

Measuring the systemic risk in the South African and United States banking sectors

GM Foggitt
22033009

Thesis submitted in fulfillment of the requirements for the degree *Philosophiae Doctor* in **Risk Management** at the Potchefstroom Campus of the North-West University

Promoter: Prof A Heymans
Co-promoter: Dr GW van Vuuren
Assistant promoter: Dr AM Pretorius

November 2016

To
Derek Foggitt
and
Elsa Foggitt

“And above all watch with glittering eyes the whole world around you, because the greatest secrets are always hidden in the most unlikely places. Those who don’t believe in magic will never find it.”
– Roald Dahl

Acknowledgements

- Frans Dreyer, thank you for seeing the potential in me way before anyone else did, for encouraging me, and believing in me. For showing an incredible amount of selflessness and for always putting my interests first. The lessons I've learnt from you extend far beyond this thesis. Your contribution was truly enormous and this would have been impossible without you. I think it's safe to say that we have now told the story right. Thank you for showing me that genuinely good people do still exist; I'm eternally grateful.
- Gary van Vuuren, thank you for providing the inspiration. Every class you gave and conversation with you left me feeling that great things were indeed possible. Thank you for your unwavering willingness to help with technical aspects, mathematical intricacies, and generally making any challenge seem surmountable. Thank you for having more belief in me than I have in myself.
- André Heymans, thank you for coming in at the 11th hour, refining the final product and undertaking a large administrative task with enthusiasm.
- Anmar Pretorius, thank you for all your insights and assistance.
- Marius Botha, thank you for the recommendation.
- The faculty of the Department of Economics of the North-West University and the students that I shared classes with. In some way, through various undergraduate and postgraduate classes, you all provided the foundation upon which this thesis could be built. I look back on my time here with fond memories.
- Mrs Paulette Henrey, thank you for shaping my writing skills and enhancing my understanding of the English language in so many ways.
- Potchefstroom High School for Boys, *Iustorum Semita Lux Splendens*. Thank you for teaching me to dream.
- My lifelong friends, if you're the average of the people you surround yourself with, then I couldn't be in better company. Although far away in distance, 'The Group' is an unmoving constant in my life and an ever-present pillar of support. Without you, I wouldn't have had the self-belief to take on seemingly unconquerable challenges.
- My family, especially my parents, for their love, support, and enormous patience. For always trusting my decisions and supporting me throughout all my mistakes and indecision. It's been a long road, but we finally got here. This thesis is just as much yours as it is mine. My heroes, I would be nowhere without you.
- Finally, to the One who guided me through dark times and tumultuous years, always providing me with unwavering strength and sense of purpose.

Abstract

Systemic risk can affect the entire global financial system and may therefore be one of the most important financial risks – yet it remains one of the least understood. The sub-prime crisis in 2008 illustrated how systemic risk in the financial sector of one country could spread to the financial sectors in other countries. The direct transfer of systemic risk was made possible by phenomena such as contagion and common shocks. It follows that the more interconnected a financial sector is, the more easily systemic risk would be spread. The failure of African Bank in 2014 and the subsequent intervention by the South African Reserve Bank (SARB) illustrated that the interconnectedness of the South African (SA) financial sector could potentially be a source of systemic risk, even though large levels of systemic risk are not an inherent part of the SA financial sector. When assessing systemic risk, the development level of the country, as well as its level of financial integration will need to be taken into account. As a result, the effective implementation of regulatory measures, such as the Basel capital requirements and other more country-specific items of legislation, should be based on an accurate, quantifiable measure of systemic risk.

In order to quantify systemic risk, it can be defined as the capital shortfall an institution is likely to experience, conditional on the entire financial sector being undercapitalised. This propensity is referred to as the Systemic Risk Index (SRISK). A key component of SRISK is the Marginal Expected Shortfall (MES). This is calculated by taking into account conditional volatilities, Dynamic Conditional Correlations (DCCs) and tail expectations. This study applies a previously unused approach based on extreme value theory to model the tail expectations.

The SRISK of the SA and United States (US) banking sectors is measured between 2001 and 2013. Additionally, the systemic risk transfer that took place over the period 2001 to 2014 from the US market to the SA market is measured by investigating potential contagion, volatility spillover effects, and the MES of the SA equity market as a hypothetical bank within the US equity market. Finally, a panel regression model is used to investigate which individual banking characteristics were the most significant determinants of systemic risk in SA and US banks over the period 2001 to 2013.

The results show that the level of systemic risk in the US decreased following the sub-prime crisis, although the total contribution of the largest banks increased. Notwithstanding that the absolute levels of systemic risk did not increase, the relative contributions of the largest banks did. The panel regression model found that the most significant determinants of systemic risk in the US were the size of the bank, the stability of its funding source, and the bank's degree of leverage. This increase in the systemic risk contributions of the large banks can therefore, most likely be attributed to their acquisition of a number of smaller banks. Furthermore, the panel regression results are in line with expected findings; however,

the fact that the total financial sector systemic risk could remain relatively unchanged or even decrease, while the individual contributions of the largest banks increased, is worth questioning. The explanation for this could potentially be that capital deficits of large banks are being offset by the surpluses held by a number of smaller banks, therefore providing the illusion of decreased systemic risk.

Contrastingly, the results for SA showed that the systemic risk of the entire financial sector was not particularly high for most of the period. However, there were significant spikes in the levels of systemic risk during periods of financial turmoil in countries apart from SA. Specifically, the stock market crash in 2002 and the sub-prime crisis in 2008. The highest systemic risk contribution during quiet periods was from Investec, the smallest bank dealt with in this study. However, during periods of financial turmoil, the contributions of other larger banks increased markedly. The implication of these spikes is that systemic risk levels may also be highly dependent on external economic factors, in addition to internal banking characteristics. Analyses were done to investigate the possibility of a direct transfer of systemic risk from the US to SA, but no significant evidence was found. The panel regression model for SA investigated the individual determinants of systemic risk and found that internal banking characteristics, such as the amount of market-based activities undertaken by a bank and its degree of leverage, were significant determinants of systemic risk. As for external factors, the levels of capital inflows were found to be a significant determinant of systemic risk.

The implications of these results for regulations differ for the two economies. For the US, systemic risk may not have worsened in absolute terms, but the contributions of large banks have. A failure of one of these banks would therefore be likely to cause a financial crisis. Regulations that address the size, degree of leverage and the stability of the bank's funding source will need to be addressed. For SA, the economic fundamentals of the country itself seem to have little effect on systemic risk. In fact, the systemic risk of the entire financial sector, as well as the individual banks within it, seems to be dependent on the stability of other financial sectors. The implication therefore, is that in addition to complying with individual banking regulations, such as Basel, and corporate governance regulations promoting ethical behaviour, such as King III, banks should always have sufficient capital reserves in order to mitigate the effects of a financial crisis in a foreign country and the subsequent outflow of capital. The use of worst-case scenario analyses (such as those in this study) could aid in determining exactly how much capital banks could need in order to be considered sufficiently capitalised during a financial crisis, and therefore safe from systemic risk.

Keywords: Systemic risk; Contagion; Volatility; Banks; Regulation; SRISK; DCC; MES; EGARCH; South Africa; United States

Opsomming

Sistemiese risiko kan die totale globale finansiële stelsel beïnvloed en daarom is dit een van die belangrikste finansiële risiko's – tog bly dit een van dié wat die minste verstaan word. Die sub-prima krisis in 2008 is 'n bewys van hoe sistemiese risiko in die finansiële sektor van een land na die finansiële sektore in ander lande kan versprei. Die direkte oordrag van sistemiese risiko word moontlik gemaak deur fenomene, soos verspreiding en algemene skokke. Dit blyk dat hoe meer interafhanklik 'n finansiële sektor is, hoe groter is die moontlikheid van verspreiding van sistemiese risiko. Die ineenstorting van African Bank in 2014 en die daaropvolgende ingryping deur die Suid-Afrikaanse Reserwebank (SARB), het bewys dat die interafhanklikheid van die SA finansiële sektor 'n potensiële bron van sistemiese risiko kan wees, al is groot vlakke van sistemiese risiko nie 'n inherente deel van die Suid-Afrikaanse (SA) finansiële sektor nie. Wanneer sistemiese risiko geassesseer word, sal die ontwikkelingsvlak van die land, sowel as die vlak van die finansiële integrasie daarvan, in ag geneem moet word. Gevolglik behoort die doeltreffende implementering van regulerende maatreëls soos Basel en ander meer land-spesifieke artikels van wetgewing, op 'n akkurate, kwantifiseerbare maatstaf van sistemiese risiko gebaseer te wees.

Om sistemiese risiko te kwantifiseer, kan dit gedefinieer word as die kapitale tekort wat 'n instelling waarskynlik sal ondervind, met die verstande dat die totale finansiële sektor ondergekapitaliseer is. Daar word na hierdie geneigdheid verwys as die Sistemiese Risiko Indeks (SRISK). 'n Sleutelkomponent van SRISK is die Marginale Verwagte Tekort (MES). Dit word bereken deur voorwaardelike wisselvalligheid, dinamiese voorwaardelike korrelasies (DCCs) en uiteindelijke verwagtinge. Die studie verteenwoordig 'n nuwe benadering gebaseer op uiterste waardeteorie om die uiteindelijke verwagtinge te modelleer.

Die SRISK van SA en die Verenigde State (VS) se banksektore is tussen 2001 en 2013 vasgestel. Bykomend hiertoe word die sistemiese risiko-oordrag wat gedurende die tydperk 2001 tot 2014, vanaf die VS sektor na die SA sektor plaasgevind het, bepaal deur die ondersoek na potensiële verspreiding, wisselvalligheidsoorvloei-invloede en die MES van die SA sektor as 'n hipotetiese bank binne-in die VS sektor. Ten slotte, is 'n paneelregressiemodel gebruik om vas te stel watter individuele bankeienskappe die beduidendste bepalers van sistemiese risiko in SA en VS banke was gedurende die tydperk 2001 tot 2013.

Die resultate dui daarop dat die vlak van sistemiese risiko in die VS as gevolg van die sub-primakrisis afgeneem het, alhoewel die totale bydrae van die grootste banke toegeneem het. Nieteenstaande die feit dat die absolute vlakke van sistemiese risiko nie verhoog het nie, het die relatiewe bydraes van die grootste banke wel verhoog. Die paneelregressiemodel het bevind dat die mees beduidende bepalers van sistemiese risiko in die VS was die grootte van die bank, die stabiliteit van die bank se befondsingsbron en

die bank se magsverhouding. Hierdie verhoging in die sistemiese risikobydraes van die groot banke kan dus heel waarskynlik toegeskryf word aan hulle verkryging van 'n aantal kleiner banke. Voorts sal die paneelregressieresultate ooreenstem met verwagte bevindings, maar die feit dat die totale finansiële sektor sistemiese risiko relatief onveranderd kan bly of selfs kan verminder, terwyl die individuele bydraes van die grootste banke toegeneem het, kan bevraagteken word. Die potensiele verduideliking hiervoor kan wees dat die kapitale tekorte van groot banke geneutraliseer word deur 'n aantal kleiner banke en so die illusie van verminderde sistemiese risiko skep.

In teenstelling hiermee, het die resultate vir SA getoon dat die sistemiese risiko van die totale finansiële sektor nie beduidend hoog was vir die grootste gedeelte van die tydperk nie. Daar was egter beduidende hindernisse in die vlakke van sistemiese risiko gedurende die tydperke van finansiële krisis in ander lande. Hier word veral verwys na die ineenstorting van die aandelemark in 2002 en die subprimakrisis in 2008. Die hoogste sistemiese risiko bydrae gedurende stil tydperke was afkomstig van die kleinste bank in die studie, Investec. Gedurende tydperke van finansiële krisis, het die bydraes van ander groter banke egter aanmerklik verhoog. Die uitwerking van hierdie hindernisse is dat sistemiese risikovlakke ook hoog kan wees afhangend van eksterne ekonomiese faktore bykomend tot interne bankeienskappe. Ontledings wat gedoen is om die moontlikheid van 'n direkte oordrag van sistemiese risiko van die VS na SA te ondersoek, het geen beduidende bewyse opgelewer nie. Die paneelregressiemodel vir SA het die individuele bepalers van sistemiese risiko ondersoek en daar is bevind dat interne bankeienskappe, soos die hoeveelheid markgebaseerde aktiwiteite wat deur 'n bank onderneem is en die bank se magshefboom, beduidende bepalers van sistemiese risiko was. Sover dit eksterne faktore aangaan, is bevind dat die vlak van kapitale invloed 'n beduidende bepaler van sistemiese risiko was.

Die uitwerking van hierdie resultate vir regulasies verskil egter van mekaar sover dit die twee ekonomieë aangaan. Vir die VS het sistemiese risiko miskien nie in absolute terme verswak nie, maar die bydraes van groot banke het wel. Dit is hoogs waarskynlik dat die ineenstorting van een van hierdie banke tot 'n finansiële krisis kan lei. Aandag moet aan die grootte, magshefboom en die stabiliteit van die bank se befondsingsbron geskenk word. Wat SA betref, het die ekonomiese grondbeginsels van die land self blykbaar nie 'n groot uitwerking op sistemiese risiko nie. Om die waarheid te sê, dit wil voorkom asof die sistemiese risiko van die totale finansiële sektor, sowel as van die individuele banke daarbinne, afhanklik is van die stabiliteit van ander finansiële sektore. Die implikasie hiervan is dat, afgesien daarvan dat voldoen moet word aan individuele bankregulasies, soos Basel, en korporatiewe bestuur regulasies wat etiese gedrag bevorder, soos King III, banke voortdurend oor genoegsame kapitale reserwes moet beskik om die uitwerking van 'n finansiële krisis in 'n vreemde land en die gevolglike uitvloei van kapitaal te versag. Die gebruik van "as die ergste gebeur-" scenario ontledings (soos in die studie aangedui) kan help

om presies te bepaal hoeveel kapitaal banke benodig om as voldoende gekapitaliseerd beskou te word tydens 'n finansiële krisis, en dus veilig is teen sistemiese risiko.

Trefwoorde: Sistemiese risiko, Verspreiding, Wisselvalligheid, Banke, Regulasie, SRISK, DCC, MES, EGARCH, Suid-Afrika, Verenigde State

Table of Contents

Acknowledgements	iii
Abstract	iv
Opsomming	vi
Table of Contents	ix
List of Tables	xiii
List of Figures	xvi
CHAPTER 1 INTRODUCTION	1
1.1 INTRODUCTION	1
1.2 BACKGROUND	4
1.3 PROBLEM STATEMENT AND RESEARCH QUESTION.....	14
1.4 RESEARCH AIMS AND OBJECTIVES.....	15
1.5 CONTRIBUTION.....	15
1.6 LITERATURE REVIEW.....	17
1.7 METHODOLOGY.....	17
1.7.1 Data and Software.....	18
1.7.2 Methodology	18
1.8 CHAPTER LAYOUT	20
CHAPTER 2 THE CONCEPT OF SYSTEMIC RISK	21
2.1 INTRODUCTION	21
2.2 THE DEFINITION OF SYSTEMIC RISK	22
2.2.1 Defining systemic risk	22
2.2.2 Section summary	27
2.3 CONTEXTUALISING SYSTEMIC RISK.....	27
2.3.1 Sub-prime crisis case study.....	27
2.3.1.1 Macroeconomic conditions.....	28
2.3.1.2 Microeconomic conditions.....	34
2.3.1.3 The accounting system.....	39
2.3.1.4 Systemic elements.....	43
2.3.1.5 Section summary.....	49
2.3.2 Contagion, common shocks, and informational spillovers.....	50

2.3.2.1	Contagion	50
2.3.2.2	Common shocks	55
2.3.2.3	Informational spillovers	57
2.3.2.4	Section summary	58
2.4	THE ROLE OF SYSTEMICALLY IMPORTANT FINANCIAL INSTITUTIONS	59
2.4.1	Systemically important financial institutions	59
2.4.2	The indicator-based measurement approach	64
2.4.3	Section summary	69
2.5	THE IMPACT OF SYSTEMIC RISK ON EMERGING MARKETS	69
2.5.1	How emerging markets were affected	70
2.5.2	The differing policy responses for emerging markets	79
2.5.3	Section summary	82
2.6	CHAPTER SUMMARY	82
CHAPTER 3 THE REGULATION OF SYSTEMIC RISK		85
3.1	INTRODUCTION	85
3.2	BASEL: THE GLOBAL FRAMEWORK	86
3.2.1	Basel I and II	86
3.2.2	Basel III	91
3.2.3	A critique of the Basel III Accord	96
3.2.4	Section summary	101
3.3	COUNTRY-SPECIFIC REGULATIONS	102
3.3.1	The US regulatory approach	102
3.3.2	The SA regulatory approach	110
3.3.3	Section summary	118
3.4	MACROPRUDENTIAL REGULATIONS	118
3.4.1	Implementing a macroprudential regulatory approach	120
3.4.2	The interaction of macroprudential policy and monetary policy	121
3.4.3	Macroprudential policy tools	124
3.4.4	Section summary	130
3.5	QUANTIFICATION MEASURES FOR SYSTEMIC RISK	131
3.5.1	Conditional Value-at-Risk (CoVaR)	131
3.5.2	Marginal Expected Shortfall (MES)	135
3.5.3	Systemic Risk Index (SRISK)	138
3.5.4	Risk Assessment Model of Systemic Institutions (RAMSI)	142

3.5.5	Other measures	144
3.5.6	Section summary	146
3.6	CHAPTER SUMMARY	146
CHAPTER 4 THE MEASURING OF SYSTEMIC RISK: METHODOLOGY		149
4.1	INTRODUCTION	149
4.2	SYSTEMIC RISK INDEX (SRISK)	150
4.2.1	Conditional volatility.....	152
4.2.2	Dynamic Conditional Correlation (DCC)	156
4.2.3	Tail expectations.....	160
4.2.3.1	Non-parametric tail expectation estimators.....	161
4.2.3.2	Extreme value theory	162
4.2.4	Marginal Expected Shortfall (MES).....	165
4.2.5	Simulations for long-run Marginal Expected Shortfall (LRMES).....	167
4.2.6	Section summary	169
4.3	SYSTEMIC RISK TRANSFER.....	170
4.3.1	Contagion.....	170
4.3.2	Volatility spillovers.....	171
4.3.2.1	Time series unit root testing	171
4.3.2.2	Time series cointegration testing.....	172
4.3.3	Marginal Expected Shortfall (MES) of the SA market.....	174
4.3.4	Section summary	174
4.4	THE DETERMINANTS OF SRISK.....	175
4.4.1	Panel regression model	175
4.4.2	Panel unit root testing	179
4.4.3	Panel cointegration testing.....	180
4.4.4	Section summary	181
4.5	CHAPTER SUMMARY	182
CHAPTER 5 THE MEASURING OF SYSTEMIC RISK: EMPIRICAL RESULTS		184
5.1	INTRODUCTION	184
5.2	DATA.....	185
5.2.1	Balance sheet data	185
5.2.2	Market data	186
5.2.3	Bank selection.....	186
5.2.4	Section summary	189

5.3	SRISK.....	189
5.3.1	SA.....	189
5.3.2	US.....	198
5.3.3	Comparisons and implications.....	207
5.3.4	Section summary.....	208
5.4	SYSTEMIC RISK TRANSFER.....	209
5.4.1	Contagion.....	209
5.4.2	Volatility spillovers.....	210
5.4.3	Marginal Expected Shortfall (MES) of the SA market.....	213
5.4.4	Section summary.....	218
5.5	PANEL REGRESSION MODEL.....	219
5.5.1	SA.....	219
5.5.2	US.....	225
5.5.3	Comparisons and implications.....	229
5.5.4	Section summary.....	231
5.6	CHAPTER SUMMARY.....	231
	CHAPTER 6 SUMMARY, CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK.....	234
6.1	SUMMARY.....	234
6.2	CONCLUSIONS AND RECOMMENDATIONS.....	236
6.3	SUGGESTIONS FOR FUTURE WORK.....	238
	APPENDICES.....	270
	APPENDIX A - US SRISK RESULTS.....	270
	APPENDIX B - REGRESSION TESTING.....	272
	LIST OF ACRONYMS.....	304

List of Tables

Table 1.1: Current (2015) regulatory responsibilities in the US financial sector	6
Table 1.2: Current regulatory responsibilities in the SA financial sector.....	9
Table 1.3: Proposed regulatory responsibilities with a Twin Peaks regulatory structure.	9
Table 1.4: Comparison of Macroprudential and Microprudential perspectives.....	12
Table 2.1: Systemic events in the financial system.....	25
Table 2.2: Stress Test: Impact of home price appreciation on ABS collateralised by sub-prime mortgage loans (Per cent impairment of ABS tranches).....	43
Table 2.3: Global systemically important financial institutions	60
Table 2.4: The two approaches to identifying systemically important financial institutions.	61
Table 2.5: Policies to facilitate systemically important financial institutions.	62
Table 2.6: Measures for assessing systemically important financial institution risk in SA and US.	68
Table 3.1: Systemic risk factors due to Basel II’s drawbacks.....	90
Table 3.2: Capital adequacy standards for Basel III.....	92
Table 3.3: The bucketing approach and additional capital requirements.	96
Table 3.4: Basel III’s response to oversights in Basel II.	98
Table 3.5: Basel III’s systemic risk solutions.	98
Table 3.6: Key financial indicators for SA financial sector on 30 June 2014.	115
Table 3.7: SA and Basel domestic systemically important financial institution assessment methodology.	
116	
Table 3.8: The macroprudential policy toolkit.	128
Table 3.9: Overall use of macroprudential instruments.	129
Table 4.1: Summary of available panel unit root tests.	180
Table 5.1: SA Banks included in the study.....	188
Table 5.2: US banks included in the study.	188
Table 5.3: SRISK of the SA financial sector.....	190
Table 5.4: SRISK of each SA bank using approximated LRMES as input.....	191

Table 5.5: SRISK of each SA bank using simulated LRMES as input.	192
Table 5.6: SRISK contribution (%) of each SA bank.	194
Table 5.7: SRISK ranking of SA Banks.	196
Table 5.8: Leverage of each SA bank.	197
Table 5.9: Approximated LRMES of each SA bank.	197
Table 5.10: SRISK of the US financial sector.	199
Table 5.11: SRISK of each US bank using approximated LRMES as input.	201
Table 5.12: SRISK of each US bank using simulated LRMES as input.	201
Table 5.13: SRISK contribution (%) of each US bank.	204
Table 5.14: SRISK ranking of US banks.	205
Table 5.15: Leverage of each US bank.	206
Table 5.16: Approximated LRMES of each US bank.	206
Table 5.17: Unit root tests (level form).	211
Table 5.18: Unit root tests (first differences form).	211
Table 5.19: EGARCH (1,1) model output.	212
Table 5.20: MES of ALSI in S&P 500 portfolio.	215
Table 5.21: MES of JSE Bank Index in Financial Select Sector SPDR exchange traded fund portfolio.	217
Table 5.22: Descriptive statistics for SA variables.	220
Table 5.23: Correlation matrix for SA variables.	221
Table 5.24: Summary of SA panel unit root test results.	222
Table 5.25: Panel regression model with fixed effects for SA.	223
Table 5.26: Final panel regression model with random effects for SA.	224
Table 5.27: Descriptive statistics for US variables.	225
Table 5.28: Correlation matrix for US variables.	226
Table 5.29: Summary of US panel unit root test results.	226
Table 5.30: Summary of cointegration test results.	227
Table 5.31: Panel regression model with fixed effects for US.	228

Table 5.32: Final panel regression model with fixed effects for the US.....229

List of Figures

Figure 1.1: Interconnection between Banks and non-bank financial institutions	8
Figure 2.1: The US Effective Funds Rate (%) and the Rate implied by the Taylor Rule, 1990-2014.	30
Figure 2.2: Loose-fitting monetary policy.	31
Figure 2.3: Global savings and investment as a share (%) of world GDP.	32
Figure 2.4: Global imbalances (in USD billions) for the period 1997 to 2013.	33
Figure 2.5: Global financial stability report for period October 2007 to April 2008.	41
Figure 2.6: Global financial stability report for period April 2008 to October 2008.	41
Figure 2.7: Credit Spreads (interest rate %) for the period 2000 to 2009.	48
Figure 2.8: Overview of the different approaches to systemically important financial institution measurement.....	63
Figure 2.9: Factors used to identify global systemically important financial institutions.....	65
Figure 2.10: The impact of accounting standards on derivatives measurement of assets during 2012. ..	67
Figure 2.11: Stock market indices of Brazil, Russia, Turkey, Mexico, and SA.....	70
Figure 2.12: Net emerging market private capital inflows.....	73
Figure 2.13: Capital inflow surges and indicators of macroeconomic vulnerability.	76
Figure 2.14: Capital inflow surges and indicators of financial sector vulnerability.....	78
Figure 2.15: Differences in crisis policy responses for emerging markets and developed economies.	80
Figure 3.1: The US regulatory structure.	104
Figure 3.2: Dodd-Frank rulemaking progress in select categories (As of 15 July 2015).....	110
Figure 3.3: SA financial system spillover coefficients (%).	113
Figure 3.4: Policies and objectives after the sub-prime crisis.	119
Figure 3.5: The effect of a countercyclical capital buffer on capital adequacy.....	124
Figure 3.6: ΔCoVaR vs VaR.....	132
Figure 3.7: RAMSI overview.	143
Figure 5.1: SRISK of the SA financial sector.....	190
Figure 5.2: SRISK of each SA bank.	193

Figure 5.3: SRISK contribution (%) of each SA bank.....	195
Figure 5.4: SRISK of the US financial sector.....	199
Figure 5.5: SRISK of each US bank.....	202
Figure 5.6: SRISK contribution (%) of each US bank.....	204
Figure 5.7: DCCs between the S&P 500 and the ALSI.....	210
Figure 5.8: Volatility spillover effect from the S&P 500 to the ALSI.....	213
Figure 5.9: MES of ALSI in S&P 500 portfolio.....	214
Figure 5.10: LRMES of ALSI in S&P 500 portfolio.....	214
Figure 5.11: MES of JSE Bank Index in Financial Select Sector SPDR exchange traded fund portfolio....	216
Figure 5.12: MES of JSE Bank Index in Financial Select Sector SPDR exchange traded fund portfolio....	217

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

One of the key elements to understanding the propagation of financial crises lies in the understanding of the nature of systemic risk (Allen, Babus & Carletti, 2010:1). As the sophistication of the world financial system has evolved, so has the understanding of systemic risk. Bernanke (2009) describes systemic risk as an externality of bank distress on the real economy or the financial system as a whole. De Nicolo, Favara and Ratnovski (2012:5) expand upon this definition to divide these externalities into three broad categories: Firstly, externalities associated with excessive or correlated risk taking; secondly, externalities related to fire sales; lastly, externalities related to interconnectedness. A different classification is then taken by De Bandt, Hartmann and Peydró (2009:636) who categorise systemic risk in both a broad and narrow sense. The narrow sense concerns contagion effects on the interbank market, while the broad sense refers to a common shock to many institutions or markets. The International Monetary Fund (IMF), Bank for International Settlements (BIS) and Financial Stability Board (FStB) have a common definition that perhaps offers the most encompassing explanation of systemic risk. This definition states that systemic risk is the risk of a disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have significant negative consequences for the real economy (IMF, BIS & FStB, 2009:2).

