using its assets to generate earnings	+	IJtsma et al. (2017); Jiménez et al. (2013)
SIFI	SIFI Bank	A dummy variable 1= classified as a systemically important institution or a domestically important institution, otherwise 0	+	N/A
Macro-economic Control Variables				
INF	Inflation	Annual inflation rate based on consumer price index	−	C.-C. Lee and Hsieh (2014); Tan and Floros (2018)
GDPc	GDP Change	Annual real GDP growth rate	+	Cubillas and González (2014); Tan and Floros (2018)
Year	Time	Time dummy variable		Fiordelisi and Mare (2014)

rather than OLS regression due to autocorrelation. As a control variable for profitability, ROA has a low 0.365 correlation score against the dependent variable LnZScore. Hartmann et al. (2014) advocate that prior to any analysis, correlation testing for this variable conducted given the role of ROA in within the calculation of the Z-Score. The relationship was expected to be positive as increased profitability should enhance stability (Albertazzi & Gambacorta, 2009; Berger, Hasan, & Zhou, 2009; Mirzaei et al., 2013, *inter alia*). The correlation score between the Lerner Index and HHiTA is 0.369, albeit weakly positive, this relationship suggests that as the Lerner Index increases (less competition), HHiTA increases (more concentration). This concurs with economic theory that monopolies persist in more concentrated markets (Athanasoglou, Brissimis, & Delis, 2008; Berger, 1995; Demsetz, Goldschmid, Mann, & Weston, 1974, *inter alia*). Other noticeable moderate relationships include learnerindex & SFAEFF (-0.540) and LIQ & NSFR (0.537). The former is due to the similar variables used in calculating both techniques. This also confirms that the use of the adjusted-Lerner Index may result in a high correlation with the efficiency measures, thus causing multicollinearity in the regression[17] (Blalock Jr, 1963). The latter is due to both variables measuring liquidity, one from the bank's perspective and the other from a regulatory requirement.

[17]Stata12 omits any independent variables that causes multicollinearity and the VIF averages will be included within the findings tables and any violations (VIF $>$ 10 will be reported).

Table 5.3: US 2000-2015 Correlation Matrix

Variables	LnZScore	L1LnZScore	LernerIndex	HHiTA	SFAEFF	ProdGrowth	DIV	CreditRisk	T1CR	FLVRG	T1LVGR	LIQ	NSFR	ROA
LnZScore	1.000													
L1LnZScore	0.611	1.000												
	(0.000)													
LernerIndex	-0.046	-0.181	1.000											
	(0.000)	(0.000)												
HHiTA	-0.077	-0.013	0.369	1.000										
	(0.000)	(0.343)	(0.000)											
SFAEFF	-0.071	0.021	-0.540	0.350	1.000									
	(0.000)	(0.232)	(0.000)	(0.000)										
ProdGrowth	-0.200	-0.057	-0.124	-0.139	-0.127	1.000								
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)									
DIV	-0.123	-0.037	0.006	-0.004	-0.039	0.012	1.000							
	(0.000)	(0.006)	(0.599)	(0.746)	(0.018)	(0.493)								
CreditRisk	-0.028	-0.046	0.024	-0.003	0.004	0.017	0.001	1.000						
	(0.048)	(0.002)	(0.064)	(0.834)	(0.817)	(0.328)	(0.930)							
T1CR	0.017	-0.010	0.106	-0.041	-0.160	-0.067	-0.011	-0.009	1.000					
	(0.200)	(0.455)	(0.000)	(0.000)	(0.000)	(0.000)	(0.323)	(0.489)						
FLVRG	-0.103	-0.125	0.022	0.017	0.052	-0.007	-0.026	0.017	-0.147	1.000				
	(0.000)	(0.000)	(0.061)	(0.130)	(0.001)	(0.701)	(0.022)	(0.185)	(0.000)					
T1LVGR	-0.008	-0.039	0.017	-0.005	-0.152	-0.013	0.002	-0.001	0.024	-0.005	1.000			
	(0.576)	(0.008)	(0.191)	(0.679)	(0.000)	(0.450)	(0.856)	(0.941)	(0.058)	(0.674)				
LIQ	-0.058	-0.023	-0.133	0.092	-0.012	0.108	-0.012	-0.018	0.014	-0.040	0.014	1.000		
	(0.000)	(0.128)	(0.000)	(0.000)	(0.521)	(0.000)	(0.369)	(0.216)	(0.294)	(0.003)	(0.335)			
NSFR	-0.008	0.006	-0.053	0.043	-0.003	0.070	-0.020	0.013	-0.102	-0.021	0.015	0.537	1.000	
	(0.615)	(0.737)	(0.000)	(0.003)	(0.879)	(0.001)	(0.178)	(0.404)	(0.000)	(0.163)	(0.338)	(0.000)		
ROA	0.365	0.196	0.017	-0.061	-0.251	-0.114	0.031	-0.041	0.052	-0.065	-0.005	0.002	-0.046	1.000
	(0.000)	(0.000)	(0.143)	(0.000)	(0.000)	(0.000)	(0.007)	(0.002)	(0.000)	(0.000)	(0.696)	(0.883)	(0.002)	

First of all, Table 5.4, presents the pool OLS regression (model 1) and fixed effects[18] regression (model 2). These were conducted to ensure that there was a relationship between the explanatory and dependent variable, before conducting GMM. These models both suffer from autocorrelation due to the lag dependent variables, however the VIF test shows no multicollinearity.

Table 5.4: US Bank Pooled and FE, Competition vs Financial Stability 2000-2015

	Pooled OLS (1)		FE (2)	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
L.LnZScore	0.477***	(0.019)	0.332***	(0.021)
LernerIndex	2.982***	(0.817)	1.111	(0.875)
HHiTA	2.218	(4.008)	-2.848	(4.033)
SFAEFF	83.405***	(5.807)	118.778**	(55.901)
ProdGrowth	-0.685	(0.708)	-0.697	(0.812)
DIV	-0.010	(0.007)	-0.014**	(0.007)
CreditRisk	-18.640***	(2.577)	-21.470***	(3.218)
T1CR	0.002	(0.010)	0.001	(0.015)
FLVRG	-0.001*	(0.009)	-0.033**	(0.014)
T1LVGR	-1.479	(1.385)	-0.121	(1.657)
LIQ	-0.247***	(0.188)	-0.059***	(0.299)
NSFR	-0.326***	(0.041)	-0.572***	(0.053)
ROA	0.805***	(0.053)	1.122***	(0.068)
SIFI	-0.050	(0.077)	-0.098*	(0.007)
INF	-0.001	(0.001)	-0.001	(0.002)
GDPc	0.012	(0.020)	0.015	(0.020)
Intercept	71.464*	(43.437)	102.936**	(47.872)
Year Dummies	Yes		Yes	
N	1766		1766	
$\chi^2_{(15)}$	1920.357***			
$F_{(231,1534)}$			97.870***	
R^2	0.523		0.489	
VIF	1.75		1.90	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

[18]Both fixed effects and random effects models were estimated, following the Hausman test (P=0.000), fixed effects was deemed to be the more fitting model.

Table 5.5: US GMM Regression, Competition vs Financial Stability 2000-2015

	(1) Base		(2) Add CR_5		(3) U-Shape		(4) Mono/Poly		(5) Comp*Con	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
L.LnZScore	0.466***	(0.003)	0.476***	(0.003)	0.469***	(0.004)	0.466***	(0.004)	0.473***	(0.004)
LernerIndex	3.764***	(0.130)	2.925***	(0.137)	19.314***	(1.671)	15.773***	(1.977)	-36.613***	(1.786)
LernerIndex2					-29.493	(53.039)	-54.113***	(4.928)		
LernerIndex3							66.308***	(5.166)		
HHiTA	-3.785	(3.779)	-15.999***	(1.629)	3.060***	(0.725)	-14.255***	(1.949)	-72.946***	(3.673)
C5TA			-11.225***	(0.730)	12.152***	(0.650)	-10.785***	(0.990)	-10.852***	(0.802)
CompCon									271.456	(82.383)
SFAEFF	37.224	(21.191)	37.224**	(15.191)	48.802***	(14.735)	38.975***	(14.588)	47.666***	(13.925)
ProdGrowth	-0.529	(0.532)	-0.781	(0.623)	-0.464	(0.529)	-0.640	(0.741)	-0.618	(0.733)
DIV	-0.013**	(0.010)	-0.012***	(0.001)	-0.013*	(0.056)	-0.012***	(0.001)	-0.013	(0.752)
CreditRisk	-19.488***	(0.829)	-21.971***	(0.915)	-20.175***	(0.786)	-22.660***	(0.945)	-23.537***	(0.891)
T1CR	0.026**	(0.009)	0.022***	(0.003)	0.023	(0.114)	0.026***	(0.005)	0.027	(0.205)
FLVRG	-0.031***	(0.001)	-0.028***	(0.001)	-0.031***	(0.001)	-0.032***	(0.001)	-0.031***	(0.001)
T1LVGR	0.474	(0.448)	0.151	(0.397)	0.015	(0.477)	0.311	(0.523)	0.614	(0.468)
LIQ	-0.364***	(0.041)	-0.291***	(0.049)	-0.306***	(0.040)	-0.266***	(0.044)	-0.239***	(0.045)
NSFR	-0.278***	(0.038)	-0.325***	(0.065)	-0.385***	(0.069)	-0.337***	(0.047)	-0.372***	(0.043)
ROA	0.978***	(0.011)	0.968***	(0.008)	0.975***	(0.012)	0.966***	(0.010)	0.960***	(0.011)
SIFI	-0.047	(0.079)	-0.071	(0.057)	-0.099	(0.076)	-0.105	(0.158)	-0.001	(0.752)
INF	-0.002***	(0.000)	-0.006***	(0.001)	-0.004***	(0.000)	-0.004***	(0.001)	-0.005***	(0.000)
GDPc	0.018***	(0.005)	0.023***	(0.005)	0.024***	(0.005)	0.036***	(0.005)	0.024***	(0.005)
Intercept	-31.230*	(13.068)	-2.637***	(0.280)	-43.479***	(12.716)	-49.458***	(12.889)	-29.012*	(11.834)
Year Dummy	Yes		Yes		Yes		Yes		Yes	
N	1766		1766		1766		1766		1766	
Groups	316		316		316		316		316	
Instruments	217		217		217		217		217	
AR(1)(p-value)	0.000		0.000		0.000		0.000		0.000	
AR(2)(p-value)	0.83		0.264		0.069		0.145		0.075	
Hansen (p-value)	0.657		0.801		0.489		0.356		0.478	
VIF	1.83		3.27		6.37(R)		1.31		15.5(R)	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 5.5 reports the system GMM estimation of equations 5.5.1 to 5.5.4. The bottom of the table presents the pre-and post diagnostics tests for the GMM specification, using the dependent variable of $LnZScore$ as a proxy for stability in models 1 to 5. Model 1 is the baseline with only one measure of concentration (same as the pooled OLS and FE estimation in Table 5.4) . Model 2 adds CR_5 following Bikker et al. (2012) suggestion of applying two types of concentration measure. Model 3 represents 5.5.2, adds a quadratic function to test for a concave/convex relationship between banking competition and stability. Model 4 further introduces a cubic function to identify any monotonic/polynomial relationship. Finally, model 5 introduces a moderating variable of competition multiplied by concentration (Equation 5.5.4) to assess whether the interaction of the competition and concentration impacts stability. From the regression diagnostics, all the Sargan and Hansen tests' null hypothesis of over-identifying restrictions (i.e. the instruments as a group are exogenous) are not rejected (Hansen test's p -value greater than 0.100). AB test for null hypothesis of no first order autocorrelation (AR(1)) in first differences is rejected (all 0.000); but AB test for null hypothesis of no first order autocorrelation in levels (AR(2)) is not rejected (all above 0.100, except model 3).

Firstly, the baseline specification (model 1) fits, however the variable for concentration (HHiTA) is not significant, with the introduction of the five bank concentration ratio (model 2) both become significant and do not alter any other variable's signage or significance. Model 2 provides evidence for both a competition and concentration fragility relationship. However, to confirm a linear relationship exists, any non-linear relationship most be discounted. In model 3, the equation itself only fits at 10% level for AR(2) and when conducting the variance inflation factor (VIF) both LearnerIndex and LearnerIndex2 variables VIF score was greater than 10, thus suffering from multicollinearity and should be removed from the regression (ultimately rejecting a u/n-shape non-linear relationship). With the introduction of a cubic function in model 4, this provides similar results to model 2 with the linear, quadratic and cubic functions of competition all being significant which suggests a monotonic/polynomial relationship. Finally, in attempting to identify any moderation effects between competition and concentration the variable CompCon was added to model 2 which resulted in model 5 only fitting at 10% level for AR(2) and an average of VIF greater than 10, thus rejecting the model.

The following interpretation of the explanatory variables is from model 4 in Table 5.5. This shows that the Lerner Index is positively polynomial[19] and significant relative to lnZScore[20] as well as both measures of concentration coefficients being negative[21]. This finding suggests that competition-fragility and concentration-fragility can co-exist (a neutral view of the competition stability nexus, X. Fu et al. (2014) found similar). Thus, having lower pricing power (Brewer & Saidenberg, 1996) and excessive concentration (De Nicoló et al., 2006; Dick, 2006) can simultaneously lead to financial fragility in the US. Regarding efficiency, cost efficiency (SFAEFF) as expected positively influences stability, thus advocating the assumption used in Chapter 3, of calculating cost efficiency rather than profit efficiency. On the other hand, productivity growth was non-significant related to stability.

Regarding the risk explanatory variables, diversification has a significant negative sign which suggests that increased diversity (higher DIV) negatively affects stability. This may be due to the increased activity away from the traditional role of a bank and an intermediator results in excess risk, further, as institutions engage in more market based activities (e.g. proprietor trading) this changes the types of risk they face. CreditRisk, as expected, provides a negative significant relationship with stability, thus confirming, increased non-performing loans relative to total loans impact profitability and then stability. In addition, increased leverage (FLVRG) and lower liquidity (LIQ) both negatively impact financial stability. Again this was expected, for example if financial institutions

[19] The linear LernerIndex is positive, the quadratic is negative and cubic is positive again, which suggests a change (a kink) in the direction of the relationship.

[20] A greater Lerner index value equals less competition (Monopoly=1) this finding suggests an increase in Lerner Index enhances Z-Score.

[21] Higher HHiTA or CR5 equal more concentration.

become more leveraged they may face higher liquidity issues if counterparts trigger a run on their assets, which would increase the likelihood of instability. When observing the regulatory explanatory variables of T1LVGR and SIFI they were non-significant. From observing Table 5.17 the former may be due to this variable consistently being higher than the 3% requirement from Basel III. From the statistical summary, the lowest average Tier 1 Leverage Ratio was in 2000 (author calculated) at 8% with a low standard deviation. Over the years to 2015 the average trend is an overall increase in this ratio, unlike the fluctuating trend of the Z-Score. Further, in the pairwise correlation matrix (Table 5.3) this variable is uncorrelated with the majority of other variables (ranging from -0.152 to 0.024). The latter may be due to only coming into effect since 2011 so this dummy variables is only relevant for a third of the full sample time-scale[22]. The Tier 1 Capital Ratio is positively associated with financial stability, thus providing evidence that this regulatory requirement is justified. In a cross-country study, (Berger, Klapper, & Turk-Ariss, 2009) similarly found that competition-fragility hypothesis exists due to riskier loan portfolios, but this is partially offset by higher capital ratios. These findings are also similar to Klomp and De Haan (2015) who found that stricter capital regulation enhanced the banks' Z-Scores. In addition Kapan and Minoiu (2018) also found similar in the US with evidence to support the idea that higher capitalised banks were able to maintain credit supply when faced with liquidity shocks during the crisis. Elsewhere in the context of Australia, Bui, Scheule, and Wu (2017) found that a moderate increase in bank capitalisation is sufficient to maintain financial system resilience, even after taking economic downturns into consideration. Contrasting this positive regulatory requirement finding, the NSFR is statistically negatively associated with financial stability which contrasts Klomp and De Haan (2015) finding that liquidity restrictions have most positive effect on stability for commercial banks. This liquidity requirement is to ensure that financial institutions have access to longer term stable funding in the event of a crisis. Nevertheless, this result suggests that there may be an

[22]There were also no significant changes in the year time dummies 2011 to 2015, suggesting the insignificance of this variable.

unintended negative consequence on profitability (Wei et al., 2017), due to higher funding costs, which affects stability. Also, Schmitz and Hesse (2014) noted banks tend to hold on to liquidity during periods of systemic uncertainty, increasing costs for banks seeking more stable funding. Another potential reason may arise from the banks changing their funding habits if they require a certain types of funding. For example, Donaldson and Micheler (2018) argue that if banks increased non-resaleable debt (repos) as a source of funding it could create new credit networks[23] which can act as a source of systemic risk i.e. a bank's default will impact its counterpart creditor and that creditors' creditors. In addition, when controlling for regulatory conditions within the GMM regression this decreases the reported estimates, thus supporting the notion that banking systems with more activity restrictions are more likely to suffer from systemic financial distress (Beck et al., 2006).

5.6.1 Robustness Checks

To address any possibility of endogeneity extra control variables were added to model 4 from Table 5.5 to observe any changes. These robustness checks are presented in Table 5.7 and they are quantitatively similar to the baseline specification. In addition table 5.6 presents a dynamic panel autoregressive model using fixed effects, which provides similar results to the GMM specifications. The values of the modified Durbin-Watson statistic and Baltagi-Wu LBI-statistic indicates no autocorrelation (the values can be between 0 and 4). For these two statistics, p-values are not reported (Born & Breitung, 2016). Bhargava, Franzini, and Narendranathan (1982) published critical values for their statistic, but no tables are available for the Baltagi–Wu (LBI). Baltagi and Wu (1999) did derive a normalized version of their statistic, but this statistic cannot be computed for datasets of moderate/large size.

Four different strategies were tested, model 2 uses the P& R H-Statistic

[23] If a bank makes a loan via non-resaleable debt and needs liquidity, it cannot sell the loan but must borrow via a new contract.

(disequilibrium approach) as a measure of competition rather than the Lerner Index (De Nicoló et al., 2006; Moch, 2013; Noman et al., 2018; Schaeck et al., 2009), model 3 incorporates an accounting based measure of cost efficiency, model 4 includes additional profitability control variables and model 5 accounts for ownership and size. Finally, all additional variables were added within the same regression (except for PRH due to multicollinearity)[24]. First, the models with extra control variables fit the GMM specifications, albeit model 3 which is only significant to 10% in the second order of autocorrelation. The first strategy to ensure this relationship between competition and stability is consistent when applying another type of competition measure. When applying the P& R H-Statistic as an alternative measure of competition this also provides a polynomial competition fragility relationship[25]. The only noticeable difference within model 2 is the change in signage for cost efficiency (SFAEFF), this may be due to the way the efficiency measure is calculated which uses similar data and approach to the calculation of the Lerner Index but not similar to the P& R H-Statistic calculation. The P&R H-Statistic was not used within the original model (Table 5.5) due to data limitations when calculating this measure of competition (unbalanced data), which may have affected the GMM results. For model 3, the ideal test to incorporate further efficiency measures would have been to use the efficiency-adjusted measures of competition (adjusted-Learner or the boone indicator). However as expected when attempting to include the adjusted-Lerner Index as another alternative measure for competition, these variables and the efficiency variables were omitted due to multicollinearity. Thus, the cost to income accounting-based efficiency ratio (C.-C. Lee & Hsieh, 2014) was incorporated instead which did not alter the baseline. Another strategy was to corporate profitability ratios (ROE and TobinQ) which are not used in the

[24]This result is not presented within this table due to size constraints, however this model was also quantitatively similar to the baseline model.

[25]Note the signage is the opposite to LernerIndex (i.e. Linear=negative, quadratic=positive, cubic=negative) this is because the higher the P& R H-Statistic the greater competition (the Lerner Index is the opposite).

calculation of the Z-Score, again these did not alter the baseline model except from increasing the lagged affects coefficient value. Finally, extra control variables for foreign ownership (Berger, Hasan, & Zhou, 2009; De Nicoló & Loukoianova, 2007; Noman et al., 2018; Schaeck et al., 2009) and size (Berger, Klapper, & Turk-Ariss, 2009; Clark et al., 2018; X. Fu et al., 2014; Tabak et al., 2012) were included. Similarly this did not alter the baseline model, noticeably, both variables for size where statistically negatively related to stability, like diversification this suggests that the larger the bank is, the greater the risk of instability.

Table 5.6: Robustness US Dynamic Panel Autoregressive Model 2000-2015

Variable	**Coefficient**	**(Std. Err.)**
L.LnZScore	0.073***	(0.025)
LernerIndex	83.525***	(6.375)
LernerIndex2	-64.717**	(37.861)
LernerIndex3	92.390**	(48.353)
HHiTA	-13.112**	(8.539)
C5TA	-7.440**	(4.303)
SFAEFF	18.302**	(8.987)
ProdGrowth	-0.322	(0.127)
DIV	0.017**	(0.007)
CreditRisk	-25.592***	(3.941)
T1CR	0.016*	(0.017)
FLVRG	-0.052***	(0.017)
T1LVGR	0.826	(2.036)
LIQ	-0.185***	(0.007)
NSFR	-0.730***	(0.024)
ROA	1.264*	(0.076)
SIFI	-0.054	(0.077)
INF	-0.007***	(0.004)
GDPc	0.066***	(0.019)
Intercept	2.570***	(0.242)

N	1549
Modified Bhargava et al. Durbin-Watson	1.701
Baltagi-Wu LBI test for autocorrelation	2.016
$F_{(224,1324)}$	47.577***

Significance levels : $*$: 10% $**$: 5% $***$: 1%

Table 5.7: Robustness GMM Regression, Competition vs Financial Stability 2000-2015

	(1) Baseline		(2) P&R H		(3) EFF		(4) Profit		(5) Ownership and Size	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
L.LnZScore	0.466***	(0.004)	0.464***	(0.003)	0.476***	(0.004)	0.504***	(0.005)	0.465***	(0.005)
LernerIndex	15.773***	(1.977)			9.116***	(2.124)	22.571***	(1.772)	16.529***	(12.753)
LernerIndex2	-54.113***	(4.928)			-10.452***	(3.936)	-36.309***	(3.258)	-55.866***	(47.769)
LernerIndex3	66.308***	(5.166)			15.245***	(1.020)	46.308***	(5.166)	65.578***	(59.272)
PRH			-0.193***	(0.021)						
PRH2			0.643***	(0.037)						
PRH3			-0.519***	(0.026)						
HHiTA	-14.255***	(1.949)	-25.675**	(3.639)	-2.514	(2.215)	-9.942***	(1.481)	-13.472***	(2.149)
C5TA	-10.785***	(0.990)	-11.678**	(2.705)	-4.464***	(1.173)	-7.060*	(0.780)	-9.568**	(1.075)
SFAEFF	38.975***	(14.588)	-135.015***	(15.645)	12.574*	(4.588)	21.054***	(9.547)	84.295**	(14.558)
CIR					-0.009*	(0.001)				
ProdGrowth	-0.640	(0.741)	-0.886	(0.441)	-0.659	(0.734)	-0.615	(0.823)	-0.635***	(0.035)
DIV	-0.012***	(0.001)	-0.015*	(0.105)	0.021***	(0.001)	-0.022***	(0.001)	-0.010*	(0.001)
CreditRisk	-22.660***	(0.945)	-20.559***	(0.770)	-21.321***	(0.824)	-21.055***	(1.156)	-20.835***	(0.874)
T1CR	0.026***	(0.005)	0.022***	(0.003)	0.021***	(0.004)	0.014**	(0.004)	0.038***	(0.004)
FLVRG	-0.032***	(0.001)	-0.033***	(0.001)	-0.021***	(0.002)	-0.144***	(0.002)	-0.045***	(0.002)
T1LVGR	0.311	(0.523)	0.116	(0.342)	0.078	(0.476)	7.082	(4.573)	0.140	(0.517)
LIQ	-0.266***	(0.044)	-0.421***	(0.052)	-0.327***	(0.082)	-0.061**	(0.072)	-0.745***	(0.141)
NSFR	-0.337***	(0.047)	-0.219*	(0.095)	-0.761***	(0.080)	-0.380***	(0.099)	-1.291**	(0.110)
ROA	0.966***	(0.010)	0.972***	(0.010)	0.877***	(0.013)	1.080***	(0.025)	1.018***	(0.018)
ROE							0.008***	(0.001)		
TobinQ							0.047	(0.001)		
Foreign									-0.052	(0.247)
LnASize									-0.794***	(0.107)
LnLSize									-0.693***	(0.109)
SIFI	-0.105	(0.158)	-0.214	(0.555)	-0.975	(0.485)	-0.005	(0.758)	-0.145	(0.254)
INF	-0.004***	(0.001)	-0.008***	(0.001)	0.001	(0.001)	-0.002***	(0.001)	-0.002**	(0.001)
GDPc	0.036***	(0.005)	0.061***	(0.007)	0.024***	(0.002)	0.025***	(0.004)	0.031***	(0.006)
Intercept	-49.458***	(12.889)	-114.753***	(13.477)	-1.203***	(0.454)	-5.158***	(0.356)	-84.910***	(12.373)
Year Dummy	Yes		Yes		Yes		Yes		Yes	
N	1766		1766		1766		1652		1754	
Groups	316		316		316		301		310	
Instruments	217		217		224		235		226	
AR(1)(p-value)	0.000		0.000		0.000		0.000		0.000	
AR(2)(p-value)	0.145		0.120		0.059		0.268		0.186	
Hansen (p-value)	0.356		0.176		0.231		0.256		0.156	
VIF	1.31		1.16		4.51		2.98		2.01	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

5.6.2 Financial Stability vs Systemic Risk

Table 5.8 assesses the competition-stability nexus using measures of systemic risk rather than financial stability. Model 1 is the baseline model identified in Table 5.5 with Z-Score as the dependent variable. Model 2 applies non-performing loans as a dependent variable as another proxy of financial stability. CoVaR[26], CISS and DIP are the dependent variables of systemic risk within model 3, 4 and 5 respectively. Firstly, models 2, 3 and 5, either failed the pre or post-regression diagnostics (1st/2nd order autocorrelation or Hansen test) thus, interpreting them would be misleading. CISS (model 4) as a dependent variable for systemic risk provided a number of statistically reliable models using GMM. Initially, CISS provided evidence supporting a competition-fragility relationship between systemic risk and competition, but not a polynomial/monotonic relationship due to limited statistical significance on the cubic and quadratic functions of Lerner. However, model 4 presents the final model for CISS which advocates a concave[27] relationship between systemic risk and competition within the US. This finding suggests when competition is low (monopoly) systemic risk is high, as competition increases systemic risk reduces however, when competition gets close to perfect competition systemic risk increases again. Similar to Leroy and Lucotte (2017), by comparing both financial stability and systemic risk independent variables, contrasting results are evidenced. Both models 1 and 4, suggests perfect competition results in increased financially fragility (low financial stability and high systemic risk) however, in the case of monopoly the results contrast (high financial stability but high systemic risk). Noticeably both models also suggest a change in direction between monopoly and perfect competition, with Z-Score being polynomial and CISS being a concave relationship. In addition, both models advocate the concentration-fragility relationship in the US.

[26]MES was applied as an independent variable too, however its results were very similar results of CoVaR, given their very high positive correlation noted in Table 5.1. Silva-Buston (2019) had a similar issue, but in their study they preferred the use of MES due to statistical significance.

[27]Mathematically $y = -x + x^2$ is a convex shape, however the interpretation of the Lerner index is the opposite, higher the score means lower competition.

Table 5.8: US GMM Regression, Competition vs Systemic Risk 2000-2015

	(1) Baseline		(2) NPL		(3) CoVaR		(4) CISS		(5) DIP	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
L.LnZScore	0.466***	(0.004)								
L.NPL			0.851***	(0.011)						
L.CoVar					0.385***	(0.010)				
L.CISS							0.365***	(0.029)		
L.DIP									0.053***	(0.008)
LernerIndex	15.773***	(1.977)	-62700.819	(70538.829)	-5.429***	(0.241)	-7.494***	(0.663)	-1.840***	(0.128)
LernerIndex2	-54.113***	(4.928)	243745.354	(265433.455)	21.605***	(0.907)	13.651***	(1.213)	8.336***	(0.480)
LernerIndex3	66.308***	(5.166)	-319992.753	(328742.026)	-28.119***	(1.121)			-11.837***	(0.595)
HHiTA	-14.255***	(1.949)	1327.207	(7164.833)	0.304***	(0.028)	8.977***	(0.578)	0.491***	(0.014)
C5TA	-10.785***	(0.990)	-1404.788	(3509.189)	-0.374***	(0.016)	9.295***	(0.328)	-0.180***	(0.008)
SFAEFF	38.975***	(14.588)	-149737.843**	(63099.752)	-1.061***	(0.227)	-7.568	(5.095)	-1.683***	(0.121)
ProdGrowth	-0.640	(0.741)	-318.486**	(124.094)	0.007***	(0.000)	0.235	(0.120)	0.002***	(0.000)
DIV	-0.012***	(0.001)	30.070***	(7.189)	0.049*	(0.027)	0.002	(0.001)	0.003***	(0.001)
CreditRisk	-22.660***	(0.945)	5036.832**	(2352.252)	0.030***	(0.008)	0.685***	(0.189)	-0.005	(0.004)
T1CR	0.026***	(0.005)	-39.136**	(15.738)	0.012	(0.006)	-0.002	(0.001)	-0.001***	(0.003)
FLVRG	-0.032***	(0.001)	8.186*	(4.351)	0.017	(0.002)	-0.004	(0.035)	0.03	(0.085)
T1LVGR	0.311	(0.523)	1773.579	(2033.690)	-0.003	(0.007)	0.090	(0.167)	0.012***	(0.004)
LIQ	-0.266***	(0.044)	167.704	(264.953)	-0.001	(0.001)	0.001	(0.023)	-0.001*	(0.001)
NSFR	-0.337***	(0.047)	-3295.576***	(343.237)	-0.002	(0.001)	0.115***	(0.030)	0.008	(0.068)
ROA	0.966***	(0.010)	-15.257	(24.894)	0.003***	(0.008)	-0.005**	(0.002)	-0.004***	(0.001)
SIFI	-0.105	(0.158)	25.044	(8.254)	0.004*	(0.001)	0.024	(0.087)	0.003	(0.085)
INF	-0.004***	(0.001)	1.720	(3.129)	0.003***	(0.001)	-0.005***	(0.000)	0.006***	(0.001)
GDPc	0.036***	(0.005)	-89.261***	(14.770)	-0.006***	(0.000)	-0.041***	(0.002)	-0.004***	(0.000)
Intercept	-49.458***	(12.889)	137402.819**	(53429.707)	1.544***	(0.192)	2.661***	(4.350)	1.597***	(0.103)
Year Dummy	Yes		Yes		Yes		Yes		Yes	
N	1766		1930		2027		2027		2027	
Groups	316		316		287		287		287	
Instruments	217		218		218		212		218	
AR(1)(p-value)	0.000		0.000		0.000		0.000		0.000	
AR(2)(p-value)	0.145		0.000(R)		0.050(R)		0.403		0.397	
Hansen (p-value)	0.356		0.982		0.066(R)		0.362		0.000(R)	
VIF	1.31		8.26		4.28		5.16		3.68	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

5.6.3 Other Countries' Results

In order to assess the banking competition-stability nexus for the other Basel jurisdictions, various connotations of equation 5.5.1 were applied to the different countries, panel datasets, without the risk and regulatory explanatory variables due to data availability. For countries where cost efficiency and productivity growth was not calculated (in Section 4.4) the cost to income ratio was included as a proxy for cost efficiency. Table 5.9 presents the final models for each country which produced a statistically sound model[28].

In summary, linear competition-fragility was found within the Indian (model 2) and European[29] (model 5) banking sectors. Due to the heterogeneous nature of different banking sectors, cross-country study comparisons should be treated with caution. For example, comparing model 5 with the previous finding from the US would be inappropriate. Further, Feng and Wang (2018) found that European banks have lower profitability compared to US banks due to lower returns on earnings assets, higher funding costs, and lower scale efficiency. Thus, the dynamics of profitability and stability in Europe would be very different than the US banking sector. Non-linear relationships were found within the Japanese (model 1) and Russian (model 4) banking sectors which were found to have a concave (n-shaped) relationship between banking competition and financial stability whilst the Indonesian banking sector (model 3) was found to have a convex (u-shape) relationship. In addition, all models suggest a concentration-fragility relationship and that cost efficiency enhances financial stability. For the sectors where a linear relationship of banking competition and financial stability was found both were tested for a monotonic/polynomial relationship however, both models with the quadratic and cubic added failed the

[28]The Basel jurisdictions which did not produce individual results include: Argentina, Australia, Belgium, Brazil, Canada, China, France, Germany, Hong Kong, Italy, South Korea, Luxembourg, Mexico, Saudi Arabia, Singapore, South Africa, Spain, Sweden, Switzerland, The Netherlands, Turkey and the United Kingdom.

[29]The calculation for Europe includes the following countries: Belgium, France, Germany, Italy, Luxembourg, Spain, Sweden, Switzerland, The Netherlands and the United Kingdom.

Hanson J test (0.000). Within the model for Europe, country dummies were added similar to Beck et al. (2006); Schaeck et al. (2009); IJtsma et al. (2017) to account for specific country heterogeneous factors as Bos, Koetter, Kolari, and Kool (2009) warned that failure to account adequately for heterogeneity can distort the regression measures.

Table 5.9: Other Country GMM Regression, Competition vs Financial Stability 2000-2015

	(1)Japan		(2) India		(3) Indonesia		(4) Russia		(5) Europe	
Variable	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**	**Coefficient**	**(Std. Err.)**
L.LnZScore	0.563***	(0.019)	0.442***	(0.033)	0.457***	(0.017)	0.215***	(0.009)	0.569***	(0.023)
LernerIndex	78.131***	(8.154)	203.454***	(28.565)	-4.147**	(1.872)	8.838***	(1.195)	2.329***	(0.355)
LernerIndex2	-104.051***	(11.064)			7.468**	(3.467)	-33.523***	(4.086)		
HHiTA	-98.761*	(60.017)	-323.175***	(41.395)	-19.772***	(4.723)	-1.794**	(0.767)	-5.531*	(2.957)
C5TA	-12.667*	(6.543)	-70.213***	(12.365)	-14.352***	(3.360)	-42.667*	(9.543)	-4.136**	(1.719)
CompCon			-1068.686***	(150.450)						
SFAEFF	347.342***	(66.157)								
ProdGrowth	-0.751	(0.994)								
CIR			0.030***	(0.004)	0.017***	(0.001)	0.009***	(0.002)	0.022***	(0.005)
ROA	1.298***	(0.119)	-0.005	(0.005)	0.094***	(0.003)	0.637***	(0.044)	0.509***	(0.060)
INF	0.022	(0.015)	-0.013***	(0.003)	0.001	(0.003)	-0.001***	(0.000)	0.006***	(0.001)
GDPc	0.110***	(0.005)	0.000	(0.008)	0.131***	(0.008)	-0.007	(0.009)	0.085***	(0.009)
Intercept	301.177***	(59.961)	5.166*	(1.973)	9.658***	(2.361)	0.368*	(0.152)	2.130**	(1.007)
Year Dummy	Yes		Yes		Yes		Yes		Yes	
Country Dummy	No		No		No		No		Yes	
N	612		332		338		180		5258	
Group	107		80		93		68		596	
Instruments	69		37		39		34		94	
AR(1)(p-value)	0.000		0.000		0.001		0.012		0.000	
AR(2)(p-value)	0.764		0.239		0.729		0.114		0.136	
Hansen(p-value)	0.525		0.546		0.904		0.904		0.974	
VIF	6.89		5.06		3.22		4.58		1.07	

Significance levels : $*$: 10% $**$: 5% $***$: 1%

5.7 Conclusion

This paper examines the role of risk, regulation and efficiency in the banking competition and financial stability relationship in the US banking sector, using system-GMM regression on panel data from 2000 to 2015. Firstly, this paper finds a neutral view of the competition-stability nexus where both the competition and concentration fragility co-exist. Interestingly, the introduction of a cubic function within this analysis, finds a unique polynomial competition-fragility relationship. This relationship also ruled out the efficiency structure paradigm within the US. These findings accepts hypotheses 6 and 8, thus reject hypothesis 7. The risk and regulatory explanatory variables found compelling results. As expected higher bank level credit and liquidity risk as well as increased leverage and diversification was found to be negatively associated with financial stability. The incorporation of bank level regulatory requirements within this study allowed for the assessment of whether they directly enhanced stability. Increased T1CR was found to improve financial stability accepting hypothesis 9. However, unexpectedly, the NSFR was found to hinder stability (rejecting hypothesis 10), providing caution to regulators as it is implemented under Basel III. This study was unable to provide support for hypothesis 11, when incorporating the dummy variables for SIFIs they were not found to be statistically related to financial stability. However, with the addition of size as a control variables within the robustness checks this highlighted the need for extra regulation for larger institutions as it was negatively associated with financial stability. Finally, this chapter attempted to identify any changes in the competition-stability nexus when using country level measures of systemic risk rather than accounting based measures of financial stability. Out of the systemic risk measures calculated in Section 3.4, only the Composite Indicator of Systemic Risk (CISS) developed by Hollo et al. (2012), produced a statistically robust model. Using CISS did indeed provide a contrasting view of the competition-stability nexus within the US banking sector. However, because only one measure of systemic risk provided evidence within this study, hypothesis 12 was rejected.

This paper highlight several important issues for policy-makers in the US.

First, to prevent excessive concentration[30], regulators should adopt a more cautious approach to evaluating and approving mergers and acquisitions at the national level. Also, in robustness checks indicate that smaller bank size may improve financial soundness. Secondly, from a regulation point of view, as Basel III's NSFR is implemented this needs to be monitored closely (by the banks management and regulators) given its potential unintended consequence of increasing funding costs (lowering cost efficiency) subsequently lowering profitability, thus, hampering financial stability. Finally, the evidence that banking competition has contrasting effect on individual bank stability and sector level systemic risk implies that new regulation/competition policy should be assessed at both microprudential and macroprudential levels to ensure before/during implementation.

[30]This is because both low competition and high concentration was found to hamper financial stability.

5.8 Chapter Appendix

Lerner Index Calculation

Table 5.10: Full Sample and European, Lerner Index Translog Specification Statistics Summary

	Full Sample 1995-2015			Europe 1995-2015		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
TC	16406	2366.451	9506.593	2093	8860.729	18973.53
TA	16525	61398.67	256687.1	2125	221585	484339.6
PL	10336	1.669	10.391	2073	1.838	4.118
PFC	13539	.037	.051	2014	.047	.068
PPC	16097	2.842	4.679	2096	3.763	7.092

Table 5.11: Country Lerner Index Translog Specification Statistics Summary

	USA 1995-2015			Japan 1999-2015			India 2001-2015			Russia 2001-2015		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
TC	9669	693.546	5823.534	1402	1441.61	4554.362	502	2088.139	3805.995	447	1305.415	4271.778
TA	9625	15204.38	131975.6	1405	95259.98	311281.3	504	28165.81	50183.21	459	16852.82	57688.81
PL	5341	1.517	14.001	112	.918	1.098	490	1.642	1.271	368	1.787	4.669
PFC	7132	.027	.021	1383	.003	.004	479	.069	.044	431	.066	.026
PPC	9450	2.425	3.006	1402	1.386	2.122	503	3.356	2.333	393	3.257	6.545
	Bazil 1995-2015			Indionesia 1995-2015			China 2003-2015			UK 1995-2015		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
TC	328	5847.251	12950.38	550	500.903	833.591	254	14028.23	20556.28	133	25500.77	23473.26
TA	334	43518.1	106450.2	556	5866.29	11246.42	254	470987.9	709965.4	134	845644.9	928278.3
PL	298	4.372	4.164	541	1.792	4.903	230	.724	.46	134	1.977	4.273
PFC	279	.172	.11	530	.088	.069	254	.021	.007	127	.03	.016
PPC	310	13.646	14.69	548	3.305	5.035	254	1.724	1.088	134	3.725	6.037
	Spain 1997-2015			Italy 1995-2015			France 1998-2015			Switzerland 1995-2015		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
TC	123	13366.88	17877.96	369	4256.804	9301.262	289	11229.3	20560.25	549	3215.062	12130.66
TA	123	322327.1	417542.7	378	105391.8	239654.1	289	324222.1	647317.6	554	84552.6	278907.7
PL	122	1.119	.587	374	1.352	1.825	282	1.611	.947	552	1.6	2.954
PFC	123	.036	.017	366	.037	.025	288	.047	.02	524	.024	.018
PPC	123	1.886	.974	377	3.445	7.006	289	3.183	1.783	552	3.046	5.248

Table 5.12: Lerner Index Per Country

Year	Full Sample	Euro	Brazil	China	France	India	Indonesia	Italy	Japan	Russia	Spain	Switzerland	UK	US
1995	0.1860	0.1439	0.1750				0.0074	0.1619				0.2289	0.1358	0.2088
1996	0.1888	0.1424	0.1664				0.0800	0.1353				0.1746	0.1504	0.2055
1997	0.1748	0.1527	0.1414				0.1142	0.1393			0.1257	0.2110	0.1317	0.2298
1998	0.2015	0.1561	0.1349		0.1080		0.1003	0.1822			0.1040	0.2159	0.1194	0.2128
1999	0.2004	0.1309	0.1942		0.0964		0.2431	0.1135	0.2290		0.1799	0.2623	0.1334	0.2378
2000	0.2194	0.1671	0.1616		0.0889		0.0684	0.1186	0.2313		0.2178	0.1603	0.2865	0.2074
2001	0.2148	0.1761	0.1922		0.1015	0.1644	0.1311	0.1719	0.3063	0.1464	0.2127	0.1224	0.0277	0.2381
2002	0.2386	0.1431	0.2205		0.1078	0.2114	0.1175	0.1472	0.3594	0.2163	0.2015	0.1648	0.0857	0.3027
2003	0.2638	0.1522	0.2437	0.2918	0.1451	0.2485	0.2035	0.1451	0.3914	0.2716	0.2854	0.1647	0.2008	0.3242
2004	0.2669	0.1969	0.2219	0.3154	0.1709	0.2994	0.3195	0.0617	0.4274	0.2005	0.3275	0.2669	0.2526	0.2946
2005	0.2779	0.2231	0.2414	0.3421	0.1814	0.2761	0.2429	0.0892	0.4346	0.2846	0.2927	0.2462	0.2766	0.2756
2006	0.2764	0.1729	0.2474	0.3381	0.1718	0.2529	0.2471	0.1058	0.4089	0.2954	0.3074	0.1890	0.2791	0.2444
2007	0.2725	0.1979	0.2572	0.3582	0.0605	0.2508	0.2815	0.0815	0.3526	0.2529	0.2660	0.1458	0.2417	0.2011
2008	0.2564	0.1527	0.1454	0.3726	0.0301	0.2430	0.2999	0.0045	0.3187	0.2462	0.2639	0.0156	0.2268	0.2053
2009	0.2554	0.1544	0.2749	0.3502	0.2120	0.2540	0.3012	0.0120	0.2944	0.0242	0.3477	0.0454	0.1542	0.2915
2010	0.2736	0.1894	0.2758	0.3745	0.1601	0.2687	0.3485	0.0696	0.3498	0.0004	0.4005	0.0129	0.2290	0.3170
2011	0.2773	0.1822	0.2422	0.3449	0.1420	0.2784	0.3443	0.0407	0.4107	0.0610	0.3026	0.1306	0.2224	0.3128
2012	0.2793	0.1800	0.2169	0.3588	0.1795	0.2554	0.3648	0.0782	0.3891	0.0711	0.3301	0.0335	0.1174	0.3148
2013	0.2879	0.2142	0.1882	0.3561	0.1883	0.2406	0.3710	0.0545	0.3892	0.0727	0.2609	0.1439	0.2421	0.3373
2014	0.3254	0.2070	0.1425	0.3842	0.2070	0.2329	0.3464	0.0802	0.3943	0.0493	0.3159	0.2108	0.2649	0.3348
2015	0.3141	0.2025	0.2364	0.3725	0.1848	0.2923	0.4326	0.0308	0.4439	0.0733	0.3757	0.0588	0.2476	0.3267

Table 5.13: Country Lerner Index Correlation Matrix

Country	Full Sample	Euro	Brazil	China	France	India	Indonesia	Italy	Japan	Russia	Spain	Switzerland	UK	USA
Full Sample	1.000													
Euro	0.759	1.000												
Brazil	0.473	0.291	1.000											
China	0.495	0.292	-0.351	1.000										
France	0.606	0.487	0.359	-0.056	1.000									
India	0.572	0.369	0.410	-0.232	0.366	1.000								
Indonesia	0.826	0.719	0.392	0.647	0.490	0.678	1.000							
Italy	-0.668	-0.432	-0.377	-0.548	-0.264	-0.621	-0.676	1.000						
Japan	0.801	0.650	0.316	-0.262	0.542	0.640	0.719	-0.218	1.000					
Russia	-0.312	-0.180	-0.024	-0.530	-0.484	-0.075	-0.584	0.397	0.151	1.000				
Spain	0.827	0.528	0.679	0.258	0.602	0.725	0.738	-0.702	0.571	-0.516	1.000			
Switzerland	-0.329	-0.042	-0.368	-0.442	-0.087	0.032	-0.536	0.550	0.106	0.552	-0.524	1.000		
UK	0.618	0.596	0.217	0.048	0.224	0.715	0.473	-0.543	0.349	0.153	0.497	0.078	1.000	
USA	0.724	0.491	0.441	-0.051	0.781	0.276	0.609	-0.403	0.598	-0.592	0.619	-0.271	0.204	1.000

Panzar & Rosse H-Statistic Calculation

Table 5.14: P&R H-Statistic Variable Cross-correlation Matrix

Variables	lnROA	lnTR	lnINT	L1.lnPL	L1.lnPFC	L1.lnPPC	lnETA	lnLTD
lnROA	1.000							
lnTR	0.134	1.000						
	(0.000)							
lnINT	0.124	0.992	1.000					
	(0.000)	(0.000)						
L1.lnPL	0.059	0.258	0.248	1.000				
	(0.031)	(0.000)	(0.000)					
L1.lnPFC	-0.086	-0.194	-0.179	-0.162	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)				
L1.lnPPC	0.095	0.224	0.199	0.979	-0.172	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
lnETA	0.171	0.019	0.012	0.036	-0.251	0.130	1.000	
	(0.000)	(0.419)	(0.609)	(0.188)	(0.000)	(0.000)		
lnLTD	0.054	0.027	0.090	-0.037	0.287	-0.006	0.179	1.000
	(0.019)	(0.247)	(0.000)	(0.174)	(0.000)	(0.793)	(0.000)	

Table 5.15: Panzar & Rosse H-Statistic Under the Disequilibrium Approach (ROA)