The most recent example of a disruption to the financial system is the global financial crisis that took place in 2007/2008. This illustrated how an impairment of the financial system resulted in a failure¹ that had negative consequences for the entire world economy. What followed in international agendas was the increased need for the creation of a policy system that would be better suited to mitigating systemic risk, as well as a greater focus on macroprudential regulation (Tarashev, Borio & Tsatsaronis, 2010:3).

The global financial crisis in 2007/2008 (henceforth referred to as the sub-prime crisis), with specific focus on the collapse² of American International Group (AIG) and Lehman Brothers in the United States (US), illustrated how single, large financial institutions can cause a contagion effect in the financial sector. The implication is that the collapse of a single financial institution would affect not only the financial sector, but also the entire economy (Georg, 2011:4). This was evidenced by a significant decrease in the Gross Domestic Product (GDP) growth rate of the US and its subsequent entrance into a recession. It decreased from 3 % in 2005 to 0 % in 2008 and then entered recession territory of -3 % during 2009 (World Bank,

¹ The word failure is used interchangeably with the word collapse throughout the study.

² The word collapse is used interchangeably with the word failure throughout the study.

2015). The level of interconnectedness, the corresponding systemic risk posed by such financial institutions, and its subsequent mitigation should become a greater priority, considering the events of the sub-prime crisis.

It is arguable that the sub-prime crisis affected not only the US economy, but to a greater extent financial markets across the world (BIS, 2009:16). This was mainly due to the advancement of information technology and computer systems, which facilitates a greater degree of linkage among global financial markets (Kim & Ryu, 2015:20). The result is that an investor seeking higher yields, as well as portfolio diversification, may invest in an emerging market that offers a greater return on investment. There can, however, also be negative consequences as a result of these linkages, in the form of contagion, and informational spillovers (Kim & Ryu, 2015:21). These are two of the three broad elements of systemic risk, with common shocks the third element. Contagion refers to the direct linkages that take place between financial institutions, such as those in the interbank market. Informational spillovers are similar to contagion, but in a more indirect sense, whereby 'bad news' concerning a large bank in a given country could result in a negative perception regarding all banks in that particular country's financial sector. Common shocks refer to indirect linkages between banks that may occur when they hold similar or identical assets. Such correlation between portfolios may lead to fire sales and result in considerably large losses (Georg, 2011:8). These elements of interconnectedness therefore ensure that an adverse shock in one financial sector has the potential to negatively affect the entire global financial sector and economy.

The effect on emerging market economies, however, differed from developed economies in the sense that their systemic risk could largely be attributed to a slow down or reversal in capital flows that are intermediated through the domestic banking sector (Claessens & Ghosh, 2013:107). Challenges which are unique to emerging markets include how to supervise and regulate the shadow banking sector and foreign banks; increasing cross-sectional risks, such as contagion and the development of systemically important financial institutions; and the driving of economic outcomes in correlation with domestic financial cycles and subsequent credit booms (Claessens & Ghosh, 2013:115). In order to respond to these challenges, certain policies could be implemented. Since the challenges were different, it would follow that the policy responses would also differ for developed, emerging, and developing economies. The exact difference between emerging and developing economies is, however, not entirely clear in the literature. The IMF World Economic Outlook Database classifies countries according to their Gross National Income, export diversification, and level of integration into the global financial system (IMF, 2015a). It can therefore be stated that emerging markets are developing economies in the middle-income group that exhibit characteristics of both a developed economy as well as a developing economy. Emerging markets essentially fall into a broad grey area between the two main categories. Compared with developed economies, developing economies and emerging markets use monetary and fiscal policy less extensively;

fiscal outlays associated with financial sector interventions – such as bank recapitalisation with public funds – are greater in emerging markets; developed economies and emerging markets experience larger output losses than developing economies do; and emerging markets experience the smallest increase in public debt compared with developed economies and developing economies (Laeven & Valencia, 2013:226). Considering the abovementioned differences in the three categories of economies, it may be prudent to investigate the regulation structure of an example of each category, taking into account the various characteristics of each country. It should, however, be kept in mind that policy responses are similar in most respects for emerging and developing markets, therefore no distinction will be made for emerging and developing economies henceforth. Instead, a developed economy and an emerging market will be used as case studies to analyse and explain the effects of systemic risk, as well as the policy responses which are unique to each economy.

The US economy was the origin of the sub-prime crisis and given the way in which systemic risk was allowed to develop to such a point where it had negative consequences for the entire world economy (Mishkin, 2010:1), it would therefore be the obvious choice for a developed economy case study. As an emerging market, South Africa (SA) demonstrates a large degree of global financial integration, and therefore has a greater susceptibility to possible contagion. This contagion could include greater international risk sharing, as well as the risk of transferring negative financial shocks across country borders, and subsequently, increasing the overall level of systemic risk. Claessens, Laeven, Igan and Dell’Ariccia (2010:8) show that this interconnectedness magnified cross-border spillovers early on through channels such as liquidity pressures, global equity sell-offs and a depletion of bank capital. Although the SA economy was not unaffected, it generally had a strong financial regulatory framework and macroeconomic fundamentals, both of which allowed the financial system to remain relatively stable during the sub-prime crisis (National Treasury, 2011:4). The sub-prime crisis may, therefore, not be the most useful example for examining systemic risk in SA. However, the banking crisis which occurred in the SA financial sector during 2014 provides a more appropriate example.

The collapse of African Bank Limited (African Bank) in SA during 2014 was a significant event (IMF, 2014:7). The failure of African Bank was brought about by a combination of issuing many loans and credit cards (mostly at a high interest rate to low-income consumers) while accepting few deposits. Additionally, a large portion of the loans they granted were to consumers who were not creditworthy. The subsequent failure by consumers to repay their loans led to losses of approximately ZAR6.4 billion and the ensuing challenge of raising ZAR8.5 billion through a second rights offer. The need for a ZAR18.5 billion³ bailout by

³ The USD1.6 billion value from the source is converted to ZAR using a December 2014 USD/ZAR exchange rate of 11.5 (INET BFA Dataset, 2015).

the South African Reserve Bank (SARB) may illustrate the point that the financial sector in SA is possibly not as well-regulated as previously believed. The swift action of the SARB was, however, decisive in preventing contagion (IMF, 2014:7). The fact that the SARB had to intervene to prevent contagion could legitimise the case for a re-examination of the financial sector and the various institutions within it, their activities, their systemic risk, and finally, how these institutions are regulated. Such an examination would, conceivably, scrutinise the risk management structure presently in place in SA. The current risk management structure is largely based on the King III Code of Governance and the Basel III Accord. The King III Code of Governance offers broad risk management objectives and a code of good practice, whereas the Basel III Accords specify the recommended capital requirements that financial institutions should meet. These codes, while being the only guidelines mentioning systemic risk in SA, are however, just that, guidelines for best practice. The actual enforcement of the minimum capital requirements is carried out by the Bank Supervision Department of the SARB via the Banks Act (Act No. 94 of 1990), as amended in January 2013 (Basel, 2015b:7). An oversight could therefore exist whereby regulations addressing systemic risk, apart from a minimum capital requirement, are not necessarily required to be implemented by banks.

It can be argued that regulation and control of systemic risk is important because the sub-prime crisis has shown that although individual institutions may have complied with the regulatory requirements on an individual level, there was no basis to measure the compliance of the financial system as a whole. The mitigation of systemic risk would promote financial stability which, along with inflation and output stability, is an important factor for sustained macroeconomic stability (Blanchard, Dell’Ariccia & Mauro, 2013:6). In order to optimally regulate the systemic risk of the financial sector, it is necessary to identify the individual financial institutions that possess the largest amount of systemic risk, and furthermore what the greatest determinants of a financial institution’s systemic risk are. Once these individual institutions and determinants have been identified, it would allow the improvement of the current systemic risk identification and control measures (Mayordomo, Rodriguez-Moreno & Peña, 2014:84).

1.2 BACKGROUND

Before the current regulatory measures for systemic risk can be assessed, a thorough review of certain elements must be undertaken. The regulatory environment of the US as a developed economy needs to be reviewed, followed by an overview of the SA regulatory environment as an emerging market, with a subsequent assessment of the approach that is taken for regulating systemically important financial institutions (both domestic and global). The Basel Accords are seen by most as the global standard for bank risk management and will therefore be discussed thoroughly in Chapter 3. It should, however, be noted that while the SA regulatory structure is largely a verbatim implementation of the Basel Accords,

the US regulatory structure is more independent and based on their own interpretation of these recommendations.

The US regulatory structure is complex and fragmented (IMF, 2015b). Adding to this complicated nature is the presence of regulators at both a federal and state level. The current structure has five independent federal regulators responsible for the oversight of depository institutions. This is illustrated in Table 1.1 below. The Federal Reserve System (Fed) is the central bank of the US and is the consolidated supervisor of roughly 520 financial holding companies, 4400 other bank holding companies, and is also the joint primary supervisor (in conjunction with the state authorities) of approximately 840 state-chartered Fed-member banks. The Federal Deposit Insurance Corporation is joint primary supervisor (in conjunction with the state authorities) for roughly 4500 state-chartered non-Fed-member banks and approximately 400 state-chartered thrifts.⁴ The Federal Deposit Insurance Corporation furthermore acts as a backup supervisor of state member banks, national banks, and federal thrifts, as well as the deposit insurer and presumptive receiver of all commercial banks and thrifts. The Office of Comptroller of Currency – a financially autonomous bureau of the Treasury – is the chartering authority and primary supervisor of roughly 1500 national banks, in addition to being primary supervisor of 50 US branches of foreign banks. The Office of Thrift Supervision – an autonomous bureau of the Treasury and successor to the now defunct Federal Home Loan Bank Board – is the consolidated supervisor of about 440 savings and loan holding companies; chartered and primary supervisor of approximately 750 federal thrifts; and joint primary supervisor of roughly 60 state thrifts. The National Credit Union Administration is the chartering authority and supervisor of roughly 5000 federal credit unions; and deposit insurer of all federal, as well as approximately 3000 state, credit unions (IMF, 2010:28).

⁴ Also known as savings and loan associations, thrifts are banks that focus on deposit taking and issuing home mortgages. They have access to low-cost funding from Federal Home Loan Banks, which grants them greater liquidity for mortgage loans and higher yields on savings accounts (Britannica, 2015).

Table 1.1: Current (2015) regulatory responsibilities in the US financial sector

Regulator	Responsibilities
US Federal Reserve	Financial holding companies Bank holding companies Joint primary supervisor of state-chartered Fed-member banks
Federal Deposit Insurance Corporation	Joint primary supervisor of state-chartered non-Fed-member banks Backup supervisor of state-member banks, national banks and federal thrifts Deposit insurer and presumptive receiver of all commercial banks and thrifts
Office of Comptroller of Currency	Chartering authority and primary supervisor of national banks Primary supervisor of US branches of foreign banks
Office of Thrift Supervision.	Consolidated supervisor of savings and loan holding companies Charter and primary supervisor of federal thrifts Joint primary supervisor of state thrifts
National Credit Union Administration	Chartering authority and supervisor of federal credit unions Deposit insurer of federal and state credit unions

Source: Compiled by the Author, IMF (2010:28).

The regulators listed above are all members of the Federal Financial Institutions Examination Council and are therefore able to propose certain principles, standards, and reporting reforms on a joint basis. In addition to these regulators, there are 50 state regulators for state-chartered commercial banks, state-chartered savings associations, and state-chartered credit unions. The coordination that takes place between the federal and state organisations is done through the participation of members from the federal and state organisations in the Federal Financial Institutions Examination Council as representatives of the State Liaison Committee (IMF, 2010:28). This abundance of regulators and complexity of the system may therefore be a weakness in the system and can lead to incompleteness and ambiguities in regulatory responsibilities. As a result of these potential regulatory shortfalls, a number of changes to the regulatory structure have been suggested. The proposed changes to the structure were underlined in the Dodd-Frank Wall Street Reform and Consumer Protection Act (henceforth referred to as the Dodd-Frank Act). This document is extensive, totalling 2 319 pages, and proposed a number of changes that should – in the opinion of President Obama – ensure that a reoccurrence of the sub-prime crisis never takes place. The entirety of the reforms that the Dodd-Frank Act proposes is discussed in Chapter 3. One of the most significant of these changes, which requires outlining, is to the governance of the largest and most systemically risky financial institutions.

Large financial institutions that possess a great degree of systemic risk are referred to as global systemically important financial institutions because their failure could trigger a global financial crisis

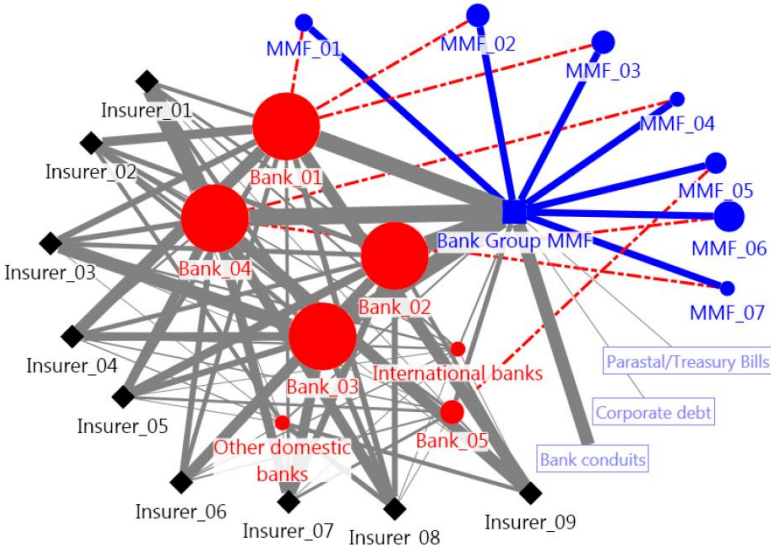
(BCBS, 2013:2). Institutions that contribute systemic risk to the global financial system are global systemically important financial institutions, while institutions that present a risk to their domestic financial systems are referred to as domestic systemically important financial institutions. The Basel III framework, in response to a request by the FStB, was employed to address the regulation of systemically important financial institutions by implementing a refined assessment methodology for these institutions based on both qualitative and quantitative indicators, the establishment of higher loss absorbency requirements, the scheduling of phase-in arrangements, and the requirement for greater public disclosure (BCBS, 2013:4). The rationale for a qualitative indicator-based approach, supplementing the quantitative-indicator approach, lies in the fact that no single approach will be able to measure the global systemic importance of institutions with varying activities and structures accurately (BCBS, 2013). The FStB (2014) set out measures which would aim to reduce the impact that the failure of a systemically important financial institution would have on the financial sector. The existence of systemically important financial institutions in a country's financial sector may therefore present significant regulatory challenges.

SA does not currently have any global systemically important financial institutions; however, it does have five domestic systemically important financial institutions, namely ABSA Bank, FirstRand Bank, Nedbank, Standard Bank – which offer complete banking services – and Investec which focuses on corporate and private banking. The rest of the banking sector is made up of seven locally owned banks, 14 foreign bank branches, and five subsidiaries of foreign banks, adding up to 31 banks in total. The sector is largely dominated by the five largest banks which control 90.5 % of the banking assets. This degree of concentration and domination also extends to the rest of the financial sector. The five largest insurance agencies make up 74 % of the insurance market, while 60 % of unit trusts are controlled by the seven largest fund managers (IMF, 2014:57).

Apart from the large degree of concentration in the SA financial sector, it is also categorised by a high degree of interconnectedness. This is illustrated in Figure 1.1 below where the transactions that take place between banks and non-bank financial institutions in the financial sector are shown. A wider band between a bank and a non-bank financial institutions indicates a stronger connection, while a larger node is representative of the institution's size. The major banks all have some degree of connection with insurance companies, either as a holding company or as a direct owner. Further concentration can be seen stemming from the Bank Group Money Market Fund (MMF), which manages 73 % of money market fund assets and subsequently invests more than half of these assets in the four commercial banks through short-term instruments (IMF, 2014:16). Further non-bank financial institution connections originate from the insurers and fund managers which are affiliated with these banks. The insurers are responsible for the underwriting of a large portion of private pension assets, while some fund managers that offer unit trusts are owned by the banks. This has led to a large number of transactions taking place among these related

parties. This concentration of the financial sector has also resulted in decreased competition, affording the dominant institutions pricing power and the achievement of returns that would not necessarily be possible in a more competitive financial sector (IMF, 2014:10).

Figure 1.1: Interconnection between Banks and non-bank financial institutions



Source: IMF (2014:11).

Bank conduits are securitisation vehicles established by banks to issue asset-backed commercial paper.

The result of this interconnectedness is that the regulation of the SA financial sector is not completely clear, in addition to being quite complex. A simplified breakdown is illustrated in Table 1.2 below. The SARB is responsible for the regulation and supervision of banks, while the Financial Services Board (FSeB) is responsible for the regulation and supervision of insurance companies, fund managers and exchanges. The Johannesburg Stock Exchange (JSE) is responsible for the supervision of listed companies, and shares the responsibility of supervising market intermediaries with the FSeB. The Department of Trade and Industry is responsible for the supervision of unlisted companies, while the National Credit Regulator reports to the Department of Trade and Industry and is responsible for regulating lending of amounts up to R1 million (IMF, 2014:23).

Table 1.2: Current regulatory responsibilities in the SA financial sector.

Regulator	Responsible for
South African Reserve Bank	Banks
Financial Services Board	Insurance Fund managers Exchanges Market intermediaries
Johannesburg Stock Exchange	Market intermediaries Listed companies
Department of Trade and Industry	Unlisted companies
National Credit Regulator	Lending < R1 million

Source: Compiled by the Author, IMF (2014:23).

The current structure of the regulation authorities has led to fragmentation among the various bodies. An overhaul of the current structure is underway, with plans to implement a Twin Peaks regulatory structure which would see a Prudential Authority and a Market Conduct Authority (IMF, 2014:23). The prudential authority is likely to be the SARB, while the Market Conduct Authority will be the FSeB. The Twin Peaks regulatory structure will lead to a situation where regulation is no longer done according to industry, but rather according to function. An example of a Twin Peaks regulatory structure is illustrated in Table 1.3 below.

Table 1.3: Proposed regulatory responsibilities with a Twin Peaks regulatory structure.

Regulator	Responsible for
South African Reserve Bank	Prudential regulation and supervision (Solvency and liquidity of financial institutions)
Financial Services Board	Market conduct (Pricing, product design, customer relations, general business conduct)

Source: Compiled by the Author, IMF (2014:23).

The Twin Peaks regulatory structure will focus on improving the macroprudential side of the regulatory architecture in SA. In terms of the risk management perspective at the microprudential level, the Third King Report on Governance for South Africa (King III) and the Basel III Accord are perhaps the most important regulation requirements – due to the limitations they can impose on a firm should they not be adopted. Failure to adopt these standards could, in the case of King III, prohibit the company from listing on the JSE, or, in the case of Basel III, lead to a significant loss of corporate reputation. In this sense, both regulatory codes are important for institutions.

King III is a code of corporate governance that was issued by the Institute of Directors in Southern Africa (IODSA) and is required to be followed by companies listed on the JSE (IODSA, 2012). Good corporate governance would naturally be concerned with minimising risk, and as a result, the governance of risk forms one of the main chapters of the report. Areas such as risk assessment, response, monitoring, assurance, and disclosure are all addressed (IODSA, 2012:39). It should however be noted that no specific attention is given to systemic risk. The King III report states that the SA corporate governance models are value-based and do not possess the same inherent dysfunction as the global financial architecture. In reference to the sub-prime crisis, the report stated that the US was the primary source and although the US underwent major regulatory overhaul, suggesting that SA should undertake similar regulatory reforms would be inappropriate (IODSA, 2012:8). This statement may have been tested following the collapse of African Bank in 2014. In response to the collapse, a member of the King committee, Suresh Kana, stated that the new King report, King IV, would become more wide-ranging, simpler and more applicable to smaller companies (Pickworth, 2014). According to the IODSA website (IODSA, 2015), King IV will attempt to be more accessible to private companies, non-profit organisations, and public sector entities. The estimated date of completion is the second half of 2016, with an aim to have the King IV report being fully effective from the middle of 2017. No specific reference is made to an update with respect to further risk management objectives. The focus on systemic risk from King III is therefore clearly lacking, although it may be argued that this is because King III is more concentrated on the management of risks related to corporate governance. As a result, scrutiny should perhaps shift to regulations that focus specifically on financial institution risk management, such as the Basel framework.

The Basel III framework is the current de facto standard for regulating financial institutions, but there are a number of criticisms that can be levelled at its approach towards regulating systemically important financial institutions. The question therefore needs to be raised whether the Basel III framework can effectively regulate systemic risk in financial institutions. Basel II was not fully implemented by the time the sub-prime crisis occurred; however, it was generally agreed by world leaders that the control measures within it were inadequate (G20, 2010). The Basel framework consists of three pillars: minimum capital requirements, the banking supervision process, and the enforcement of market discipline and transparency (BCBS, 2011).

The changes made to the first pillar of Basel II formed the foundation of Basel III. They entailed the improvement of the banks' loss-absorption capabilities, and therefore a subsequent reduction in the probability of a bank failure. Furthermore, Basel III establishes a non-risk-based leverage ratio that will act as a supplementary measure to the existing risk-based capital ratios. The rationale for the additional ratio is that during the sub-prime crisis, an accumulation of off-balance sheet leverage occurred that was not reflected by the risk-based capital ratios. An ensuing deleveraging process took place that forced asset

prices lower and subsequently amplified the positive feedback loop between losses, declining bank capital and credit availability. The non-risk-based ratio will therefore be able to restrain an accumulation of leverage in the banking sector, while also avoiding a deleveraging process that could potentially destabilise the greater financial system and economy. Additionally, the ratio will act as a non-risk-based measure of last resort (BCBS, 2011:61).

Basel III also introduced two additional liquidity measures, the liquidity coverage ratio and the net stable funding ratio. The liquidity coverage ratio is short-term in nature, in that it assesses the bank's ability to survive a severe stress test scenario for one month and encourages the holding of higher quality liquid assets. The net stable funding ratio is long-term in nature and aims to provide incentives to banks that structure their assets and liabilities with a more sustainable maturity and therefore avoid liquidity mismatches (BCBS, 2011:9). The introduction of these ratios formed part of the Basel Committee's implementation of global liquidity standards. The initial phase of the sub-prime crisis exhibited how banks with adequate levels of capital could still experience financial difficulties due to a lack of liquidity. Liquidity and illiquidity exhibit contrary characteristics, in which liquidity dissipates quickly, while illiquidity can remain for a longer period of time. Many banks did not follow the fundamental principles of liquidity risk management and therefore additional liquidity measures are necessary (BCBS, 2011:8).

The changes made in Basel III, specifically to Pillar 2, will improve the authorities' ability to manage various kinds of risk, such as liquidity risk, concentration risk and off-balance sheet risk, while the implementation of stress tests will assist in identifying systemic risk (Georg, 2011:4). Additional changes made in Basel III also affect Pillar 3, where market disclosure standards are improved and transparency regarding the balance sheets of banks is increased (BCBS, 2011:3). The success of the Basel Accords is conditional – in the sense that it is largely dependent on whether they are completely adopted by the institution. Management at the firm level is therefore responsible for their accurate implementation, although in SA it is not a legal requirement to meet the Basel requirements. Conversely, a large degree of credibility will be forgone by not meeting the requirements set out in the Basel Accords. The sub-prime crisis, however, illustrated the necessity for a movement away from risk management measures dependent on implementation at the firm level, known as a bottom-up approach. Instead, a move towards a top-down approach should be made. A top-down approach would give a greater degree of control to governors at a country level through monetary policies and other macro policies (Guidara, Lai, Soumaré & Tchana, 2013:3373). The case can therefore be made for a switch from a more microprudential-based approach towards a more macroprudential-based approach.