Variable	**LnROA 1D**	**LnROA 2D**	**LnROA 1S**	**LnROA 2S**
L.lnROA	0.252**	0.204***	0.5321***	0.5524***
L.lnPL	2.340	1.8780*	-0.5837	-0.5335
L.lnPFC	-0.185	-0.0830	-0.2015***	-0.1792***
L.lnPPC	-1.557	-1.189	0.6024	0.5612
lnETA	-0.038	0.1263	0.0694	0.0989
lnLTD	0.153	0.1244	0.0633	0.0082
2001.Year	0.012	0.032	-0.9402**	0.3477***
2002.Year	0.158	0.1743	-0.6905*	0.5732***
2003.Year	-0.060	0.0003	-0.8861**	0.3763***
2004.Year	-0.184	-0.0819	-0.9185**	0.3691***
2005.Year	-0.182	-0.0909	-0.9417**	0.3519***
2006.Year	-0.193	-0.1340	-0.9555***	0.3270***
2007.Year	-0.172	-0.1352	-0.9411***	0.3465***
2008.Year	-0.382**	-0.3740***	-1.1463***	0.1656
2009.Year	-0.482***	-0.4984***	-1.2674***	0.0421
2010.Year	-0.173	-0.1931	-1.0487***	0.2633***
2011.Year	-0.217	-0.1990	-1.1371***	0.1638***
2012.Year	-0.263	-0.2088	-1.1695***	0.1192**
2013.Year	-0.399	-0.2967	-1.285***	0.0129
2014.Year	-0.458	-0.3153	-1.3105***	0.000
2015.Year	-0.576	-0.4049	-1.40424***	-0.0946***
Instrument	68	68	121	121
Group	112	112	114	114
AR(1)	0.000	0.000	0.000	0.000
AR(2)	0.344	0.245	0.822	0.807
Hansen	0.444	0.444	0.565	0.565
H-Statistic	0.7995	0.7613	-0.3907	-0.3358
$\chi^2_{(22)}$	170.596***	185.67***	814.67***	723.88***
Obs.	946	946	1116	1116

Table 5.16: Panzar & Rosse H-Statistic Under the Disequilibrium Approach (TR and INT)

Variable	LnTR 1D	LnTR 2D	LnTR 1S	LnTR 2S	LnINT 1D	LnINT 2D	LnINT 1S	LnINT 2S
L.lnTR	0.5128**	0.5253**	0.9925***	0.9908***				
L.lnINT					0.5057***	0.4534***	0.9882***	0.9877***
L.lnPL	0.0630	0.0735	-0.0808	-0.0590	-0.1780	-0.1147	-0.0441	-0.0113
L.lnPFC	-0.0866	-0.0457	-0.0446*	-0.0466**	-0.0120	-0.0138	-0.0383	-0.0371
L.lnPPC	-0.1415	-0.1736	0.0409	0.0252	0.1790	0.0999	-0.0054	-0.0381
lnETA	-0.0110	-0.0099	0.0079	0.0040	-0.0028	0.0145	0.0134	0.0079
lnLTD	0.0437	0.0586	0.0369	0.0458	0.2346***	0.2260***	0.0777**	0.0845*
2001.Year	0.013	-0.1073	0.0567	-0.0581	0.000	-0.2010	0.0089	0.0229
2002.Year	-0.0678***	-0.1750	-0.0190	-0.1343	-0.1073***	-0.3041**	-0.1116	-0.0947
2003.Year	-0.0861*	-0.1757	-0.0065	-0.1256	-0.0784*	-0.2834***	-0.0601	-0.0447
2004.Year	-0.0850	-0.1657*	0.0200	-0.0969	-0.0356	-0.2570***	-0.0138	-0.0038
2005.Year	0.0399	-0.0389	0.1345***	0.0165	0.1575**	-0.0669	0.1652	0.1693***
2006.Year	0.1340	0.0324	0.1410***	0.0220	0.2429***	0.0279	0.1544	0.1604***
2007.Year	0.1836***	0.0632	0.1060**	-0.0170	0.2483***	0.0416	0.0841	0.0923
2008.Year	0.1248	-0.0050	-0.0089	-0.1298	0.1403**	-0.0640	-0.0757	-0.0726
2009.Year	0.1230	0.0021	0.0026	-0.1222	0.1205*	-0.0917	-0.0940	-0.0890
2010.Year	0.0885	-0.0131	-0.0289	-0.1504	0.1487	-0.0660	-0.0377	-0.0278
2011.Year	0.0524	-0.0323	-0.0425	-0.1603	0.1401	-0.0841	-0.0598	-0.0513
2012.Year	0.0363	-0.0387	-0.0440*	-0.1641	0.1434	-0.0832*	-0.0701	-0.0587**
2013.Year	-0.0052	-0.0693*	-0.0647***	-0.1821	0.1354	-0.0894***	-0.0818	-0.0747***
2014.Year	0.0220	-0.0416***	-0.0188	-0.1435	0.1832	-0.0473***	-0.0363	-0.0244
2015.Year	0.0507	0.000	0.000	-0.1229	0.2259	0.000	-0.0138	0.000
Instrument	68	68	121	121	68	68	121	121
Group	112	112	114	114	112	112	114	114
AR(1)	0.000	0.000	0.000	0.000	0.000	0.000	0.124(R)	0.256(R)
AR(2)	0.240	0.300	0.353	0.347	0.204	0.287	0.004(R)	0.004(R)
Hansen	0.204	0.204	0.564	0.564	0.097(R)	0.097(R)	0.521	0.521
H-Statistic	-0.3389	**-0.3072**	-11.3070	-8.7204	-0.0222	-0.05212	-7.4535	-42.5934
$\chi^2_{(22)}$	1787.81***	1683.22***	36927.04***	1.75e+06***	2149.85***	1417.51***	1.62e+06***	30836.59***
Obs.	946	946	1116	1116	946	946	1116	1116

Significance levels : * : 10% ** : 5% *** : 1%

Table 5.17: US Bank Data Statistical Summary per Year

	2000			2001			2002			2003		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
ZScore	265	15.789	21.876	297	15.262	21.755	349	12.832	14.665	354	14.043	18.684
SFAEFF	233	.8514682	.000647	233	.8514243	.0005618	233	.8508806	.0005435	233	.8506131	.0005066
ProdGrowth				233	2.139184	.1441777	233	2.264351	.1078278	233	2.278662	.0897878
DIV	396	.7	1.118	396	.513	3.812	432	.857	3.03	434	-.341	31.478
CreditRisk	165	.005	.004	179	.007	.008	186	.007	.009	199	.09	1.174
T1CR	387	13.147	10.2	389	11.852	4.171	425	12.17	6.536	428	12.232	6.182
FLVRG	370	11.319	4.492	382	11.451	4.688	381	11.605	5.594	404	12.09	12.745
T1LVGR	166	.08	.04	175	.079	.032	181	.082	.029	200	.084	.031
LIQ	342	.823	.162	330	.83	.169	357	.805	.184	379	.817	.226
NSFR	236	.934	.092	252	.93	.094	263	.917	.094	280	.922	.096
ROA	370	.887	1.565	382	.693	4.076	381	.811	4.186	404	1.039	.561
	2004			**2005**			**2006**			**2007**		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
ZScore	349	18.065	28.413	372	30.232	179.412	389	17.555	26.551	475	12.024	15.998
SFAEFF	233	.8504767	.0004539	233	.8509025	.0003962	233	.851483	.0003636	233	.8517447	.0003681
ProdGrowth	233	2.154787	.1444895	233	1.933258	.1313388	233	1.870692	.1162483	233	1.94046	.1094215
DIV	520	.668	1.739	538	.983	4.707	548	1.43	33.004	551	1.231	7.181
CreditRisk	304	.006	.008	398	.005	.007	433	.005	.007	501	.009	.011
T1CR	516	12.407	5.981	531	12.461	5.359	539	12.935	7.597	536	12.186	5.205
FLVRG	415	11.409	3.891	499	11.461	4.134	530	11.034	3.472	529	10.793	3.517
T1LVGR	316	.087	.026	418	.09	.027	471	.096	.049	528	.096	.034
LIQ	463	.834	.231	468	.843	.198	463	.865	.183	467	.892	.174
NSFR	358	.937	.1	371	.943	.091	366	.954	.118	364	.952	.105
ROA	416	.995	.556	499	1.037	.582	529	.933	1.219	529	.735	.841

Variable	2008 Obs	2008 Mean	2008 Std. Dev.	2009 Obs	2009 Mean	2009 Std. Dev.	2010 Obs	2010 Mean	2010 Std. Dev.	2011 Obs	2011 Mean	2011 Std. Dev.
ZScore	490	5.653	11.424	484	4.568	27.183	480	5.271	14.414	479	6.581	17.29
SFAEFF	233	.8513615	.0004384	233	.851358	.0005823	233	.8511438	.0005089	233	.8509728	.0004831
ProdGrowth	233	2.729239	.3408884	233	2.316827	.316714	233	2.115565	.2201283	233	2.11716	.1332425
DIV	546	2.474	22.32	536	.748	7.984	536	3.583	76.622	553	-15.837	360.449
CreditRisk	502	.021	.031	492	.031	.028	492	.033	.03	495	.029	.028
T1CR	518	11.863	4.363	508	12.445	5.713	507	13.679	7.091	508	14.125	5.235
FLVRG	522	11.362	3.979	518	12.362	5.765	512	14.384	35.198	506	13.979	19.643
T1LVGR	509	.094	.028	497	.094	.03	494	.098	.034	489	.098	.03
LIQ	458	.904	.228	385	.846	.15	346	.81	.158	312	.792	.151
NSFR	375	.953	.104	306	.935	.117	294	.93	.128	261	.922	.132
ROA	522	.043	1.539	517	-.241	1.706	513	.142	1.278	511	.254	2.299

Variable	2012 Obs	2012 Mean	2012 Std. Dev.	2013 Obs	2013 Mean	2013 Std. Dev.	2014 Obs	2014 Mean	2014 Std. Dev.	2015 Obs	2015 Mean	2015 Std. Dev.
ZScore	460	12.929	81.618	443	12.007	21.371	444	12.005	14.591	452	13.54	19.73
SFAEFF	233	.8507923	.0004896	233	.8505874	.0005023	233	.8504324	.000557	233	.8503713	.0005614
ProdGrowth	233	2.090742	.1194777	233	2.076538	.1010007	233	2.082867	.1207849	233	2.051759	.1027117
DIV	545	.22	22.875	510	1.073	9.948	505	1.243	4.671	508	.888	3.596
CreditRisk	473	.024	.035	445	.017	.027	455	.012	.018	457	.01	.021
T1CR	479	14.528	4.966	447	14.549	4.287	455	14.601	4.663	464	14.132	4.806
FLVRG	496	14.383	50.413	489	11.288	15.485	471	10.527	8.108	475	9.911	4.678
T1LVGR	455	.101	.036	413	.343	4.85	420	.102	.028	428	.101	.028
LIQ	315	.796	.153	277	.81	.152	240	.824	.159	218	.841	.153
NSFR	257	.933	.123	239	.936	.099	223	.948	.101	230	.951	.098
ROA	501	.67	1.059	491	.829	1.028	473	.8	.68	477	.892	.782

Chapter 6

Conclusion

6.1 Summary of Thesis Findings and Implications

The motivation for this study was to identify the impact of market competition and banking risk management on the wider banking system and how this has changed following the financial crisis of 2007/8. The three linked papers within this thesis aimed to address relevant elements of this motivation to provide theoretical and practical contributions within this area. From the original aims and objectives in Section 1.2 the following research questions were derived:

1. How does the academic literature define and measure systemic risk? This thesis surveys the previous literature to answers this question in Chapters 2 and 3.

2. What are the determinants of banking efficiency in the Basel jurisdictions? This thesis empirically answers this question in Chapter 4.

3. How does banking competition impact stability in the Basel jurisdictions? This thesis empirically answers this question in Chapter 5.

In order to answer research questions two and three, 12 research hypotheses were identified (see Section 1.6 for more details) for empirical testing. Table 6.1 provides a summary of which hypotheses were accepted or rejected with their implications for regulation in the context of the US banking sector. Although the aim of this thesis was to address all the Basel jurisdictions due to data availability (outlined in Sections 1.3, 4.4.3 and 5.5) the majority of the empirical evidence made use of US banking sector data. Where possible efficiency, competition, concentration and systemic risk measure were calculated for all jurisdictions for descriptive statistics purposes.

Table 6.1: Hypothesis Summary

Chapter	Hypothesis	Summary	Implications in the context of the US Banking Sector
4	**Hypothesis 1:** *The use of econometric calculations of efficiency is superior to traditional accounting measures.*	Rejected*	This thesis found that the use of SFA as a measure of efficiency was statistically significant within the efficiency determinates regression analysis. However, the use of both DEA (another econometric measure) and CIR (an accounting based measure) was not constant. This finding suggests studies of efficiency determinates in the US banking sector should make more use of SFA as an econometric relative objective measure of efficiency.
4	**Hypothesis 2:** *Business model diversification has a negative impact on efficiency.*	Accepted	This finding implies that a more diversified banks business model negatively impacts cost efficiency. Thus, as banks become more diverse the management need to be mindful of the overall impact on cost efficiency. As they seek new revenue streams this may hamper the cost base and increase other risks such as credit risk and leverage.
4	**Hypothesis 3:** *Increased credit risk has a negative impact on efficiency.*	Accepted	This association of credit risk to cost efficiency implies that higher credit risk (associated with increased provisions for NPLs) contributes to lower cost efficiency. Such findings advocate that banks should improve their credit risk management in order to lower the levels of NPLs. This is because from an efficiency measure viewpoint, input costs of NPLs negativity impacts the banks via the cost of recourse and re-investment costs.
4	**Hypothesis 4:** *Increased capital requirement regulations enhances efficiency.*	Rejected	Basel III regulations require banks to hold further capital, however this was found to negatively impact cost efficiency. Higher capital requirements increase institutions' cost of capital and premia on potentially costly risk management activities. Regulators need to be aware of the unintended cost of regulation. Capital requirements may make banks safer from a buffer point of view however, it may hamper banks cost base and profitability.

Table 6.1 Continued

Chapter	Hypothesis	Summary	Implications in the context of the US Banking Sector
4	**Hypothesis 5:** *Increased liquidity has a negative impact on efficiency.*	Accepted	As banks become less liquid this negatively impacts cost efficiency. If customer deposits reduce this negatively affects SFA cost efficiency. Less liquid institutions could have higher credit risk, resulting in them facing higher funding costs to enhance liquidity. Furthermore, the NSFR was negatively statistically significant, which implies that institutions who are seeking/holding extra funds face lower cost efficiency. Again, this could be a result of institutions facing higher funding costs as they aim to meet the new statutory requirements.
5	**Hypothesis 6:** *The market power paradigm persists.*	Accepted	From Figure 2.1 the market power paradigm was empirically found in the context of the US banking sector. This thesis found a neutral view of the competition-stability nexus, where both competition (relative market power) and concentration (structure conduct performance) fragility co-exist. From a competition regulation point of view, such empirical findings advocate a more oligopoly/monopolistic market structure to improve overall stability.
5	**Hypothesis 7:** *The efficiency structure paradigm persists.*	Rejected	Due to the acceptance of hypothesis 6, this simultaneously rejects hypothesis 7 and a no relationship, quiet life, paradigm in the US banking sector (see Figure 2.1).
5	**Hypothesis 8:** *Increased levels of competition negatively affects financial stability.*	Accepted	In line with hypothesis 6, this thesis found that increased banking competition negatively impacts stability i.e. competition-fragility in the US banking sector. Thus, competition policy regulators should be more cautious when a banking market becomes more competitive (entry restrictions) as, for example, banks may take excess risk to attract new customers.
5	**Hypothesis 9:** *Increased capital requirement regulation positively affects financial stability.*	Accepted	Increases in the Tier 1 Capital Ratio is positively associated with financial stability, thus providing evidence that this regulatory requirement is justified from a financial stability point of view. Note the implications from hypothesis 4.

Table 6.1 Continued

Chapter	Hypothesis	Summary	Implications in the context of the US Banking Sector
5	**Hypothesis 10:** *Increased liquidity regulation positively affects financial stability.*	Rejected	NSFR was statistically negatively associated with financial stability. This liquidity requirement is to ensure that financial institutions have access to longer term stable funding in the event of a crisis. Nevertheless, this result suggests that there may be an unintended negative consequence on profitability, due to higher funding costs, which affects stability. A potential reason may be the banks changing their funding habits if they require certain types of funding. Thus, as this regulation is implemented banks and regulators need to closely monitor this unintended consequence. Note the implications from hypothesis 5.
5	**Hypothesis 11:** *Being named as a SIFI or D-SIB positively affects the institutions financial stability.*	Rejected*	This thesis was unable to provide support for hypothesis 11, when incorporating the dummy variables for SIFIs they were not found to be statistically related to financial stability. However, the addition of size as a control variables within the robustness checks highlighted the need for extra regulation for larger institutions as it was negatively associated with financial stability.
5	**Hypothesis 12:** *The use of recently developed models to measure systemic risk provides contrasting results in the competition-stability nexus compared to traditional accounting measures of financial stability.*	Rejected*	Only the Composite Indicator of Systemic Risk (CISS) was statistically significant within the competition-stability regression analysis. Using CISS did indeed provide a contrasting view of the competition-stability nexus within the US banking sector. However, because only one measure of systemic risk provided evidence within this study, more empirical studies are encouraged to understand how systemic risk measures as a dependent variable impact the competition-stability nexus.

*Within this thesis empirical evidence was found to support these hypotheses albeit not in its entirety, thus rejected.

To summarise the findings for research question 1, Chapter 3 determined the main challenge regarding systemic risk, is that there is no single definition and given that at least 56 measures have been developed to measure systemic risk, there is limited consistency in the understanding of this phenomena. In addition, each individual measure of systemic risk only addresses specific aspects where authors use a definition to suit their model. The more recent measurement techniques attempt to create a more holistic view by incorporating institutional level risk within country level networks. Such methods, however, require more granular or competitively sensitive data as well as computing power. The majority of these techniques (network and contagion measures) lack transparency making them difficult to interpret and replicate.

Chapter 4 addresses research question 2, as empirical evidence found that following the financial crisis the US banking system as a whole did not improve cost efficiency as measured by SFA. Compared to traditional accounting based ratios of efficiency (e.g. cost to income ratio), relative econometric measurements of efficiency were statistically significant within the regression models, thus advocating their use in empirical studies (Abuzayed et al., 2009; Beccalli et al., 2006; Fiordelisi, 2008). The assessment of the determinants of cost efficiency found that in all empirical models diversification was negatively associated with cost efficiency (Beck et al., 2016; Rossi et al., 2009; Thoraneenitiyan & Avkiran, 2009). Also both leverage and credit risk were found to be negatively associated with cost efficiency (Bhatia et al., 2018; Sun & Chang, 2011). Investigating the implications of regulation on cost efficiency found that capital requirement designed to protect institutions from capital shocks hampers cost efficiency (contrasting previous empirical findings). Also, increased liquidity holdings advocated by regulators negatively impact the cost efficiency . Both highlight the potential unintended consequence of regulation cost.

Chapter 4 has both policy implications and evaluates various econometric techniques as potentially valuable analytical tools for supervisors. First, the empirical results both overall and pre/post crisis highlight the importance of the prudential supervisory role in controlling the level of risk in the banking sector, as the elevation in risk measures coupled with the growth of the sector has resulted in declining measures of efficiency, a result that is robust to several econometric specifications (using both econometric and accounting based measures). The policy implication is that regulators may want better capitalised banks and somewhat smaller or less diverse banking systems, as this is likely to imply a more efficiently functioning banking industry. However, this is not necessarily the case with the rejection that increased capital requirement improves efficiency. Thus, regulators should focus on ensuring banks business models do not diversify too much (increasing the level of credit risk and leverage) rather than the sole emphasis being on capital requirements to enhance banking cost efficiency.

To summarise the findings for research question 3, Chapter 5 evidenced a neutral view of the competition-stability nexus where both competition and concentration fragility co-exists in the US banking sector. To the best of my knowledge, the only other time this relationship was found was by X. Fu et al. (2014) who studied the Asian Pacific region. In addition a unique polynomial competition-fragility relationship was found. This relationship also ruled out the efficiency structure paradigm. As expected from the explanatory variables higher bank level credit and liquidity risk as well as increased leverage and diversification were found to be negatively associated with financial stability (Azar et al., 2016; De Nicoló et al., 2006; Leroy & Lucotte, 2017; Turk-Ariss, 2010). In assessing the role of regulatory requirements in improving financial stability, increased Tier 1 Capital Ratio (T1CR) was found to improve financial stability (Kapan & Minoiu, 2018; Klomp & De Haan, 2015). However, unexpectedly, the NSFR was found to hinder stability, again a potential unintended consequence of holding cash or the cost of seeking stable funding, on profitability and subsequently stability. Empirical evidence was unable to find if being classified as SIFI enhances or hampers financial stability as the variables were not statistically significant within the regression analysis. However, the addition of size as a control variables within the robustness checks highlighted the need for extra regulation for larger institutions as size was negatively associated with financial stability. Lastly, this chapter attempted to identify any changes in the competition-stability nexus when using country level measures of systemic risk rather than accounting based financial stability measures similar to Leroy and Lucotte (2017). Out of the systemic risk measures calculated in chapter 3, only the Composite Indicator of Systemic Risk (CISS), produced a statistically robust model. Using CISS did provide a contrasting view of the competition-stability nexus within the US banking sector. Given limited previous empirical evidence and as only one measure of systemic risk provided statistically significant evidence within this thesis this advocates for more future research to understand this phenomenon.

These findings highlight several important issues for policy-makers in the US. First, to prevent excessive concentration[1], regulators should adopt a more cautious approach to evaluating and approving mergers and acquisitions at the national level. Also, in robustness checks indicate that smaller bank size may improve financial soundness. Secondly, from a regulation point of view, as Basel III's NSFR is implemented this needs to be monitored closely (by the banks' management and regulators) given its potential unintended consequence of increasing funding costs (lowering cost efficiency) subsequently lowering profitability, thus, hampering financial stability. Finally, the evidence that banking competition has contrasting effects on individual bank stability and sector level systemic risk implies that new regulation/competition policy should be assessed at both microprudential and macroprudential levels before/during implementation.

6.2 Generalisability of Findings

Generalisability describes the extent to which research findings can be applied to settings other than that in which they were originally tested (Øvretveit, Leviton, & Parry, 2011). Within this thesis the main findings discussed were all from regression models that fit the required statistical specifications outlined in the methodology

[1]This is because both low competition and high concentration were found to hamper financial stability.

sections and only the variables that were statistically significant to 99%[2]. This significance level is saying is that a result (relationship or difference) of the size found in the sample has a low probability of having occurred if there is no relationship in the population. However, there is still a probability (of 1%, using a significance level of 0.01 for example) that the findings are a coincidence of the sample (Bell, Bryman, & Harley, 2018; Muijs, 2004).

Despite the efficiency determinants paper (chapter 4) making use of data from the US banking sector, the majority of the empirical findings can be generalised elsewhere. This is because the paper focuses on bank level data rather than sector level. The variables that were found to be determinants of efficiency are all common variables which are available irrespective of the banking sector under examination[3]. However the regulatory bank level data (such as capital requirements T1CR) is only relevant to the banking sectors under the jurisdiction of the Basel Accords. Thus, the interpretation of the regulation implications can only be generalised to other Basel jurisdictions. Elsewhere, the regulatory implications of this thesis provide insightful information for policy-makers, and aim to ensure consistency amongst banking sector jurisdictions (homogeneous banking sectors). The finding that the use of SFA is preferred in the context of the US banking sector regressions cannot be generalised as this is a relative measure of the sample only. From Chapter 5, the main findings of a neutral view of banking competition and financial stability relationships in the context of the US cannot be generalised elsewhere, as this finding is from sector level specific data. The methodology can be replicated elsewhere to identify the relationship in different countries subject to data availability. This was attempted in Section 5.6.3 to evidence the banking competition and financial stability relationship within the other Basel jurisdictions. The findings from this chapter specific to bank level and regulatory variables can be generalised elsewhere, similar to the findings in Chapter 4.

[2]The empirical findings that were significant to 90% or 95% were also discussed, with caution, as the thesis emphasised on the findings which were 99% statistically significant.

[3]This is dependent on the data availability and the accounting standards within the country of observation.