The term 'macroprudential regulation' came to the fore after the sub-prime crisis in 2007/2008. Clement (2010:65) noted that the term 'macroprudential regulation' refers to an approach whereby prudential tools are used to promote the stability of the financial system as a whole, and not to focus on the

individual institutions within it. The sub-prime crisis illustrated the point that a microprudential regulation-based approach that deals only with firm-specific risks is inadequate in dealing with systemic risks (Georg, 2011:4). Basel III therefore placed a greater degree of emphasis on the macroprudential perspective, with an aim of reducing the amount of systemic risk in the financial sector as a whole. Consequently, the risk management approach will shift from mitigating only exogenous risks towards the mitigation, additionally, of endogenous risks. A comparison of the macroprudential and microprudential perspectives is represented in Table 1.4 below.

Table 1.4: Comparison of Macroprudential and Microprudential perspectives.

	Macroprudential	Microprudential
Proximate objective	Limit financial system-wide distress	Limit distress of individual institutions
Ultimate objective	Avoid output (GDP) costs	Consumer (investor/depositor) protection
Model of risk	(in part) Endogenous	Exogenous
Correlations and common exposures across institutions	Important	Irrelevant
Calibration of prudential controls	In terms of system-wide distress; top-down	In terms of risk of individual institutions; bottom up

Source: Borio (2003:2).

Considering all the various aspects laid out above, the regulation measures that will best suit a specific country will depend on the amount of systemic risk in a country’s financial sector. Subsequently, it will be necessary to identify what the individual determinants of an institution’s systemic risk are, as well as the amount of systemic risk that individual institutions contribute to the financial sector as a whole.

The abovementioned definitions of systemic risk focus on the individual systemic risk that an institution possesses but do not address the institution’s contribution to a system-wide collapse. Acharya, Engle and Richardson (2012:59) postulate that the failure of an individual institution would not have significant consequences because another institution would be able to take the failed institution’s place. It becomes problematic when aggregate levels of capital are low for all institutions and financial intermediation can no longer take place between the institutions. Acharya, Pedersen, Philippon and Richardson (2010:16) make use of a model which sets systemic risk equal to the product of three components:

Real systemic risk of a firm

$$\begin{aligned} &= \text{Real social costs of a crisis per dollar of capital shortage} \\ &\times \text{Probability of a crisis (i.e. an aggregate capital shortfall)} \\ &\times \text{Expected capital shortfall of the institution in a crisis.} \end{aligned}$$

Acharya *et al.* (2012:60) use the above equation for the basis of their paper and focus on the third component, as this captures most of the characteristics typically associated with systemic risk, namely size, leverage, and interconnectedness. These characteristics are chosen because they increase the capital shortfall a firm will experience when the financial sector is enduring losses. Laeven, Ratnovski and Tong (2014:15) further define a financial institution as systemically risky if it is likely to experience a capital shortage when the financial sector as a whole is not functioning optimally. Acharya *et al.* (2012:60) explain that the measurement of an expected capital shortfall is done by multiplying the degree of leverage a firm has by the predicted equity loss during a financial crisis. The Marginal Expected Shortfall (MES) is defined as the expected equity loss that a firm experiences when the market as a whole declines below a certain threshold level over a given period of time. The Systemic Risk Index (SRISK) is determined using the expected capital shortfall of an institution during a financial crisis. The institution with the highest SRISK value would contribute the most to the undercapitalisation of the market, and would therefore be the most systemically risky institution.

In addition to calculating SRISK, the study by Laeven *et al.* (2014) examined the effects of banks' sizes on their systemic risk and forms a good reference point for this study. The study used the SRISK measure as set out by Acharya *et al.* (2012:60) and Brownlees and Engle (2012:8). The study used the data of 1250 banks from 52 countries, of which 137 were large banks. Laeven *et al.* (2014:23) found that large banks, on average, contributed more systemic risk to the financial sector than smaller banks did, and this risk was magnified during certain conditions, such as when their market activities were overly complex or the banks failed to meet regulatory requirements. The study focused mostly on identifying the problem broadly, but as it was shown earlier, systemic risk is experienced differently by individual countries, depending on their development and level of integration. Therefore, the analysis of the effect of capital flows or external volatility is lacking, both of which are factors which may affect the levels of systemic risk in emerging market economies. Furthermore, the technique used to measure systemic risk could also potentially be refined.

1.3 PROBLEM STATEMENT AND RESEARCH QUESTION

The SA financial sector demonstrates a large degree of interconnectedness, and as a result of this, contagion is likely during times of financial crisis. The case of African Bank – although small in size and therefore suggesting no systemic implications – may serve as a reminder that systemic risk can be produced by smaller institutions due to this high degree of interconnectedness (IMF, 2014:7). Additionally, although individual banks are not reliant on external capital flows, SA's current account and fiscal deficits are dependent on external financing. The large current account deficit can be attributed to slow growth, low savings and a large amount of public expenditure, while the fiscal deficit can be attributed to a consistently increasing level of government debt (IMF, 2014:12). The result of such weaknesses in the macroeconomic landscape is that a reversal of flows could affect domestic funding market pricing and also have systemic implications (IMF, 2014:16).

Considering these factors that illustrate systemic risk's complexity, the way in which it can affect countries in differing ways, and originate from many different sources, it follows that systemic risk is difficult to measure. Furthermore, since systemic risk is such a broad concept, finding a measure that sufficiently encompasses the entire risk and all its complexities poses an additional challenge (Bisias, Flood, Lo & Valavanis, 2012:2). As a result, the risk could potentially be completely overlooked or underreported because the correct measurements have not yet been found nor formulated.

If a risk cannot be accurately identified and measured, it cannot be effectively regulated and managed. Additionally, robust regulations based on inaccurate measures are as ineffectual as incorrect regulations based on accurate measurements. Therefore, it is equally as important to have appropriate regulations as it is to have an accurate measure for systemic risk. If the systemic risk of a country's financial sector is left underreported and unregulated, the result could be a complete collapse of the financial sector (Batrancea & Bechis, 2013:178).

Based on the problem statement, the research question that can therefore be posed is: Are the current regulatory measures effectively managing systemic risk through a quantification approach which considers the country's level of development and how this level influences the manifestation and effects of systemic risk – to the extent that the collapse of a large bank, or a sudden change in a factor which influences systemic risk, would not result in the collapse of the financial sector?

1.4 RESEARCH AIMS AND OBJECTIVES

This study will focus on the financial sectors, and the banks in particular, of SA and the US as proxies of developed and developing financial markets. Banks are the focus of the study as they are considered the starting point for systemic risk given their role in financial intermediation (Cerutti, Claessens & McGuire, 2012; Laeven *et al.*, 2014), while other financial institutions such as insurance companies and the activities they undertake are not generally considered to be systemically risky (Bell & Keller, 2009; Harrington, 2009). As financial intermediaries, the importance of banks can further be explained in the context of the practice of fractional-reserve banking – whereby banks are the only market participants that provide loans and take deposits – and are only required to hold reserves equal to a fraction of their deposit liabilities (Mishkin, 2007b:208). The aims of this study are to determine if systemic risk is being adequately mitigated in the financial sectors of the US and SA and to examine the different ways in which systemic risk manifests in these two markets.

The primary objective of the study is to measure the levels of systemic risk in the SA and US financial sectors and to determine if the current regulatory measures are sufficient to regulate systemic risk. In order to achieve this primary objective, a number of secondary objectives must also be achieved:

- i. Determine the contribution that each bank makes to the total systemic risk of the entire financial sector.
- ii. Determine if systemic risk was transferred from the US market to the SA market.
- iii. Identify the determinants of an individual bank's contribution to systemic risk and examine the differences for the US and SA.
- iv. Assess the respective approaches of the Basel III frameworks and country-specific legislation to regulating systemic risk.

1.5 CONTRIBUTION

In order to achieve the primary and secondary objectives illustrated above, this study makes various intended new contributions to the field:

- i. The MES measure which must be calculated to measure systemic risk is comprised of volatility, correlation, and tail distribution components. This study used a parametric approach based on extreme value theory and the Hill estimator to calculate the expected shortfall of the banks and the market below a certain threshold level. This method (discussed in Section 4.2.3.2) has the advantage of shifting the focus to modelling the tail behaviour of the distribution alone and therefore requires fewer degrees of freedom. It also does not suffer the disadvantages of the alternative method (discussed in Section 4.2.3.1). These disadvantages includes the assumption

that the data do not come from any particular distribution, therefore potentially leading to inaccurate modelling of the tail distribution (Nadarajah, Zhang & Chan, 2014:284; Skoglund & Chen, 2015:104). Additionally, it also does not suffer from the negative effects of smoothing associated with the kernel based-method, which could result in increased bias and a subsequent increase in the mean-squared error of the kernel estimator – the result of which renders the entire process of smoothing counterproductive (Chen, 2008:93). The use of such an approach to model the tail expectations of MES, represents a new contribution to the field. Furthermore, the sub-prime crisis showed that systemic risk in developed economies, such as the US occurred as a result of large, highly leveraged banks undertaking complex activities that left them undercapitalised. Given the inherent interconnected nature of these banks (and financial institutions), systemic effects can also rapidly transfer between these institutions.

- ii. Phenomena such as contagion, common shocks, and informational spillovers are three ways in which systemic risk can be transferred between markets (discussed in Section 2.3.2). As a way to determine if systemic risk is transferred from the US market to the SA market, an MES model is used where the SA equity market is specified as a hypothetical bank within the US equity market. MES refers to the one-day decline in the equity value of the bank, given that the equity market as a whole has declined by 2 %. This is widely accepted to be representative of a one-day systemic event (Brownlees & Engle, 2012:10; Laeven *et al.*, 2014:28). This study proposes that the assessment of the MES of the ALSI relative to the S&P 500 could provide an indication of the systemic response of the SA market to the US market. This will provide a measure of the decline in equity value of the ALSI conditional on a decline in the S&P 500 by 2 %. Additionally, the simulation procedure outlined in Section 4.2.5 will also be used to produce long-run MES (LRMES) values for a hypothetical crisis period. This specification of the SA equity market as a hypothetical bank in the US equity market, and the subsequent assessment of a potential systemic response represents a new contribution to the field.
- iii. To provide an MES measure for a longer period and a worst-case scenario simulation, the LRMES is calculated. In order to accomplish this, a different technique is used to calculate LRMES, whereby a Monte Carlo simulation procedure and Cholesky decomposition were used. The novelty in this approach lies in the use of simulated returns that preserve the sub-prime crisis period volatilities and correlations.
- iv. In order to determine which factors are most responsible for producing systemic risk in US and SA banks, a panel regression analysis is conducted which takes into account the traditional variables associated with systemic risk, as well as new variables applicable to emerging markets. These variables are based on the systemic risk literature for emerging market economies and may

therefore be more relevant than the traditional variables are. The new variables include a volatility spillover effect from the US market to the SA market (the variance series produced by an EGARCH model), as well as capital inflows to SA (proxied by foreign portfolio investment into SA). The use of these variables in a panel regression model investigating the determinants of systemic risk in SA banks represents a new contribution to the field.

1.6 LITERATURE REVIEW

In order to achieve the objectives set out above, a comprehensive literature review will be included in the study. The literature review will include a summary of the following:

- i. The definition and concept of systemic risk (Section 2.2), as well as the various phenomena which are associated with systemic risk, with specific reference to:
 - a. contagion (Section 2.3.2.1)
 - b. common shocks and (Section 2.3.2.2)
 - c. informational spillovers (Section 2.3.2.3).

This will provide an all-encompassing review of systemic risk and its various causes and effects. This will be followed by a comparison of systemic risk in both developed economies and emerging markets (Section 2.5).

- ii. The systemic risk that individual banks possess, the determinants of systemic risk within individual banks, and the concept of systemically important financial institutions (Section 2.4).
- iii. A review of the current SA regulatory structure, including a thorough review of the Basel Accords (Section 3.2). A discussion of how the proposed changes to the SA regulatory structure may affect systemic risk regulation in the future, with specific reference to the King III report and the implementation of a Twin Peaks regulatory structure (Section 3.3.2).
- iv. A review of the US regulatory structure, with a focus on their interpretation of the Basel Accords (Section 3.2). A discussion of the previous regulatory structure that was in place, followed by the changes that have been made to the regulatory structure, with specific reference to the Dodd-Frank Act and the Volcker rule, as these have the most bearing on systemic risk (Section 3.3.1).
- v. The quantification of systemic risk, using empirical measures (Section 3.5).

1.7 METHODOLOGY

In order to ensure that a uniform order in the methodology takes place, it is sensible to divide the section into two subsections. Firstly, the proposed data and software will be explained, followed by the methods that will be applied to the data.

1.7.1 Data and Software

The empirical study will be in the form of a quantitative analysis, the determination of which will then facilitate a qualitative analysis. Proprietary data are acquired from Fitch Ratings and stock return data are acquired from Bloomberg (2015) and the INET BFA Dataset (2015). The data covers the period of 2001 to 2013. The study will consist of financial modelling conducted in Microsoft Excel™ (2013). The subsequent econometric analysis will be done using EViews™ 8 econometrics software (QMS, 2013).

1.7.2 Methodology

The empirical analysis (Section 4) will be based upon the framework set by Laeven *et al.* (2014) in which they examine the effect that bank size has on its systemic risk. The SRISK component as set out by Acharya *et al.* (2012:60) and Brownlees and Engle (2012:8) will be used as a proxy measure for the systemic risk of a bank and measures the expected capital shortfall that a bank experiences during a period of financial distress. This can be illustrated by Equation 1.1:

$$SRISK_{i,t} = kD_{i,t} - (1 - k) \cdot E_{i,t}\{1 - MES_{i,t+h|t}(C_{t+h|t})\}, \quad (1.1)$$

where:

- k is the minimum fraction of capital (as a ratio of total assets) that the Basel Committee requires each bank to hold. This is set at 8 % (BCBS, 2011:27). Although the SARB have set the minimum capital requirement to 10 % (BCBS, 2015b:5) for consistency and comparative purposes, Basel's minimum global regulatory requirement of 8 % has been used in this analysis;
- $D_{i,t}$ is the book value of the bank's debt (total liabilities);
- $E_{i,t}$ is the market value of the bank's equity.

MES can be defined as the tail expectation of a bank's equity return on the condition that the market declines. This is represented by Equation 1.2:

$$MES_{i,t+h|t}(C) = -E_t(R_{i,t+h|t} \mid R_{m,t+h|t} < C). \quad (1.2)$$

The terms $R_{i,t+h|t}$ and $R_{m,t+h|t}$ represent the stock return for the bank and the market for the period t and $t+h$. The stock return is calculated as $\frac{R_t - R_{t-1}}{R_{t-1}}$. C is the threshold of the decline in the market index. The daily return of a stock market index will be used as a proxy for the market return. h will be set as one day, and t will be measured in days. C is equal to -2 %, because the MES is the one-day loss that will be expected if market returns are < -2 %. The specific value of -2 % is widely accepted to be representative of a one-day systemic event (Brownlees & Engle, 2012:10; Laeven *et al.*, 2014:28). The return model will be estimated using daily data over the period from 2001 to 2013.

In order to calculate the one-day MES for the sub-prime crisis period, the average of the predicted MES values for the 180 day period of 1 July 2007 to 31 December 2008 are determined. In $C_{t+h|t}$ the h is set equal to 180 days, with $C_{t+180|t} = -40\%$. The following approximation is used to calculate the long-run MES, where $C_{t+1|t} = -2\%$:

$$MES_{i,t+180|t}(C_{t+180|t}) = 1 - \exp\{-18 \times MES_{i,t+1|t}(C_{t+1|t})\}. \quad (1.3)$$

Alternatively, a dynamic simulation procedure is used to simulate long-run MES. The SRISK measure is constructed by estimating the return model using daily data over the period 2001 to 2013. The SRISK is then calculated using the average of the predicted values for MES over the period of 1 July 2007 to 31 December 2008. The crisis period is set to end on 31 December 2008 so that the impact of policy interventions will not be reflected. The negative values of SRISK will be translated into an increasing measure of systemic risk, i.e. capital surpluses. SRISK will be reported in USD billions for the US and in ZAR billions for SA.

The SRISK is therefore determined by:

- bank stock volatility during periods of distress,
- the covariance of bank stock with the market during periods of distress (the focus on covariance distinguishes systemic risk from individual bank risk measures),
- bank leverage and
- bank size.

SRISK will be used as the dependent variable in a multivariate regression model, based on the model used by Laeven *et al.* (2014:18). The independent variables are the traditional determinants of systemic risk and will include:

- bank size, measured using the total value of banks assets and transformed using logs,
- bank capitalisation, where two alternative measures are proposed. The Tier 1 capital ratio and a simple leverage ratio,
- the bank funding structure, with two alternative measures proposed. The share of depository funding and an index of funding fragility. The funding fragility index is defined as deposits from other banks, other deposits, and short-term borrowing as a fraction of total deposits plus money market and short-term funding,
- bank activities, where two alternative measures are proposed, the share of loans in total assets and the share of non-interest income in total income. A lower share of loans in total assets and a higher share of non-interest income in total income will indicate a greater degree of bank involvement in market-based activities,

- bank organisational complexity, measured as the number of subsidiaries and transformed using logs and
- bank leverage, where the leverage of the bank i at time t measured as (total liabilities + market capitalisation)/market capitalisation (Laeven *et al.*, 2014:13).

The regression analysis will facilitate in the identification of which individual measure is the largest and most significant determinant of a bank's SRISK.

1.8 CHAPTER LAYOUT

The study will be set out as follows:

I. Introduction (Section 1)

This section provides a background to the research problem, an explanation of the motivation for the study, a problem statement, the research question, and the various research objectives.

II. Background – Literature review (Chapter 2 and Chapter 3)

The literature review consists of:

- a. The concept of systemic risk (Chapter 2)
 - i. The definition of systemic risk (Section 2.2)
 - ii. Contextualising systemic risk (2.3)
 - iii. The role of systemically important financial institutions (Section 2.4)
 - iv. The impact of systemic risk on emerging markets (Section 2.5)
- b. The regulation of systemic risk (Chapter 3)
 - i. Basel: The global framework (Section 3.2)
 - ii. The SA regulatory approach (Section 3.3.1)
 - iii. The US regulatory approach (Section 3.3.2)
 - iv. Macroprudential regulations (Section 3.4)
 - v. Quantification measures for systemic risk (Section 3.5)

III. The measuring of systemic risk: Methodology (Chapter 4)

IV. The measuring of systemic risk: Results (Chapter 5)

V. Summary, conclusions and suggestions for future work (Chapter 6)

CHAPTER 2

THE CONCEPT OF SYSTEMIC RISK

“One of the most feared events in banking is the cry of systemic risk. It matches the fear of a cry of “fire!” in a crowded theatre or other gatherings. But unlike fire, the term systemic risk is not clearly defined.” —

George G. Kaufman and Kenneth E. Scott (2003)

2.1 INTRODUCTION

Systemic risk is a complex phenomenon and the attention given to it has significantly increased in the wake of the sub-prime crisis (Wang, 2013:5). In order to measure the systemic risk of a bank, or the financial sector as a whole, a clear definition of what is being measured should be identified. Section 2.2 reviews various definitions for systemic risk in order to reach consensus and to provide clarity as to what systemic risk actually is.

Once the various definitions of systemic risk have been highlighted, Section 2.3 puts the concept of systemic risk into the correct context. Section 2.3.1 provides a practical explanation of systemic risk by examining the sub-prime crisis. This was, in terms of systemic risk and financial stability, potentially one of the most defining and relevant financial occurrences in recent times, especially when one considers that some of the affected institutions were considered to be at the forefront of risk management and profitability (Hellwig, 2009:130). Systemic risk has the unique characteristic of being able to spread rapidly from one institution, market, or financial sector to another (Cerutti *et al.*, 2012:1). Section 2.3.2 explains the mechanisms through which this spreading occurs. The three mechanisms include contagion, which refers to the losses of one bank being transferred to other banks during time of financial distress, and common shocks, which refers to the negative effects that several banks can be subjected to when the financial sector experiences a negative shock. Informational spillovers complete this section and illustrate that if banks are holding portfolios concentrated in a similar industry, bad news about that particular industry could negatively affect all banks. The manner in which these mechanisms can spread systemic risk may be amplified even more when there is a larger degree of interconnectedness in the financial sector.

The failure of large, interconnected financial institutions during the sub-prime crisis illustrated how a single financial institution could affect an entire financial sector and economy (Barth, Brummer, Li & Nolle, 2013:2). This prompted a re-evaluation of the activities these institutions undertake, but perhaps more importantly, how they contribute to systemic risk and the way in which this can be addressed. As part of this re-evaluation, Section 2.4 examines the role that systemically important financial institutions play in generating systemic risk, as well as how these institutions can be identified.

No SA institutions are classified as global systemically important financial institutions, although some institutions are classified as domestic systemically important financial institutions. This does not mean that SA was unaffected by the sub-prime crisis, but rather that the effects of the sub-prime crisis were different for emerging markets and developed economies. Section 2.5 discusses the unique way in which systemic risk affected emerging markets, as well as the different policy responses undertaken in response to these effects. Finally, Section 2.6 provides a summary of the chapter.

2.2 THE DEFINITION OF SYSTEMIC RISK

In order to analyse systemic risk, it must be recognised that the risk being discussed is that of a system and not an individual. Therefore, as opposed to being concerned with choosing the correct direction of a trade, one should be concerned with maintaining the correct balance – since it can be argued that most systemic risks are imbalances that have accumulated over time (Caruana, 2010:3). For example, prior to the sub-prime crisis the housing risk – based on the house prices and their appreciation over time – at an individual level may have been seen as being low. This was the case because an individual who purchased a home could view predictions that the house price would increase over time. However, as a collective system it would be evident that there were a number of imbalances that existed in the affordability index and in the number of housing start units,⁵ as well as an increase in the amount of speculative investing taking place (Wang, 2013:14). As stated in the quote at the beginning of the chapter, systemic risk can be viewed as one of the most feared events in banking, yet it can be argued that there is no clear definition for it. Furthermore, as the financial system evolves and becomes more complex, so does our understanding of systemic risk. In order to find a definition of systemic risk that best suits this study, this section will review the various existing definitions proposed in the literature.

2.2.1 Defining systemic risk

Systemic risk may be the centre of global financial stability, so in order to ensure this financial stability, it would be necessary to understand where systemic risk emanates from. Subsequently – in order to accurately define the sources of systemic risk – a coherent definition of what constitutes systemic risk is necessary (Liedtke, 2010:1). There is currently no single definition describing the concept of systemic risk that all authors seem to agree on. It may be useful to examine the definition of systemic risk that is utilised in non-financial sectors – such as evolutionary biology, and telecoms – where systemic stability is also studied. In these fields, a systemic risk is defined as the risk of a phase transition from one equilibrium to another much less optimal equilibrium, and is characterised by multiple self-reinforcing feedback

⁵ A housing start is an economic indicator for the health of the home construction industry. According to the US Census Bureau (2015), a housing start comes into existence when the excavation for the foundations of the building begins.

mechanisms which make it challenging to reverse (Hendricks, 2009:2). There are similarities between these non-financial entities and financial markets. For example, financial markets are similar to liquids in the sense that they can also freeze, and they are similar to telecoms networks, in the sense that they can also break down. They represent similarities with the human body and epidemics, in that a disease can wipe out a significant portion of the population, and a systemic risk can wipe out a financial system. The origin of the concept of systemic risk is therefore clear, although the interpretation of it in the financial sector has been mixed.

In order to begin defining systemic risk, it may be necessary to note that systemic risk can exist in two dimensions, namely the cross-sectional dimension and the time dimension. Caruana (2010:2) explains that the cross-sectional dimension refers to the structure of the financial system and how it influences, responds to, and has the potential to amplify shocks. Borio and Drehmann (2009:3) illustrate that systemic risk in the cross-section refers to the systemic risk at a particular point in time across all institutions. The cross-sectional dimension of systemic risk therefore focuses on the common exposures and interconnections in the financial system and the potential of a specific shock to propagate throughout the system due to either interconnected balance sheets or direct common exposures.

Caruana (2010:3) clarifies the point that the time dimension refers to the build-up of risk that occurs over time with the macroeconomic cycle and the subsequent pro-cyclicality of the financial system. The pro-cyclicality of the financial system refers to positive feedback mechanisms which have the potential to cause financial instability. An expansionary economic period is typically characterised by periods of financial innovation where institutions and individuals may undertake more risk and make use of untested financial instruments, while credit may grow quickly and result in higher asset prices. The pro-cyclicality of systemic risk is therefore the underlying build-up of risk over time in areas that may be hidden or under-priced, the result being that during economic contractions, these risks appear and amplify the retrenchment that is already occurring. Borio and Drehmann (2009:3) illustrate the fact that viewing the build-up of systemic risks as an endogenous cycle indicates that it occurs during both expansions and contractions, which suggests that risk-taking should be restrained during an expansionary phase when it is likely to be greater. The implication of this definition is that a countercyclical prudential approach may be best for regulating systemic risk. The time dimension therefore focuses on the pro-cyclicality of the business and financial cycles and how they reinforce each other, creating a progressive building of risk and increasing financial instability – with the financial sector endogenously creating systemic risk (Caruana, 2010:3).

Apart from these more causal definition approaches, some definitions in the literature have focused on systemic risk as a whole, such as that of Billio, Getmansky, Lo and Pelizzon (2012:537) which defines systemic risk as any set of circumstances threatening the stability of public confidence in the financial

system, while Bernanke (2009) describes it as an externality of bank distress on the real economy or financial system as a whole. Other authors have focused on specific mechanisms within systemic risk such as information disruptions (Mishkin, 2007a:1), correlated exposures (Acharya, Pedersen, Philippon & Richardson, 2010), imbalances (Caballero, 2010:2), asset bubbles (Rosengren, 2010) and feedback behaviour (Kapadia, Drehmann, Elliott & Sterne, 2012:32). The Financial Stability Oversight Council (FSOC), which was created by the US Dodd-Frank Act and is comprised of the heads of a number of federal financial regulators, has no formal definition for systemic risk, but has stated that all definitions attempt to capture risks to the stability of the entire financial system as opposed to the risk for individual institutions (FSOC, 2011:132). Taylor (2010a:33) suggests that it is important that a clear operational definition and measurement should exist for systemic risk, because such a definition would limit the amount of bailouts that occur for institutions. The explanation behind this is that a more restrictive definition would allow an accurate assessment of whether an institution's failure was due to systemic risk, and subsequently when a bailout would be appropriate. Biais *et al.* (2012:2), however, propose that a single measure of systemic risk is undesirable, since it may lead to the missing of vulnerabilities in other parts of the financial system. Biais *et al.* (2012) further define 31 different measures of systemic risk including its various aspects – such as its macroeconomic measures, granular foundations, and cross-sectional measures – and the possible channels through which it can cause financial distress. The cross-sectional measures include the Conditional Value-at-Risk (CoVaR), and Marginal and Systemic Expected Shortfall – all of which will be discussed in Section 5 of Chapter 3.

In light of these different approaches to define systemic risk, and in order to ensure that all underlying factors are addressed, it may also be necessary to distinguish between the conditions required for systemic risk and the events that trigger it. A financial system may exist for a long period of time while accumulating a large amount of systemic risk, but a systemic event may be required in order to cause the sudden changes in the system. An example of this could be the fiscal imbalance caused by the large US government deficit and unfunded long-term liabilities during 2013. This was a systemic risk condition, but there was no trigger. Another example of a systemic risk condition could be seen prior to the sovereign debt crisis in Greece during 2010. For many years prior to the crisis, Greece had a poor business environment and ranked low on the ease of doing business scale – both of which could be considered a systemic risk condition (Wang, 2013:11). De Bandt *et al.* (2009:636) categorise systemic events into both a broad and narrow sense. A summary of this is illustrated in Table 2.1 below.

Table 2.1: Systemic events in the financial system.

Type of initial shock	Single systemic events (affect only one institution or one market in the second round effect)		Wide systemic events (affect many institutions or markets in the second round effect)	
	Weak (no failure or crash)	Strong (failure of one institution or crash of one market)	Weak (no failure of crash)	Strong (failures of many institutions or crashes of many markets)
Narrow shock that propagates:				
• Idiosyncratic shock	Yes	Yes – contagion	Yes	Yes – contagion leading to a systemic crisis
• Limited systematic shock	Yes	Yes – contagion	Yes	Yes – contagion leading to a systemic crisis
Wide systematic shock			Yes	Yes – systemic crisis

Source: De Bandt and Hartmann (2000:12).
 “Yes” in the above table indicates that the combination of events is a systemic event.

De Bandt and Hartmann (2000:12) explain that a systemic event in the narrow sense concerns contagion effects on the interbank market, while the broad sense refers to a common shock to many institutions or markets. A systemic event in the narrow sense is defined as strong if financial institutions actually fail as a result of it, even though they had been financially sound prior to the shock. A systemic event in the narrow sense is categorised as weak if the financial institution does not fail. A strong event in the narrow sense is therefore defined as contagion. A systemic event in the broad sense is categorised as strong if large portions of the bank are simultaneously affected and fail. A systemic crisis can then be defined as a systemic event, in both the broad and narrow sense, that strongly affects a number of banks and therefore impairs the functioning of a large portion of the financial system to transform savings into real investments. Systemic risk can therefore be described as the risk of experiencing systemic events in the strong sense. It should be noted that in the definition, the concept of a systemic event contains two elements, namely the shocks – either idiosyncratic or systematic – and their subsequent propagation mechanisms. Consequently, in the extreme sense, idiosyncratic shocks initially only affect a single financial institution or the price of a single asset, whereas systematic (or wide) shocks affect the entire economy. Furthermore, a systematic shock may imply a systemic event, but a systemic event does not necessarily originate from a systematic shock. An example of an idiosyncratic shock could include the failure of a regional bank, whereas a systematic shock could include business cycle fluctuations, sudden changes in

inflation rates, a stock market crash, devaluation of a currency, or a liquidity shortage (De Bandt & Hartmann, 2000:12).

Possibly the most relevant and encompassing definition – following on from the sub-prime crisis – is from a joint paper by the IMF, BIS & FStB. They define systemic risk as a disruption to financial services that is caused by an impairment of all or parts of the financial system and have the potential to have significant negative consequences for the real economy (IMF, BIS & FStB, 2009:2). The criteria set out to describe the relevance of specific institutions include size, interconnectedness and substitutability, while complexity, leverage, liquidity risk, and a large mismatch between assets and liabilities are all factors which increase the institution's vulnerability to financial failure. They do, however, go on to state that this definition is subject to interpretation by each country's regulatory authorities, whereby some may focus on the impact on the financial system, whereas others may focus on the end impact on the real economy (IMF, BIS & FStB, 2009:5). The interpretive nature of this definition was criticised by Liedtke (2010:3) who argued that it fails to differentiate between an event that is systemically important and an event that is systemically relevant, indicating that relevance does not imply riskiness. It may, however, be inferred that greater levels of the criteria mentioned above – which increase the institution's vulnerability – could result in the institution becoming more risky.

De Nicolo *et al.* (2012:5) broaden the definition of the IMF, BIS and FStB to include market failures that propagate systemic risk. These include externalities in three broad categories. Firstly, externalities associated with excessive or correlated risk taking by financial institutions during a financial upswing, as a result of strategic complementarities.⁶ Secondly, externalities related to fire sales that have arisen as a result of large scale sell-offs of financial assets, resulting in decreasing asset prices and an impairment of the intermediaries' balance sheets during a contractionary financial phase. Lastly, externalities related to interconnectedness that are caused by the transmission of shocks from systemic institutions, or through financial networks.

Georg (2011:7) also provides a definition which expands systemic risk to include three broad sources. The original definition prior to the sub-prime crisis was that systemic risk is the probability of contagion effects that cause cascades of default – however, this has been expanded to include two more sources. Firstly, in the form of a common shock which results in several financial institutions defaulting simultaneously; and secondly, informational spillovers where bad news regarding one bank can result in increased refinancing costs for all other banks. It can be contended that these three elements of systemic risk – contagion,

⁶ Strategic complementarities entail a set of financial decisions taken to mutually reinforce one another. This concept is defined completely in Bulow, Geanakoplos & Klemperer (1985).

common shocks, and informational spillovers – are what gives it the potential to negatively affect the entire economy, and they will therefore be examined in more detail in Section 2.3.2.

2.2.2 Section summary

Based on the evidence above, it can be argued that although no single definition is generally agreed upon for systemic risk, it is clear that its importance is widely accepted. Systemic risk manifests itself in two forms, namely the cross-sectional dimension which refers to how the failure of a single bank can have negative effects on other banks, and the time dimension which refers to how aggregate risk evolves over time, therefore including pro-cyclicality. In order to measure the systemic risk in a financial sector, an accurate definition of systemic risk is needed, and although no definition is agreed upon by all authors, a common theme is followed. A broad outline refers to the effects of externalities and subsequent financial sector impairment, with the potential to negatively affect the real economy.

Moving on from the definition of systemic risk, it becomes necessary to contextualise the concept of systemic risk and further examine the implications that it may have for various entities. Arguably, one of the most significant events in terms of renewing the interest in systemic risk, as well as illustrating the effects that systemic risk can have, was the sub-prime crisis. The sub-prime crisis provided a case study of how specific financial sector and economic conditions could promote a build-up of systemic risk.

2.3 CONTEXTUALISING SYSTEMIC RISK

Section 2.2 showed that systemic risk can take a number of forms and may be caused by many different factors. In the context of this study, it is therefore necessary to analyse the environment in which systemic risk manifests itself, as well as how it spreads. Section 2.3.1 examines the sub-prime crisis as a case study for systemic risk. The reason for this is that it provides an example of both a financial and economic environment, possessing the conditions necessary to facilitate a build-up of systemic risk. Subsequently, Section 2.3.2 analyses the phenomena that occur when these systemic risk conditions are in place and allow the negative effects associated with one institution, market, or sector to rapidly propagate to another.

2.3.1 Sub-prime crisis case study

The sub-prime crisis is seen by many as the worst financial crisis to occur since the Great Depression in the 1930s, mainly because of its worldwide reach (Bernanke, 2009). This section discusses the various causes of the financial crisis and the economic effects it had on the economy of the US. Furthermore, it explains the role that systemic interdependence – and therefore systemic risk – played in exposing the entire world economy to these negative effects. Much of the backlash from the crisis has centred on the moral hazard of the individuals at the head of large institutions, the flaws in sub-prime mortgage

financing, and the rapid advancement of securitised financial products – but this only provides part of the explanation for the crisis. The systemic linkages and repercussions of the sub-prime crisis are what differentiate it from other crises, causing it to be amplified into a global financial crisis (Hellwig, 2009:169). In the following sections, it will be argued that the macroeconomic conditions (Section 2.3.1.1) were the unstable foundations upon which the financial system was being laid, the microeconomic conditions (Section 2.3.1.2) were the cracks which formed in this foundation and grew ever wider, while the accounting system (Section 2.3.1.3) and systemic elements (Section 2.3.1.4) were the fundamental flaws in the architecture of the financial system.

2.3.1.1 Macroeconomic conditions

The banking crisis that occurred in the US in 2007 is an example of a crisis that began as a small shock, followed by a ripple effect throughout the economy, and an eventual evolution into a systemic crisis (Laeven & Valencia, 2013:227). The fundamental cause of the sub-prime crisis has generally been attributed to a combination of a rapid credit expansion and a bubble in the housing market, but in order for these expansions to take place, certain macroeconomic conditions had to be present. During the period of 2002 to 2007, the average house price grew at a rate of 11 % per year, while the ratio of debt to national income increased from 3.75:1 to 4.75:1. An increase in the ratio of this size took ten years prior to 2002, and prior to 1992 it took at least 25 years to develop. This ease with which credit could be obtained meant that the market was flooded with a significant amount of liquidity. Liquidity of this magnitude is obtained when interest rates are low due to expansionary monetary policy (Acharya, Cooley & Richardson, 2010:249).

It is arguable that the ease with which credit could be obtained was a direct result of lower interest rates. This implies that interest rates were set at lower rates by the Fed for a specific reason, one of which was due to their interpretation and implementation of the Taylor rule. The Taylor rule is an equation that specifies at what rate a central bank should set the nominal interest rate in response to a change in inflation, output or other economic conditions (Taylor, 1993:202). This is specified in Equation 2.1.

$$i_t = \pi + r_t^* + 0.5(\pi_t - \pi_t^*) + 0.5(y_t - \bar{y}_t^*), \quad (2.1)$$

where:

- i_t = short-term nominal interest rate
- π_t = rate of inflation (measured by the GDP deflator)
- r_t^* = equilibrium interest rate
- π_t^* = target inflation rate
- y_t = Logarithm of real GDP

- \bar{y}_t^* = Logarithm of potential output.

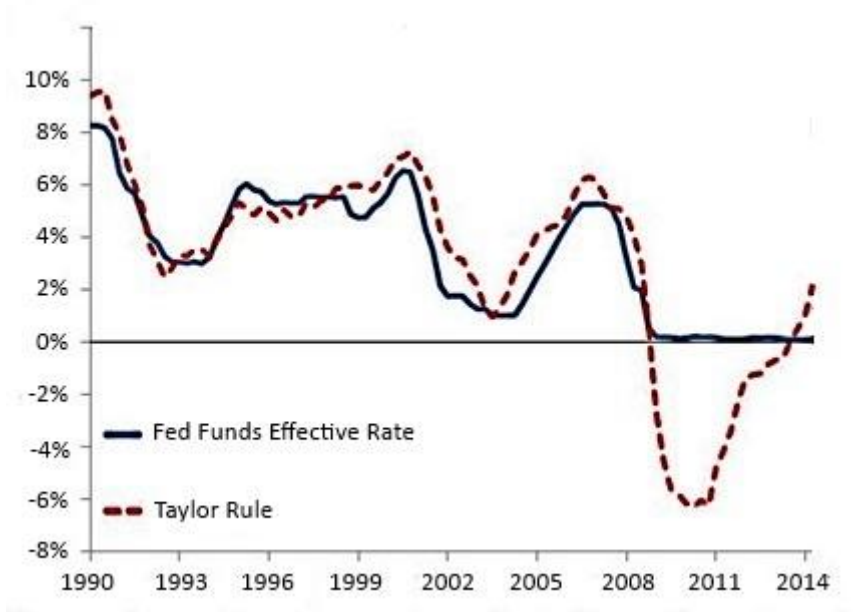
If the Fed were following the Taylor rule and basing its interest rates on macroeconomic variables such as inflation and GDP, the interest rate would have been significantly higher than it was – this is clear from both Figures 2.1 and 2.2 below. It can therefore be argued that interest rates were set at this level purposefully, perhaps in order to ease fears of downside risk and deflation, similar to that which occurred in Japan during the 1990s. This fear of deflation is also confirmed by the information reflected in Figure 2.1, where negative interest rates are seen to have been avoided at all costs in the wake of the sub-prime crisis. The end result being that monetary policy for the period leading up to 2007 may not have been restrictive enough, interest rates might have been too low, and this potentially allowed credit to be obtained too easily – the so-called monetary excess (Taylor, 1993:202).

A lower interest rate, or federal funds rate in the US, has a number of negative consequences. Firstly, lower interest rates lead to cheaper credit and an increased value of assets – due to increased demand. This can in turn lay the foundation for booms in asset prices and credit – this was evident leading up to the sub-prime crisis where housing and real estate prices increased significantly (Mohan, 2009:3). Secondly, low interest rates may encourage excessive risk taking by investors in financial markets who are searching for a greater return. A long period of these low rates may cause borrowers and lenders to underestimate the cost of debt, as well as the risk of a higher future cost of debt servicing. Lastly, the problem of moral hazard will be present if market participants know that the central banks can be relied on as the backstop if a negative shock occurs (Danthine, 2013:5). This is because market participants assume that the Fed would take action to prevent the market from failing, therefore insuring them against any possibility of a market crash (Miller, Weller & Zhang, 2002:171).

In Figure 2.1 below, the US Effective Funds Rate is shown as a blue line, while a rate implied by the Taylor rule⁷ is illustrated by the red dotted line.

⁷ It should be noted that the variables set in this version of the Taylor rule are fairly aggressive.

Figure 2.1: The US Effective Funds Rate (%) and the Rate implied by the Taylor Rule, 1990-2014.



Source: Buiter and Rahbari (2015:3).

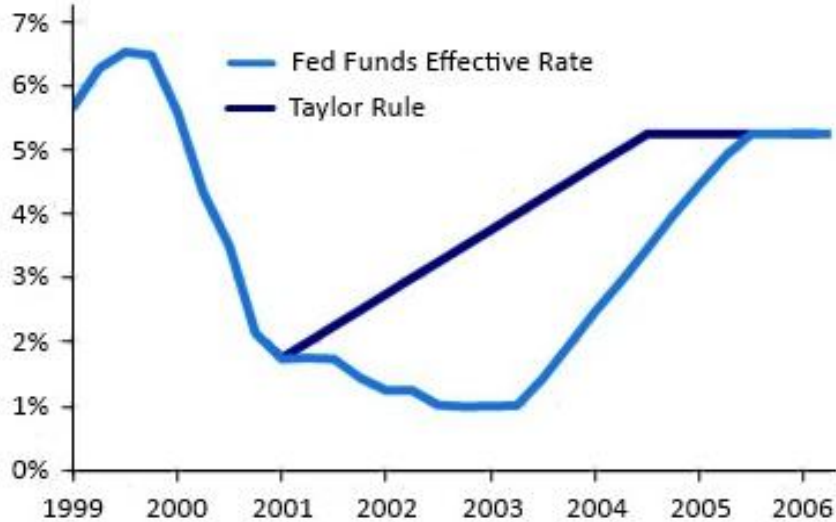
Note: The Taylor rule uses a coefficient of 1.5 for the inflation gap and 2 for the unemployment gap. Neutral nominal interest rate is 4.2 %.

In Figure 2.1 it can be observed that there are clear deviations from the Taylor rule, most significant for this study being the period prior to the sub-prime crisis, where the rates were kept low even though the Taylor rule indicated that they should have been higher. Following on from the sub-prime crisis, the Taylor rule further indicated that rates should have been cut to negative, but instead the Fed chose a different, more unconventional monetary policy in the form of quantitative easing.⁸

In Figure 2.2 below, a closer look at the period leading up to the sub-prime crisis is provided. We observe that the actual rate was kept below the rate that would be suggested by the Taylor rule.

⁸ Quantitative easing is when a central bank begins purchasing public and private sector assets using central bank money in order to increase liquidity in the economy. This provides additional stimulus to nominal spending so that the inflation target can be met (Benford, Berry, Nikolov, Young & Robson, 2009:90).

Figure 2.2: Loose-fitting monetary policy.



Source: Taylor (2009:2).

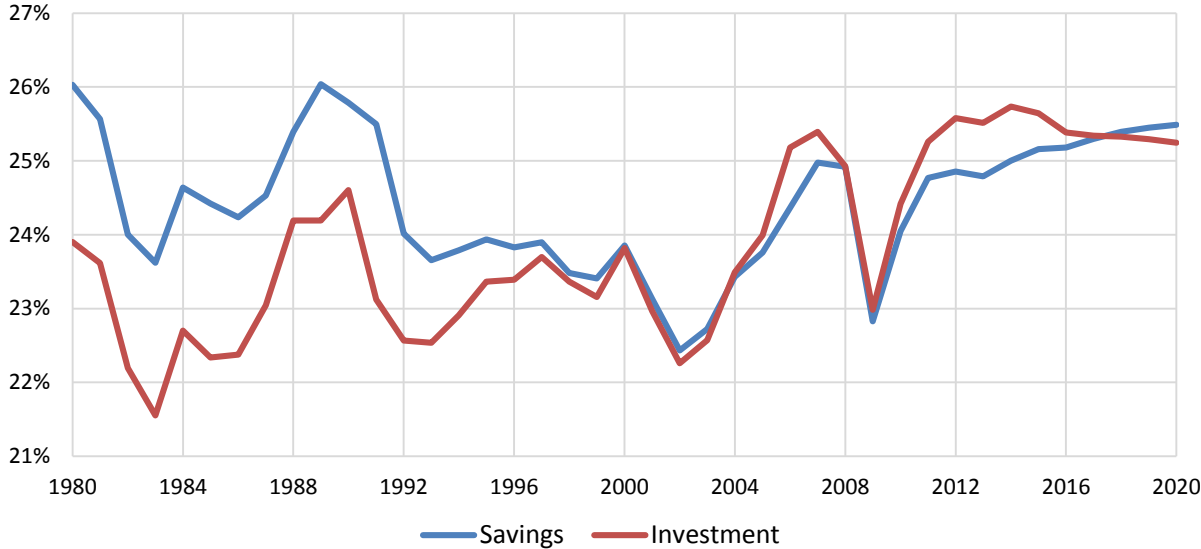
In response to the criticism of low interest rates leading up to the sub-prime crisis, Bernanke (2010) justified the use of a modified version of the Taylor rule which used the Fed’s inflation forecasts in place of current measured inflation. The Fed’s forecasts were lower and therefore would have given lower interest rates. Bernanke further criticised the Taylor rule’s forecasts by questioning the statistically significant relationship between low interest rates and the housing bubble. Greenspan (2009) also criticised the use of the Taylor rule in a global economy in which structural characteristics had significantly changed. Taylor (2010b) responded to this critique by questioning the use of inflation forecasts over actual inflation and citing the work of Orphanides and Wieland (2008), and Ahrend, Cournède and Price (2008) as proof of the existence of a statistically significant relationship.

An alternative explanation for the low interest rates in the US is seen in the global economic conditions, namely the presence of a global savings glut. This savings glut took place due to a number of factors. The oil price fluctuations that occurred in the early 2000s would be one of these factors. An increase in the oil price would have led to increased profits for oil producers, who are also known for saving a large portion of their profits (Higgins, Klitgaard & Lerman, 2006:3) – resulting in increased global savings. The case for low savings rates in emerging markets is slightly different, considering that they had put certain policies in place when the global economy began its recovery from the 2001 recession.⁹ Overall savings in emerging markets increased significantly from USD83.2 billion in 2002 to USD633.4 billion in 2007 (IMF,

⁹ The recession in 2001 was a short recession that took place in the US due to investment shocks and an unexpected decrease in real net exports in 2000 (Kliesen, 2003:36).

2009). This increase in savings and decline in investment in Organisation for Economic Co-operation and Development countries further decreased interest rates, while China also implemented policies that promoted savings and decreased investments in order to slow depreciation in its currency and prevent a rise in unwanted inflation. The combination of all these factors therefore led to a global economy that had high levels of savings and investment in oil exporters accompanied by high consumption levels, whereas the US had low levels of savings (Belke & Gros, 2010:5). The problem with this explanation, however, becomes evident when looking at long-term data. Figure 2.3 below illustrates global savings and investment as a share of world GDP.

Figure 2.3: Global savings and investment as a share (%) of world GDP.

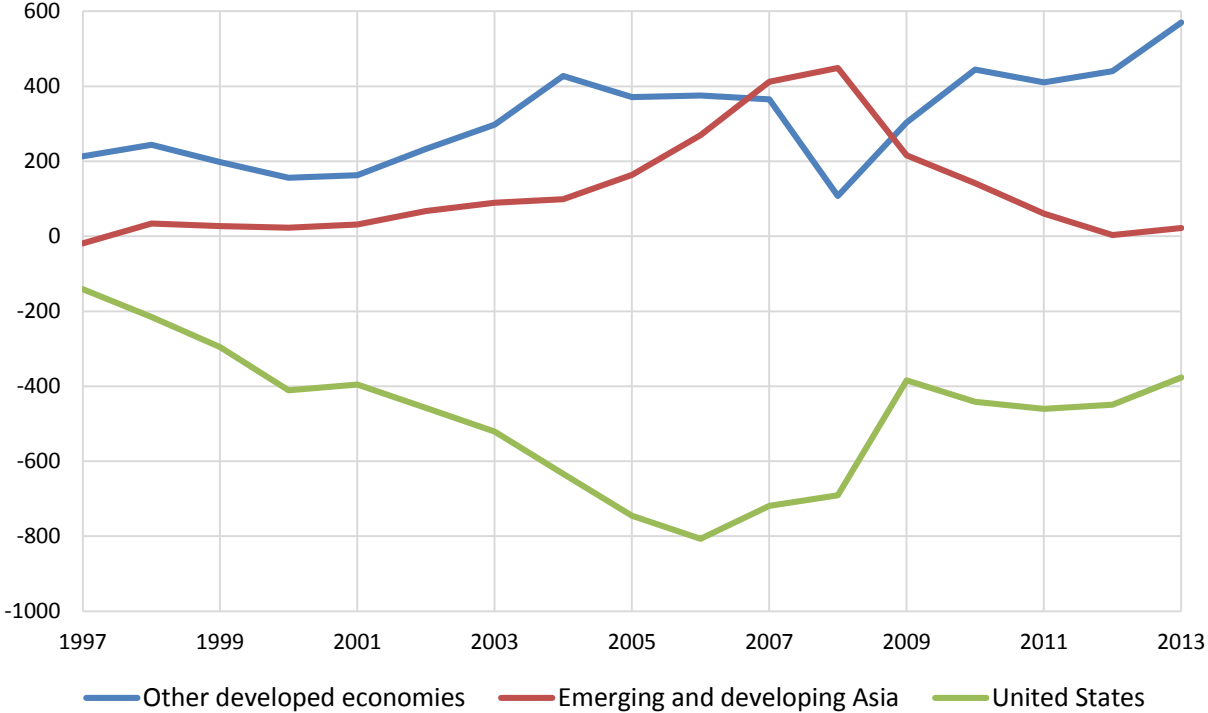


Source: Compiled by the Author, IMF (2015a).
 Figures for 2016 onwards are IMF forecasts.