6.3 Original Contribution to Theory and Literature

The findings of this thesis enrich the existing literature in several important ways. In order to contribute to the developing literature of banking systemic risk, this thesis aimed to take a more holistic view of this topic in order to identify the many interpretations of this phenomena. The *Systemic Risk Measures and Regulation Challenges* paper (Chapter 3) is one of the first systematic literature reviews in this area. The paper contributes to theory in a number of ways, firstly by identifying and critiquing the various techniques developed (56 models) to measure systemic risk by academics and regulators. This systematic literature review aimed to provide a comprehensive overview of the models developed to measure systemic risk. Thus, this paper can inform future research as it identifies what has been done before in order to generate new ideas and learn from previous limitations. Secondly, the data required for these models were also collated and presented within a table (3.8) to illustrate the most commonly used datasets. This paper advocates for an increase in research using network theory as this area aims to provide a more comprehensive overview of systemic risk. Furthermore, the use of foreign exchange data to measure systemic risk was only identified three times, despite these studies finding the foreign exchange rates to be a statistically significant indicator of systemic risk. To the best of my knowledge table 3.8 is the first of its kind. This table, which identifies the most common dataset applied, can be used to inform future research. Researchers can use this table identify the data gaps to investigate different datasets or a combination of alternative datasets. Finally, in conjunction with Chapter 2, the various definitions and types of macro-prudential regulation were visited, in order to identify a number of challenges of regulating systemic risk adding to a growing area of policy-oriented research (Carretta et al., 2015; Clark & Jokung, 2015; Masciandaro & Volpicella, 2016).

The *Banking Efficiency Determinant* paper (Chapter 4) introduced new additional empirical evidence to the ongoing debate of what impacts cost efficiency within the banking sector. The literature review featured various trends, issues and advances within efficiency analysis that could be useful in future academic research to identify best practice and areas of concern. By understanding the multiple aspects of banking efficiency, researchers within this area can create methodologies to identify industry best practice and advocate preferred business models to the rest of the sector. This paper has contributed to the banking efficiency literature by: (i) evidencing that the use of SFA to measure cost efficiency within the US banking sector is preferred as a relative measure within regression analysis; (ii) identified that increased business model diversification (which may be strategic) can have the unintended consequence of hindering cost efficiency due to its interaction with credit risk; (iii) provided a unique breakdown of how cost efficiency determinants changed pre and post-crisis; (iv) and assessed bank level regulatory requirements rather than country level, which allows institutions management and regulators to observe a more direct impact of regulation. Noticeably, the requirements of T1CR and NSFR under Basel III both hindered cost efficiency. Such findings add to the literature surrounding the costs of regulation compliance. These regulations are designed to enhance the institution's balance sheets to withstand shocks, however, their practical implication results in lowering cost efficiency which could ultimately affect long-term profitability. To the best of my knowledge this is the first empirical study of efficiency determinants to find a statistical significance of such bank level regulatory ratios, providing an incentive for further research[4].

The *Banking Efficiency, Concentration, Competition and Financial Stability* paper (Chapter 5) combines the knowledge from Chapters 2 and 3 and calculations from Chapters 3 and 4, in order to contribute to knowledge. Adding to the extensive body of empirical findings in this area, a neutral view of the competition-stability nexus was found within the US banking sector for the first time. Both competition and concentration fragility were found to co-exist, suggesting having lower pricing power (high competition) and excessive market

[4]Previous empirical evidence by Pasiouras et al. (2009); Chortareas et al. (2012); J. R. Barth, Lin, et al. (2013); Manlagnit (2015) found a positive relationship between capital requirement regulation (dummy variable or sector level indicators) and efficiency.

concentration can simultaneously cause financial fragility. Such empirical findings advocate a more oligopoly/monopolistic market structure to improve stability. As a unique polynomial competition fragility relationship was found, this suggests that as competition moves from monopoly to perfect competition, financial stability drops, but at a given level of competition (oligopoly or monopolistic) there is a positive change in stability until competition increases further. In addition, the concave relationship found using a measure of systemic risk also suggests that oligopoly/monopolistic market would be safer. In reaching such findings well-established methodologies were adopted, however a number of novel explanatory variables such as T1CR, T1LVRG and NSFR were explored. Uniquely, no other empirical study in this area has introduced a cubic function to test for a monotonic or polynomial relationship. Potentially, previous studies that identified a linear relationship (but ruled out a concave/convex relationship) may have not explored this alternative relationship. The polynomial relationship suggests risk-shifting effects between the different levels of competition, thus, stressing the importance to incorporate risk-based explanatory/control variables within this type of regression analysis. Further, helping to advance this literature, measures of systemic risk (which were identified and measured in Chapter 3), were used as dependant variables to assess any changes in the competition-stability relationship. To date, the use of systemic risk measure within this empirical literature is rather limited (Leroy & Lucotte, 2017). This chapter found contrasting results between financial stability (Z-Score) and systemic risk (CISS) and competition, which advocates the notation for future research in the area to help explain this phenomenon.

From the bank level regulatory explanatory variables, the majority were found to be statistically significant in line with existing literature and theory. However, complementing the finding in Chapter 4 that NSFR hindered cost efficiency, it was also found to hinder stability. This empirical evidence suggests as financial institutions seek to enhance stable long-term funding this could hinder profitability and subsequently stability. As the NSFR requirement is implemented under Basel III and financial institutions start reporting their actual figures, its impact at the bank level should be explored further.

6.4 Original Contribution to Practice

As well as the contributions to literature, the findings of this thesis are of interest to practitioners and regulators. From Chapter 3, when determining cost efficiency within banks empirically all the independent variables in this study were predetermined, thus practitioners and policy-makers can correctly infer what enhances cost efficiency. For continuous monitoring of cost efficiency SFA is a relative measure of efficiency that can be used by practitioners to identify industry best practice. Regulators can seek to understand how the best practice banks maintain this status to encourage others to do the same or to introduce new management principles. For example, because more diverse business models were found to hamper cost efficiency, when banks seek regulatory approval to expand or create new business entities, regulators could require additional efficiency feasibility studies. This would force banks to understand the unintended consequences of expanding further to enhance their implementation strategy and risk management. Also, the sector level efficiency measures using SFA can help supervisors monitor efficiency levels following mergers and acquisitions (sector consolidation).

Drawing from Chapter 4's results policy-makers can infer what any changes to competition level will do to levels of financial stability or identify which financial institutions are more likely to be in trouble given their poor capital ratios, diversified business model and/or too much reliance on market funding. Whether excess credit/liquidity risk or more risky business models are driven by market competition levels (or from the risk preferences of management), this is of interest to policy-makers and should be explored during future regulation changes consultations. Also, with the introduction of the NSFR under Basel III, both banks and regulatory authorities should carefully consider their long-term liquidity levels to balance its impact from increased competition with decreased cost efficiency.

The finding that competition affects both financial stability and systemic risk differently has important policy repercussions. First, the fact that competition has contrasting effects on individual bank stability and sector level systemic risk implies that new regulation/competition policy should be assessed at both microprudential and macroprudential levels. As discussed in Section 2.3.3 the Federal Trade Commission's Bureau of competition is responsible for anti-competitive mergers and acquisitions, however, the banking supervisors and the Department of Justice can overturn any decision if it is in the national interest (e.g. in the event of financial stability issue). Thus, secondly on a practical level for such bodies, this thesis' results suggest that more anti-competitive policy should be introduced in the US banking system to maintain micro-financial stability. However, a monopolistic market should also be avoided as this hampers systemic risk (macro) and a concentration-fragility relationship was empirically found. Further, the empirical evidence suggested that any potential negative effect of this type of policy on individual risk-taking behaviour should not arise because the Basel III regulatory requirements corrects incentives for individual risk-taking. In addition, the effectiveness of bank level regulations in shaping financial stability, such as Basel III, should be investigated along with the level of competition and concentration in a disaggregated method to help ascertain more efficiency policies.

As Basel III's liquidity regulations are implemented, the finding of this thesis that the NSFR hampers both cost efficiency and financial stability provides a warning to banks and regulators of its unintended consequences. As noted in Section 3.4.3 its introduction has been widely seen as a positive step to prevent future liquidity crises (Ashraf et al., 2016; Chiaramonte & Casu, 2017; P. King & Tarbert, 2011; Pakravan, 2014). However, this thesis' findings adds to a growing body of research which seeks to assess its impact before it fully comes into effect (DeYoung et al., 2018; Dietrich et al., 2014; Goodhart et al., 2012; Wei et al., 2017). The empirical evidence within this thesis supports the ideas discussed by Schmitz and Hesse (2014) that banks tend to hold on to liquidity during periods of systemic uncertainty. Thus, if banks require to seek more stable funding this could significantly increase costs hampering both cost efficiency and profitability (Wei et al., 2017)[5]. In addition, the factor increases on customer deposits as a source of funding from BIS (2010a) to BIS (2014)(See Table 3.4) can lead to increased competition levels which again was found to hamper stability, therefore these factor increases should be reviewed. Regulatory authorities also should identify the nature of the competitive pressure banks face while implementing optimal regulatory regimes. As the banking sectors empirically analysed within this thesis tend to be homogeneous, individual banks' business models may be heterogeneous, thus this 'one size fits all' regulatory requirement may not be appropriate for all institutions. This may force banks to diversify (to enhance funding sources) which again was found to hamper cost efficiency and financial stability. These multifaceted conflicts require careful consideration and review by regulators.

Because this study is based on a NSFR proxy, a direct comparison with results from the BCBS (e.g. the most recent BIS (2019)) cannot be conducted. As mentioned previously (see Section 3.4.3), there are gaps between annual report data and the data required for calculating the new liquidity ratios, justifying calls for further disclosure. Thus, it is likely that this thesis' results are less accurate than BCBS's research. Nevertheless, the empirical findings clearly highlight a need for a better understanding of the banks' business models and their evolutions as the NSFR is implemented. For these reasons, more policy-oriented research and monitoring is necessary to better align the regulatory initiatives with the inherent risks of different business models and market structures.

6.5 Limitations and Future Research

Although the present research employed well-known and reliable methodologies, there are certain limitations that need to be considered. These limitations can potentially be addressed by future research. This section also provides direction for further research and identifies areas that require extra academic/regulatory attention.

The first limitation is related to the data utilised in this thesis. This study

[5]The market value of certain securities which constitutes a stable funding increase with demand.

used annual panel data (converted into dollars if required) supplied by Bloomberg Professional Service. However, empirical research within the competition-stability nexus is more frequently making use of quarterly panel data when investigating individual countries. As US banks are required to submit quarterly results (10-Q Filings) to the Securities and Exchange Commission, more gradual data is available. However, whenever conducting cross-country empirical analysis this is not available everywhere. Further, this thesis aimed to provide empirical finding from all the Basel jurisdictions, however, due to bank level data limitations this was not possible. Within the relevant chapter all efforts were made to produce findings from as many jurisdictions as possible. Lastly, as shown in Section 3.5, the data used to calculate systemic risk ranges greatly. Thus, it is not possible to replicate each measure of systemic risk. Also, the more unique techniques are only available to researchers or regulators with privileged data access, thus advocating for more data to become available to help researcher advance this area.

A second limitation despite various robustness checks in each empirical paper to control for endogeneity and the use of GMM, the relationships noted in this research should be treat with caution. The results presented within the empirical papers by design are more correlation than causal relationships, due to the possible endogeneity concerns affecting the estimates (Altunbas et al., 2017; Laeven & Levine, 2009). As an example, financial institutions that have a higher risk appetite are more likely to have characteristics associated with a riskier profile (i.e. higher credit risk and leverage), thus higher distress indicators during crisis periods. In such a scenario the causality chain would transmit from risk to the banking variables, rather than the opposite, which is noted throughout the literature review in this thesis. Despite whether the findings within this research cannot be given as a causal interpretation, the results remain of interest to regulators and policy-makers, from a forecasting relationship perspective. Given that all dependent variables are predetermined from institutions' annual reports, managers, stakeholders and policy-makers can infer which banks may be more cost efficient (Chapter 4) or which market structure is more likely to suffer during a crisis period (Chapter 5).

6.5.1 Future Research

Identified from Chapter 4

In order to enhance Chapter 4 further, the data used could have been scrutinised further for extreme outliers using a technique called Jackknifing (Shao & Tu, 2012). Furthermore, this method could have been used as a robustness test to compare DEA scores with and without Jackknifing. However, within Chapter 3 bootstrapping was used as an alternative, this resampling technique is considered as a more transparent approach (Baxter, 2001). In addition, Moradi-Motlagh and Saleh (2014) emphasised that bootstrap DEA provides confidence intervals and bias corrected estimates of pure technical efficiency scores. Bootstrap results show the importance of incorporating sample variation and bias in estimating efficiency scores.

To progress the banking efficiency literature, Kuosmanen and Kortelainen (2012) developed Stochastic Semi-Nonparametric Envelopment of Data (StoNED) which is a hybrid approach that combines the DEA-type non-parametric frontier, with the SFA-style stochastic homoscedastic composite error term. StoNED has less restrictive assumptions which allows it to have a wide application range. It is also more robust to uncertainty surrounding stochastic noise and the functional form of the frontier (Kuosmanen, 2012). It is worth noting that this method does not aim to provide specific sources of inefficiency. Extensions of this method have aimed to understand more about the efficiency transmission[6]. In addition, Färe and Grosskopf (2000) introduced the network model to understand the carry-over effects of efficiency, Tone and Tsutsui (2010) enhanced this model using a slacks-based measure, which can deal with inputs and outputs and carry-overs separately. They then further enhanced this model with a dynamic model after discovering that carry-over transmits from a division to the same division at the next period (Tone & Tsutsui, 2014). Such recent developments could be used in the future to compare with previous empirical research conducted using SFA

[6]See Avkiran (2015) for a conceptual framework of the current article's on efficiency analysis for banks and Tone and Tsutsui (2014) for a graphical representation of the different DEA models.

and/or DEA.

Identified from Chapter 5

The novel findings within Chapter 5 can be explored further. As suggested previously, empirical studies which have found a linear relationship between banking competition and financial stability (which may have already discounted a concave/convex relationship) should assess whether a monotonic or polynomial relationship exists. Such reassessment may provide a more holistic view of the banking competition and financial stability relationship. As systemic risk measurement techniques become more readily available (more transparency and data), such measures should be explored within the competition-stability nexus literature. Currently, very little empirical research has investigated the impact of competition or concentration on systemic risk. Such research has provided contrasting results, thus, it is an attractive area to progress the literature. The challenges regarding measuring systemic risk are outlined in Chapter 3, but briefly, various techniques require certain datasets and enhanced computing capabilities, whilst others need to be more transparent (e.g. open source code). Lastly, as found within this thesis, at the bank level regulatory requirements such as T1CR and NSFR have unintended consequences by reducing efficiency, profitability and stability. Therefore as these requirements come into force under Basel III, further research of their direct impact on banks would be welcome.

6.6 Concluding Remarks

This research has provided a number of insights into the competition-stability nexus and has contributed to the growing literature of systemic risk, the most significant finding of the research is that a polynomial relationship between competition and stability can exist. This phenomenon to date has not been attempted, thus, previous empirical results, which suggest a linear relationship, may need to be reviewed. In addition, the inclusion of systemic risk measures into this body of literature can produce contrasting empirical results, suggesting competition levels affect microeconomic and macro-economic factors differently. This has entirely justified the time and effort that has gone into this thesis and, in conjunction with the identification of further areas, has resulted in the articulation of significant original thought in an increasingly important area of study.

References

Abarbanell, J. S., & Meyendorff, A. (1997). Bank privatization in post-communist Russia: the case of Zhilsotsbank. *Journal of Comparative Economics*, *25*(1), 62–96.

Abedifar, P., Giudici, P., & Hashem, S. Q. (2017). Heterogeneous market structure and systemic risk: Evidence from dual banking systems. *Journal of Financial Stability*, *33*, 96–119.

Abuzayed, B., Molyneux, P., & Al-Fayoumi, N. (2009). Market value, book value and earnings: is bank efficiency a missing link? *Managerial Finance*, *35*(2), 156–179.

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015a). Networks, shocks, and systemic risk. *National Bureau of Economic Research*(No.20931).

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015b). Systemic risk and stability in financial networks. *American Economic Review*, *105*(2), 564–608.

Acerbi, C., Nordio, C., & Sirtori, C. (2001). Expected shortfall as a tool for financial risk management. *Abaxbank arXiv Preprint*(No.0102304).

Acharya, V. V. (2009). A theory of systemic risk and design of prudential bank regulation. *Journal of Financial Stability*, *5*(3), 224–255.

Acharya, V. V., Berger, A. N., & Roman, R. A. (2018). Lending implications of US bank stress tests: Costs or benefits? *Journal of Financial Intermediation*, *34*, 58–90.

Acharya, V. V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *The American Economic Review*, *102*(3), 59–64.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2010). Measuring systemic risk. *Technical Report, Department of Finance, NYU Stern School of Business*.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies*, *30*(1), 2–47.

Acharya, V. V., Pedersenn, L., Philipponn, T., & Richardson, M. (2011). Regulating wall street: the dodd-frank act and the new architecture of global finance. In V. V. Acharya (Ed.), (pp. 87–119). Hoboken, N.J: Wiley.

Acharya, V. V., & Richardson, M. (2009a). Causes of the financial crisis. *Critical Review*, *21*(2–3), 195–210.

Acharya, V. V., & Richardson, M. (2009b). *Restoring financial stability: How to repair a failed system*. Hoboken, N.J: Wiley.

Acharya, V. V., & Yorulmazer, T. (2007). Too many to fail—an analysis of time-inconsistency in bank closure policies. *Journal of Financial Intermediation*, *16*(1), 1–31.

Acharya, V. V., & Yorulmazer, T. (2008). Cash-in-the-market pricing and optimal resolution of bank failures. *The Review of Financial Studies*, *21*(6), 2705–2742.

Achen, C. H. (2001). Why lagged dependent variables can suppress the explanatory power of other independent variables. *Princeton Univesity Working Papers*.

Adalsteinsson, G. (2014). *The liquidity risk management guide: From policy to pitfalls*. John Wiley & Sons.

Adrian, T. (2015). Discussion of: Systemic risk and the solvency-liquidity nexus of banks. *International Journal of Central Banking*, *11*(3), 229–240.

Adrian, T., & Ashcraft, A. B. (2016). Banking crises: Perspectives from the new palgrave dictionary. In G. Jones (Ed.), (pp. 282–315). London: Palgrave Macmillan UK.

Adrian, T., & Brunnermeier, M. K. (2008). Covar. *Federal Reserve Bank of New York, Staff Report*, *No. 348*.

Adrian, T., & Shin, H. S. (2008). Liquidity and financial contagion. *Banque de France Financial Stability Review: Special Issue on Liquidity*, *11*, 1–7.

Ahn, S. C., & Sickles, R. C. (2000). Estimation of long-run inefficiency levels: a dynamic frontier approach. *Econometric Reviews*, *19*(4), 461–492.

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics*, *6*(1), 21–37.

Aikman, D., Alessandri, P., Eklund, B., Gai, P., Kapadia, S., Martin, E., ... Willison, M. (2009). Funding liquidity risk in a quantitative model of systemic stability. *Bank of England Working Paper*, *No.372*.

Akinci, O., & Olmstead-Rumsey, J. (2018). How effective are macroprudential policies? an empirical investigation. *Journal of Financial Intermediation*, *33*, 33–57.

Albertazzi, U., & Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability*, *5*(4), 393–409.

Aldasoro, I., & Alves, I. (2016). Multiplex interbank networks and systemic importance an application to European data. *Journal of Financial Stability*, *35*, 17–37.

Alessi, L., Antunes, A., Babeckỳ, J., Baltussen, S., Behn, M., Bonfim, D., ... others (2015). Comparing different early warning systems: Results from a horse race competition among members of the macro-prudential research network. *Munich Personal RePEc Archive*, *No.62194*.

Alessi, L., & Detken, C. (2009). 'real time'early warning indicators for costly asset price boom/bust cycles: a role for global liquidity. , *No.1039*.

Alessi, L., & Detken, C. (2018). Identifying excessive credit growth and leverage. *Journal of Financial Stability*, *35*, 215–225.

Allen, B., Chan, K. K., Milne, A., & Thomas, S. (2012). Basel III: Is the cure worse than the disease? *International Review of Financial Analysis*, *25*, 159–166.

Allen, F., & Babus, A. (2009). The network challenge : Strategy, profit, and risk in an interlinked world. In P. R. Kleindorfer, Y. Wind, & R. E. Gunther (Eds.), (pp. 367–382). Upper Saddle River, N.J: Pearson Education.

Allen, F., & Gale, D. (1998). Optimal financial crises. *Journal of Finance*, *53*(4), 1245–1284.

Allen, F., & Gale, D. (2000). Financial contagion. *Journal of Political Economy*, *108*(1), 1–33.

Allen, F., & Gale, D. M. (2004). Competition and financial stability. *Journal of Money, Credit and Banking*, *36*(3), 453-486.

Allen, J., Clark, C. R., & Houde, J.-F. (2008). Market structure and the diffusion of e-commerce: Evidence from the retail banking industry. *Bank of Canada Working Paper*(No.32).

Allen, L., Bali, T. G., & Tang, Y. (2012). Does systemic risk in the financial sector predict future economic downturns? *Review of Financial Studies*, *25*(10), 3000–3036.

Allenspach, N., & Monnin, P. (2008). Common exposure and systemic risk in the banking sector. *Available at SSRN 1494269*.

Al-Sharkas, A. A., Hassan, M. K., & Lawrence, S. (2008). The impact of mergers and acquisitions on the efficiency of the US banking industry: Further evidence. *Journal of Business Finance & Accounting*, *35*(1–2), 50–70.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589–609.

Altunbas, Y., Manganelli, S., & Marques-Ibanez, D. (2017). Realized bank risk during the great recession. *Journal of Financial Intermediation*, *32*, 29–44.

Amidu, M., & Wolfe, S. (2013). Does bank competition and diversification lead to greater stability? evidence from emerging markets. *Review of Development Finance*, *3*(3), 152–166.

An, Q., Chen, H., Wu, J., & Liang, L. (2015). Measuring slacks-based efficiency for commercial banks in China by using a two-stage DEA model with undesirable output. *Annals of Operations Research*, *235*(1), 13–35.

Anand, K., van Lelyveld, I., Banai, Á., Friedrich, S., Garratt, R., Hałaj, G., ... others (2018). The missing links: A global study on uncovering financial network structures from partial data. *Journal of Financial Stability*, *35*, 107–119.

Anderson, T. W., & Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association*, *76*(375), 598–606.

Andreou, I., Dufrénot, G., Sand-Zantman, A., & Zdzienicka-Durand, A. (2009). A forewarning indicator system for financial crises: the case of six central and eastern European countries. *Journal of Economic Integration*, 87–115.

Andrievskaya, I., & Semenova, M. (2016). Does banking system transparency enhance bank competition? cross-country evidence. *Journal of Financial Stability*, *23*, 33–50.

Anginer, D., & Demirguc-Kunt, A. (2014). Has the global banking system become more fragile over time? *Journal of Financial Stability*, *13*, 202–213.

Anginer, D., Demirgüç-Kunt, A., & Mare, D. S. (2018). Bank capital, institutional environment and systemic stability. *Journal of Financial Stability*, *37*, 97–106.

Anundsen, A. K., Gerdrup, K., Hansen, F., & Kragh-Sørensen, K. (2016). Bubbles and crises: The role of house prices and credit. *Journal of Applied Econometrics*, *31*(7), 1291–1311.

Aparicio, J., Duran, M. A., Lozano-Vivas, A., & Pastor, J. T. (2018). Are charter value and supervision aligned? a segmentation analysis. *Journal of Financial Stability*, *37*, 60–73.

Arellano, M. (2003). *Panel data econometrics.* London, UK: Oxford university press.

Ariff, M., & Luc, C. (2008). Cost and profit efficiency of chinese banks: A non-parametric analysis. *China Economic Review*, *19*(2), 260–273.

Arner, D. (2009). The global credit crisis of 2008: Causes and consequences. *The International Lawyer*, 91–136.

Arner, D., & Taylor, M. (2009). The global credit crisis and the financial stability board: Hardening the soft law of international financial regulation? *University of New South Wales Law Journal*, *32*, 488–513.

Ashraf, D., Rizwan, M. S., & L'Huillier, B. (2016). A Net Stable Funding Ratio for Islamic banks and its impact on financial stability: An international investigation. *Journal of Financial Stability*, *25*, 47–57.