Figure 2.3 indicates that there was in fact a global savings shortage, when compared with data from the 1980s to 1990s. It could, however, be argued that the savings glut was observed in countries other than the US during the period 2002 to 2004 since the US was running a current and budget account deficit, implying that savings were less than investment. The rules of global accounting would therefore dictate that the positive savings gap outside the US would be offset by an equally sized negative savings in the US, and there would be no effect on world interest rates expected (Taylor, 2009:4). It should be noted that interest rates in developed economies have a spillover effect on emerging markets. For example, an increased interest rate differential in the US could cause a large amount of capital to flow from the US to emerging markets instead, while the risk of a reversal would be inherent, even if the fundamentals of the emerging market remain unchanged (Koepke, 2015:23). The result of this is the possible inflation of asset prices, and destabilising effects, as well as upward pressure on the exchange rate.

As a result of these long periods of excessively loose monetary policy, large global imbalances were allowed to form. These imbalances were evident in a number of key countries. The deficit in the US was mirrored by surpluses in China – and Asia in general – with oil exporting countries in the Middle East and Russia also exhibiting surpluses during the early 2000s. This is illustrated in Figure 2.4.

Figure 2.4: Global imbalances (in USD billions) for the period 1997 to 2013.



Source: Compiled by the Author, IMF (2015a).

Figure 2.4 shows that the external surpluses of China, as well as those of commodity exporters such as the Middle East, increased steadily while the surpluses for developed economies, excluding the US, had risen prior to 2004 before reaching a peak and then slowly declining, with the US deficit continuing to increase through 2006. This led to an increased overall deficit for developed economies, and therefore an increased world demand for excess savings (Obstfeld & Rogoff, 2009:21). According to Portes (2009:23), these global macroeconomic imbalances and the large, subsequent cross-border financial flows placed enormous stress on the financial intermediation process. In addition to these large imbalances, an accumulation of foreign exchange reserves occurred in emerging markets, particularly in China. This accumulation was done as a form of self-insurance in the event that capital flows reversed. Much of these reserves were accumulated through trade surpluses and it is argued that this led to a misalignment of exchange rates and therefore prevented an adjustment of these global imbalances (Mohanty, 2009:3). These global imbalances interacted with the flaws inherent in the financial markets and the newly developed financial instruments so as to generate the crisis.

It can therefore be argued that the excessively loose monetary policy explained above and low interest rates allowed the market to be flooded with liquidity and led to a rapid credit expansion. These macroeconomic conditions could have made the possibility of a housing bubble more likely, while subsequent developments of a microeconomic nature made it more of a reality. As a consequence, the macroeconomic conditions laid the foundation for the sub-prime crisis, while the microeconomic conditions forced open any cracks that had begun appearing.

2.3.1.2 Microeconomic conditions

The microeconomic conditions in the US financial sector that played a role in the sub-prime crisis include the lowering of credit standards and subsequent credit boom (Gates, Perry & Zorn, 2002:386), rapid financial innovation (Acharya, Schnabl & Suarez, 2013:515), inadequate corporate governance, and an inappropriate incentive scheme (Engel & McCoy, 2002:1276). This was supplemented by years of deregulation and the removal of laws which inevitably eased lending to customers with unproven credit records (Crotty, 2009:7).

It is arguable that the practice of deregulation played a pivotal role in the structural change that occurred within the financial system, as well as the eventual sub-prime crisis. Economic regulation is defined as limitations on the products that a firm can offer, the price of these products, and the location in which it can conduct this business (Funk & Hirschman, 2014:671). Deregulation would therefore be the removal of these limitations. The process of deregulation can be divided into two distinct phases. The first period, which began in the 1970s, focused on the repeal of economic regulations that were anti-competitive in nature, reduced consumer welfare, and created monopoly rents. The second period began in the 1980s and focused on social regulations, such as environmental laws and occupational safety laws (Prasad, 2006).

The current US credit market and the transactions taking place within it are sparsely regulated by a number of state and federal laws that are both ambiguous in nature and possess a number of loopholes (McCoy & Renuart, 2008:2). Furthermore, the state laws have the potential to be undermined by the federal banking laws. These loopholes and ambiguities were only added to the regulatory structure during the 21st century, due to an increase in high-cost salary lending¹⁰ and the emergence of loan sharking.¹¹ In order to drive out exploitative lending, individual states passed special usury laws¹² allowing interest rates to be charged on specific products that are higher than conventionally allowed by the general usury laws

10 High cost salary lending was the precursor to payday lending, which entailed the granting of a short-term loan for a small amount from between seven to 30 days (Stegman, 2007:169).

11 Loan sharking is lending that takes place at high interest rates and on the security of a wage assignment, and is generally considered predatory lending (Mayer, 2012:811).

12 Usury laws are legislated caps on interest rates (Rigbi, 2013:1238).

(Drysdale & Keest, 1999:621; Peterson, 2003:863). Mortgage lending remained under the general usury laws until the National Housing Act was adopted in 1934 in order to respond to the national housing crisis. This introduced a usury and credit regulation that limited interest rates to 5 %, with the administrative option of raising this to 6 %, imposed maximum loan amounts and loan-to-value ratios, and required a certain assessment of a borrower's ability to repay the loan, while also specifying that the mortgage lien be in first position (McCoy & Renuart, 2008:3).

Apart from these general mortgage laws under the National Housing Act, other specific considerations were also altered. One of note was The Servicemen's Readjustment Act of 1944 which gave the Veterans' Administration the authority to guarantee interest rates for members at 4 % on home mortgages of USD2000. This was later repealed by Congress in 1983 for loans under the Housing Act and in 1992 for Veterans' Administration loans (Mansfield, 1999:483). Also, in 1968, Congress passed the Truth in Lending Act which required a greater disclosure of credit terms and devolved the responsibility onto states to regulate consumer credit. A landmark court case in the 1970s and 1980s essentially saw an end to any potential uniformity for usury laws across state lines. The court gave national banks the right to pre-empt the usury law of a borrower's home state, effectively allowing them to charge interest rates based on the state in which they are situated, which may have had a high cap, or none at all. In order to promote economic development, the states of South Dakota and Delaware repealed their usury caps in order to attract the lending industry. Their tax revenues from banks increased exponentially, and had the effect of weakening the already waning resolve of other states to retain their consumer credit protection acts (McCoy & Renuart, 2008:5).

Following on from these decisions, the Federal Reserve Board (2015) published figures showing that the mortgage interest rates began to rise significantly from 7.38 % per year in 1972 to a high of 16.63 % per year in 1981. The decision by Congress to pass the Depository Institutions Deregulation and Monetary Control Act in 1980 essentially removed interest rate ceilings for first lien mortgages on residences and mobile homes, and extended the most favoured lender status from national banks to other kinds of depository institutions, allowing them to choose either the federal rate or the rate set by the state, whichever would be higher (Mansfield, 1999:495). In 1982, the Alternative Mortgage Transactions Parity Act was implemented in order to restructure mortgage loans and undermine state laws that restricted the variable rate terms, balloon payments and negative amortisation. The motivation for the implementation of these acts was to resuscitate the mortgage market following the increase in inflation which occurred during the 1970s (McCoy & Renuart, 2008:6). This may, however, have had effects that were structurally adverse in nature over the long term, as the sub-prime crisis loomed.

Deregulation played a large role in removing the legal barriers to the sub-prime market, but other technological innovations had a role in its emergence. Technological advances in the 1970s and 1980s,

such as statistical credit scoring models and automated underwriting, introduced the possibility of disparate credit risk pricing which in turn increased the pool of qualified loan applicants. The introduction of these statistical models meant that traditionally strict underwriting standards could be relaxed and requirements such as large down payments, employment records, high credit scores, and low debt ratios were not as necessary, while not increasing the risk of default. These statistical models were eventually adopted by mortgage lenders who then offered home loans with the same relaxed requirements (Gates *et al.*, 2002:386).

The mortgage market for homes in 2007 was vastly dissimilar to the market from preceding years. The introduction of securitisation made the process of extending loans to consumers with less than perfect credit records much simpler. Securitisation can be defined as a financial engineering technique that integrates the residential mortgage market with the capital markets by pooling home loans, removing the cash flows from the receivables, and converting the cash flows into bonds that are secured by the mortgages. In this case, the bonds are known as residential Mortgage-Backed Securities (MBS) but can also be Asset-Backed Securities (ABS) if a different asset is used instead of a mortgage (Engel & McCoy, 2007:107). The securitisation process is essentially a restructuring process, because the loan pool is isolated from the original lender by selling the pool to a special purpose vehicle that is legally separate from the lender, but still owned by the lender. This loan pool is then sold for a second time to another independent special purpose vehicle which would usually be a trust. It is therefore difficult for the creditors of a lender to access the assets which back the securities in the event that the lender goes bankrupt, making this two-tiered structuring process successful in protecting the investor (Schwarcz, 1994:135). This removal of the bankruptcy risk would improve the credit rating of the securitised loan pool and allowed it to achieve a greater credit rating than the actual lender, thereby resulting in the creation of investment grade transactions from non-investment grade originators. The loans transferred to the second special purpose vehicle then have their principal amounts and interest payments divided into tranches which each receive their own credit risk rating based on historical performance forecasts (Baron, 1996:88). The assessment of credit risk is therefore not based on the risk of the underlying loans. In the lead up to the financial crisis, banks used the securitisation process in order to reduce the amount of regulatory capital they were required to hold. They were able to do this because the financial risks they were meant to be undertaking were now spread across the entire economy (Acharya, *et al.*, 2013:515).

The process of securitisation was largely embraced by the Federal Home Loan Mortgage Corporation (Freddie Mac) and the Federal National Mortgage Association (Fannie Mae) during the 1980s, while the Secondary Mortgage Market Enhancement Act of 1984 made the issuance of private MBSs, as well as the purchasing of these securities, much simpler (Gambro & Leichtner, 1997:141). Once the practices of automated underwriting and other statistical modelling were embraced for pricing sub-prime loans,

securitisation began to be more widely used and played a significant role in the emergence of the sub-prime market (Engel & McCoy, 2002:1273). Securitisation improved the process of sub-prime lending in a number of ways for lenders. Firstly, the term mismatch problem which forced lenders to hold mortgages in their portfolios was solved since lenders could now sell their mortgages for cash and remove them from their books. Secondly, it divided and spread the risk of the sub-prime mortgages across a larger number of investors who in turn could diversify this risk even more. Thirdly, since there was no longer a need to maintain large capital reserves, these newly available funds could be used to create new loans which in turn could again be securitised – freeing up more funds and thus repeating the cycle. Lastly, the securitisation process led to a large amount of capital flowing from investors to lenders who were searching for high returns. This process eventually created the so-called non-bank sub-prime lender with the characteristics of being regulation free, indifferent to reputation constraints, and thinly capitalised (McCoy & Renuart, 2008:9).

The final development in the formation of the sub-prime market entailed government incentives which encouraged lending to lower- and middle-income borrowers. Affordable housing goals, which are essentially quotas, were established for Fannie Mae and Freddie Mac. This entailed the purchasing of a certain number of loans from lower- and middle-income borrowers, and high minority or low-income census tracts. This mandate essentially forced both Fannie Mae and Freddie Mac into the widespread purchase of sub-prime MBS. The Community Reinvestment Act had a similar mandate in that it rewarded federally insured banks and thrift banks that originated and bought mortgages from minority and low-income borrowers (Engel & McCoy, 2002:1276). The Ownership Society initiative and the American Dream Downpayment Act of 2003 authorised yearly subsidies to approximately 40 000 lower-income households in order to aid down payments and closing costs. The demand for loans among traditionally oppressed black and Hispanic citizens was significantly high and therefore meant that these individuals could now easily obtain homes (Engel & McCoy, 2008:81).

The combination of these legislative and financial developments resulted in a rapid rise in sub-prime mortgages for the period 1994 to 2006. This rise is evident when the two years are compared. In 1994 the originations for sub-prime mortgages totalled USD35 billion, which accounted for 5 % of total new mortgages originated that year. Comparatively, in 2005 the originations for sub-prime mortgages totalled USD625 million, which accounted for 20 % of total new mortgage originations (Gramlich, 2007:6). The appreciation in the value of homes in large metropolitan markets, such as Florida and other parts of the East Coast, led to a situation where lenders were competing with each other by offering larger loans and therefore allowing the borrower to purchase either a larger home, or a home in a more attractive area. The loans granted by these lenders had certain special terms attached to them, such as interest only repayment options, higher debt-income ratios, and low down payments (Immergluck, 2009:342).

Conditions such as these facilitated a cycle of high-risk lending and price increases, where one caused the other.

Another of these causal relationships was the supply of high-risk capital in the market, which stemmed from the high-risk lending and price increases, and now contributed to the high-risk mortgage market. Following on from the bursting of the dot-com stock market bubble¹³ in the early 2000s, a large amount of high-risk capital was available and in search of an investment destination. The destination it found was the real estate market that had been empowered by securitisation and decreased regulations (Carswell, 2012:713). Further innovations began to take place in securitisation markets, such as the increased use of collateralised debt obligations and credit default swaps. A collateralised debt obligation is a debt-backed security in which different collateralised debt obligations, known as tranches, are organised according to their varying risks and return characteristics. These characteristics result from the different priorities of claims on the payments generated by the underlying debt (Chance & Brooks, 2008:498). For the case of collateralised debt obligations, the pooling of lower-rated residential MBSs with higher-rated residential MBSs resulted in the formation of AAA rated collateralised debt obligations,¹⁴ essentially negating the influence of the lower grade MBSs completely. A credit default swap is an over-the-counter credit derivative in which the credit default swap buyer makes periodic payments to the credit default swap seller in exchange for a payment in the occurrence of default on the underlying reference entity, which in this case would be the mortgage (Chance & Brooks, 2008:548). These credit default swaps essentially allowed investors to hedge their investments in residential MBSs and collateralised debt obligations, thereby allowing even greater investment into these assets. The implementation of these credit derivatives had the effect of decreasing the risk associated with MBSs, and therefore investments of a greater scale took place.

The ease with which high-risk capital could flow through securitisation would not have been possible without the so-called New Financial Architecture. The New Financial Architecture refers to the practice of light government regulation and the integration of modern financial firms – such as commercial and investment banks, mutual, hedge and private equity funds, as well as structured investment vehicles¹⁵ created by banks – with the markets (Crotty, 2009:564). The implementation of the New Financial Architecture may also be seen as a fundamental shift away from the Glass-Steagall regulatory system which was put into place following the Great Depression during the 1930s. It essentially separated

13 The dot-com stock market bubble was a boom and subsequent bust which took place due to the commercialisation of the internet between 1995 and 2000 (Crain, 2014:372).

14 AAA rated collateralised debt obligations are those which would be of the highest quality and possess the lowest credit risk (Polito & Wickens, 2014:205).

15 Structured investment vehicles are off-balance sheet investment vehicles that raise funds by selling short-term asset backed commercial paper with a 90-day average maturity and medium term notes with just over a one year maturity. These sales took place mostly to money market funds (Brunnermeier, 2008:4).

commercial and investment banking activities, ensuring that bank deposits could not be used to finance speculation in the capital markets (Russell, 2007:4). The Federal Deposit Insurance Corporation insured all bank depositors against the risk of a loss, while the US Securities and Exchange Commission applied light regulations, only requiring banks to provide more detailed information to the public regarding their securities. The Federal Home Loan Bank was responsible for guaranteeing residential mortgage loans, a move that made mortgages significantly safer for lenders. The Glass-Steagall system encouraged commercial banks to avoid overly risky loans and provide liquidity to other financial institutions during times of market uncertainty by outlining the requirement that commercial banks must originate and retain consumer and commercial loans. This ability to provide liquidity was protected by strict government regulations regarding the risks they could take, meaning that banks could act as the lender of next-to-last resort for other financial institutions, while the Fed and Federal Deposit Insurance Corporation would be the lenders of last resort. This system was successful in reducing bank failures and systemic financial crises from the late 1930s up until the 1970s (Crotty, 2009:6). The elimination of the legislation and subsequent deregulation of the financial system therefore led to a capital market based, highly integrated financial system that was lightly regulated – the so-called New Financial Architecture (Crotty, 2009:7).

An anecdotal proof of how these deregulations provided the foundation for the sub-prime crisis can be evidenced in the fact that the median family's house was allowed to be highly leveraged and had an equity holding equal to 35 % of its total wealth (Acharya & Richardson, 2009:196). The severity of the crisis, however, cannot be explained by these events alone and there are other elements of a systemic nature which played a significant role in amplifying the risk inherent in the financial system and creating a vicious circle of falling prices. This may have occurred as a result of how the market values of these assets were measured, and therefore the accounting system employed by these financial institutions needs to be examined.

2.3.1.3 The accounting system

Fair value or mark-to-market accounting was the standard for measurement leading up to and during the sub-prime crisis. Fair value is defined as the price that would be received for selling an asset, or paid to transfer a liability, in an orderly transaction between market participants at the measurement date (FASB, 2010:8; IASB, 2011:538). The accounting system has the potential to influence how and when gains and losses are valued, as well as their magnitude. The potential of a fair value accounting system to amplify systemic risk during a crisis has led to many parties, such as the US Congress, questioning its use in financial institutions. This potential to amplify systemic risk is a result of what is referred to as the fire-sale externality problem whereby an institution's desire to sell a potentially illiquid downgraded asset – for risk management or capital adequacy reasons – could create a spillover effect onto the entire financial

system. Further selling pressure can also be placed on the financial institution during a crisis due to feedback effects created by these trading pressures. This amplification of systemic risk is therefore brought about by a single institution's forced selling that results in a subsequent downward spiral of prices and illiquidity. There is also a further potential for contagion, since other institutions recognise the decreased value of the assets, magnifying capital adequacy issues and forcing the selling pressure system-wide (Ellul, Jotikasthira, Lundblad & Wang, 2013:2).

Bessis (2010:14) noted that in an inactive and illiquid market, assets are inaccurately valued and their fair values are substituted with their perceived values. This inaccuracy in valuation occurred because of significant differences between the market and the book value of the assets held by US banks. Over the period 2001 to 2008, the market value of assets such as MBSs decreased significantly, partly due to information asymmetries regarding the quality of the assets. Gorton (2009:2) explains that sub-prime mortgages have a security design whereby the mortgages were of short maturity and required financing. For example, 80 % of the mortgages originated during 2006 and 2007 were securitised mortgages. The securitisation of these mortgages meant that they reflected the sensitivity of home prices, while also involving a build-up of credit enhancement as the underlying mortgage was refinanced and paid cash into the securitisation. The implication was that the sub-prime mortgages could be refinanced on the condition that house prices appreciated. House prices are calculated with a lag, therefore when the prices began declining in 2006, it was not immediately discernible how this would affect sub-prime securities and products. This led to uncertainty regarding the quality of the assets, as well as uncertainty regarding the exact location of these risks – and a subsequent loss of confidence in credit (Gorton, 2009:12).

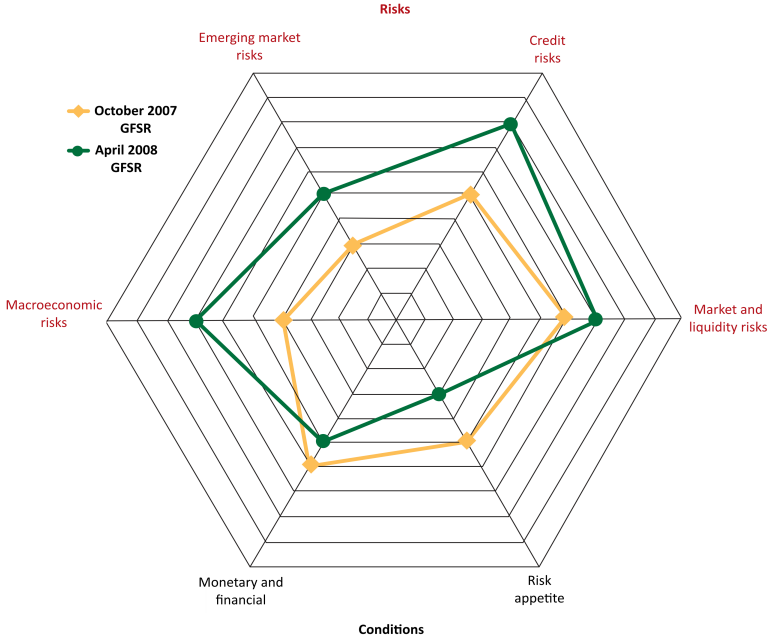
These events should arguably have led to a large decline in the ratio of Tier 1 capital to bank assets,¹⁶ but a decrease of only 1 %, from 12 % to 11 %, took place (Huizinga & Laeven, 2012:614). The implication was that the market value of the banks' equity decreased significantly, while the banks' book capital remained virtually the same. It may therefore be stated that if the house prices, mortgage values, and bank equity values were inaccurately estimated, the losses that took place could also be inaccurate.

Inaccuracies of this nature can be evidenced in the measurement of losses that took place before, during, and after the sub-prime crisis. Since April 2008, the predicted aggregate losses amounted to USD945 billion overall, including USD565 billion in US residential real estate lending (IMF, 2008a:50). This prediction was increased in October 2008 to USD1.4 trillion overall, including USD750 billion in US residential real estate lending (IMF, 2008b:14). It is, however, important to note that these figures for the securities could potentially be below the expected present value of future cash flows, which would result in the market values providing inaccurate long-term value-maximising signals (IMF, 2008a:66). It can

¹⁶ Tier 1 capital includes only permanent shareholders' equity and disclosed reserves (BCBS, 2011:2).

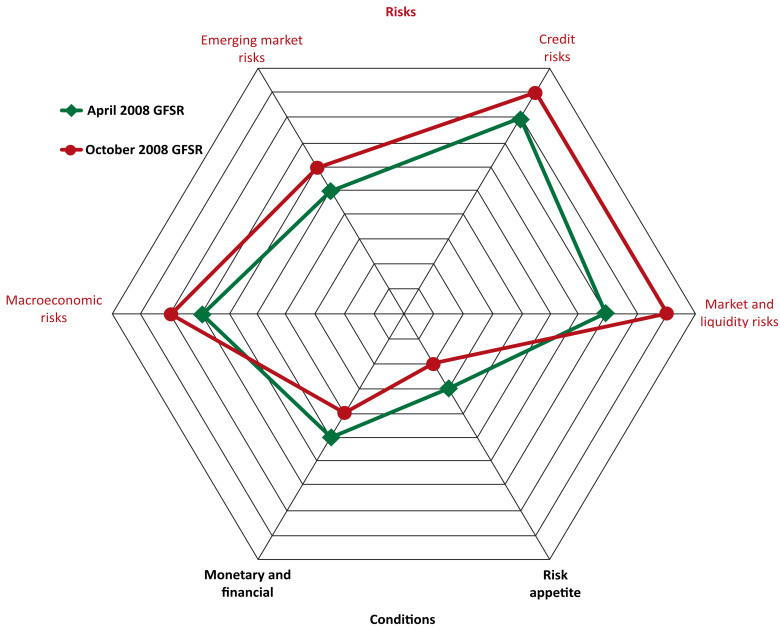
therefore be stated that such a market malfunction would have had a significant role in the financial crisis. A possible explanation for this increase in loss estimates may have been due to an increase in the amount of risk in the financial sector. Figures 2.5 and 2.6 below represent how the amount of risk increased from October 2007 to October 2008, in correlation with a decrease in the risk appetite.

Figure 2.5: Global financial stability report for period October 2007 to April 2008.



Source: IMF (2008a:2).

Figure 2.6: Global financial stability report for period April 2008 to October 2008.



Source: IMF (2008b:2).

Figures 2.6 and 2.6 illustrate a feedback loop between the global economy and the banking system, where the entire economy deteriorates as a result of a crisis in the financial system. The residential real-estate lending losses predicted are mostly for MBSs. The total outstanding volume of these MBSs is estimated to be USD1.1 trillion. If one then considers the 2008 IMF April and October estimates of a loss of USD450 billion out of USD565 billion and a loss of USD500 billion out of USD750 billion, respectively, the average loss rate is between 40 % to 45 % (Hellwig, 2009:131). If a predicted original equity position of 5 % is used for the borrower (i.e. the down payment required for the home loan), the loss rate calculated above would imply that the property value declined by between 45 % and 50 % due to the inclusion of the equity position. According to the S&P/Case-Shiller U.S. National Home Price Index (2015), the average decline in residential real estate prices from 2006 to 2008 was actually approximately 19 %, which is nearly half of the IMF estimate. The losses estimated on MBSs by the IMF are not necessarily losses per se, but rather estimates based on incidences of borrower defaults representing declines in market valuations of MBSs. Declines in market valuations would not be problematic in a well-functioning market, but this may not have been the case. The IMF has stated that the market prices could be significantly below the expected present value of the future cash flow for some securities – meaning that the market values do not accurately reflect the value of the instruments (IMF, 2008a:65). Due to these inaccuracies in market estimations, it could be said that market malfunctioning therefore played a large role in the sub-prime crisis.

The possible malfunctioning of the market brings into question the validity of fair value accounting and the role it may have played in worsening the effects of the sub-prime crisis. The alternative to this system would be the historical cost accounting method. Historical cost is defined as the amount of cash or cash equivalent paid, or the fair value of the consideration given, to acquire the asset at the time of acquisition (IASB, 2010:45). Ryan (2008) argues that the fair value accounting system has the advantage of being more accurate, timely and comparable than does a historical cost accounting system, while also limiting a company's ability to manipulate its income, since gains and losses are reported in the period they occur. Furthermore, these reported gains and losses can also indicate economic events that may be worthy of additional disclosure. The use of a fair value accounting system, however, could explain why – in the wake of the sub-prime crisis – financial institutions continually discovered that their losses were greater than initially thought, due to continual changes in the market valuation of the instruments. The fair value accounting system is therefore largely influenced by market sentiment, i.e. a pessimistic market sentiment will result in lower market valuations. A caveat, then, to this is that a malfunction in the market will essentially be reflected in the prices of securities. Since the value of the securities in a bank's books is based on the market price of the security, it must continually be adjusted as the market price changes. A readjustment of prices has significant implications for capital adequacy, in the sense that a decrease in

the security price will force the bank to either decrease its overall operations, or recapitalise by issuing new equity. As a result, a malfunctioning in the market can lead to a large impairment in the banking system (Hellwig, 2009:133). It can therefore be argued that the fair value accounting system was just one of several systemic elements which were responsible for amplifying the sub-prime crisis into a global financial crisis.

2.3.1.4 Systemic elements

The evidence presented thus far has illustrated that the macroeconomic and microeconomic conditions, as well as the accounting practices employed, had both individual and collective effects in contributing towards systemic risk. Prior to the sub-prime crisis, a bubble could be observed in the residential real-estate market, and the underlying frailties in the economy had been recognised; however, the magnitude of the fallout was not anticipated. Table 2.2 below indicates that even if the housing prices in the US were to decrease by 12 % per year for five years in a row, AAA and AA rated sub-prime mortgages would still be unaffected.

Table 2.2: Stress Test: Impact of home price appreciation on ABS collateralised by sub-prime mortgage loans (Per cent impairment of ABS tranches).

Tranche	Home Price Appreciation Scenarios (Average 5-year home price appreciation in % per year)								Memo Item: Per cent of sub-prime deals in 2006 ¹
	-12	-8	-4	0	4	8	12	16	
AAA	0	0	0	0	0	0	0	0	75.0
AA	0	0	0	0	0	0	0	0	10.1
A	79	48	0	0	0	0	0	0	4.5
BBB	100	100	96	32	0	0	0	0	2.9
BB	100	100	100	100	25	0	0	0	0.7

Source: IMF (2007:7).

¹Not rated or not available amounts to 6.7 %.

Stress test conducted by Lehman Brothers.

It should nevertheless be noted that the stress tests results presented in Table 2.2 were conducted by Lehman Brothers and it can be argued that given its collapse, its stress tests have limited credibility. A counter argument could be that the tests were based on inaccurate risk modelling, but an even more pessimistic view than the one taken in Table 2.2 would still not have predicted losses to the extent that occurred. The Global Financial Stability Report of April 2007 from the IMF further reported that the losses that could be experienced from sub-prime mortgages would be fairly limited, since approximately 85 % of the total ABS issues are rated at least A (IMF, 2009:7). The fact that the BIS Annual report (2008:3) asks the question as to how the relatively small sector of the US sub-prime mortgage market had the ability to

cause a global financial crisis is indicative of just how unaware the market was of the systemic elements involved. Hellwig (2009:181) summarises these main systemic elements as the interplay of market malfunctioning during the crisis, and fair value accounting, together with the insufficiency of bank capital, regulatory requirements and bank corrective actions.

Before addressing the malfunction of the market, it is important to analyse the extent to which maturity transformations took place in real-estate finance through the use of MBSs. Investors generally prefer assets with short maturities, such as money market funds, because they can withdraw these funds quickly to satisfy their needs (Allen & Gale, 2007). Large investment projects and mortgages by comparison have maturities measured in several years, and potentially require reinvestment. It should be noted that a maturity mismatch could potentially lead to funding liquidity risk whereby investors stop buying short-term assets while the long-term liabilities remain in need of funding (Brunnermeier, 2008:5). Leverage in the banking sector of structured investment vehicles and conduits¹⁷ was very high, with leverage ratios close to 100 %. These structured investment vehicles and conduits were set up in order to invest in illiquid long-term securities and then refinance themselves by issuing very short-term debt that would continually need to be refinanced (IMF, 2008a:90). A maturity transformation essentially took place whereby long-term securities are bought and short-term securities are sold. Transforming the maturity in this way can create a large amount of risk for the institutions, as well as systemic risk. If a shock occurs that makes refinancing impossible, the institution will not be able to repay its short-term debt, and may need to obtain finance through other means. If an alternative method cannot be found, a fire sale of its longer-term assets can be undertaken at depressed prices, further pressuring all institutions that hold such assets. As mentioned earlier, mark-to-market accounting forces these institutions to then adjust the value of these assets immediately, leading to doubts from market participants and the possibility of them removing their funds from the institutions, subsequently causing a knock-on effect. A readjustment may occur even if there are no doubts regarding the quality of the long-term assets, but simply because refinancing could not take place (Hellwig, 2009:170).

Such a breakdown is precisely what occurred in the period following August 2007. The refinancing market mentioned above collapsed, which at the time held securities to the value of USD1 trillion –equivalent to 90 % of sub-prime MBSs. The market breakdown significantly contributed to the spreading of the crisis through the entire financial system and the subsequent magnification of the sub-prime crisis into a global crisis (Dodd & Mills, 2008:17). This breakdown was due to the downgrading of ABSs by several grades by the credit rating agencies – due to rising mortgage delinquencies and foreclosures which had severe

¹⁷ A conduit is a financial organisation that has the sole purpose of buying loans or other financial assets from correspondents with the goal of earning a profit by repackaging and selling the assets as securities (Elmer, 1999:28).

negative impacts on the value of the securities, as well as increasing the liabilities to insurers (Dodd & Mills, 2008:17). These events and the subsequent attempts of two hedge funds to sell these securities led to scepticism regarding the value of such securities and the solvency of institutions, conduits, structured investment vehicles and money market funds. Large international banks such as BNP Paribas, Industriekreditbank, and Sächsische Landesbank that had deposits with US banks were affected by this breakdown, with Landesbank only managing to avoid bankruptcy after additional equity was provided. BNP Paribas, in particular, suspended share redemptions from some money market funds because of this. When banks are affected by a breakdown in this manner, it may lead to doubts regarding many other banks, the logic being that if one bank was facing these problems, there might be a possibility that another bank could be hiding the same problem – the result of these doubts leading to a halt on interbank market¹⁸ transactions. In this way, the entire world banking system was affected by the breakdown in refinancing, leading to the need for central bank interventions to inject the missing liquidity back into the market. The central banks could, however, only limit the damage and not remove the systemic risk entirely (Hellwig, 2009:172). The market malfunctioning during the crisis therefore manifested in uncertainty surrounding the quality of ABSs. As the crisis began unfolding, the various individuals in the markets withdrew their funding and demanded large discounts on these assets. This was because of doubts regarding the assets' quality and the counterparties' quality, as well as the future of the financial system. Due to such a large-scale selling of assets, the potential buyers were either apprehensive about buying them, or insisted on significant discounts (Hellwig, 2009:173).

The market malfunctioning would not have mattered if the institutions involved in the malfunction were independent of the market. The system of fair value accounting provided an extra channel with which to influence financial institutions. The intricacies of the fair value system have already been mentioned above, but it should be restated that fair value accounting is generally not suited to a crisis situation in which the market is not functioning optimally, due to banks taking corrective action to fix book losses and these actions being fed back into the financial system (Blum & Hellwig, 1995:747). The market malfunctioning and system of fair value accounting can therefore combine to reinforce each other and have pro-cyclical¹⁹ effects that magnify the consequences of a financial crisis and deepen its roots in the financial system.

In order to protect an institution against the pro-cyclical effects of market malfunctions and mark-to-market accounting, adequate equity capital buffers were needed. The levels held were largely insufficient

18 The interbank market can be defined as a financial network that consists of a number of a set of nodes (Georg, 2011:8). These nodes can include banks or other financial institutions.

19 Pro-cyclicality in this sense relates to capital, and implies that institutions will expand during upswings and contract during downswings (Landau, 2009:2).

due to the relative non-existence of equity buffers for structured investment vehicles and conduits, as well as the attempt by banks to hold as little equity capital as possible in order to maximise their earnings. Financial institutions were able to keep lower levels of capital because the capital requirement rules were changed, allowing banks to base their capital buffers for market risk on the calculations done by their own internal models, as stated by the 1996 amendment to Basel I (BCBS, 2014:3). Furthermore, the levels of capital that banks held in excess of the requirements had also greatly reduced. Throughout the 1990s, these levels had been significantly reduced – due in part to losses from small business and real estate lending, as well as the escalation of competition in the financial sector and the increased use of more – presumably – precise quantitative risk models (Hellwig & Staub, 1996:762). This lack of capital buffers led to vulnerability in two ways. Firstly, the institution’s leeway to absorb shocks is reduced, especially since they must correct immediately by deploying capital reserves to the affected area, and secondly, a shock can significantly affect the solvency of the institution.

Two such solvency issues could be seen in the case of Fannie Mae and Freddie Mac, and Lehman Brothers. The problems of the first set of institutions were essentially caused by being undercapitalised, even though they had securitised prime, rather than sub-prime, mortgages. The problem was exacerbated by the spread of the crisis to prime mortgages in 2008, and by the mandate of the US Congress to purchase sub-prime MBSs which would eventually need to be written down. In the case of Lehman Brothers, many banks and investors throughout the world had funds deposited with them, and the failure of the Fed to offer a bailout resulted in decreased confidence in other banks – since a bailout of other banks was not a certainty – resulting in a breakdown of interbank markets (Mishkin, 2010:4). During the interbank market breakdown, the questions raised regarded the solvency position of the institutions, as opposed to their liquidity. The solvency problem is more serious than the liquidity problem because the latter can be solved by central banks lending against collateral, whereas the former can only be solved by the finance minister making use of tax funds (Hellwig, 2007:31). It can therefore be argued that capital adequacy and prudential requirements can have significant systemic effects on financial institutions due to their pro-cyclical nature.

The pro-cyclical nature of financial institutions was evidenced in the latter part of 2007 when ABS prices declined and the fair value accounting system forced this price decline to be reflected in the institutions’ books immediately and obligated them to respond – either through acquiring more equity or through deleveraging.²⁰ Since the institutions were required to meet a certain regulatory capital requirement, an institution’s opinion of whether the market values of the assets were accurate became almost irrelevant.

²⁰ What occurred was an adjustment of the institution’s scale of operations to a lower level of equity, through either a reduction in lending, or a sale of assets.

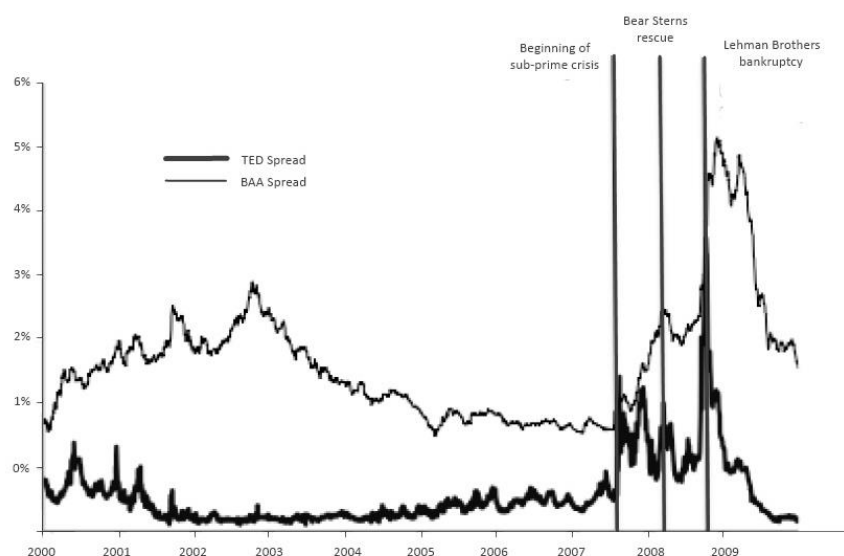
The inadequacy of the equity capital held above the regulatory amount to absorb shocks therefore led to asset price declines followed by write-offs, and write-offs that were followed by asset sales. In many cases, the book value of the asset did not accurately reflect the intrinsic value of the asset, which caused significant solvency issues for an institution (Hellwig, 2009:179).

Following on from this, a number of runs on financial institutions developed, which in the traditional sense entails the run of bank depositors to withdraw those deposits, which becomes problematic because the bank cannot convert all its long-term assets into cash quickly enough in order to meet the withdrawal requirements. Gorton and Metrick (2012:426), however, argue that this was not a run in the traditional sense, but instead a run on the securitised banking system.²¹ A run on the securitised banking system would entail the institutions holding short-term liabilities, such as repurchase agreements backed by collateral in the form of long-term assets such as MBSs, instead of deposits backed by government. A significant component of such lending entails the use of a 'haircut'. A haircut requires that the collateral posted by the borrower have a greater value than the loan. In the case above, for example, a repurchase agreement of USD200 million would require collateral in the form of a USD210 million MBS. A 5 % haircut takes place. The fall in value of MBS caused haircuts of this nature to increase to 50 % in some cases, resulting in deleveraging by financial institutions. The subsequent fire sale of assets had a negative feedback effect in which declining asset values led to decreased collateral values, resulting in increased haircuts and a further cycle of deleveraging. A manifestation of the disruption that occurred could be viewed in the Treasury Bill and Eurodollar (TED) spread, which indicates the difference between the interest rate on interbank lending²² and the interest rate on three-month US Treasury bills. The difference can be viewed in Figure 2.7 below, where certain disruptions are represented by the credit spread.

21 Gorton & Metrick (2012) comprehensively discuss the differences between the traditional banking sector and the securitised banking sector.

22 Measured by the London interbank offered rate interest rate on three month Eurodollar deposits.

Figure 2.7: Credit Spreads (interest rate %) for the period 2000 to 2009.



Source: Mishkin (2010:29).

BAA spread represents the difference between the constant maturity BAA rate and the 10-year constant maturity Treasury bond rate.

1 % = 100 basis points.

The credit spread reflects the credit risk and liquidity risk concerns that may be evident in the interbank market. In March 2008, Bear Sterns ran out of short-term financing, when its longer-term assets could not be converted into cash quickly enough. This would be one of the most significant runs on the securitised banking sector and would signify that a larger group of financial institutions could pose a large systemic risk to the financial sector. J.P. Morgan/Chase ended up purchasing Bear Sterns in a deal brokered by the Fed (Cecchetti, 2009:70). The deal was successful in restoring calm to the market, which can be seen in Figure 2.7, where in March 2008 the TED spread increased to over 200 basis points, although following the takeover it decreased back to less than 100 basis points. A clear increase in the amount of market credit risk was evident during the middle of 2008 when the spread between interest rates on Treasury bonds and BAA corporate bonds was increasing – signifying that the markets were perhaps expecting adverse conditions.

These expectations and increase in market credit risk was confirmed when Lehman Brothers collapsed near the end of 2008. This event signified the beginning of the financial crisis as one of a global nature. Mishkin (2010:4), however, has argued that three other events were just as significant, namely the collapse of AIG, the run on the Reserve Primary Fund, and the difficulty in getting the Troubled Asset Relief Plan approved by Congress. For the case of Lehman Brothers, the Fed chose not to offer a bailout and instead tried to broker a deal with a third party, in a bid to discourage moral hazard from investment banks in the future and serve as a warning regarding excessive risk taking – especially since Lehman

Brothers was the most leveraged of the investment banks and had a substandard risk management reputation (Sorkin, 2009).

While the large investment banks were characterised by excessive leverage, risk taking and moral hazard, AIG's Financial Products Unit had issued USD526 billion worth of credit default swaps²³ – which were required to make payments if sub-prime mortgages experienced losses (Sjostrom, 2009:945). When Lehman Brothers collapsed, it became apparent that large payments would need to be made, and subsequent short-term funding to AIG therefore dried up. AIG was eventually loaned over USD170 billion by the US government and the Fed (Sjostrom, 2009:975). The problems faced by AIG were an indication that institutions posing a systemic risk to the financial sector were not limited to banks alone – evidenced by the fact that AIG was effectively running a hedge fund within an insurance company (Torres & Son, 2009). On the same day as the AIG collapse, a run on a large money market mutual fund – the Reserve Primary Fund – took place. The Reserve Primary Fund held USD785 million worth of Lehman Paper and as a result of the Lehman bankruptcy, shares could no longer be redeemed at USD1 par value. The result was that shareholders withdrew all their money and the fund lost 90 % of its assets. A subsequent run on other money market funds occurred, with the assets in institutional money market mutual funds declining to USD0.97 trillion from USD1.36 trillion in a single month. Since a large portion of bank funding was being obtained from bank commercial paper and certificates of deposits held by money market mutual funds, this run put pressure on banks (Kacperczyk & Schnabl, 2009:2). As a result of these events, the Troubled Asset Relief Program was proposed, which would essentially give the US Treasury the authority to spend USD700 billion on the purchase of sub-prime mortgage assets from financial institutions that were facing difficulty. The plan was changed and instead it became a case of direct capital injections into the institutions. These ad hoc bailouts were problematic because they suggested to markets that problems in the credit market may have been worse than was initially thought (Mishkin, 2010:17).

2.3.1.5 Section summary

The sub-prime crisis not only illustrated the fact that systemic risk is arguably still the largest threat to financial stability, but also that when it reaches large enough proportions, it can threaten global economic stability. The sub-prime crisis was an example of a perfect storm for systemic risk. The macroeconomic and microeconomic conditions laid a foundation upon which a systemic risk base could be built, while the fair value accounting system amplified these risks. These factors combined with a number of other systemic elements to translate the sub-prime crisis into a global financial crisis. These developments essentially manifest into the three broad elements of systemic risk – contagion, informational spillovers,

23 Credit default swaps were described in Section 2.3.1.2.

and common shocks – the mechanisms through which negative effects in one sector could be transferred to another sector.

2.3.2 Contagion, common shocks, and informational spillovers

The systemic risk concepts of chain reactions and common shocks are predicated on the idea of contagion taking place quickly, and therefore requiring some degree of direct or indirect connection between the parties involved (Kaufman, 1994). Kaufman and Scott (2003:375) argue that banks can be connected both directly and indirectly. The direct connections include interbank deposits, loans, and payments systems clearing, while the indirect connections occur when banks serve the same or similar deposit or loan markets. Since these connections give banks the ability to operate across national borders, a large enough shock to one bank may be propagated to other banks. It can therefore be stated that in terms of contagious systemic risk, the probability, strength, and breadth are greater the larger a financial institution is (Kaufman & Scott, 2003:375).

It was illustrated in the previous section that certain developments that were systemic in nature allowed the sub-prime crisis to translate into a global financial crisis. All these developments can manifest into three broad sources of systemic risk, namely contagion (Section 2.3.2.1), common shocks (Section 2.3.2.2), and informational spillovers (Section 2.3.2.3) (Georg, 2011:8). It should be noted that although these three sources are separated for discussion purposes, it does not imply that they do not interact with each other. The largest body of literature exists for the concept of contagion.

2.3.2.1 Contagion

In order to discuss contagion in the banking sector, it is necessary to distinguish between the two different channels in which contagion can take place. These two channels are the real exposure channel, and the informational channel, although these channels can work in conjunction or independently (De Bandt *et al.*, 2009:643). For the purposes of this study, “contagion” refers to the real exposure channel, while Section 2.3.2.4 on informational spillovers will discuss the information channel.

Contagion may be a difficult concept to measure, but can generally be defined as a spread of market disturbances from one market to another (Collins & Biekpe, 2003:286). In Section 2.3.1, it was noted that the failure of BNP Paribas to provide share redemptions resulted in a breakdown of interbank markets. Similarly, the failure of the Fed to bail out Lehman Brothers also resulted in an interbank market breakdown. Both these events are examples of contagion that takes place via interbank markets. There are two approaches taken in the literature to define contagion. The first involves the analysis of direct linkages which result in contagion, while the second examined indirect balance sheet linkages.

Contagion effects via direct linkages – the first way contagion can be modelled – constitute an example of how hedging against a particular type of risk can result in other risks. Allen and Gale (2000) show that in order to protect themselves against liquidity risk, banks would exchange interbank deposits, thereby creating connections and exposing the system to contagion. It was argued that a better-connected network of banks would be less susceptible to contagion than an incomplete network of banks. This is because a greater degree of connectedness would imply that a single bank's portfolio losses are transferred to a greater number of banks as a result of their interbank agreements (Allen & Gale, 2000:15). Babus (2007) expands upon this viewpoint and puts forth a model where banks form these connections with each other in order to reduce the risk of contagion. The difference in their study is that it argues that there is a connectivity threshold, below which contagion occurs, and above which it does not. Banks subsequently form these connections in order to reach the threshold, but there is an implicit cost associated with these connections in that smaller shocks can then propagate throughout the entire system (Babus, 2007:2). Gai and Kapadia (2010:2421) support the idea that greater connectivity in the financial system can reduce the likelihood of contagion, but add that if contagion does occur, it will be more severe and institutions can be affected multiple times. Haldane (2009) argues that this connectivity is essentially a knife-edge property, and that these financial networks and interbank linkages serve as a mutual insurance of the financial system up to a point – thereby contributing to systemic stability – but beyond this point, it can amplify shocks and increase systemic fragility.

Expanding on this fragility, the uncertainty about where consumers will withdraw their funds can also be a liquidity risk for banks. The study by Freixas, Parigi and Rochet (2000) follows a similar line of thought to that of Allen and Gale (2000), although in their model the connections between banks take place through interbank credit lines, enabling the hedging of regional liquidity shocks. The finding was that when faced with a liquidity shock, banking system stability would depend on whether the depositors withdrew their funds at the location of a bank that serves as a money centre (Freixas *et al.*, 2000:630). Money centre banks are banks which occupy key positions in the interbank network system due to payments being channelled through them, and may also be referred to as too-big-to-fail banks (Freixas *et al.*, 2000:614). The finding then is that the banking system stability, in a system with a large degree of interbank connections, is dependent on whether depositors withdraw their funds from the money centre banks. To expand upon the theory of a financial network, Kahn and Santos (2008:4) find that when there is a shortage of exogenous liquidity, banks can become too risky by not finding the correct degree of interdependence between exogenously supplied liquidity and liquidity created by the bank.

Other authors have focused more on the link between financial innovation and contagion. Shin (2009b:310) found that given securitisation's propensity to encourage higher leverage throughout the entire financial system, and therefore credit expansion, it could lower lending standards. As a result of

this credit expansion, credit risk mitigation measures are undertaken. The impact of hedging against credit risk with either a credit default swap or loan sales is analysed by Parlour and Winton (2013) and they find that the main determining factor is capital costs. In this case, capital costs refer to the rate of return that could be earned in the best alternative investment with the same amount of risk. A credit default swap allows the originating bank to retain control rights to the loan, while loan sales do not. The finding made is that loan sales are the dominant choice when capital costs are low, while credit default swaps and loan sales are both used when capital costs are high (Parlour & Winton, 2013:27). The study by Allen and Carletti (2006) expand upon the idea of credit risk transferring contagion across sectors. In their model, liquidity is the main determinant of asset prices. When banks are faced with a uniform liquidity demand, a sufficient amount of short-term assets is kept and there is no need to raise more liquidity in the market, thereby making credit risk transfer beneficial. An uneven liquidity demand and the subsequent hedging of this risk in the interbank market may lead to credit risk transfer having a negative effect on welfare and subsequent contagion transfer among sectors (Allen & Carletti, 2006:110).

The causes of contagion transfer are separated into two categories by Dornbusch, Park and Claessens (2000). The first type of contagion is as a result of fundamental spillovers caused by the normal interdependence among economies, while the second is as a result of investor behaviour. An example of the first type of contagion would be the fundamental trade or financial connections that exist between economies. An example of the second type would include a decrease in asset prices and large capital losses, which cause the selling off of emerging market securities in order to raise cash for redemptions (Dornbusch *et al.*, 2000:8). These categorisations therefore illustrate that contagion can take place through both trade and financial links, although the way in which shocks are transmitted, especially during a crisis, may differ due to institutional factors.

In addition to the categorisation of contagion, the structure of financial markets might have an effect on the stabilising function of the interbank market, as evidenced by Haldane (2009) who argues that the complexity and homogeneity of the financial system leading up to the sub-prime crisis was responsible for its fragility. Iori, Jafarey and Padilla (2006) construct a model to simulate interbank lending among homogenous and heterogeneous banks. Homogenous banks have similar characteristics, such as investment opportunities or size, thus ensuring that no institution is a significant borrower or lender. They find that the probability of contagion is lower if the institutions interacting with each other are homogenous (Iori *et al.*, 2006:540). Georg (2013) contradicts this finding, with the conclusion that a heterogeneous financial system will have no effect on financial stability. It is also argued by Nier, Yang, Yorulmazer and Alentorn (2007:2054) that structural factors may reduce the probability of direct contagion taking place in the interbank market. They conclude that higher capitalisation levels, a less

concentrated interbank market, and smaller interbank liabilities decrease the probability of direct contagion taking place in the interbank market.

From these findings, the interbank market may be regarded as significant because of its high liquidity and because it is one of the only forms of regular direct transaction between banks. An approach based on linear algebra was developed by Eisenberg and Noe (2001) in which they constructed a liabilities matrix for the interbank market and estimated the impact that a bank default will have on the system. They find that unsystematic, non-dissipative shocks to the financial system will decrease the value of the system and subsequently lower the value of equity of some of the individual firms (Eisenberg & Noe, 2001:236). In a related study, Mistrulli (2011:1125) applied this framework to determine the risk of contagion in the Italian interbank market and finds that it is conducive to financial contagion – but only in certain cases is this contagion considerable enough to trigger a systemic crisis. This premise that a single bank failure could cause the subsequent failure of a large number of other banks was also investigated in the US by Furfine (2003). Data detailing the bilateral credit exposures that arose from overnight federal funds transactions was used with the subsequent finding that contagion resulting from direct linkages in the interbank market is unlikely to have a system-wide impact (Furfine, 2003:125).