Asmild, M., & Zhu, M. (2016). Controlling for the use of extreme weights in bank efficiency assessments during the financial crisis. *European Journal of*

Operational Research, *251*(3), 999–1015.

Asteriou, D., & Hall, S. G. (2015). *Applied econometrics* (3rd ed.). London: Macmillan International Higher Education.

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions and Money*, *18*(2), 121–136.

Attanasio, J. B. (1988). The principle of aggregate autonomy and the calabresian approach to products liability. *Virginia Law Review*, 677–750.

Avkiran, N. K. (2013). Efficiency and productivity growth, modelling in the financial services industry. In F. Pasiouras (Ed.), (pp. 171–192). Chichester: John Wiley & Sons Ltd.

Avkiran, N. K. (2015). An illustration of dynamic network DEA in commercial banking including robustness tests. *Omega*, *55*, 141–150.

Avramidis, P., & Pasiouras, F. (2015). Calculating systemic risk capital: A factor model approach. *Journal of Financial Stability*, *16*, 138–150.

Aymanns, C., Caccioli, F., Farmer, J. D., & Tan, V. W. (2016). Taming the Basel leverage cycle. *Journal of Financial Stability*, *27*, 263–277.

Azar, J., Raina, S., & Schmalz, M. C. (2016). Ultimate ownership and bank competition. *Available at SSRN 2710252*.

Babeckỳ, J., Havranek, T., Mateju, J., Rusnák, M., Smidkova, K., & Vasicek, B. (2012). Banking, debt and currency crises: early warning indicators for developed countries. *European Central Bank, Working Paper Series*, *No.1485*.

Bach, W., & Nguyen, T. (2012). On the systemic relevance of the insurance industry: Is a macroprudential insurance regulation necessary? *Journal of Applied Finance and Banking*, *2*(1), 127.

Bae, K.-H., Karolyi, G. A., & Stulz, R. M. (2003). A new approach to measuring financial contagion. *Review of Financial Studies*, *16*(3), 717–763.

Bagliano, F. C., & Morana, C. (2014). Determinants of US financial fragility conditions. *Research in International Business and Finance*, *30*, 377–392.

Bai, J., Krishnamurthy, A., & Weymuller, C.-H. (2018). Measuring liquidity mismatch in the banking sector. *The Journal of Finance*, *73*(1), 51–93.

Bai, J. J., Carvalho, D., & Phillips, G. M. (2017). The impact of bank credit on labor reallocation and aggregate industry productivity. *National Bureau of Economic Research*(No.24081).

Bain, J. S. (1951). Relation of profit rate to industry concentration: American manufacturing, 1936–1940. *The Quarterly Journal of Economics*, 293–324.

Baker, A. (2013). The gradual transformation? the incremental dynamics of macroprudential regulation. *Regulation & Governance*, *7*(4), 417–434.

Balk, B. M., Färe, R., Grosskopf, S., & Margaritis, D. (2008). Exact relations between luenberger productivity indicators and malmquist productivity indexes. *Economic Theory*, *35*(1), 187–190.

Baltagi, B. H. (2008). *Econometric analysis of panel data* (4th ed.). Chichester: John Wiley & Sons.

Baltagi, B. H., & Wu, P. X. (1999). Unequally spaced panel data regressions with AR(1) disturbances. *Econometric Theory*, *15*(6), 814–823.

Barroso, J. B. R. B., Silva, T. C., & de Souza, S. R. S. (2018). Identifying systemic risk drivers in financial networks. *Physica A: Statistical Mechanics and its Applications*, *503*, 650–674.

Barth, A., & Seckinger, C. (2018). Capital regulation with heterogeneous banks–unintended consequences of a too strict leverage ratio. *Journal of Banking & Finance*, *88*, 455–465.

Barth, J. R., Caprio Jr, G., & Levine, R. (2004). Bank regulation and supervision: what works best? *Journal of Financial Intermediation*, *13*(2), 205–248.

Barth, J. R., Caprio Jr, G., & Levine, R. (2008). *Rethinking bank regulation: Till angels govern*. London, UK: Cambridge University Press.

Barth, J. R., Caprio Jr, G., & Levine, R. (2013). Bank regulation and supervision in 180 countries from 1999 to 2011. *Journal of Financial Economic Policy*, *5*(2), 111–219.

Barth, J. R., Lin, C., Ma, Y., Seade, J., & Song, F. M. (2013). Do bank regulation, supervision and monitoring enhance or impede bank efficiency? *Journal of Banking & Finance*, *37*(8), 2879–2892.

Bartram, S. M., Brown, G. W., & Hund, J. E. (2007). Estimating systemic risk in the international financial system. *Journal of Financial Economics*, *86*(3), 835–869.

Barwell, R. (2013). *Macroprudential policy: Taming the wild gyrations of credit flows, debt stocks and asset prices.* Houndmills, Basingstoke: Palgrave Macmillan.

Battese, G. E., Rao, D. P., & O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis*, *21*(1), 91–103.

Baxter, M. J. (2001). Methodological issues in the study of assemblage diversity. *American Antiquity*, *66*(4), 715–725.

Beccalli, E., Casu, B., & Girardone, C. (2006). Efficiency and stock performance in European banking. *Journal of Business Finance & Accounting*, *33*(1–2), 245–262.

Beck, T., Chen, T., Lin, C., & Song, F. M. (2016). Financial innovation: The bright and the dark sides. *Journal of Banking & Finance*, *72*, 28–51.

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: cross-country heterogeneity. *Journal of Financial Intermediation*, *22*(2), 218–244.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2006). Bank concentration, competition, and crises: First results. *Journal of Banking & Finance*, *30*(5), 1581–1603.

Beck, T., Levine, R., & Levkov, A. (2010). Big bad banks? the winners and losers from bank deregulation in the United States. *The Journal of Finance*, *65*(5), 1637–1667.

Bell, E., Bryman, A., & Harley, B. (2018). *Business research methods* (3rd ed.). London: Oxford university press.

Berger, A. N. (1995). The profit-structure relationship in banking–tests of market-power and efficient-structure hypotheses. *Journal of Money, Credit and Banking*, *27*(2), 404–431.

Berger, A. N., Bonime, S. D., Covitz, D. M., & Hancock, D. (2000). Why are bank profits so persistent? the roles of product market competition, informational opacity, and regional/macroeconomic shocks. *Journal of Banking & Finance*, *24*(7), 1203–1235.

Berger, A. N., & Bouwman, C. H. (2009). Bank liquidity creation. *Review of Financial Studies*, *22*(9), 3779–3837.

Berger, A. N., & Bouwman, C. H. (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics*, *109*(1), 146–176.

Berger, A. N., Demirgüç-Kunt, A., Levine, R., & Haubrich, J. G. (2004). Bank concentration and competition: An evolution in the making. *Journal of Money, Credit and Banking*, *36*(3), 433–451.

Berger, A. N., & DeYoung, R. (2001). The effects of geographic expansion on bank efficiency. *Journal of Financial Services Research*, *19*(2–3), 163–184.

Berger, A. N., & Di Patti, E. B. (2006). Capital structure and firm performance: A new approach to testing agency theory and an application to the banking industry. *Journal of Banking & Finance*, *30*(4), 1065–1102.

Berger, A. N., & Hannan, T. H. (1998). The efficiency cost of market power in the banking industry: A test of the "quiet life" and related hypotheses. *Review of Economics and Statistics*, *80*(3), 454–465.

Berger, A. N., Hanweck, G. A., & Humphrey, D. B. (1987). Competitive viability in banking: Scale, scope, and product mix economies. *Journal of Monetary Economics*, *20*(3), 501–520.

Berger, A. N., Hasan, I., & Zhou, M. (2009). Bank ownership and efficiency in China: What will happen in the world's largest nation? *Journal of Banking & Finance*, *33*(1), 113–130.

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175–212.

Berger, A. N., Klapper, L. F., & Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, *35*(2), 99–118.

Berger, A. N., & Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking*

& Finance, *21*(7), 895–947.

Berger, A. N., & Mester, L. J. (2003). Explaining the dramatic changes in performance of US banks: technological change, deregulation, and dynamic changes in competition. *Journal of Financial Intermediation*, *12*(1), 57–95.

Berndsen, R. J., León, C., & Renneboog, L. (2018). Financial stability in networks of financial institutions and market infrastructures. *Journal of Financial Stability*, *35*, 120–135.

Berninger, M., Kiesel, F., & Schiereck, D. (2018). When your regulator becomes your new neighbor: Bank regulation and the relocation of eba and ema. *Economics Letters*, *167*, 108–111.

Bertrand, M., Schoar, A., & Thesmar, D. (2007). Banking deregulation and industry structure: Evidence from the french banking reforms of 1985. *The Journal of Finance*, *62*(2), 597–628.

Bhansali, V., Gingrich, R., & Longstaff, F. A. (2008). Systemic credit risk: What is the market telling US? *Financial Analysts Journal*, *64*(4), 16–24.

Bhargava, A., Franzini, L., & Narendranathan, W. (1982). Serial correlation and the fixed effects model. *The Review of Economic Studies*, *49*(4), 533–549.

Bhatia, V., Basu, S., Mitra, S. K., & Dash, P. (2018). A review of bank efficiency and productivity. *OPSEARCH*, *55*, 1–44.

Bikker, J. A. (2004). *Competition and efficiency in a unified European banking market.* Edward Elgar Publishing.

Bikker, J. A., & Haaf, K. (2002). Competition, concentration and their relationship: An empirical analysis of the banking industry. *Journal of Banking & Finance*, *26*(11), 2191–2214.

Bikker, J. A., Shaffer, S., & Spierdijk, L. (2012). Assessing competition with the panzar-rosse model: The role of scale, costs, and equilibrium. *Review of Economics and Statistics*, *94*(4), 1025–1044.

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2010). Measuring systemic risk in the finance and insurance sectors. *MIT Sloan School Working Paper*, *4774*.

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559.

BIS. (2001). *Group of ten: Report on consolidation in the financial sector* (Tech. Rep.). http://www.bis.org/publ/gten05.pdf: Bank of International Settlement.

BIS. (2009). *Strengthening the resilience of the banking sector - consultative document* (Tech. Rep.). http://www.bis.org/publ/bcbs164.pdf: Bank of International Settlement.

BIS. (2010a). *Basel III: International framework for liquidity risk measurement, standardsand monitoring* (Tech. Rep.). http://www.bis.org/publ/bcbs188.pdf: Bank of International Settlement.

BIS. (2010b). *Sound practices for backtesting counterparty credit risk models* (Tech. Rep.). https://www.bis.org/publ/bcbs185.htm: Bank of International Settlement.

BIS. (2011a). *Basel III: A global regulatory framework for more resilient banks and banking systems- revised version june 2011* (Tech. Rep.). http://www.bis.org/publ/bcbs189.htm: Bank of International Settlement.

BIS. (2011b). *Global systemically important banks: Assessment methodology and the additional loss absorbency requirement* (Tech. Rep.). http://www.bis.org/publ/bcbs207.htm: Bank of International Settlement.

BIS. (2013a). *Basel III: The liquidity coverage ratio and liquidity risk monitoring tools* (Tech. Rep.). http://www.bis.org/publ/bcbs238.htm: Bank of International Settlement.

BIS. (2013b). *Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement* (Tech. Rep.). http://www.bis.org/publ/bcbs255.htm: Bank of International Settlement.

BIS. (2014). *Basel III: The Net Stable Funding Ratio* (Tech. Rep.). http://www.bis.org/publ/bcbs271.htm: Bank of International Settlement.

BIS. (2016). *Basel committee on banking supervision membership* (Tech. Rep.). http://www.bis.org/bcbs/membership.htm: Bank of International Settlement.

BIS. (2018). *Fourteenth progress report on adoption of the Basel regulatory framework* (Tech. Rep.). https://www.bis.org/bcbs/publ/d440.htm: Bank of International Settlement.

BIS. (2019). *Basel III Monitoring Report, March 2019* (Tech. Rep.). https://www.bis.org/bcbs/publ/d461.htm: Bank of International Settlement.

Bisias, D., Flood, M., Lo, A. W., & Valavanis, S. (2012). A survey of systemic risk analytics. *Annual Review of Financial Economics*, *4*(1), 255–296.

Blalock Jr, H. M. (1963). Correlated independent variables: The problem of multicollinearity. *Social Forces*, *42*(2), 233–237.

Bliemel, M. J., McCarthy, I. P., & Maine, E. (2014). An integrated approach to studying multiplexity in entrepreneurial networks. *Entrepreneurship Research Journal*, *4*(4), 367–402.

Bloomberg, L. P. (2016). *Company Financial Analysis.* Retrieved August 8, 2016 From Bloomberg Terminals.

Bloomberg, L. P. (2017). *SIFI Company Financial Analysis.* Retrieved January 13, 2017 From Bloomberg Terminals.

Bloomberg, L. P. (2018). *Company Ownership Analysis.* Retrieved June 29, 2018 From Bloomberg Terminals.

Bloomberg, L. P. (2019). *Bloomberg professional serivce excel add–in API help.* Retrieved January 12, 2019 From Bloomberg Terminals.

Bluhm, M., & Krahnen, J. P. (2014). Systemic risk in an interconnected banking system with endogenous asset markets. *Journal of Financial Stability*, *13*, 75–94.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, *87*(1), 115–143.

Blundell-Wignall, A., & Atkinson, P. (2010). Thinking beyond Basel III. *OECD Journal: Financial Market Trends*, *2010*(1), 9–33.

BOE. (2013). A framework for stress testing the UK banking system. *Bank of England Discussion Paper*.

Bolt, W., & Humphrey, D. (2015). A frontier measure of US banking competition. *European Journal of Operational Research*, *246*(2), 450–461.

Bongini, P., Nieri, L., & Pelagatti, M. (2015). The importance of being systemically important financial institutions. *Journal of Banking & Finance*, *50*, 562–574.

Bonin, J. P., Hasan, I., & Wachtel, P. (2005). Bank performance, efficiency and ownership in transition countries. *Journal of Banking & Finance*, *29*(1), 31–53.

Boone, J. (2008a). Competition: Theoretical parameterizations and empirical measures. *Journal of Institutional and Theoretical Economics*, *164*(4), 587–611.

Boone, J. (2008b). A new way to measure competition. *The Economic Journal*, *118*(531), 1245–1261.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance*, *45*, 182–198.

Borio, C. E., & Drehmann, M. (2009). Towards an operational framework for financial stability:'fuzzy' measurement and its consequences. *BIS Working Paper*, *WP/09/284*.

Born, B., & Breitung, J. (2016). Testing for serial correlation in fixed-effects panel data models. *Econometric Reviews*, *35*(7), 1290–1316.

Born, B., Ehrmann, M., & Fratzscher, M. (2014). Central bank communication on financial stability. *The Economic Journal*, *124*(577), 701–734.

Bos, J. W., Koetter, M., Kolari, J. W., & Kool, C. J. (2009). Effects of heterogeneity on bank efficiency scores. *European Journal of Operational Research*, *195*(1), 251–261.

Boussemart, J.-P., Briec, W., Kerstens, K., & Poutineau, J.-C. (2003). Luenberger and malmquist productivity indices: theoretical comparisons and empirical illustration. *Bulletin of Economic Research*, *55*(4), 391–405.

Boyd, J. H., & Nicoló, G. D. (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance*, *60*(3), 1329–1343.

Bremus, F. M. (2015). Cross-border banking, bank market structures and market power: Theory and cross-country evidence. *Journal of Banking & Finance*, *50*, 242–259.

Brewer, E., & Saidenberg, M. R. (1996). Franchise value, ownership structure, and risk at savings institutions. *Federal Reserve Bank of New York*(No.9632).

Brownlees, C. T., & Engle, R. F. (2012). Volatility, correlation and tails for systemic risk measurement. *New York University Stern School of Business, Working Paper Available at SSRN 1611229*.

Brummer, C. (2014). *Minilateralism: How trade alliances, soft law and financial engineering are redefining economic statecraft.* Cambridge University Press.

Brummer, C., & Smallcomb, M. (2015). Oxford handbook of financial regulation. In N. Moloney, E. Ferran, & J. Payne (Eds.), (pp. 129–156). Oxford: Oxford University Press.

Brunnermeier, M. K., & Pedersen, L. H. (2009). Market liquidity and funding liquidity. *Review of Financial Studies*, *22*(6), 2201–2238.

Brzoza-Brzezina, M., Kolasa, M., & Makarski, K. (2018). Crisis, contagion and international policy spillovers under foreign ownership of banks. *Journal of Financial Stability*, *36*, 293–304.

BSA. (2015). *List of demutualised building societies* (Tech. Rep.).

Bui, C., Scheule, H., & Wu, E. (2017). The value of bank capital buffers in maintaining financial system resilience. *Journal of Financial Stability*, *33*, 23–40.

Caccioli, F., Shrestha, M., Moore, C., & Farmer, J. D. (2014). Stability analysis of financial contagion due to overlapping portfolios. *Journal of Banking & Finance*, *46*, 233–245.

Cai, J., Eidam, F., Saunders, A., & Steffen, S. (2018). Syndication, interconnectedness, and systemic risk. *Journal of Financial Stability*, *34*, 105–120.

Caiazza, S., Pozzolo, A. F., & Trovato, G. (2016). Bank efficiency measures, m&a decision and heterogeneity. *Journal of Productivity Analysis*, *46*(1), 25–41.

Campbell, G., Coyle, C., & Turner, J. D. (2016). This time is different: Causes and consequences of british banking instability over the long run. *Journal of Financial Stability*, *4*(2), 74–94.

Canales, R., & Nanda, R. (2012). A darker side to decentralized banks: Market power and credit rationing in sme lending. *Journal of Financial Economics*, *105*(2), 353–366.

Canedo, J. M. D., & Jaramillo, S. M. (2009). A network model of systemic risk: stress testing the banking system. *Intelligent Systems in Accounting, Finance and Management*, *16*(1/2), 87-110.

Cao, J., & Illing, G. (2010). Regulation of systemic liquidity risk. *Financial Markets and Portfolio Management*, *24*(1), 31–48.

Căpraru, B., & Andrieş, A. M. (2015). Nexus between concentration and fragility across eu banking systems. *Procedia Economics and Finance*, *32*, 1140–1147.

Caprio, G., & Klingebiel, D. (1996). Bank insolvencies cross-country experience. *World Bank Policy Research Working Paper*(No.1620).

Carletti, E. (2008). Handbook of financial intermediation and banking. In A. V. Thakor & A. W. A. Boot (Eds.), (pp. 449–482). Amsterdam: North-Holland: Elsevier.

Carlton, D. W., & Loury, G. C. (1980). The limitations of pigouvian taxes as a long-run remedy for externalities. *The Quarterly Journal of Economics*, *95*(3), 559–566.

Carretta, A., Farina, V., Fiordelisi, F., Schwizer, P., & Lopes, F. S. S. (2015). Don't stand so close to me: The role of supervisory style in banking stability. *Journal of Banking & Finance*, *52*, 180–188.

Caruana, J., & Narain, A. (2008). Banking on more capital-the subprime crisis has made Basel II implementation more important–and challenging. *Finance & Development*, *45*(2), 24.

Casu, B., & Girardone, C. (2006). Bank competition, concentration and efficiency in the single European market. *The Manchester School*, *74*(4), 441–468.

Casu, B., & Girardone, C. (2009). Testing the relationship between competition and efficiency in banking: A panel data analysis. *Economics Letters*, *105*(1), 134–137.

Cerutti, E., Claessens, S., & Laeven, L. (2017). The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability*, *28*, 203–224.

Cetina, J., & Loudis, B. (2016). The influence of systemic importance indicators on banks' credit default swap spreads. *Journal of Risk Management in Financial Institutions*, *9*(1), 17–31.

Cetina, J., Paddrik, M., & Rajan, S. (2017). Stressed to the core: Counterparty concentrations and systemic losses in CDS markets. *Journal of Financial Stability*.

Cetorelli, N., & Gambera, M. (2001). Banking market structure, financial dependence and growth: international evidence from industry data. *Journal of Finance*, *56*(2), 617–648.

Cetorelli, N., & Strahan, P. E. (2006). Finance as a barrier to entry: Bank competition and industry structure in local US markets. *The Journal of Finance*, *61*(1), 437–461.

Chambers, R. G. (2002). Exact nonradial input, output, and productivity measurement. *Economic Theory*, *20*(4), 751–765.

Chan, N., Getmansky, M., Haas, S. M., & Lo, A. W. (2006). Do hedge funds increase systemic risk? *Economic Review- Federal Reserve Bank of Atlanta*, *91*(4), 49.

Chan, S.-G., Koh, E. H., Zainir, F., & Yong, C.-C. (2015). Market structure, institutional framework and bank efficiency in ASEAN 5. *Journal of Economics and Business*, *82*, 84–112.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444.

Chen, H., & Wang, S. (2009). A network model approach to systemic risk in the financial system. *Policy*, *33*.

Chiaramonte, L., & Casu, B. (2017). Capital and liquidity ratios and financial distress. evidence from the European banking industry. *The British Accounting Review*, *49*(2), 138–161.

Chiaramonte, L., Croci, E., & Poli, F. (2015). Should we trust the Z-score? evidence from the European banking industry. *Global Finance Journal*, *28*, 111–131.

Chiu, Y.-H., Jan, C., Shen, D.-B., & Wang, P.-C. (2008). Efficiency and capital adequacy in Taiwan banking: BCC and super-DEA estimation. *The Service*

Industries Journal, *28*(4), 479–496.

Chortareas, G. E., Girardone, C., & Ventouri, A. (2011). Financial frictions, bank efficiency and risk: evidence from the Eurozone. *Journal of Business Finance & Accounting*, *38*(1–2), 259–287.

Chortareas, G. E., Girardone, C., & Ventouri, A. (2012). Bank supervision, regulation, and efficiency: Evidence from the European Union. *Journal of Financial Stability*, *8*(4), 292–302.

Chortareas, G. E., Girardone, C., & Ventouri, A. (2013). Financial freedom and bank efficiency: Evidence from the European Union. *Journal of Banking & Finance*, *37*(4), 1223–1231.

Cihák, M., & Podpiera, R. (2006). Is one watchdog better than three? international experience with integrated financial sector supervision. *IMF Working Papers*, *WP/06/57*.

Claessens, S., Dell'Ariccia, G., Igan, D., & Laeven, L. (2010). Cross-country experiences and policy implications from the global financial crisis. *Economic Policy*, *25*(62), 267–293.

Claessens, S., & Laeven, L. (2004). What drives bank competition? some international evidence. *Journal of Money, Credit and Banking*, *36*(3), 563–583.

Claessens, S., & Ratnovski, L. (2015). Shadow banking within and across national borders. In S. Claessens, D. Evanoff, G. Kaufman, & L. Laeven (Eds.), (pp. 405–412). World Scientific.

Clark, E., & Jokung, O. (2015). The role of regulatory credibility in effective bank regulation. *Journal of Banking & Finance*, *50*, 506–513.

Clark, E., Radić, N., & Sharipova, A. (2018). Bank competition and stability in the cis markets. *Journal of International Financial Markets, Institutions and Money*, *54*, 190–203.

Clement, P. (2010). The term 'macroprudential': origins and evolution. *BIS Quarterly Review, March*.

Clerides, S., Delis, M. D., & Kokas, S. (2015). A new data set on competition in national banking markets. *Financial Markets, Institutions & Instruments*, *24*(2–3), 267–311.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis* (2nd ed.). New York: Springer Science & Business Media.

Constantin, A., Peltonen, T. A., & Sarlin, P. (2018). Network linkages to predict bank distress. *Journal of Financial Stability*, *35*, 226–241.

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (dea)–thirty years on. *European Journal of Operational Research*, *192*(1), 1–17.

Cornett, M. M., McNutt, J. J., Strahan, P. E., & Tehranian, H. (2011). Liquidity risk management and credit supply in the financial crisis. *Journal of Financial Economics*, *101*(2), 297–312.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*(2), 479–512.