Alternatively, contagion via indirect balance sheet linkages is the second way in which contagion can be modelled. An example of this may be a model where one party's portfolio returns are dependent on the allocations in other parties' portfolios (Lagunoff & Schreft, 2001:250). In this model, it was shown that a shock would cause a party to reallocate their portfolio and thereby break some linkages – resulting in either a gradual spreading of losses and subsequent link breakages, or the instantaneous pre-emptive moving of funds to portfolios that are safer in order to avoid future contagion. De Vries (2005:806) has a similar finding in that the fat tail property²⁴ of the underlying assets in the banks' portfolios increases their dependency on each other, while Cifuentes, Ferrucci and Shin (2005:564) find that contagion is driven mostly by changes in asset prices in a complete network where all parties hold the same asset. These indirect balance sheet linkages are also similar to common shocks (Section 2.3.2.2).

Longstaff (2010:437) takes an alternative approach to contagion via direct and indirect linkages when he separates the literature discussing contagion according to the three mechanisms through which contagion propagate into other markets. The first mechanism proposes that a negative shock in one market can lead to the revelation of bad financial or economic news that may have direct effects on the value of collateral or cash flows from securities in other markets. This is essentially an informational spillover (Section 2.3.2.3) from a more liquid market or a market that has quicker price discovery (Kaminsky, Reinhart &

24 A fat tail refers to the distribution of predicted returns and losses of an asset. A fat tail would indicate a higher probability for large profits or losses than those indicated by a standard normal distribution (Stoyanov, Rachev, Racheva-Iotova & Fabozzi, 2011:3).

Vegh, 2003:6). A study was conducted by Dornbusch *et al.* (2000:181) which found that a financial crisis in one country can have direct effects, such as decreased trade credits, Foreign Direct Investment (FDI) and capital flows to other countries. The second mechanism refers to a liquidity shock across all markets, whereby investors who have experienced a loss in one market are subsequently unable to acquire funding. This may then lead to situation where investors seek out higher quality assets, resulting in a downward spiral in market liquidity as a whole and in terms of asset prices (Allen & Gale, 2000:15). Brunnermeier and Pedersen (2009:2228) argue that institutions are affected in this channel because they are unable to obtain funding and therefore cause liquidity in other assets to decrease, due to a shock event causing credit to be less available and trading activity in other markets to increase. The third mechanism proposes that a large negative shock in one market may result in the risk premium being increased in other markets, i.e. that market participants are subsequently unwilling to undertake risks. Contagion therefore takes place due to negative returns in one market undergoing financial distress and subsequently affecting the returns in other markets through a time-varying risk premium (Longstaff, 2008:13). Acharya and Pedersen (2005:405) model this premise and show that shocks occurring from events result in significant changes in assets' risk premium at equilibrium. There may also be further feedback effects that cause predictability in the realised asset returns' time series. This may occur because an increase in the risk premium of an asset will impact on the distribution of future asset returns (Longstaff, 2010:438).

The various channels through which contagion can occur are different in terms of the implications they have for prices, but there may also be similarities. An example of this could be the relationship between credit risk and liquidity that was observed during the sub-prime crisis – illustrated by Longstaff (2010:438). Two cases of this example are as follows. Firstly, credit risk that was caused by illiquidity – where large financial institutions were at risk of defaulting because they could not liquidate their positions and collateralise their liabilities. Secondly, illiquidity that was caused by credit risk – where investors may have been tentative in taking positions in securities related to mortgages.

Expanding on the effect contagion can have on prices, Englert and Stracca (2015:1) identify three channels through which contagion can propagate. Firstly, the counterparty channel involves a shock affecting one financial institution and then, due to a large exposure, having a negative impact on another financial institution as a counterparty. Secondly, the information channel involves a shock hitting one institution and then market participants reassessing the probability that another institution could also be affected because it shares similar characteristics with the originally affected institutions. Lastly, the competition channel involves a form of negative contagion, where good news for one institution could actually be bad news for another institution, if they compete in the same market (Englert & Stracca, 2015:1).

The different forms of contagion and the various channels through which contagion can be propagated show how losses in one sector or market can quickly spread to other sectors and markets. The definition of contagion that will be used in this study is put forth by Forbes and Rigobon (2002:2224). They define contagion as a significant increase in cross-market linkages following a shock to a single or group of countries. The implication of this is that contagion is only evidenced when the correlations between the two countries increase during a crisis period. As a result, correlation during periods of stability is not necessarily indicative of contagion (Forbes & Rigobon, 2002:2224). When considering how interconnected and integrated financial markets have become, it is therefore clear that controlling contagion may be important when attempting to regulate systemic risk. Furthermore, it will also be necessary to pay attention to correlations between the portfolios of institutions, and therefore the concept of common shocks must also be addressed.

2.3.2.2 Common shocks

The traditional strands of literature on systemic risk tend to focus on the effects that it will have through contagion effects. This is evidenced by the proposal of the FStB (2010b:4) that international policy reform focus on reducing interconnectedness and contagion risks by strengthening core financial infrastructures and markets. In order to investigate the influence that the activity of a central bank has on the interbank market, Georg and Poschmann (2010) put forth a model where banks optimise a portfolio of risky investments and riskless excess reserves to align with their risk and liquidity preferences. These banks are linked through interbank loans and a supply of household deposits. The default of a large bank was simulated and it is found that common shocks are in fact a greater threat to systemic stability than contagion (Georg & Poschmann, 2010:22).

Common shocks are a source of systemic risk that arises when several financial institutions are in possession of the same or similar assets, with the implication being that such a correlation among their portfolios may have the potential to lead to fire sales and significant losses for the institutions (Georg, 2011:9). This correlation among portfolios occurs because although it may prevent costs arising from potential information spillovers, the negative consequence is that the risk of an endogenous common shock is greater (Acharya & Yorulmazer, 2008:216). The intricacies of these decisions have to do with the signals that bank returns of the previous period give to risk-averse depositors about returns in the future. For example, if a pair of banks has a situation where one has a positive signal and the other a negative signal, depositors may expect these occurrences to persist in the future. In order to compensate, the bank which realised negative returns would need to ensure that future deposit rates²⁵ are higher to

²⁵ The deposit rate refers to the interest rate paid to the deposit holder, in this case the bank which realised negative returns (Acharya & Yorulmazer, 2008:216).

compensate for the expected lower returns. The bad news regarding one bank essentially spilled over onto the other bank. Similarly, since deposit rates were increased by one bank, the other bank needs to ensure that they offset this through higher borrowing costs.²⁶ As a result, the bank with the positive signal may become subject to higher borrowing costs due to the other bank setting a negative signal. Therefore, it is in the interest of both banks to correlate their portfolios – thereby increasing the probability of a joint success, but also a joint failure (Acharya & Yorulmazer, 2008:216).

Considering that a bank failure can have both positive and negative effects on the surviving competitors, an endogenous common shock may be introduced in order for banks to avoid negative externalities that occur as a result of a bank failure (Acharya, 2009:249). These negative effects occur as a result of some depositors not lending their money to a bank, resulting in the bank having a higher refinancing cost, but also cause a reduction of monitoring and information costs. The payoffs of the bank's surviving shareholders may either increase or decrease, depending on whether the positive or negative effect prevails. Therefore, if the failure generates negative externalities, banks may increase the correlation of their portfolios ex ante in order to avoid them, subsequently resulting in increasing the probability of a joint failure (Acharya, 2009:249).

Although these correlations among portfolios are problematic for the financial system when they occur between smaller institutions, it becomes a systemic risk when this occurs between large and complex financial institutions. Lehar (2005:2598) measures the correlations between bank asset portfolios for a sample of international banks over the period of 1988 to 2002. It was found that correlations all increased to a greater degree in North American banks, compared with European banks. This trend of correlations between returns in US banks is further illustrated by De Nicolo and Kwast (2002:866) who find a significant positive trend in the stock returns of large and complex financial institutions in the US during the 1990s – therefore also resulting in an increased potential for systemic risk.

Although contagion and common shocks can have similar effects, they are essentially different. The concept of contagion refers to how losses from one bank can transfer rapidly to other banks during times of financial distress. Common shocks, on the other hand, refer to how an individual shock to a financial system can negatively affect a number of banks due to them holding the same or similar portfolios. Contagion can also take place in a non-financial way through the spreading of bad news during times of financial distress. This may technically be referred to as contagion in the stricter sense, but can arguably be more of a spillover effect through the informational channel.

²⁶ Borrowing costs refers to the interest rate received by the loan originator, in this case, the bank which did not realise the negative returns (Acharya & Yorulmazer, 2008:216).

2.3.2.3 Informational spillovers

The informational channel is the other main channel through which contagion in banking can take place. The information channel refers to funding problems, such as contagious deposit withdrawals that occur when creditors have imperfect information regarding whether the shock affecting a bank is systematic or idiosyncratic and regarding the physical exposure of the bank (De Bandt *et al.*, 2009:643). Nier *et al.* (2007:2035) state that informational contagion should be taken into consideration, since it is based on imperfect information on either common exposure across banks or direct linkages – it may result in funding problems for banks, even when they are financially sound.

The idea that the insolvency of one bank can result in greater refinancing costs for the surviving banks is related to the idea of information contagion. Since financial markets display herding behaviour, particularly during a financial crisis, information contagion could take place (Acharya & Yorulmazer, 2003:15). The term ‘informational contagion’, however, may be misleading since an informational spillover poses a systemic risk in the broad sense of systemic risk, as stated by De Bandt *et al.* (2009:636) in Section 2.1, where an event is systemic in nature if it affects a number of institutions or markets. The impact with which such a systemic event affects financial markets and the way it exacerbates systemic risk is usually through herding behaviour. The herding behaviour of banks is explained as follows. Firstly, the borrowing costs of the surviving banks will increase in relation to the situation where both banks had survived, and this is therefore an example of a negative spillover from the bank’s failure. This will also result in decreased profits for banks that survived, but have peers that failed. Finally, the profitability of the surviving bank’s investments is important because if it is low, increased borrowing costs may lead to the entire bank being an unviable business, since depositors will invest in other areas with greater returns. This can essentially be stated as a run on the surviving bank that is caused by depositors updating the state of the economy as a response to a bank’s failure, i.e. an informational contagion (Acharya & Yorulmazer, 2003:15).

Acharya and Yorulmazer (2003) developed a model to exhibit bank herding behaviour. The model was based on the incentive a bank has to minimise the informational spillover that occur when bad news about other banks is received. In this model, the returns received from a bank’s loans are dependent on a systematic component (the overall state of the economy) and an idiosyncratic component. Bad news about a particular bank may reveal information about a common underlying factor that may affect all banks, and therefore banks are incentivised to herd with other banks. It should be noted that the herding behaviour exhibited by banks is an ex ante decision by banks to simultaneously undertake investments that are correlated – which subsequently causes the portfolios of banks to be correlated (Acharya & Yorulmazer, 2003:3). By lending to similar industries, banks increase their interbank correlations and

therefore minimise the possibility of contagion taking place, but this increases the possibility of all banks failing simultaneously.

If banks increase their correlations by lending to similar industries, they may all be negatively affected if bad news about that specific industry is received. The concept of informational spillovers can therefore in a sense be explained as contagion that takes place through a correlated-information channel. The attempt of rational agents to infer information from changes in price that may occur in other markets is modelled by King and Wadhvani (1990:30) and they find that contagion effects can take place due to correlated-information. “Contagion” in this sense, can therefore occur rapidly through a price-discovery process – with the implication that if the affected market has an adequate degree of liquidity, immediate effects on the price should be seen in the affected market (Longstaff, 2010:438). It should be noted that this process is dependent on the assumption that all markets are informationally efficient – which is not always the case. If there is a delay before the market reflects the effects of the information spillover, it will be challenging to determine precisely what the cause of the price changes were (Longstaff, 2010:438).

2.3.2.4 Section summary

Contagion, common shocks, and informational spillovers can individually result in negative effects being transferred from one financial institution to another, or from one financial sector to another. They can also interact with each other to further amplify the negative effects that take place when a negative shock occurs. A negative shock can take many forms, but during the sub-prime crisis, the failure of a bank that contributed a large degree of systemic risk could have been the most significant.

Informational spillovers may be seen as a less important source of systemic risk, but it should be noted that contagion and common shocks are likely to cause informational spillovers, just as informational spillovers are likely to cause contagion and common shocks. Although it may be possible to identify the forms of systemic risk by their source, their separation in practice may be more challenging. It should be noted that these different forms of systemic risk do not operate independently of one another. They may interact with each other as a bank default begins to build up.

A bank may, for instance, begin deleveraging and selling assets, which results in fire sales in certain asset classes, causing a subsequent amplification of the bank’s problems. Such an event would undoubtedly lead to the spreading of rumours regarding the bank and other similar banks which may cause participants to tighten their liquidity provisions. These tightened liquidity situations can exacerbate the problems the initial bank is already facing and lead to it defaulting, which may cause contagion to take place and the potential defaulting of banks who may have issued interbank loans to the first bank. Arguably, the rate at which such systemic events will take place would depend on the number and the size of the financial institutions involved.

2.4 THE ROLE OF SYSTEMICALLY IMPORTANT FINANCIAL INSTITUTIONS

An analysis was undertaken by Viñals, Pazarbasioglu, Surti, Narain, Erbenova and Chow (2013:5) which found that only a relatively small number of financial institutions account for a majority of the financial intermediation that takes place across borders. This financial intermediation includes capital flows and the allocation of global savings. This small number of institutions are able to account for the majority of intermediation because of their size and their interconnectedness with other institutions and financial markets, but this also means that in times of distress, they can generate negative externalities for the rest of the financial system. The implication of this is that compared to other institutions, the largest institutions may have greater influence over the regulatory and legislative processes, as well as a significant funding advantage (Viñals, Pazarbasioglu, Surti, Narain, Erbenova & Chow, 2013:5).

In order to identify the amount of systemic risk a bank can contribute during a financial crisis, it may be necessary to determine how much individual risk the bank possessed before the crisis. The amount of individual risk that a bank possesses may be dependent on certain inherent characteristics of the bank. The risk of a bank is therefore split into two categories, namely: (i) the individual risk that the bank possesses; and (ii) the bank's systemic risk contribution to the entire financial sector. The individual bank risk is measured through the stock performance of the bank during a crisis, while the systemic risk contribution of the bank is measured by correlations in returns between the bank and the financial system, as well as by bank size (Laeven *et al.*, 2014:12). Although the focus in this study is on the systemic risk contribution of individual banks and not the individual risk of banks, the individual characteristics should still be considered when assessing a bank's systemic risk.

Global banks can have a large influence on financial globalisation and international finance, particularly during periods of financial distress (Cetorelli & Goldberg, 2011:72). Subsequently, systemically important financial institutions and their inherent characteristics may play a significant role in explaining how systemic risk can manifest itself in institutions.

2.4.1 Systemically important financial institutions

The sub-prime crisis may have had many causes, but it can be argued that a significant factor was the behaviour and failure of global systemically important financial institutions (Claessens, Herring & Schoenmaker, 2010:1). Global systemically important financial institutions are large financial institutions that possess a great degree of systemic risk and are referred to as such because their failure could trigger a global financial crisis (BCBS, 2013:2). Institutions that contribute systemic risk to the global financial system are global systemically important financial institutions, while institutions that present a risk to

their domestic financial systems are referred to as domestic systemically important financial institutions. Table 2.3 provides a breakdown of the global systemically important financial institutions and their respective loss absorbency buckets²⁷ as at 2013.

Table 2.3: Global systemically important financial institutions

Bucket	Higher loss absorbency requirement (common equity as a percentage of risk-weighted assets)	Global systemically important financial institutions
5	3.5%	-
4	2.5%	HSBC (United Kingdom) JP Morgan Chase (United States)
3	2.0%	Barclays (United Kingdom) BNP Paribas (France) Citigroup (United States) Deutsche Bank (Germany)
2	1.5%	Bank of America (United States) Credit Suisse (Switzerland) Goldman Sachs (United States) Group Crédit Agricole (France) Mitsubishi UFJ FG (Japan) Morgan Stanley (United States) Royal Bank of Scotland (United Kingdom) UBS (Switzerland)
1	1.0%	Bank of China (China) Bank of New York Mellon (United States) BBVA (United States) Groupe BPCE (France) Industrial and Commercial Bank of China Limited (China) ING Bank (Netherlands) Mizuho FG (Japan) Nordea (Sweden) Santander (Spain) Société Générale (France) Standard Chartered (United Kingdom) State Street (United States) Sumitomo Mitsui FG (Japan) Unicredit Group (Italy) Wells Fargo (United States)

Source: BCBS (2013:12).

Table 2.3 illustrates 29 banks and the various countries in which these banks are located. The US has the most representation among the countries and occupies eight positions. The majority position of the US in

²⁷ Higher loss absorbency buckets and the methodology employed to carry out this classification are explained in Section 3.2.2.

this ranking further qualifies its inclusion in this study as a case study for systemic risk in a developed economy.

The collapse of Lehman Brothers and AIG – both systemically important financial institutions – illustrated how single financial institutions could generate contagion effects and common shocks in the financial sector that eventually affect the entire economy. This is because these institutions have characteristics such as size, interconnectedness and financial system importance – meaning that their failure or distress can have destabilising and adverse effects on the entire economy (Barth *et al.*, 2013:2).

There are two methods for identifying systemically important financial institutions and are explained by Tarashev *et al.* (2010:5) as follows. The first method involves the presupposition that a certain financial institution collapses and the subsequent after-effects that occur as a result of its failure. The after-effects can include the institution defaulting on its liabilities and the subsequent triggering of fire sales. The institution’s contribution to systemic risk therefore refers to the failed institution’s liabilities to the rest of the financial system. The second involves the presupposition that a large shock to the financial system takes place, such as the bursting of a housing bubble, and the subsequent extent to which a certain institution participates in the ensuing systemic event. The participation of an institution is therefore determined by the expected losses that it causes to its non-bank creditors, providing an illustration of an institution’s importance to the deposit system and its vulnerability to a systemic shock. Table 2.4 below provides a clear breakdown of the two approaches.

Table 2.4: The two approaches to identifying systemically important financial institutions.

	Contribution to systemic risk	Participation in systemic event
Concept	Marginal distress of the system, conditional on the institution failing	Expected participation of the bank in a systemic event; losses to the bank creditors
Risk indicators	<ul style="list-style-type: none"> • Intersystem liabilities • Liquidity and maturity mismatch • Transparency and resolvability 	<ul style="list-style-type: none"> • Asset correlations • Leverage • Risk bearing capacity
Policy objectives	<ul style="list-style-type: none"> • Contain systemic impact upon failure • Avoid moral hazard 	<ul style="list-style-type: none"> • Ensure survivorship in systemic event

Source: Weistroffer, Speyer, Kaiser and Mayer (2011:4).

In terms of the policy objectives illustrated above, the contribution approach may be better suited to identifying the institutions that create negative externalities and therefore contribute more to systemic risk, while the participation method is better suited to identifying whether a systemically important financial institution will survive a systemic event, and therefore maintain financial and economic stability. It can be argued that both approaches have their merits and can be used in conjunction to each other. A brief illustration of policies that may be implemented to facilitate systemically important financial

institutions is summarised in Table 2.5 below. As the viability of the policies decrease from left to right, the elimination of externalities is the most viable policy, while the eradication of systemically important financial institutions is the least viable.

Table 2.5: Policies to facilitate systemically important financial institutions.

Eliminate externalities	Charge for externalities	Increase likelihood of survival	Eradicate systemically important financial institutions
Provide resolution mechanism allowing maintenance of systemically important functions of failing institution	Charge levies based on an institution’s systemic risk contribution	Increase capital and liquidity requirements	Limit size and range of viable activities
Provide bail-in mechanisms so creditors do not have a bailout expectation	Request additional capital and liquidity buffers	Restrict leverage	Fragmentation of systemically important financial institutions
Reduce the risk of contagion through enhanced market infrastructure.			

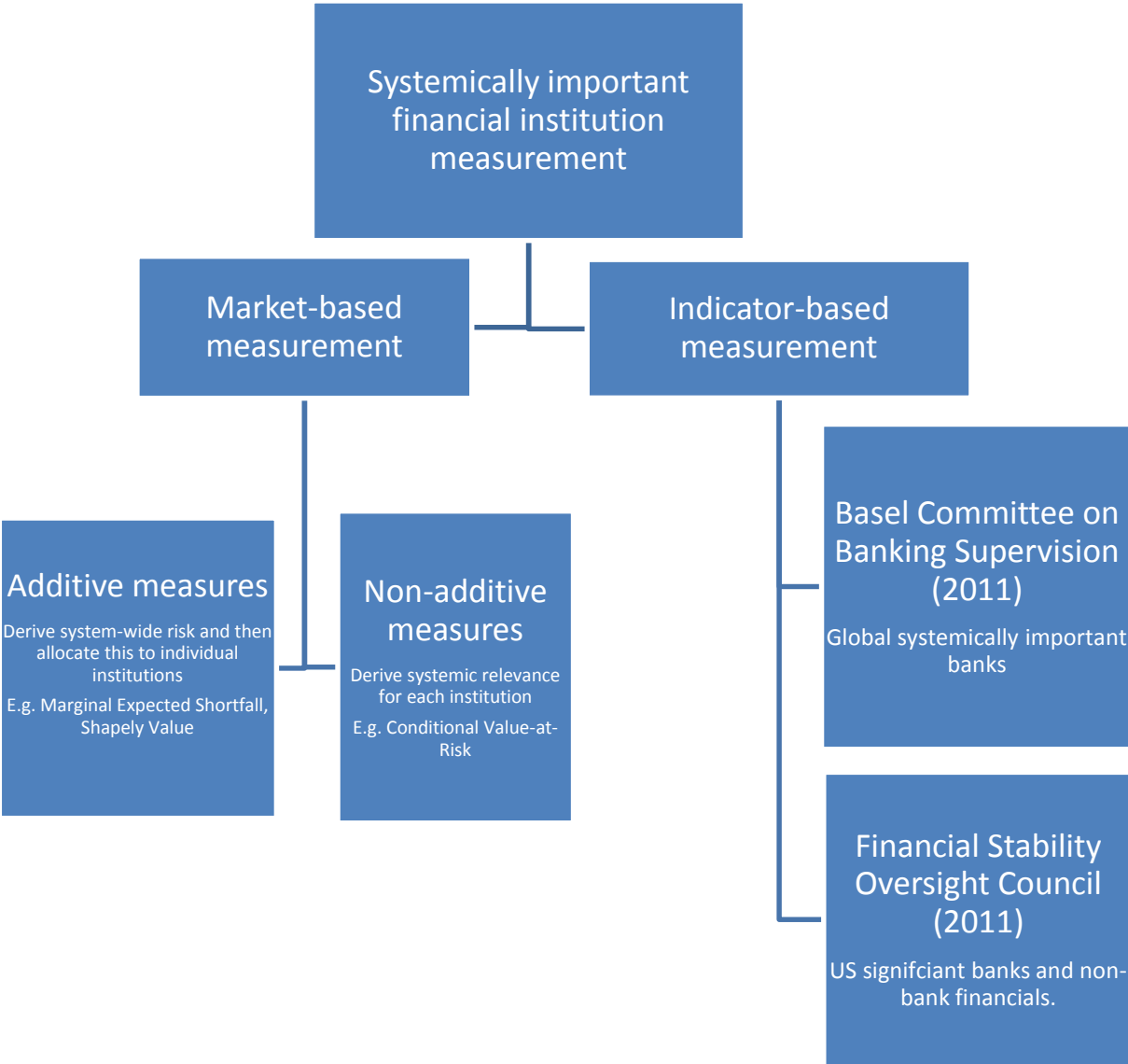
Source: Weistroffer *et al.* (2011:9).

The elimination of externalities could potentially occur by ensuring that creditors are fully bailed-in, thereby eliminating any negative effects that may occur upon the systemically important financial institution’s failure. The charging of systemically important financial institutions for externalities may be done through taxes or surcharges and could discourage systemically important financial institutions from entering into a position where they could create externalities. Increasing the likelihood of survival of a systemically important financial institution would be dependent on restricting the range of activities they might undertake, while completely eradicating systemically important financial institutions could take place through either fragmentation or imposing limits on size.

The contribution of systemic risk is not necessarily limited to banks exclusively. An institution should be considered systemically relevant if its failure would be a threat to the stability of the entire financial system. This would therefore include entities such as securities houses, insurance companies, and investment funds, as well as institutions outside of the financial markets such as public guarantors or government sponsored entities (Elliott & Litan, 2011:10). The most accurate way in which systemically important financial institutions can be identified would therefore lie in their measurement.

Two approaches can be undertaken in measuring systemic importance, a market-based measurement approach, and an indicator-based measurement approach. A breakdown of the two approaches is illustrated in Figure 2.8 below.

Figure 2.8: Overview of the different approaches to systemically important financial institution measurement



Source: Weistroffer *et al.* (2011:7).