Crockett, A. (2000). Marrying the micro-and macro-prudential dimensions of financial stability. *BIS Speeches*, *21*.

Crotty, M. (1998). *The foundations of social research: Meaning and perspective in the research process*. London: Sage.

Cubillas, E., & González, F. (2014). Financial liberalization and bank risk-taking: International evidence. *Journal of Financial Stability*, *11*, 32–48.

Cummings, J. R., & Durrani, K. J. (2016). Effect of the Basel Accord capital requirements on the loan-loss provisioning practices of Australian banks. *Journal of Banking & Finance*, *67*, 23–36.

Cummins, J. D., & Weiss, M. A. (2014). Systemic risk and the US insurance sector. *Journal of Risk and Insurance*, *81*(3), 489–528.

Danielsson, J., & Shin, H. S. (2003). *Endogenous risk*. Risk Books London.

Daraio, C., & Simar, L. (2005). Introducing environmental variables in nonparametric frontier models: a probabilistic approach. *Journal of Productivity Analysis*, *24*(1), 93–121.

Das, A., & Ghosh, S. (2006). Financial deregulation and efficiency: An empirical analysis of Indian banks during the post reform period. *Review of Financial Economics*, *15*(3), 193–221.

Das, A., & Kumbhakar, S. C. (2016). Markup and efficiency of Indian banks: an input distance function approach. *Empirical Economics*, *51*(4), 1689–1719.

Davis, E. P., & Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial Stability*, *4*(2), 89–120.

De Bandt, O., & Hartmann, P. (2000). Systemic risk: A survey. *ECB Working Paper*(No.35).

De Chiara, A., Livio, L., & Ponce, J. (2018). Flexible and mandatory banking supervision. *Journal of Financial Stability*, *34*, 86–104.

Dees, S., Henry, J., & Martin, R. (2017). Stress-test analytics for macroprudential purposes: Introducing stamp€. *European Central Bank, Technical Report*.

Degl'Innocenti, M., Kourtzidis, S. A., Sevic, Z., & Tzeremes, N. G. (2017). Investigating bank efficiency in transition economies: A window-based weight assurance region approach. *Economic Modelling*, *67*, 23–33.

Deli, Y. D., Delis, M. D., Hasan, I., & Liu, L. (2019). Enforcement of banking regulation and the cost of borrowing. *Journal of Banking & Finance*, *101*, 147–160.

Delis, M. D., & Papanikolaou, N. I. (2009). Determinants of bank efficiency: evidence from a semi-parametric methodology. *Managerial Finance*, *35*(3), 260–275.

Delis, M. D., & Tsionas, E. G. (2009). The joint estimation of bank-level market power and efficiency. *Journal of Banking & Finance*, *33*(10), 1842–1850.

Demirgüç-Kunt, A., & Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. *IMF Staff Papers*, *45*(1), 81–109.

Demirguc-Kunt, A., Detragiache, E., & Merrouche, O. (2013). Bank capital: Lessons from the financial crisis. *Journal of Money, Credit and Banking*, *45*(6), 1147-1164.

Demirgüç-Kunt, A., & Huizinga, H. (2013). Are banks too big to fail or too big to save? international evidence from equity prices and CDS spreads. *Journal of Banking & Finance*, *37*(3), 875–894.

Demsetz, H. (1973). Industry structure, market rivalry, and public policy. *Journal of Law and Economics*, 1–9.

Demsetz, H., Goldschmid, H., Mann, H., & Weston, J. (1974). Mergers and acquisitions. In S. Peck & P. Temple (Eds.), (pp. 164–184). London: Routledge.

De Nicoló, G., Jalal, A. M., & Boyd, J. H. (2006). Bank risk-taking and competition revisited: New theory and new evidence. *International Monetary Fund Working Papers*, *297*(6–297).

De Nicoló, G., & Loukoianova, E. (2007). Bank ownership, market structure and risk. *International Monetary Working Papers*, *215*(7–215).

Detken, C., Weeken, O., Alessi, L., Bonfim, D., Boucinha, M. M., Castro, C., ... others (2014). Operationalising the countercyclical capital buffer: indicator selection, threshold identification and calibration options. *ESRB Occasional Paper*, *5*.

DeYoung, R., Distinguin, I., & Tarazi, A. (2018). The joint regulation of bank liquidity and bank capital. *Journal of Financial Intermediation*, *34*, 32–46.

Diallo, B. (2018). Bank efficiency and industry growth during financial crises. *Economic Modelling*, *68*, 11–22.

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401–419.

Dick, A. A. (2006). Nationwide branching and its impact on market structure, quality and bank performance. *Journal of Business*, *79*(2), 567–592.

Dietrich, A., Hess, K., & Wanzenried, G. (2014). The good and bad news about the new liquidity rules of Basel III in Western European countries. *Journal of Banking & Finance*, *44*, 13–25.

Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: A multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis*, *30*, 46–56.

Distinguin, I., Roulet, C., & Tarazi, A. (2013). Bank regulatory capital and liquidity: Evidence from US and European publicly traded banks. *Journal of Banking & Finance*, *37*(9), 3295–3317.

Donaldson, J. R., & Micheler, E. (2018). Resaleable debt and systemic risk. *Journal of Financial Economics*, *127*(3), 485–504.

Dovonon, P., & Hall, A. R. (2018). The asymptotic properties of gmm and indirect inference under second-order identification. *Journal of econometrics*, *205*(1), 76–111.

Drechsler, I., Savov, A., & Schnabl, P. (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics*, *132*(4), 1819–1876.

Du, K., & Sim, N. (2016). Mergers, acquisitions, and bank efficiency: Cross-country evidence from emerging markets. *Research in International Business and Finance*, *36*, 499–510.

Duca, M. L., Koban, A., Basten, M., Bengtsson, E., Klaus, B., Kusmierczyk, P., … others (2017). *A new database for financial crises in European countries* (Tech. Rep.). European Central Bank.

Duca, M. L., & Peltonen, T. A. (2013). Assessing systemic risks and predicting systemic events. *Journal of Banking & Finance*, *37*(7), 2183-2195.

Duygun, M., Sena, V., & Shaban, M. (2013). Schumpeterian competition and efficiency among commercial banks. *Journal of Banking & Finance*, *37*(12), 5176–5185.

Duygun, M., Sena, V., & Shaban, M. (2014). Trademarking status and economic efficiency among commercial banks: Some evidence for the UK. *Journal of Banking & Finance*, *49*, 506–514.

Duygun, M., Sena, V., & Shaban, M. (2016). Trademarking activities and total factor productivity: Some evidence for british commercial banks using a metafrontier approach. *Journal of Banking & Finance*, *72*, S70–S80.

Eder, A., & Keiler, S. (2015). CDS spreads and contagion amongst systemically important financial institutions–a spatial econometric approach. *International Journal of Finance & Economics*, *20*(4), 291–309.

Eisenbeis, R., Ferrier, G., & Kwan, S. (1999). The informativeness of stochastic frontier and programming frontier efficiency scores: Cost and other measures of bank holding company performance. *Federal Reserve Bank of Atlanta Working Paper*(No.99).

Eisenberg, L., & Noe, T. H. (2001). Systemic risk in financial systems. *Management Science*, *47*(2), 236–249.

Ellis, L., Haldane, A., & Moshirian, F. (2014). Systemic risk, governance and global financial stability. *Journal of Banking & Finance*, *45*, 175–181.

Elsinger, H., Lehar, A., & Summer, M. (2006). Risk assessment for banking systems. *Management Science*, *52*(9), 1301–1314.

Eskelinen, J., & Kuosmanen, T. (2013). Intertemporal efficiency analysis of sales teams of a bank: stochastic semi-nonparametric approach. *Journal of Banking & Finance*, *37*(12), 5163–5175.

Fall, F., Akim, A.-m., & Wassongma, H. (2018). Dea and sfa research on the efficiency of microfinance institutions: A meta-analysis. *World Development*, *107*, 176–188.

Färe, R., & Grosskopf, S. (2000). Network DEA. *Socio-Economic Planning Sciences*, *34*(1), 35–49.

Färe, R., Grosskopf, S., Norris, M., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *The American Economic Review*, 66–83.

Färe, R., Grosskopf, S., & Weber, W. L. (2004). The effect of risk-based capital requirements on profit efficiency in banking. *Applied Economics*, *36*(15), 1731–1743.

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, 253–290.

Favara, G., & Giannetti, M. (2017). Forced asset sales and the concentration of outstanding debt: evidence from the mortgage market. *The Journal of Finance*, *72*(3), 1081–1118.

FDIC. (2016). *Risk management manual of examination policies* (Tech. Rep.). https://www.fdic.gov/regulations/safety/manual/: Federal Deposit Insurance Corporation.

Fecht, F., Grüner, H. P., & Hartmann, P. (2012). Financial integration, specialization, and systemic risk. *Journal of International Economics*, *88*(1), 150–161.

Feng, G., & Serletis, A. (2009). Efficiency and productivity of the US banking industry, 1998–2005: evidence from the fourier cost function satisfying global regularity conditions. *Journal of Applied Econometrics*, *24*(1), 105–138.

Feng, G., & Wang, C. (2018). Why European banks are less profitable than US banks: A decomposition approach. *Journal of Banking & Finance*, *90*, 1–16.

Fernandez de Guevara, J., Maudos, J., & Perez, F. (2005). Market power in European banking sectors. *Journal of Financial Services Research*, *27*(2), 109-137.

Ferran, E., & Alexander, K. (2011). Can soft law bodies be effective? soft systemic risk oversight bodies and the special case of the European systemic risk board. *University of Cambridge Faculty of Law Research Paper*(No.36).

Fiordelisi, F. (2008). Efficiency and shareholder return in banking. *International Journal of Banking, Accounting and Finance*, *1*(2), 114–132.

Fiordelisi, F., & Mare, D. S. (2014). Competition and financial stability in European cooperative banks. *Journal of International Money and Finance*, *45*, 1–16.

Fique, J. (2017). The macrofinancial risk assessment framework (MFRAF), version 2.0. *Bank of Canada, Technical Report*, *No.111*.

Flood, M., Jagadish, H., & Raschid, L. (2016). Big data challenges and opportunities in financial stability monitoring. *Financial Stability Review*(20), 129–142.

Fonseca, A. R., & Gonzalez, F. (2008). Cross-country determinants of bank income smoothing by managing loan-loss provisions. *Journal of Banking & Finance*, *32*(2), 217–228.

Frankel, J. A., & Rose, A. K. (1996). Currency crashes in emerging markets: An empirical treatment. *Journal of International Economics*, *41*(3), 351–366.

Frankel, J. A., & Saravelos, G. (2012). Can leading indicators assess country vulnerability? evidence from the 2008–09 global financial crisis. *Journal of International Economics*, *87*(2), 216–231.

FSA. (2009). *Strenghening liquidity standards* (Tech. Rep.). Financial Services Authority.

FSB. (2009a). The financial crisis and information gaps. *Report to G20 Ministers of Finance and Central Bank Governors*.

FSB. (2009b). Financial stability board charter. *Financial Stability Board*.

FSB. (2011a). *Key attributes of effective resolution regimes for financial institutions*

(Tech. Rep.). Financial Stability Board.

FSB. (2011b). *Shadow banking: strengthening oversight and regulation* (Tech. Rep.). http://www.fsb.org: Financial Stability Board.

FSB. (2014a). *2014 update of group of global systemically important banks (G-SIBs)* (Tech. Rep.). http://www.financialstabilityboard.org/2014/11/2014-update-of-list-of-global-systemically-important-banks/: Financial Stability Board.

FSB. (2014b). *Adequacy of loss-absorbing capacity of global systemically important banks in resolution* (Tech. Rep.). http://www.financialstabilityboard.org/2014/11/adequacy-of-loss-absorbing-capacity-of-global-systemically-important-banks-inresolution/: Financial Stability Board.

Fu, T.-T., Juo, J.-C., Chiang, H.-C., Yu, M.-M., & Huang, M.-y. (2016). Risk-based decompositions of the meta profit efficiency of taiwanese and chinese banks. *Omega*, *62*, 34–46.

Fu, X., Lin, Y. R., & Molyneux, P. (2014). Bank competition and financial stability in Asia pacific. *Journal of Banking & Finance*, *38*, 64–77.

Fujii, H., Managi, S., & Matousek, R. (2014). Indian bank efficiency and productivity changes with undesirable outputs: A disaggregated approach. *Journal of Banking & Finance*, *38*, 41–50.

Fukuyama, H., & Weber, W. L. (2009). Output slacks-adjusted cost efficiency and value-based technical efficiency in DEA models. *Journal of the Operations Research Society of Japan*, *52*(2), 86–104.

Fungáčová, Z., Solanko, L., & Weill, L. (2010). Market power in the Russian banking industry. *Economie Internationale*(4), 127–145.

Fungáčová, Z., & Weill, L. (2013). Does competition influence bank failures? evidence from Russia. *Economics of Transition*, *21*(2), 301–322.

Gadanecz, B., & Jayaram, K. (2008). Measures of financial stability-a review. *Irving Fisher Committee Bulletin*, *31*, 365–383.

Gaganis, C., & Pasiouras, F. (2013). Financial supervision regimes and bank efficiency: International evidence. *Journal of Banking & Finance*, *37*(12), 5463–5475.

Gaganis, C., Pasiouras, F., Doumpos, M., & Zopounidis, C. (2010). Modelling banking sector stability with multicriteria approaches. *Optimization Letters*, *4*(4), 543–558.

Galati, G., & Moessner, R. (2013). Macroprudential policy–a literature review. *Journal of Economic Surveys*, *27*(5), 846–878.

Gane, M. (2006). *Auguste comte.* Abingdon, Oxon: Routledge.

García-Cestona, M., & Surroca, J. (2008). Multiple goals and ownership structure: Effects on the performance of Spanish savings banks. *European Journal of Operational Research*, *187*(2), 582–599.

Gardener, E., Molyneux, P., & Nguyen-Linh, H. (2011). Determinants of efficiency in South East Asian banking. *The Service Industries Journal*, *31*(16), 2693–2719.

Garmaise, M. J., & Moskowitz, T. J. (2006). Bank mergers and crime: The real and social effects of credit market competition. *The Journal of Finance*, *61*(2), 495–538.

Garriga, A. C. (2017). Regulatory lags, liberalization, and vulnerability to banking crises. *Regulation & Governance*, *11*(2).

Gelos, R. G., & Roldós, J. (2004). Consolidation and market structure in emerging market banking systems. *Emerging Markets Review*, *5*(1), 39–59.

Gibson, H. D., Hall, S. G., & Tavlas, G. S. (2018). Measuring systemic vulnerability in European banking systems. *Journal of Financial Stability*, *36*, 279–292.

Gideon, F., Petersen, M. A., Mukuddem-Petersen, J., & Hlatshwayo, L. (2013). Basel III and the Net Stable Funding Ratio. *ISRN Applied Mathematics*, *2013*.

Giesecke, K., & Kim, B. (2011). Systemic risk: What defaults are telling US. *Management Science*, *57*(8), 1387-1405.

Giglio, S. (2016). Credit default swap spreads and systemic financial risk. *European Systemic Risk Board Working Paper Series*, *15*.

Girardi, G., & Ergün, A. T. (2013). Systemic risk measurement: Multivariate garch estimation of covar. *Journal of Banking & Finance*, *37*(8), 3169–3180.

Gobat, J., Yanase, M., & Maloney, J. F. (2014). The Net Stable Funding Ratio:

Impact and issues for consideration. *IMF Working Paper*, *WP/14/106*, 1-42.

Goddard, J., Liu, H., Molyneux, P., & Wilson, J. O. (2011). The persistence of bank profit. *Journal of Banking & Finance*, *35*(11), 2881–2890.

Goetz, M. R. (2018). Competition and bank stability. *Journal of Financial Intermediation*, *35*, 57-69.

Goodhart, C. A. E., Hartmann, P., Llewellyn, D. T., Rojas-Suarez, L., & Weisbrod, S. (1998). *Financial regulation: Why, how, and where now?* Psychology Press.

Goodhart, C. A. E., Kashyap, A. K., Tsomocos, D. P., & Vardoulakis, A. P. (2012). Financial regulation in general equilibrium. *National Bureau of Economic Research*, *No.17909*.

Gormley, T., Gupta, N., & Jha, A. (2018). Quiet life no more? corporate bankruptcy and bank competition. *Journal of Financial and Quantitative Analysis*, *53*(2), 581–611.

Greene, W. H. (1981). On the asymptotic bias of the ordinary least squares estimator of the tobit model. *Econometrica: Journal of the Econometric Society*, 505-513.

Greene, W. H. (2005). Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis*, *23*(1), 7-32.

Greene, W. H. (2018). *Econometric analysis* (8th ed.). New York: Pearson.

Gropp, R., & Moerman, G. (2004). Measurement of contagion in banks' equity prices. *Journal of International Money and Finance*, *23*(3), 405-459.

Guevara, J. F. D., & Maudos, J. (2002). Inequalities in the efficiency of the banking sectors of the European Union. *Applied Economics Letters*, *9*(8), 541–544.

Guzman, I., & Reverte, C. (2008). Productivity and efficiency change and shareholder value: evidence from the Spanish banking sector. *Applied Economics*, *40*(15), 2037-2044.

Haar, B. (2015). Oxford handbook of financial regulation. In N. Moloney, E. Ferran, & J. Payne (Eds.), (p. 188-215). Oxford: Oxford University Press.

Haber, S., & Perotti, E. (2008). *The political economy of financial systems* (Tech. Rep.). Tinbergen Institute Discussion Paper.

Hagendorff, J., Casu, B., & Girardone, C. (2009). Competition issues in European banking. *Journal of Financial Regulation and Compliance*, *17*(2), 119–133.

Hakenes, H., & Schnabel, I. (2011). Capital regulation, bank competition, and financial stability. *Economics Letters*, *113*(3), 256–258.

Haldane, A. G., & May, R. M. (2011). Systemic risk in banking ecosystems. *Nature*, *469*(7330), 351–355.

Halkos, G. E., & Salamouris, D. S. (2004). Efficiency measurement of the greek commercial banks with the use of financial ratios: a data envelopment analysis approach. *Management Accounting Research*, *15*(2), 201-224.

Halkos, G. E., & Tzeremes, N. G. (2013). Estimating the degree of operating efficiency gains from a potential bank merger and acquisition: A DEA bootstrapped approach. *Journal of Banking & Finance*, *37*(5), 1658-1668.

Hall, A. R. (2005). *Generalized Method of Moments: Advanced Texts in Econometrics)* (1st ed.). New York: Oxford University Press.

Hannan, T. H. (1991). Foundations of the structure-conduct-performance paradigm in banking. *Journal of Money, Credit and Banking*, 68-84.

Hannoun, H. (2010). Towards a global financial stability framework. In *Speech at the 45th seacen governors' conference, siem reap province, cambodia* (p. 26-27).

Härle, P., Lüders, E., Pepanides, T., Pfetsch, S., Poppensieker, T., & Stegemann, U. (2010). Basel III and European banking: Its impact, how banks might respond, and the challenges of implementation. *EMEA Banking*, 16-17.

Hartmann, P., De Bandt, O., & Peydro-Alcalde, J.-L. (2014). The oxford handbook of banking. In A. N. Berger, P. Molyneux, & J. O. S. Wilson (Eds.), (2nd ed., p. 633-673). Oxford: Oxford University Press.

Hassan, M. K., & Aliyu, S. (2018). A contemporary survey of islamic banking literature. *Journal of Financial Stability*, *34*, 12-43.

Hauner, D. (2005). Explaining efficiency differences among large german and Austrian banks. *Applied Economics*, *37*(9), 969-980.

Hautsch, N., Schaumburg, J., & Schienle, M. (2015). Financial network systemic risk contributions. *Review of Finance*, *19*(2), 685-738.

Heath, D., Delbaen, F., Eber, J., & Artzner, P. (1999). Coherent measures of risk.

Mathematical Finance, *9*(3), 203–228.

Hermes, N., & Meesters, A. (2015). Financial liberalization, financial regulation and bank efficiency: a multi-country analysis. *Applied Economics*, *47*(21), 2154-2172.

Hicks, J. R. (1935). Annual survey of economic theory: the theory of monopoly. *Econometrica: Journal of the Econometric Society*, *3*, 1-20.

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind* (Vol. 2). London: McGraw-Hill.

Hollo, D., Kremer, M., & Lo Duca, M. (2012). CISS-a composite indicator of systemic stress in the financial system. *ECB Working Paper*, *1426*.

Holod, D., & Lewis, H. F. (2011). Resolving the deposit dilemma: A new DEA bank efficiency model. *Journal of Banking & Finance*, *35*(11), 2801-2810.

Homar, T., & van Wijnbergen, S. J. (2017). Bank recapitalization and economic recovery after financial crises. *Journal of Financial Intermediation*, *32*, 16–28.

Hong, H., Huang, J.-Z., & Wu, D. (2014). The information content of Basel III liquidity risk measures. *Journal of Financial Stability*, *15*, 91-111.

Hoque, H., Andriosopoulos, D., Andriosopoulos, K., & Douady, R. (2015). Bank regulation, risk and return: Evidence from the credit and sovereign debt crises. *Journal of Banking & Finance*, *50*, 455–474.

Horsky, D., & Nelson, P. (2006). Testing the statistical significance of linear programming estimators. *Management Science*, *52*(1), 128-135.

Hou, X., Wang, Q., & Zhang, Q. (2014). Market structure, risk taking, and the efficiency of chinese commercial banks. *Emerging Markets Review*, *20*, 75-88.

Houston, J. F., Lin, C., Lin, P., & Ma, Y. (2010). Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics*, *96*(3), 485–512.

Howarth, D., & Quaglia, L. (2016). The comparative political economy of Basel III in Europe. *Policy and Society*, *35*(3), 205–214.

Hsiao, C. (2003). *Analysis of panel data*. Cambridge university press.

Hsu, J. C., & Moroz, M. (2009). The banking crisis handbook. In G. Gregoriou (Ed.), (Vol. 39, p. 49). CRC Press.

Hu, G. X., Pan, J., & Wang, J. (2013). Noise as information for illiquidity. *The Journal of Finance*, *68*(6), 2341-2382.

Huang, M.-Y., & Fu, T.-T. (2013). An examination of the cost efficiency of banks in taiwan and China using the metafrontier cost function. *Journal of Productivity Analysis*, *40*(3), 387-406.

Huang, X., Zhou, H., & Zhu, H. (2009). A framework for assessing the systemic risk of major financial institutions. *Journal of Banking & Finance*, *33*(11), 2036-2049.

Hung, C.-H. D., Jiang, Y., Liu, F. H., & Tu, H. (2018). Competition or manipulation? an empirical evidence of determinants of the earnings persistence of the US banks. *Journal of Banking & Finance*, *88*, 442-454.

Ibragimov, R., Jaffee, D., & Walden, J. (2011). Diversification disasters. *Journal of Financial Economics*, *99*(2), 333-348.

IJtsma, P., Spierdijk, L., & Shaffer, S. (2017). The concentration-stability controversy in banking: New evidence from the EU-25. *Journal of Financial Stability*, *33*, 273-284.

IMF. (2012). *Global financial stability report: Restoring confidence and progressing on reforms* (Tech. Rep.). Author.

Inanoglu, H., Jacobs, M., Liu, J., & Sickles, R. (2016). The handbook of post crisis financial modeling. In E. Haven, P. Molyneux, J. O. Wilson, S. Fedotov, & M. Duygun (Eds.), (p. 110-146). Springer.

Iwanicz-Drozdowska, M., Altman, E. I., Laitinen, E., & Suvas, A. (2014). Bankruptcy prediction in an international context: a review and an empirical analysis of Altman's Z-score model. In *International risk management conference.* Warsaw School of Economics.

Jaffry, S., Ghulam, Y., & Cox, J. (2013). Trends in efficiency in response to regulatory reforms: The case of Indian and Pakistani commercial banks. *European Journal of Operational Research*, *226*(1), 122-131.

Jayakumar, M., Pradhan, R. P., Dash, S., Maradana, R. P., & Gaurav, K. (2018). Banking competition, banking stability, and economic growth: Are feedback effects at work? *Journal of Economics and Business*, *96*, 15–41.

Jeitschko, T. D., & Jeung, S. D. (2005). Incentives for risk-taking in banking–a unified approach. *Journal of Banking & Finance*, *29*(3), 759–777.

Jeon, B. N., Olivero, M. P., & Wu, J. (2011). Do foreign banks increase competition? evidence from emerging Asian and Latin American banking markets. *Journal of Banking & Finance*, *35*(4), 856-875.

Jeon, J. Q., & Lim, K. K. (2013). Bank competition and financial stability: A comparison of commercial banks and mutual savings banks in korea. *Pacific-Basin Finance Journal*, *25*, 253–272.

Jesson, J., Matheson, L., & Lacey, F. M. (2011). *Doing your literature review: traditional and systematic techniques*. London: Sage.

Jiménez, G., Lopez, J. A., & Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability*, *9*(2), 185-195.

Jobst, A. A. (2014). Measuring systemic risk-adjusted liquidity (SRL) -A model approach. *Journal of Banking & Finance*, *45*, 270-287.

Jobst, A. A., & Gray, D. F. (2013). Systemic contingent claims analysis-estimating market-implied systemic risk. *IMF Working Paper*, *WP/13/54*, 1-42.

Jordà, Ò., Schularick, M., & Taylor, A. M. (2015). Leveraged bubbles. *Journal of Monetary Economics*, *76*, S1–S20.

Jun, D., Ahn, C., & Kim, G. (2017). Analysis of the global financial crisis using statistical moments. *Finance Research Letters*, *21*, 47-52.

Kahn, C., Pennacchi, G., & Sopranzetti, B. (2005). Bank consolidation and the dynamics of consumer loan interest rates. *The Journal of Business*, *78*(1), 99-134.

Kaminsky, G., Lizondo, S., & Reinhart, C. M. (1998). Leading indicators of currency crises. *IMF Staff Papers*, *45*(1), 1-48.

Kapan, T., & Minoiu, C. (2018). Balance sheet strength and bank lending: Evidence from the global financial crisis. *Journal of Banking & Finance*, *92*, 35-50.

Kasman, A., & Carvallo, O. (2014). Financial stability, competition and efficiency in Latin American and Caribbean banking. *Journal of Applied Economics*, *17*(2), 301-324.

Kasman, S., & Kasman, A. (2015). Bank competition, concentration and financial stability in the turkish banking industry. *Economic Systems*, *39*(3), 502-517.

Kaufman, H. (2009). *The road to financial reformation: Warnings, consequences, reforms*. John Wiley & Sons.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American Economic Review*, 1183-1200.

Keister, T., & Bech, M. (2012). On the liquidity coverage ratio and monetary policy implementation. *BIS Quarterly Review*.

Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance*, *34*(11), 2767-2787.

Khanna, T., & Yafeh, Y. (2005). Business groups and risk sharing around the world. *The Journal of Business*, *78*(1), 301–340.

Khanna, T., & Yafeh, Y. (2007). Business groups in emerging markets: Paragons or parasites? *Journal of Economic Literature*, *45*(2), 331–372.

Kim, J. (2018). Bank competition and financial stability: Liquidity risk perspective. *Contemporary Economic Policy*, *36*(2), 337–362.

Kim, S., Plosser, M. C., & Santos, J. A. (2018). Macroprudential policy and the revolving door of risk: Lessons from leveraged lending guidance. *Journal of Financial Intermediation*, *34*, 17–31.

King, M. R. (2013). The Basel III Net Stable Funding Ratio and bank net interest margins. *Journal of Banking & Finance*, *37*(11), 4144-4156.

King, P., & Tarbert, H. (2011). Basel III: an overview. *Banking & Financial Services Policy Report*, *30*(5), 1-18.

Kirkwood, J., & Nahm, D. (2006). Australian banking efficiency and its relation to stock returns. *Economic Record*, *82*(258), 253-267.

Kleinow, J., Moreira, F., Strobl, S., & Vähämaa, S. (2017). Measuring systemic risk: A comparison of alternative market-based approaches. *Finance Research Letters*, *21*, 40-46.

Kleinow, J., Nell, T., Rogler, S., & Horsch, A. (2014). The value of being systemically important: event study on regulatory announcements for banks. *Applied Financial Economics*, *24*(24), 1585-1604.

Klomp, J., & De Haan, J. (2015). Bank regulation and financial fragility in developing countries: Does bank structure matter? *Review of Development Finance*, *5*(2), 82-90.

Knight, M. D. (2006). Marrying the micro and macroprudential dimensions of financial stability: six years on. *BIS Speeches*, *119*.

Knott, A. M., & Posen, H. E. (2005). Is failure good? *Strategic Management Journal*, *26*(7), 617–641.

Koetter, M., Kolari, J. W., & Spierdijk, L. (2012). Enjoying the quiet life under deregulation? evidence from adjusted lerner indices for US banks. *Review of Economics and Statistics*, *94*(2), 462-480.

Koetter, M., & Meesters, A. (2013). Efficiency and productivity growth: Modelling in the financial services industry. In F. Pasiouras (Ed.), (p. 215-236). Wiley Online Library.

König, P., & Pothier, D. (2016). Design and pitfalls of Basel's new liquidity rules. *DIW Economic Bulletin*, *6*(21), 251-259.

Košak, M., & Zajc, P. (2006). Determinants of bank efficiency differences in the new EU member countries. *Financial Stability Report: Expert Papers on Financial Stability, Bank of Slovenia.*

Kreis, Y., & Leisen, D. P. (2018). Systemic risk in a structural model of bank default linkages. *Journal of Financial Stability*, *39*, 221–236.

Kritzman, M., & Li, Y. (2010). Skulls, financial turbulence, and risk management. *Financial Analysts Journal*, *66*(5), 30–41.

Kritzman, M., Li, Y., Page, S., & Rigobon, R. (2011). Principal components as a measure of systemic risk. *Journal of Portfolio Management*, *37*(4), 112-126.

Krüger, S., Rösch, D., & Scheule, H. (2018). The impact of loan loss provisioning on bank capital requirements. *Journal of Financial Stability*, *36*, 114–129.

Kumar, S., & Gulati, R. (2008). Evaluation of technical efficiency and ranking of public sector banks in India: An analysis from cross-sectional perspective. *International Journal of Productivity and Performance management*, *57*(7), 540-568.

Kumar, S., & Gulati, R. (2009a). Did efficiency of Indian public sector banks converge with banking reforms? *International Review of Economics*, *56*(1), 47.

Kumar, S., & Gulati, R. (2009b). Technical efficiency and its determinants in the Indian domestic banking industry: an application of DEA and tobit analysis. *American Journal of Finance and Accounting*, *1*(3), 256-296.

Kuosmanen, T. (2012). Stochastic semi-nonparametric frontier estimation of electricity distribution networks: Application of the stoned method in the finnish regulatory model. *Energy Economics*, *34*(6), 2189-2199.

Kuosmanen, T., & Kortelainen, M. (2012). Stochastic non-smooth envelopment of data: semi-parametric frontier estimation subject to shape constraints. *Journal of Productivity Analysis*, *38*(1), 11-28.

Kupiec, P. H. (1995). Techniques for verifying the accuracy of risk measurement models. *The Journal of Derivatives*, *3*(2).

Kupiec, P. H. (2016). Will TLAC regulations fix the G-SIB too-big-to-fail problem? *Journal of Financial Stability*, *24*, 158-169.

Kupiec, P. H., Lee, Y. Y., & Rosenfeld, C. M. (2017). Does bank supervision impact bank loan growth? *Journal of Financial Stability*, *28*, 29-48.

Kyj, L., & Isik, I. (2008). Bank X-efficiency in Ukraine: An analysis of service characteristics and ownership. *Journal of Economics and Business*, *60*(4), 369-393.

Laeven, L., & Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, *93*(2), 259-275.

Laeven, L., & Valencia, F. (2008). Systemic banking crises: A new database. *IMF Working Papers*, *WP/08/224*.

Laeven, L., & Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, *61*(2), 225-270.

LaFond, R., & You, H. (2010). The federal deposit insurance corporation improvement act, bank internal controls and financial reporting quality. *Journal of Accounting and Economics*, *49*(1), 75-83.

Laurenceson, J., & Qin, F. (2008). Has minority foreign investment in China's banks improved their cost efficiency? *China & World Economy*, *16*(3), 57-74.

Laurent, J.-P., Sestier, M., & Thomas, S. (2016). Trading book and credit risk: How fundamental is the Basel review? *Journal of Banking & Finance*, *73*, 211–223.

Lazopoulos, I., & Gabriel, V. (2019). Policy mandates and institutional architecture. *Journal of Banking & Finance*, *100*, 122–134.

Lee, C.-C., & Hsieh, M.-F. (2014). Bank reforms, foreign ownership, and financial stability. *Journal of International Money and Finance*, *40*, 204-224.

Lee, S. H. (2013). Systemic liquidity shortages and interbank network structures. *Journal of Financial Stability*, *9*(1), 1-12.

Lee, T.-H., & Chih, S.-H. (2013). Does financial regulation affect the profit efficiency and risk of banks? evidence from China's commercial banks. *The North American Journal of Economics and Finance*, *26*, 705-724.

Leeney, S. (2015). Bloomberg credit risk DRSK GO framework, methodology & usage. *A Bloomberg Proffestional Service Offering Document*, *2079487*.

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, *29*(10), 2577-2603.

Leibenstein, H. (1966). Allocative efficiency vs. X-efficiency. *The American Economic Review*, *56*(3), 392-415.

Lensink, R., & Meesters, A. (2014). Institutions and bank performance: A stochastic frontier analysis. *Oxford Bulletin of Economics and Statistics*, *76*(1), 67-92.

Leon, F. (2015). Does bank competition alleviate credit constraints in developing countries? *Journal of Banking & Finance*, *57*, 130-142.

Lepetit, L., & Strobel, F. (2015). Bank insolvency risk and Z-score measures: A refinement. *Finance Research Letters*, *13*, 214–224.

Leroy, A., & Lucotte, Y. (2017). Is there a competition-stability trade-off in European banking? *Journal of International Financial Markets, Institutions and Money*, *46*, 199-215.

Li, J. Y., & Tang, D. Y. (2016). The leverage externalities of credit default swaps. *Journal of Financial Economics*, *120*(3), 491–513.

Lim, C. H., Krznar, I., Lipinsky, F., Otani, A., & Wu, X. (2013). the macroprudential framework: policy responsiveness and institutional arrangements. *IMF Working Papers*, *WP/13/116*.

Liu, H., Molyneux, P., & Nguyen, L. H. (2012). Competition and risk in South East Asian commercial banking. *Applied Economics*, *44*(28), 3627-3644.

Liu, H., Molyneux, P., & Wilson, J. O. (2013). Competition and stability in European banking: A regional analysis. *The Manchester School*, *81*(2), 176-201.

Lloyd-Williams, D. M., Molyneux, P., & Thornton, J. (1994). Market structure and performance in Spanish banking. *Journal of Banking & Finance*, *18*(3), 433-443.

Loipersberger, F. (2018). The effect of supranational banking supervision on the financial sector: Event study evidence from Europe. *Journal of Banking & Finance*, *91*, 34-48.

Lombardi, D., & Siklos, P. L. (2016). Benchmarking macroprudential policies: An initial assessment. *Journal of Financial Stability*, *27*, 35-49.

Longstaff, F. A. (2010). The subprime credit crisis and contagion in financial markets. *Journal of Financial Economics*, *97*(3), 436-450.

López-Espinosa, G., Moreno, A., Rubia, A., & Valderrama, L. (2015). Systemic risk and asymmetric responses in the financial industry. *Journal of Banking & Finance*, *58*, 471-485.

Love, I., & Martínez Pería, M. S. (2014). How bank competition affects firms' access to finance. *The World Bank Economic Review*, *29*(3), 413–448.

Lozano-Vivas, A., & Pasiouras, F. (2010). The impact of non-traditional activities on the estimation of bank efficiency: international evidence. *Journal of Banking & Finance*, *34*(7), 1436-1449.

Luo, Y., Tanna, S., & De Vita, G. (2016). Financial openness, risk and bank efficiency: Cross-country evidence. *Journal of Financial Stability*, *24*, 132-148.

Ly, K. C., Liu, F. H., & Opong, K. (2018). Can parents protect their children? risk comparison analysis between affiliates of multi-and single-bank holding companies. *Journal of Financial Stability*, *37*, 1-10.

Mainik, G., & Schaanning, E. (2014). On dependence consistency of covar and some other systemic risk measures. *Statistics & Risk Modeling*, *31*(1), 49-77.

Malherbe, F. (2014). Self-fulfilling liquidity dry-ups. *The Journal of Finance*, *69*(2), 947–970.

Malmquist, S. (1953). Index numbers and indifference surfaces. *Trabajos de estadística*, *4*(2), 209–242.

Manlagnit, M. C. V. (2015). Basel regulations and banks' efficiency: The case of the Philippines. *Journal of Asian Economics*, *39*, 72-85.

Martínez-Jaramillo, S., Pérez, O. P., Embriz, F. A., & Dey, F. L. G. (2010). Systemic risk, financial contagion and financial fragility. *Journal of Economic Dynamics and Control*, *34*(11), 2358-2374.

Martinez-Miera, D., & Repullo, R. (2010). Does competition reduce the risk of bank failure? *Review of Financial Studies*, *23*(10), 3638-3664.

Masciandaro, D., & Volpicella, A. (2016). Macro prudential governance and central banks: Facts and drivers. *Journal of International Money and Finance*, *61*, 101-119.

Matousek, R., Nguyen, T. N., & Stewart, C. (2016). Performance of the banking sector of a developing country: A non-structural model using the disequilibrium approach. *Kingston University Economics Discussion Papers*, *2*.

Maudos, J., & de Guevara, J. F. (2007). The cost of market power in banking: Social welfare loss vs. cost inefficiency. *Journal of Banking & Finance*, *31*(7), 2103–2125.

McNelis, P. D., & Yoshino, N. (2016). Finding stability in a time of prolonged crisis: Unconventional policy rules for Japan. *Journal of Financial Stability*, *27*, 122-136.

Meeks, R., Nelson, B. D., & Alessandri, P. (2014). Shadow banks and macroeconomic instability. *Bank of England Working Paper*, *487*.

Meeusen, W., & Van den Broeck, J. (1977). Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review*, *18*(2), 435-444.

Merton, R. C. (1973). A rational theory of option pricing. *Bell Journal of Economics* *and Management Science*, *4*, 141-183.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449-470.

Mester, L. J. (2008). Handbook of financial intermediation & banking. In A. V. Thakor & A. W. A. Boot (Eds.), (p. 133-162). Amsterdam: Elsevier.

Miles, D., Yang, J., & Marcheggiano, G. (2013). Optimal bank capital. *The Economic Journal*, *123*(567), 1–37.

Mirzaei, A., Moore, T., & Liu, G. (2013). Does market structure matter on banks' profitability and stability? Emerging vs. Advanced economies. *Journal of Banking & Finance*, *37*(8), 2920-2937.

Mishkin, F. S. (1999). Financial consolidation: Dangers and opportunities. *Journal of Banking & Finance*, *23*(2), 675-691.

Mishkin, F. S., Stern, G., & Feldman, R. (2006). How big a problem is too big to fail? a review of gary stern and ron feldman's "too big to fail: The hazards of bank bailouts". *Journal of Economic Literature*, *44*(4), 988-1004.

Mobarek, A., Muradoglu, G., Mollah, S., & Hou, A. J. (2016). Determinants of time varying co-movements among international stock markets during crisis and non-crisis periods. *Journal of Financial Stability*, *24*, 1–11.

Moch, N. (2013). Competition in fragmented markets: New evidence from the german banking industry in the light of the subprime crisis. *Journal of Banking & Finance*, *37*(8), 2908–2919.

Mohanty, S. K. (2008). Basel II: Challenges and risks. *Academy of Banking Studies Journal*, *7*(1/2), 109.

Molyneux, P., & Williams, J. (2013). Bank efficiency in Latin America. In F. Pasiouras (Ed.), (p. 1-18). Wiley Online Library.

Moosa, I. A. (2010). Basel II as a casualty of the global financial crisis. *Journal of Banking Regulation*, *11*(2), 95–114.

Moradi-Motlagh, A., & Saleh, A. S. (2014). Re-examining the technical efficiency of Australian banks: A bootstrap DEA approach. *Australian Economic Papers*, *53*(1-2), 112-128.

Mügge, D., & Stellinga, B. (2015). The unstable core of global finance: Contingent valuation and governance of international accounting standards. *Regulation & Governance*, *9*(1), 47-62.

Muijs, D. (2004). Doing quantitative research in education with spss. In D. Muijs (Ed.), (pp. 64–84). London: SAGE Publications Ltd.

Mukherjee, K., Ray, S. C., & Miller, S. M. (2001). Productivity growth in large US commercial banks: The initial post-deregulation experience. *Journal of Banking & Finance*, *25*(5), 913-939.

Müller, C., & Noth, F. (2018). Market power and risk: Evidence from the US mortgage market. *Economics Letters*, *169*, 72-75.

Nathan, A., & Neave, E. H. (1989). Competition and contestability in canada's financial system: Empirical results. *Canadian Journal of Economics*, *22*(3), 576–594.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, 1417-1426.

Nicoló, G. D., Boyd, J. H., & Smith, B. D. (2004). Crisis in competitive versus monopolistic banking systems. *Journal of Money, Credit and Banking*, *36*(3), 487–510.

Nicoló, G. D., & Kwast, M. L. (2002). Systemic risk and financial consolidation: Are they related? *Journal of Banking & Finance*, *26*(5), 861–880.

Nirei, M., Sushko, V., & Caballero, J. (2016). Bank capital shock propagation via syndicated interconnectedness. *Computational Economics*, *47*(1), 67–96.

Noman, A. H. M., Gee, C. S., & Isa, C. R. (2018). Does bank regulation matter on the relationship between competition and financial stability? evidence from Southeast Asian countries. *Pacific-Basin Finance Journal*, *48*, 144-161.

Northcott, C. A. (2004). Competition in banking: A review of the literature. *Bank of Canada Working Paper*, *24*.

O'Donnell, C. J., Rao, D. P., & Battese, G. E. (2008). Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. *Empirical Economics*, *34*(2), 231–255.

OECD. (2010). Competition, concentration and stability in the banking sector. *OECD Policy Roundtables*, 1-366.

Olgu, O., & Weyman-Jones, T. G. (2008). Parametric and nonparametric malmquist productivity decomposition: a case study of European commercial banks. *International Journal of Business Performance Management*, *10*(4), 344-365.

Øvretveit, J., Leviton, L., & Parry, G. (2011). Increasing the generalisability of improvement research with an improvement replication programme. *BMJ Quality & Safety*, *20*(Supplement 1), i87–i91.

Pakravan, K. (2014). Bank capital: the case against Basel. *Journal of Financial Regulation and Compliance*, *22*(3), 208–218.

Panzar, J. C., & Rosse, J. N. (1987). Testing for 'monopoly' equilibrium. *The Journal of Industrial Economics*, *35*(4), 443–456.

Papanikolaou, N. I. (2018a). To be bailed out or to be left to fail? a dynamic competing risks hazard analysis. *Journal of Financial Stability*, *34*, 61-85.

Papanikolaou, N. I. (2018b). To screen or not to screen? let the competition decide. *Economics Letters*, *170*, 175-178.

Park, K. H., & Weber, W. L. (2006). A note on efficiency and productivity growth in the korean banking industry, 1992–2002. *Journal of Banking & Finance*, *30*(8), 2371-2386.

Pasiouras, F. (2008). International evidence on the impact of regulations and supervision on banks' technical efficiency: an application of two-stage data envelopment analysis. *Review of Quantitative Finance and Accounting*, *30*(2), 187-223.

Pasiouras, F., Tanna, S., & Zopounidis, C. (2009). The impact of banking regulations on banks' cost and profit efficiency: Cross-country evidence. *International Review of Financial Analysis*, *18*(5), 294-302.

Patro, D. K., Qi, M., & Sun, X. (2013). A simple indicator of systemic risk. *Journal of Financial Stability*, *9*(1), 105-116.

Paul, S., & Kourouche, K. (2008). Regulatory policy and the efficiency of the banking sector in Australia. *Australian Economic Review*, *41*(3), 260-271.

Peltzman, S. (1977). The gains and losses from industrial concentration. *The Journal of Law and Economics*, *20*(2), 229–263.

Perotti, E. C., & Suarez, J. (2011). A pigovian approach to liquidity regulation.

International Journal of Central Banking, *7*(4), 3-41.

Persaud, A. D. (2013). Handbook of safeguarding global financial stability. In J. G. Caprio et al. (Eds.), (p. 443-449). San Diego: Academic Press.

Petria, N., Capraru, B., & Ihnatov, I. (2015). Determinants of banks' profitability: evidence from eu 27 banking systems. *Procedia Economics and Finance*, *20*, 518-524.

Pierret, D. (2015). Systemic risk and the solvency-liquidity nexus of banks. *International Journal of Central Banking*, *11*(3), 193-227.

Poledna, S., Molina-Borboa, J. L., Martínez-Jaramillo, S., van der Leij, M., & Thurner, S. (2015). The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *Journal of Financial Stability*, *20*(1), 70-81.

Popper, K. (2005). *The logic of scientific discovery*. London: Routledge.

Pozsar, Z., Adrian, T., Ashcraft, A. B., & Boesky, H. (2012). Shadow banking. *Federal Reserve Bank of New York Staff Report*, *458*.

Puzanova, N., & Düllmann, K. (2013). Systemic risk contributions: A credit portfolio approach. *Journal of Banking & Finance*, *37*(4), 1243-1257.

Radić, N., Fiordelisi, F., Girardone, C., et al. (2011). Price competition, efficiency and riskiness in investment banking. *Centre for EMEA Banking Finance and Economics working paper series*, *2011*(7), 1-27.

Reinhart, C. M., & Rogoff, K. S. (2009). *This time is different: eight centuries of financial folly*. Princeton University Press.

Rhoades, S. A. (1977). Structure-performance studies in banking: A summary and evaluation. *Federal Reserve Board Staff Economic Studies*, *92*(1).

Rhoades, S. A. (1995). Market share inequality, the hhi, and other measures of the firm-composition of a market. *Review of Industrial Organization*, *10*(6), 657–674.

Rhoades, S. A., & Rutz, R. D. (1982). Market power and firm risk: a test of the 'quiet life'hypothesis. *Journal of Monetary Economics*, *9*(1), 73-85.

Rixen, T. (2013). Why reregulation after the crisis is feeble: Shadow banking, offshore financial centers, and jurisdictional competition. *Regulation &*

Governance, *7*(4), 435-459.

Rodriguez, J. C. (2007). Measuring financial contagion: A copula approach. *Journal of Empirical Finance*, *14*(3), 401-423.

Rodríguez, L. J. (2002). International banking regulation: Where's the market discipline in Basel II? *Cato Institute Policy Analysis*(No.455).

Rodríguez-Moreno, M., & Peña, J. I. (2013). Systemic risk measures: The simpler the better? *Journal of Banking & Finance*, *37*(6), 1817-1831.

Roll, R. (2013). Volatility, correlation, and diversification in a multi-factor world. *Journal of Portfolio Management*, *39*(2), 11–18.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system gmm in stata. *The Stata Journal*, *9*(1), 86-136.

Roodman, D. (2009b). A note on the theme of too many instruments. *Oxford Bulletin of Economics and statistics*, *71*(1), 135-158.

Rose, A. K., & Spiegel, M. M. (2010). Cross-country causes and consequences of the 2008 crisis: International linkages and american exposure. *Pacific Economic Review*, *15*(3), 340-363.

Rose, A. K., & Spiegel, M. M. (2012). Cross-country causes and consequences of the 2008 crisis: early warning. *Japan and the World Economy*, *24*(1), 1-16.

Rossi, S. P., Schwaiger, M. S., & Winkler, G. (2009). How loan portfolio diversification affects risk, efficiency and capitalization: A managerial behavior model for Austrian banks. *Journal of Banking & Finance*, *33*(12), 2218-2226.

Roukny, T., Battiston, S., & Stiglitz, J. E. (2018). Interconnectedness as a source of uncertainty in systemic risk. *Journal of Financial Stability*, *35*, 93-106.

Ruckes, M. (2004). Bank competition and credit standards. *Review of Financial Studies*, *17*(4), 1073–1102.

Russel, F. (2018). *Industry classification benchmark (ICB)* (Tech. Rep.). http://www.ftserussell.com/financial-data/industry-classification-benchmark-icb.

Ryan, B., Scapens, R., & Theobald, M. (2002). *Research method and methodology in finance and accounting*. London: Thomson Learning.

Sahoo, B. K., & Tone, K. (2009). Decomposing capacity utilization in data envelopment analysis: An application to banks in India. *European Journal of Operational Research*, *195*(2), 575-594.

Samad, A. (2008). Market structure, conduct and performance: Evidence from the Bangladesh banking industry. *Journal of Asian Economics*, *19*(2), 181-193.

Sarlin, P. (2016). Macroprudential oversight, risk communication and visualization. *Journal of Financial Stability*, *27*, 160-179.

Saunders, A., & Wilson, B. (1996). Bank capital structure: charter value and diversification effects. *New York University Salomon Center Working Papers*, *52*.

Schaeck, K., & Cihak, M. (2012). Banking competition and capital ratios. *European Financial Management*, *18*(5), 836-866.

Schaeck, K., & Cihák, M. (2014). Competition, efficiency, and stability in banking. *Financial Management*, *43*(1), 215–241.

Schaeck, K., Cihak, M., & Wolfe, S. (2009). Are competitive banking systems more stable? *Journal of Money, Credit and Banking*, *41*(4), 711-734.

Schaub, A. (2005). The lamfalussy process four years on. *Journal of Financial Regulation and Compliance*, *13*(2), 110-120.

Schimmelpfennig, M. A., Roubini, N., & Manasse, P. (2003). Predicting sovereign debt crises. *IMF Working Papers*, *WP/03/221*.

Schmitt, M., & Schmaltz, C. (2016). Potential implications of a NSFR on German banks' credit supply and profitability. *Deutsche Bundesbank Discussion Paper*, *37*.

Schmitz, S. W., & Hesse, H. (2014). Recent studies reinforce the case for the liquidity coverage ratio. *Vox: Research-based policy analysis and commentary from leading economists*.

Schneider, P., Sögner, L., & Veža, T. (2010). The economic role of jumps and recovery rates in the market for corporate default risk. *Journal of Financial and Quantitative Analysis*, *45*, 1517–1547.

Schooner, H. M., & Taylor, M. (1998). Convergence and competition: The case of bank regulation in Britain and the United States. *Michigan Journal of International Law*, *20*, 595.

Schwaab, B., Koopman, S. J., & Lucas, A. (2011). Systemic risk diagnostics: coincident indicators and early warning signals. *ECB Working Paper*, *1327*.

Scott, H. S. (2010). Reducing systemic risk through the reform of capital regulation. *Journal of International Economic Law*, *13*(3), 763-778.

Sealey, C. W., & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *The Journal of Finance*, *32*(4), 1251-1266.

Segoviano Basurto, M., & Goodhart, C. A. E. (2009). Banking stability measures. *IMF Working Papers*, *WP/09/4*, 1-54.

Seiford, L. M., & Thrall, R. M. (1990). Recent developments in DEA: the mathematical programming approach to frontier analysis. *Journal of Econometrics*, *46*(1-2), 7–38.

Sensoy, A., Ozturk, K., & Hacihasanoglu, E. (2014). Constructing a financial fragility index for emerging countries. *Finance Research Letters*, *11*(4), 410-419.

Shaban, M., & James, G. A. (2018). The effects of ownership change on bank performance and risk exposure: Evidence from indonesia. *Journal of Banking & Finance*, *88*, 483–497.

Shaffer, S. (2004). Patterns of competition in banking. *Journal of Economics and Business*, *56*(4), 287–313.

Shao, J., & Tu, D. (2012). *The jackknife and bootstrap*. New York, US: Springer Science & Business Media.

Sharma, S., Lavery, J., & Polyanskiy, K. (2010). Challenges in maintaining the regulatory capital requirements. *International Journal of Financial Services Management*, *4*(4), 243-259.

Shepherd, W. G. (1983). Economies of scale and monopoly profits. In *Industrial organization, antitrust, and public policy* (pp. 165–204). Springer.

Shleifer, A., & Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance*, *47*(4), 1343-1366.

Silva, T. C., da Silva Alexandre, M., & Tabak, B. M. (2017). Bank lending and systemic risk: A financial-real sector network approach with feedback. *Journal* *of Financial Stability*.

Silva, T. C., Guerra, S. M., Tabak, B. M., & de Castro Miranda, R. C. (2016). Financial networks, bank efficiency and risk-taking. *Journal of Financial Stability*, *25*, 247–257.

Silva-Buston, C. (2019). Systemic risk and competition revisited. *Journal of Banking & Finance*, *101*, 188–205.

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31-64.

Simkovic, M. (2013). Competition and crisis in mortgage securitization. *Indiana Law Journal*, *88*, 213.

Simon, W. H. (2010). Optimization and its discontents in regulatory design: Bank regulation as an example. *Regulation & Governance*, *4*(1), 3-21.

Smirlock, M. (1985). Evidence on the (non) relationship between concentration and profitability in banking. *Journal of Money, Credit and Banking*, *17*(1), 69-83.

Sosa-Padilla, C. (2018). Sovereign defaults and banking crises. *Journal of Monetary Economics*, *99*, 88–105.

Spokeviciute, L., Keasey, K., & Vallascas, F. (2019). Do financial crises cleanse the banking industry? evidence from us commercial bank exits. *Journal of Banking & Finance*, *99*, 222–236.

Staat, M. (2001). The effect of sample size on the mean efficiency in DEA: Comment. *Journal of Productivity Analysis*, *15*(2), 129-137.

Stavarek, D. (2006). Banking efficiency in the context of European integration. *Eastern European Economics*, *44*(4), 5-31.

Stern, G. H., & Feldman, R. J. (2004). *Too big to fail: The hazards of bank bailouts.* Brookings Institution Press.

Stiglitz, J. E. (2010). Risk and global economic architecture: Why full financial integration may be undesirable. *American Economic Review*, *100*(2), 388-392.

Sufian, F. (2007). The efficiency of islamic banking industry in malaysia: Foreign vs domestic banks. *Humanomics*, *23*(3), 174-192.

Sun, L., & Chang, T.-P. (2011). A comprehensive analysis of the effects of risk measures on bank efficiency: Evidence from emerging Asian countries. *Journal of Banking & Finance*, *35*(7), 1727-1735.

Tabak, B. M., Fazio, D. M., & Cajueiro, D. O. (2012). The relationship between banking market competition and risk-taking: Do size and capitalization matter? *Journal of Banking & Finance*, *36*(12), 3366–3381.

Tan, Y., & Floros, C. (2018). Risk, competition and efficiency in banking: Evidence from China. *Global Finance Journal*, *35*, 223–236.

Tarashev, N., Borio, C., & Tsatsaronis, K. (2010). Attributing systemic risk to individual institutions. *BIS Working Paper*, *308*.

Tarashev, N. A., Borio, C. E., & Tsatsaronis, K. (2009). The systemic importance of financial institutions. *BIS Quarterly Review, September*.

Tarullo, D. K. (2008). *Banking on Basel: the future of international financial regulation.* Peterson Institute.

Tasche, D. (2002). Expected shortfall and beyond. *Journal of Banking & Finance*, *26*(7), 1519-1533.

Tayler, G. (2003). UK building society demutualisation motives. *Business Ethics: A European Review*, *12*(4), 394-402.

Thoraneenitiyan, N., & Avkiran, N. K. (2009). Measuring the impact of restructuring and country-specific factors on the efficiency of post-crisis East Asian banking systems: Integrating DEA with SFA. *Socio-Economic Planning Sciences*, *43*(4), 240-252.

Tirole, J. (1988). *The theory of industrial organization.* Cambridge, London: MIT press.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: Journal of the Econometric Society*, 24–36.

Tone, K., & Tsutsui, M. (2010). Dynamic DEA: A slacks-based measure approach. *Omega*, *38*(3), 145-156.

Tone, K., & Tsutsui, M. (2014). Dynamic DEA with network structure: A slacks-based measure approach. *Omega*, *42*(1), 124-131.

Tonzer, L. (2015). Cross-border interbank networks, banking risk and contagion. *Journal of Financial Stability*, *18*, 19-32.

Tortosa-Ausina, E., Grifell-Tatjé, E., Armero, C., & Conesa, D. (2008). Sensitivity analysis of efficiency and malmquist productivity indices: An application to Spanish savings banks. *European Journal of Operational Research*, *184*(3), 1062-1084.

Trapp, M., & Wewel, C. (2013). Transatlantic systemic risk. *Journal of Banking & Finance*, *37*(11), 4241-4255.

Tufano, P. (2003). Handbook of the economics of finance. In G. Constantinides, M. Harris, & R. Stulz (Eds.), (p. 307—336). Amsterdam, Netherland: Elsevier.

Turk-Ariss, R. (2010). On the implications of market power in banking: Evidence from developing countries. *Journal of Banking & Finance*, *34*(4), 765–775.

Uchida, H., & Satake, M. (2009). Market discipline and bank efficiency. *Journal of International Financial Markets, Institutions and Money*, *19*(5), 792-802.

Uhde, A., & Heimeshoff, U. (2009). Consolidation in banking and financial stability in Europe: Empirical evidence. *Journal of Banking & Finance*, *33*(7), 1299-1311.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability*, *7*(3), 111-125.

USTD. (2009). *Financial regulatory reform: A new foundation rebuilding financial supervision and regulation* (Tech. Rep.). US Treasury Department.

Vallascas, F., & Hagendorff, J. (2011). The impact of European bank mergers on bidder default risk. *Journal of Banking & Finance*, *35*(4), 902-915.

Van Leuvensteijn, M., Bikker, J. A., Van Rixtel, A. A., & Sørensen, C. K. (2011). A new approach to measuring competition in the loan markets of the euro area. *Applied Economics*, *43*(23), 3155-3167.

Vazquez, F., & Federico, P. (2015). Bank funding structures and risk: Evidence from the global financial crisis. *Journal of Banking & Finance*, *61*, 1-14.

Vento, G. A., & La Ganga, P. (2009). Bank liquidity risk management and supervision: which lessons from recent market turmoil. *Journal of Money, Investment and Banking*, *10*, 79-126.

Vincent, K. S. (1995). Auguste comte: An intellectual biography. *History of*

European Ideas, *21*(1), 111-114.

Virtanen, T., Tölö, E., Virén, M., & Taipalus, K. (2018). Can bubble theory foresee banking crises? *Journal of Financial Stability*, *36*, 66–81.

Wagner, W. (2009). Efficient asset allocations in the banking sector and financial regulation. *International Journal of Central Banking*, *5*(1), 75-95.

Wang, M.-H., & Huang, T.-H. (2007). A study on the persistence of farrell's efficiency measure under a dynamic framework. *European Journal of Operational Research*, *180*(3), 1302-1316.

Wei, X., Gong, Y., & Wu, H.-M. (2017). The impacts of Net Stable Funding Ratio requirement on banks' choices of debt maturity. *Journal of Banking & Finance*, *82*, 229–243.

Weill, L. (2004). Measuring cost efficiency in European banking: A comparison of frontier techniques. *Journal of Productivity Analysis*, *21*(2), 133-152.

Weiß, G. N., Neumann, S., & Bostandzic, D. (2014). Systemic risk and bank consolidation: International evidence. *Journal of Banking & Finance*, *40*, 165-181.

Wilcox, J. A. (2005). The increasing integration and competition of financial institutions and of financial regulation. In *Research in finance* (pp. 215–238). Emerald Group Publishing Limited.

Williams, J., & Nguyen, N. (2005). Financial liberalisation, crisis, and restructuring: A comparative study of bank performance and bank governance in South East Asia. *Journal of Banking & Finance*, *29*(8-9), 2119–2154.

Wilson, J. O., Casu, B., Girardone, C., & Molyneux, P. (2010). Emerging themes in banking: recent literature and directions for future research. *The British Accounting Review*, *42*(3), 153-169.

Wilson, M. V. (1927). Auguste comte's conception of humanity. *The International Journal of Ethics*, *38*(1), 88–102.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step gmm estimators. *Journal of Econometrics*, *126*(1), 25-51.

Wójcik-Mazur, A., & Szajt, M. (2015). Determinants of liquidity risk in commercial banks in the European Union. *Argumenta Oeconomica*, *35*(2), 25-47.

Xiaogang, C., Skully, M., & Brown, K. (2005). Banking efficiency in China: Application of DEA to pre-and post-deregulation eras: 1993–2000. *China Economic Review*, *16*(3), 229-245.

Yan, M., Hall, M. J., & Turner, P. (2012). A cost–benefit analysis of Basel III: Some evidence from the UK. *International Review of Financial Analysis*, *25*, 73–82.

Ye, W., Luo, K., & Du, S. (2014). Measuring contagion of subprime crisis based on mvmq-caviar method. *Discrete Dynamics in Nature and Society*, *46*(1).

Yellen, J. (2013, Jan). Interconnectedness and systemic risk: Lessons from the financial crisis and policy implications. *American Economic Association/American Finance Association Joint Luncheon.*

Yeyati, E. L., & Micco, A. (2007). Concentration and foreign penetration in Latin American banking sectors: Impact on competition and risk. *Journal of Banking & Finance*, *31*(6), 1633-1647.

Yildirim, S. H., & Philippatos, G. C. (2007). Efficiency of banks: recent evidence from the transition economies of Europe, 1993–2000. *European Journal of Finance*, *13*(2), 123-143.

You, L., & Daigler, R. T. (2010). Is international diversification really beneficial? *Journal of Banking & Finance*, *34*(1), 163-173.

Zhang, Q., Vallascas, F., Keasey, K., & Cai, C. X. (2015). Are market-based measures of global systemic importance of financial institutions useful to regulators and supervisors? *Journal of Money, Credit and Banking*, *47*(7), 1403–1442.

Zhao, T., Casu, B., & Ferrari, A. (2010). The impact of regulatory reforms on cost structure, ownership and competition in Indian banking. *Journal of Banking & Finance*, *34*(1), 246-254.

Zhao, X. (2000). State-owned commercial banks efficiency analysis. *Journal of Economic Science*, *6*(2), 45–50.

Zhivaikina, A., & Peresetsky, A. (2017). Russian bank credit ratings and bank license withdrawal 2012-2016. *Journal of the New Economic Association*, *36*(4), 49–80.

Zigraiova, D., & Havranek, T. (2016). Bank competition and financial stability: Much ado about nothing? *Journal of Economic Surveys*, *30*(5), 944-981.

Zouari, A. (2010). Efficient structure versus market power: theories and empirical evidence. *International Journal of Economics and Finance*, *2*(4), 151-166.

Appendix

Table 6.2: Summary of Variables Used within this Thesis

Variable	Variable Name	Description	Bloomberg Mnemonic/Calculation
C3/5	3 or 5 Firm Concentration Ratio	This is a country level measure of market concentration. Calculated by comparing the top 3 or 5 banks (via market shares) assets relative to the markets total assets.	Code in Stata
CIR	Cost to Income Ratio (Efficiency Ratio)	This measures the managerial quality, approximated by the cost to income ratio. A low values of CIR indicates a better managerial quality. This is calculated by dividing the operating costs (administrative & fixed costs, such as salaries and property expenses, this does not include write offs and non-performing loans) by operating income.	eff_ratio
CreditRisk	Credit Risk (Assets Quality)	Calculated as a ratio of non-performing loans divided by total loans. The higher the ratio, indicates the lower the quality of the banks loan portfolio.	$\frac{\text{bs\_non\_perform\_loans}}{\text{bs\_tot\_loan}}$
Crises	Indicates a country in crisis	This is a Dummy variable, 1 indicates if the country the bank is located is classed as in a crisis period , 0 if not	Following Laeven and Valencia (2013) definition of crisis timing.
DEA	Data Envelopment Analysis (DEA)	A non-parametric method to estimation the production efficiency frontier. It is used to empirically measure productive efficiency of decision making units (Banks in this case). The Malmquist Productivity Index (MPI) measures the productivity changes along with time variations and can be decomposed into changes in efficiency, taking into account time variants of technology (Färe et al., 1994).	Linear Programming in Stata

Table 6.2 Continued

Variable	Variable Name	Description	Bloomberg Mnemonic/Calculation
Deposits	Total Customer Deposits	Total deposits received from customers (Both demand and term deposits) and amounts due to banks.	bs_customer_deposits
DIP	Distressed Insurance Premium	Distressed Insurance Premium is as an *ex ante* country level systemic risk metric which represents a hypothetical insurance premium against a systemic financial distress, defined as total losses that exceed a given threshold of total bank liabilities (15%).	Code in Matlab
DIV	Diversification	This is a proxy for a banks' business model, calculated via net non-interest income to net operating income. Such a proxy is used because the magnitude of non-interest income greatly reflects bank participation within the financial markets such as securities trading and asset management services.	$\frac{\text{non\_int\_inc}}{\text{is\_oper\_inc}}$
Expenses	Expenses	This is a proxy for operational expenses of the bank. This is calculated by operating costs divided by total assets. Higher the ratio suggests more the bank makes us of less expenses, thus more cost efficient.	$\frac{\text{is\_operating\_expn}}{\text{bs\_tot\_assets}}$
FLVRG	Leverage	Financial Leverage is defined as the ratio of average total assets to average total common equity. The higher the ratio would indicate a more riskier business strategy.	fncl_lvrg
G-SIB	Globally Systemic Important Banks	This is a Dummy variable, 1 if the bank is classed as a G-SIB (by their countries regulatory body), 0 if not.	

Table 6.2 Continued

Variable	Variable Name	Description	Bloomberg Mnemonic/Calculation
HHI	The Herfindahl-Hirschman Index	This is a country level measure of market concentration. This is calculated by squaring the market share of each bank competing in a market and then summing the resulting numbers.	Code in Stata
IntIncome	Interest Income	This is the total interest income from loans, federal funds sold, resale agreements and other short-term interbank investments. Additionally this includes federal funds sold and repurchase agreements, deposits at interest with other banks and interest from direct financing lease receivables.	is_int_inc
LIQ	Liquidity	The Banking balance sheet liquidity is measured by the ratio of net loans to deposits and short term funding (LIQ). An increase in LIQ would suggest to a higher probability of bank distress.	$\frac{\text{bs\_tot\_loans}}{\text{bs\_st\_borrow} + \text{bs\_customer\_deposits}}$
LLP	Provisions for loan losses	This is the accounted provisions for loan losses. This variable could be negative when the bank has recovered previous loan losses. Note this figure, may include other provisions if they are not disclosed separately.	is_prov_for_loan_loss
LnASIZE	Bank Size	Natural log of total assets. This includes the sum of cash & bank balances, Federal funds sold & resale agreements, Investments for trade & sale, net loans, investments held to maturity, net fixed assets, other assets, customers' acceptances and liabilities.	bs_tot_asset
LnLSIZE	Bank Size	Natural log of total loans. Includes Commercial, Consumer & Other loans.	bs_tot_loan

Table 6.2 Continued

Variable	Variable Name	Description	Bloomberg Mnemonic/Calculation
MarketCap	Market Capitalisation	This is the total monetary market value of all of a bank's outstanding shares at accounting period end date.	historical_market_cap
NETIN	Net Income	This is the profits of the bank after all expenses have been deducted.	net_income
NPL	Non-performing Loans	Gross Non-performing Loans, which are loans in default or close to default, and do not accrue interest. All loans that have an impairment provision are classified as non-accrual.	bs_non_perform_loans
NSFR	Net Stable Funding Ratio	The Net Stable Funding Ratio as proposed in Basel iii, seeks to calculate the proportion of available Stable funding via the liabilities over required stable funding for the assets.	NSFR is approximated using equation 5.5.15 (Chiaramonte & Casu, 2017) as discussed in section 3.4.3.
OEA	Other earning assets	This is the sum of marketable securities, short-term investments, interbank assets, long-term investments and long-term receivables.	earn_asset - bs_tot_loan
PFC	Price of Financial Capital	This is calculated via total interest expenses divided by short term assets.	$\frac{\text{is\_int\_expenses}}{\text{st\_borrowing\_and\_repo} + \text{bs\_customer\_deposits}}$
PL	Price of Labour	This is calculated via the banks personal expense dived by total assets.	$\frac{\text{is\_personnel\_exp}}{\text{bs\_net\_fix\_asset}}$

Table 6.2 Continued

Variable	Variable Name	Description	Bloomberg Mnemonic/Calculation
PPC	Price of Physical Capital	This is calculated via the banks non-interest expenses divided by fixed assets.	$\frac{\text{non\_int\_exp}}{\text{bs\_net\_fix\_asset}}$
PRH	Panzar-Rosse H Statistic (disequilibrium approach)	This is an alternatively measure of market competition, follow the method proposed by Matousek et al. (2016).	GMM regression using Stata
ProdGrowth	Productivity Growth	Following the method proposed by (Park & Weber, 2006) to calculate productivity growth following the malmquist index.	effch + techch
ROA	Return on Assets	ROA is calculated as the ratio of its net income in a given period to the total value of its assets. Return on Assets (ROA) in percentage is an indicator of how profitable a company is relative to its total assets.	return_on_asset
ROE	Return on Common Equity	Measure of a bank's profitability by revealing how much profit a company generates with the money shareholders have invested, in percentage.	return_com_eqy
SFAEFF	Stochastic Frontier Analysis (SFA)	SFA is used to examine cost efficiency, using a fixed-effects model Greene (2005) with a half-normal distribution for the inefficiency term.	Code in Stata
SDROA	Standard deviation of ROA	This is a calculation of the 3 years rolling standard deviation of ROA.	Code in Stata

Table 6.2 Continued

Variable	Variable Name	Description	Bloomberg Mnemonic/Calculation
Solvency	Solvency risk (also known as ETA)	Proxy of for banking solvency. A low Solvency suggests high leverage, which makes banks less resilient to shocks, all else being equal.	$\frac{\text{total\_equity}}{\text{bs\_tot\_asset}}$
T1CR	Tier 1 Capital Ratio	This is The ratio of Tier 1 capital to risk-weighted assets as proposed within the Basel Accords. The minimum ratios set by the U.S. Federal Reserve and the OTC are 4% for commercial banks and 3% for savings and loans, respectively.	bs_tier1_cap_ratio
T1LVGR	Tier 1 leverage ratio	The Tier 1 leverage ratio is the relationship between a banking organisation's core capital and its total assets, as proposed within the Basel Accords. The Tier 1 leverage ratio is calculated by dividing Tier 1 capital by a bank's average total consolidated assets and certain off-balance sheet exposures.	$\frac{\text{bs\_tier1\_capital}}{\text{bs\_tot\_assets}}$
TAHHI	The Herfindahl-Hirschman Index based on Total Assets	An alternative measure of market concentration using total assets.	Stata Code
TC	Total Cost	A proxy of the banks total costs following method proposed by S. Kasman and Kasman (2015).	non_int_exp + is_int_expenses
TEHHI	The Herfindahl-Hirschman Index based on Total Equity	An alternative measure of market concentration using total equity.	Stata Code

Table 6.2 Continued

Variable	Variable Name	Description	Bloomberg Mnemonic/Calculation
TLOAN	Total Loans	This is the sum of loans includes, commercial loans, consumer loans and other loans.	bs_tot_loan
ZScore	Z-Score	Proxy for bank default which is measured as a bank level financial stability measure. This calculation is discussed in section 5.5.2.	$Z = \frac{(\mathrm{ROA} + \mathrm{ETA})}{\mathrm{SDROA}}$