Firstly, the market-based measurement approach extrapolates information from market prices by using regression techniques and financial modelling. Weistroffer *et al.* (2011:7) explains that this approach to the measurement of systemic importance is undertaken in a portfolio context, whereby systemic risk is attributed to individual institutions. Models of this nature are based on market-based risk measures such as asset correlations, Value-at-Risk (VaR), and Marginal Expected Shortfall (MES), as well as data on leverage or interbank claims and liabilities. Market-based measurement can be divided into two categories, additive measures, which derive measures of system-wide risks and attribute them to individual institutions, and non-additive measures, which are based on the VaR or expected shortfall of the entire system, conditional on the default of a particular institution. Market-based measures do, however, have a number of disadvantages. These include the fact that market-based indicators are only

available for publicly listed and traded institutions, and may also understate systemic effects during downswings or overstate them during upswings. Furthermore, the ability of these measures to anticipate policy actions may lead to a case where, during a period of distress, systemically important financial institutions are seen as more likely to receive government assistance since they have been accurately quantified (Weistroffer *et al.*, 2011:8).

Secondly, the indicator-based measurement approach incorporates bank-level data, such as balance sheet data and the volume of transactions. This approach has a number of advantages, namely that it can be applied to listed and non-listed institutions, it is more robust than market-based measures which rely on volatile indicators are, and it is more transparent and therefore can be traced more easily by affected institutions (Weistroffer *et al.*, 2011:8). The disadvantages of this method include its inability to differentiate between the institution's participation in a systemic event and its contribution to systemic risk, as well as the choice of indicators, peer group composition, and definition of weighting and threshold schemes (Weistroffer *et al.*, 2011:8). Although the transparency offered by this approach may be an advantage, it could also lead to a situation where institutions only control their exposures in the indicators that are considered by the approach. This is why systemic importance should rather be measured relative to the market system. It should be noted that the market-based measures form a large portion of the empirical part of this study and will therefore be discussed in Section 3.5 as part of the quantification measures of systemic risk. This does not mean that the indicator-based approach should be disregarded, since a combination of these measures would arguably be optimal for evaluating and measuring systemic importance.

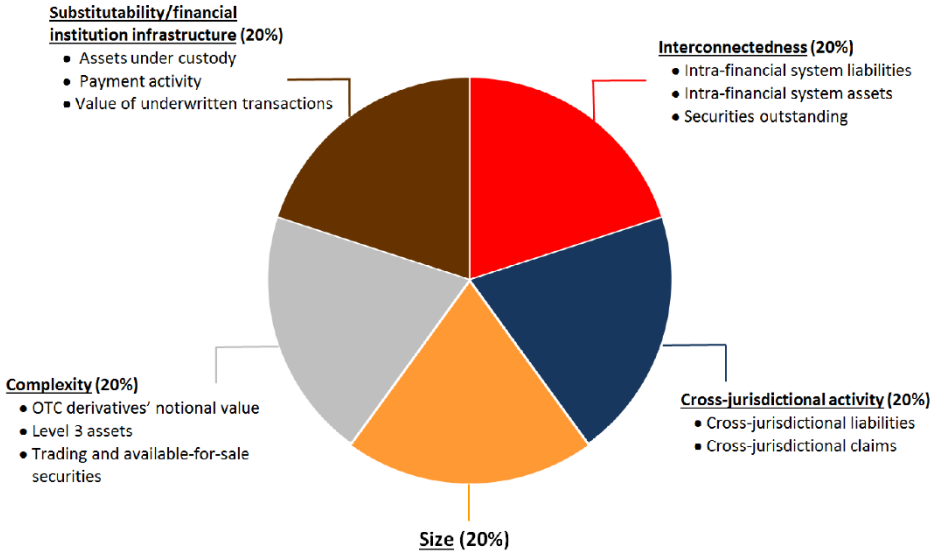
2.4.2 The indicator-based measurement approach

While market-based measurement approaches are used by supervisory authorities as a cross-check, they tend to prefer the indicator-based measurement approach, mainly due to their universal applicability to both listed and non-listed institutions (Weistroffer *et al.*, 2011:8). Basel employs an indicator-based measurement approach for determining the systemic risk of an individual financial institution (BCBS, 2013:5). These indicators are as follows:

- i. the size of the financial institution,
- ii. the interconnectedness,
- iii. the availability (or lack thereof) of substitutes,
- iv. global, cross-jurisdictional activity and
- v. complexity.

A graphical depiction of these indicators is provided in Figure 2.9 below.

Figure 2.9: Factors used to identify global systemically important financial institutions.



Source: Barth et al. (2013:18).

Since each of the five determinants in Figure 2.9 carries a weight of 20 %, they are considered equally important. The BCBS (2013:7) states that the size of a financial institution is important because the likelihood that a financial institution’s failure will affect the entire world economy is dependent on how large a portion its activities make up on the global financial market. A larger institution will be more difficult to replace and has a greater propensity to disrupt the entire market and damage investor confidence. The size of the institution is measured by its total exposures. The total exposures measure includes the counterparty exposure of derivatives contracts, the gross value of securities financing transactions, the counterparty exposures of securities financing transactions, other assets not specified above, potential future exposure of derivative contracts, the notional amount of off-balance sheet items with a 0 %, 20 %, 50 %, and 100 % credit conversion factor, entities that are consolidated for accounting purposes and not for risk-based regulatory purposes, and regulatory adjustments (BCBS, 2015a:10). It can be argued, however, that limiting the size of an institution would not necessarily decrease systemic risk. The allocation of credit risk, as well as maturity and liquidity transformation, can create systemic interdependencies that cannot simply be allocated to a single institution. Furthermore, systemic risk can also occur in a largely decentralised system comprised of a number of small institutions (Weistroffer *et al.*, 2011:11). It could potentially even be more difficult to resolve the failure of a number of smaller or medium-sized institutions than of a single large institution. This could be particularly challenging if these smaller institutions all display some degree of interconnectedness.

The interconnectedness determinant is argued by the BCBS (2013:7) to be important because considering the network of contractual obligations that exists for these financial institutions, financial trouble at one institution can increase the probability of financial trouble at another institution. Entities defined as

financial institutions in the interconnectedness indicator include banks, bank holding companies, securities dealers, insurance companies, hedge funds, mutual funds, pension funds, investment banks, and central counterparties (BCBS, 2015a:10). Additionally, the availability of substitute measures refers to the ability with which consumers can find a financial institution which provides services comparative with those offered by the distressed institution. If there are no substitutes, the impact of the institution's failure on the entire financial sector is likely to be greater (BCBS. 2013:7).

The global, cross-jurisdictional activity of a financial institution alludes largely to the concept of global systemically important financial institutions. The BCBS (2013:7) state that this indicator will measure the impact that a financial institution's distress could have internationally through spillover effects and the subsequent coordination of its resolution, given that the particular institution has significant activities outside of its home jurisdiction. It can also be argued that a globally active bank may be more of a solution as opposed to a problem. This may be because global banks are able to better diversify their country-specific credit risk while maintaining a stable funding base – thereby allowing them to provide credit when local banks no longer can (Weistroffer *et al.*, 2011:12).

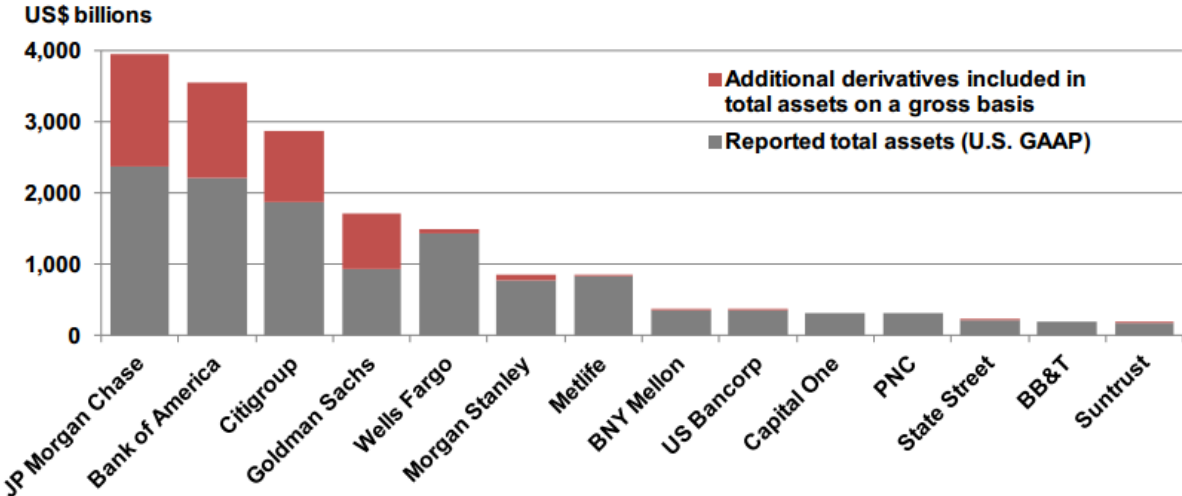
It is demonstrated by the BCBS (2013:8) that the more complex a financial institution is – in terms of its structure, operation and business activities – the greater the costs and amount of time needed to resolve it are. It can, however, be argued that a certain degree of engagement in complex products is necessary, given that the role of financial intermediaries is to undertake the risks that are not easily undertaken by public markets. The holding of complex assets is therefore a natural result of this function and an important measure to consider when identifying systemically important financial institutions (Weistroffer *et al.*, 2011:14).

Each of these five measures is assigned a 20 % weighting, with every individual indicator making up a smaller portion of that 20 % weighting. For example, the 20 % weighting for interconnectedness is made up of intra-financial system assets (6.67 %), intra-financial system liabilities (6.67 %) and securities outstanding (6.67 %). The only potential problem with the method employed by Basel is that its indicators are not based on publicly available data and therefore this approach may not be applicable to countries that do not have such strenuous disclosure requirements (Laeven *et al.*, 2014:16).

The advantage of using a 20 % weighting for each indicator is that one indicator is not overly emphasised. For example, considering that the largest institutions are not necessarily the riskiest, this approach will therefore not result in the largest institutions always being classified as systemically important financial institutions. The implications of an institution being classified as a global systemically important financial institution is that it will be subjected to increased regulatory requirements in the future such as greater capital standards, and improved requirements for risk management and reporting (Englert & Stracca,

2015:6). Another advantage of this indicator-based ranking methodology is that it is not subject to the accounting standards that a particular country uses. Other methods which focus only on a ranking based on total assets will be subject to such accounting standards. For example, the US uses the Generally Accepted Accounting Principles, while most other countries would use the International Financial Reporting Standards. A significant divergence occurs with the case of derivatives, whereby they are measured at gross value under the International Financial Reporting Standards, but at a net basis under Generally Accepted Accounting Principles. An illustration of this is shown in Figure 2.10.

Figure 2.10: The impact of accounting standards on derivatives measurement of assets during 2012.



Source: Barth et al. (2013:22).

From Figure 2.10 it is therefore clear that the different approaches a country takes to measurement can have significant impacts on the amount of systemic risk that is believed to be in the financial sector. A World Bank Survey conducted for a number of countries regarding the measures used for assessing whether an institution is systemically important or not yielded mixed results. A summary of the results is illustrated in Table 2.6 below.

Table 2.6: Measures for assessing systemically important financial institution risk in SA and US.

Measures	Countries	
	SA	US
Bank capital ratios	Yes	Yes
Bank leverage ratios	Yes	Yes
Bank profitability ratios	Yes	Yes
Bank liquidity ratios	Yes	Yes
Growth in bank credit	Yes	Yes
Sectoral composition of bank loans portfolios	Yes	Yes
Bank Foreign Exchange (FX) position	Yes	Yes
Bank non-performing loan ratios	Yes	Yes
Bank provisioning ratios	No	Yes
Stock market prices	No	Yes
Housing prices	No	Yes
Other	Yes	Yes

Source: World Bank (2013).

Table 2.6 presents a set of results which would generally be expected, with the US utilising all factors to assess systemically important financial institution risk and SA using slightly fewer. The survey also investigated whether each country had a department which would deal specifically with financial stability and supervision. Interestingly, SA does have such a department, while the US does not. The dominant finding from the survey was, however, that nearly every country considers capital ratios to be an important measure for assessing systemic risk. The implication of this is that an indicator-based measurement approach alone may be one of many useful methods, but it should not necessarily be the only method used. A combination of a number of different methods is likely to be the best way for identifying systemically important financial institutions and the risks that they can pose.

Apart from the risks that systemically important financial institutions pose to the greater financial system upon their failure, the question needs to be asked if the mere identification and disclosure of what constitutes a systemically important financial institution is not further propagating the problem. The idea of moral hazard is that a financial institution that is insulated from risk may take on extra risks since it knows that it is considered too systemically important to be allowed to fail – and in the event that it does collapse, it will receive a public sector bailout (Yuksel, 2014:63). The argument can therefore be made that systemically important financial institutions should not be identified and disclosed, and regulations should be based on a top-down approach. Such regulations will be discussed in greater detail in Chapter 3.

2.4.3 Section summary

It is clear from the evidence presented that systemically important financial institutions are an important part of the financial system. They can provide many advantages due to their economies of scale and scope, but this can also be a weakness during times of distress. The fact that these institutions contain a large degree of systemic risk and pose such a threat to global financial stability may therefore necessitate subjecting them to more stringent regulations. Before these regulations can be implemented, however, the systemically important financial institutions need to be identified and there remains conjecture as to how this should be done. That being said, during the sub-prime crisis the failure of systemically important financial institutions had negative effects not only for the domestic financial sector, but also for the financial sector in other countries. This was an example of how the levels of systemic risk inherent in the financial sectors of emerging markets could increase their vulnerability to negative shocks – such as the failure of a systemically important financial institution – in a developed economy.

2.5 THE IMPACT OF SYSTEMIC RISK ON EMERGING MARKETS

In Section 2.3.1, it was illustrated how the macroeconomic conditions in the US and other developed economies – to a lesser extent – presented a foundation upon which the sub-prime crisis was built. Section 2.3.2 then explained the concepts that could facilitate the spreading of the effects of the crisis to other institutions and regions. Section 2.4 described the role that systemically important financial institutions played in propagating negative effects throughout a financial sector, and the subsequent spreading of these effects to the financial sectors in other countries that also had high levels of systemic risk. It may furthermore be necessary to consider how macro-financial conditions can lead to a build-up of systemic risk in emerging markets in order to understand the different ways in which these countries are affected by systemic risk.

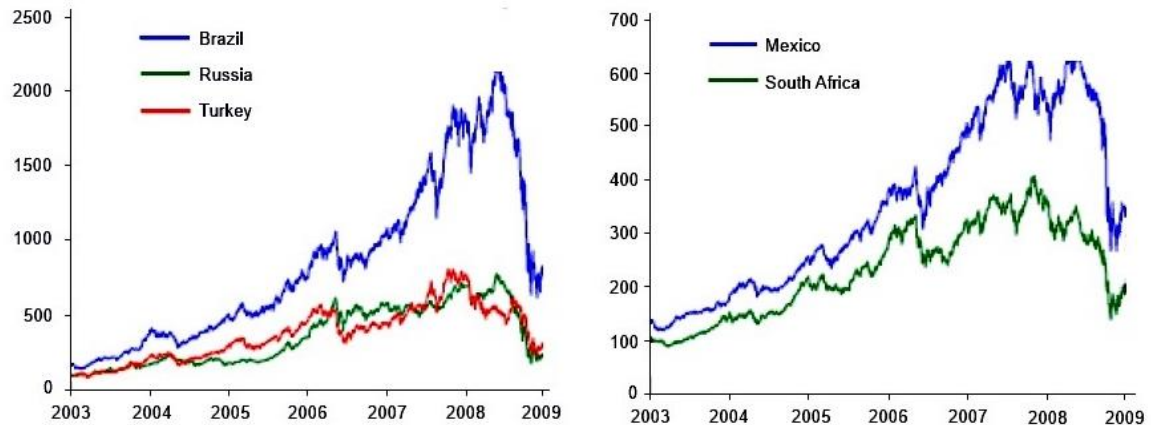
The sub-prime crisis illustrated the level of integration in the global financial sector and the various repercussions as a result of this – in particular, how the real sector can be amplified by the financial sector – subsequently resulting in a high degree of pro-cyclicality and a build-up of systemic risk in the financial sector (Canuto & Ghosh, 2013:1). It was also shown that the sub-prime crisis had mostly affected developed economies initially. The level of advancement of information technology and computer systems may have facilitated a greater degree of linkage among global financial markets. The practical implication of this is that investors in developed economies may look to find investment opportunities in emerging markets that propose greater expected returns (Kim & Ryu, 2015:20). As a result, the manner in which the sub-prime crisis affected emerging markets, the manifestation of systemic risk, and the policy responses were different from developed economies.

2.5.1 How emerging markets were affected

It was shown in Sections 2.3.1 and 2.3.2 that interconnectedness has the potential to pose a systemic risk to the financial sector, but systemic risk also has the potential to be cyclical – in that financial institutions and markets undertake greater risks during upswings of the financial cycle and are then subsequently overexposed to these risks when a downswing occurs – resulting in greater vulnerabilities to booms and recessions (Claessens, Ghosh & Mihet, 2013:157). Such a situation may become problematic when one considers that systemic risk due to cyclicality can interact with systemic risk due to interconnectedness so as to amplify existing vulnerabilities in the financial system. It may be argued that emerging markets have had much more pronounced financial and business cycles over recent years due to their exposure to risks such as volatile international capital flows and commodity price shocks (Claessens *et al.*, 2013:155).

Emerging markets were less affected by the sub-prime crisis during the initial stages – evidenced by a peak in their equity markets’ stock indices during November of 2007 – but the deterioration of developed economies’ fundamentals, increasing global risk aversions, and persistent market dislocations had significant effects on emerging markets by the end of 2008 (Frank & Hesse, 2009:7). This peak in the equity markets are observed in Figure 2.11.

Figure 2.11: Stock market indices of Brazil, Russia, Turkey, Mexico, and SA.



Source: Frank and Hesse (2009:12).

In Figure 2.11 it can be observed that the equity markets in emerging markets continued on their upward trend well into the financial crisis. Turkey, Mexico, and SA peaked in November 2007, while Russia and Brazil reached their peaks in May 2008 – followed by an abrupt reversal once the contagious effects had taken place. It appears that these markets moved in tandem in relation to events that occurred in developed economies. Many of the recessions that took place following the sub-prime crisis were accompanied by financial disruptions, such as contractions in credit supply and decreased asset prices

(Claessens, Kose & Terrones, 2012:178). The interactions that take place between the financial sector and the real sector could therefore play an important role.

The financial sectors of emerging markets are for the most part dominated by banks, and therefore bank lending against collateral is more widespread with approximately 72 – 85 % of loans requiring the pledging of collateral (Claessens & Ghosh, 2012:14). The implication of such large collateral amounts is that a change in asset prices – and therefore the value of collateral – can lead to an adverse effect on bank lending and subsequent negative effects on the real economy as a whole. There are also a number of factors that may lead to shocks being both magnified and spread more easily. These factors include weak legal regimes and enforcement, unconvincing market discipline due to lower standards for disclosure and transparency, and greater degrees of linkages between firms and financial institutions, as well as smaller investor bases and capital markets (Claessens & Ghosh, 2012:15). The tendency of shocks to be transmitted more easily can therefore lead to fluctuations in investor confidence and as a result may affect capital flows to emerging markets.

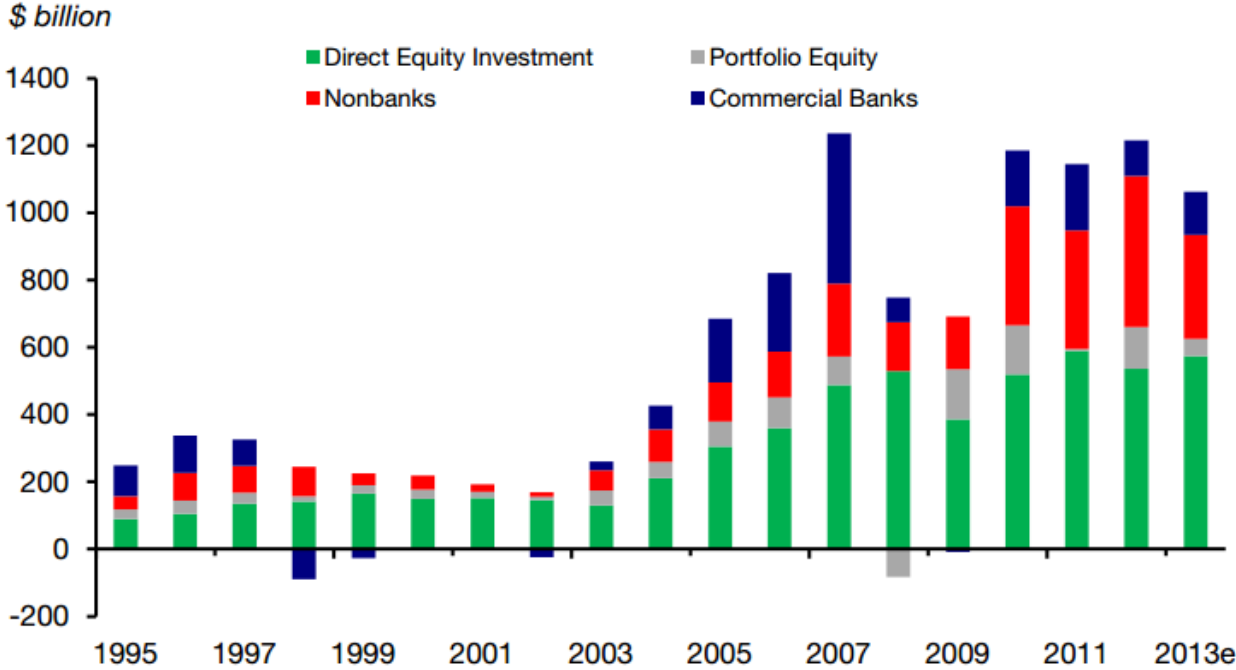
Blanchard, Faruquee, Das, Forbes and Tesar (2010:266) explain that capital flows to emerging markets were primarily affected by external shocks to their economies through two channels. Firstly, the trade channel, which illustrated a marked decrease in exports and terms of trade for commodity producers; and secondly, the financial channel, which illustrated a marked decrease in net capital flows. It may be argued that a large negative wealth shock was suffered by consumers in developed economies during the sub-prime crisis as the stock markets began to fall (Didier, Hevia & Schmukler, 2012:2064). A wealth effect of this nature led to lower demand for goods from other countries – the result of such a decreased demand potentially being a lower price. Consequently, a lower volume of exports caused a decrease in all commodity prices which in turn may have increased the impact of the decreased global demand – causing the effects of the sub-prime crisis to be amplified even more. Since the exporters were now receiving less income, they in turn lowered their demand for other imports, further amplifying a decrease in global demand. It can therefore be argued that an economy more open to trade and more dependent on exports would have been more severely affected. The negative wealth effect mentioned above also had the outcome of decreasing foreign investment from developed economies – the consequence of which would be lesser availability of capital in the world economy. This can, however, be amplified by factors that affect the transmission between financial intermediaries such as exposure and regulatory requirements, internal provisioning practices or margin calls. Furthermore, if a parent bank is situated in an economy currently undergoing a financial crisis, it may cause the branches of those banks in other economies to sell their assets or decrease their lending as well (Didier *et al.*, 2012:2065).

It may be necessary to further examine how certain developments in the global financial system played a role in amplifying the effects of the sub-prime crisis on emerging markets. Didier *et al.* (2012:2065) argue

that financial globalisation and securitisation were the two main developments that could have allowed the creation of a web of interconnectedness between financial institutions in economies throughout the world and explain the process as follows. The creation of assets via securitisation – which were more challenging to value on the balance sheets of banks – and the subsequent increasing of leverage and short-term debt, while holding less capital, may have been indicative of moral hazard and excessive risk taking (facilitated by assumed government bailouts). Following the failure of Lehman Brothers, the safety of interconnected banks was no longer guaranteed and investor uncertainty increased, the result of which was increased spreads in the interbank market, and banks exposed to non-performing loans being subjected to a sizeable decrease in short-term funding. These developments resulted in a process whereby risks were re-priced and a deleveraging cycle took place, which resulted in decreased credit to the non-financial sector. Investors then responded to these increased risks by removing their funds from risky assets in both developed economies and emerging markets and placed them in safer assets such as US Treasury Bills (Didier *et al.*, 2012:2065).

As a result of the increased uncertainty, risk re-pricing, and subsequent search for higher quality assets highlighted above, asset prices and capital flows decreased around the world, especially capital inflows by foreign investors into developed economies and emerging markets. Didier *et al.* (2012:2065) estimates this drop to have been about 11 % of GDP, and also further suggests that a decline in capital flows may have caused an asset price collapse and worsened the conditions in these financial systems, making them less conducive to future capital inflows. A visual breakdown of capital inflows pre- and post-crisis are illustrated in Figure 2.12 below.

Figure 2.12: Net emerging market private capital inflows.



Source: Collyns (2013).
 The values for 2013 are estimates.

In Figure 2.12 an illustration of the net private capital inflows to emerging markets is shown. A steady build-up of capital inflows began from the year 2000 before a peak was reached in 2007. A sharp decrease occurred in 2008, but it is important to note that most of this decrease was from capital inflows to commercial banks. In the post-crisis years, the capital inflows experienced by commercial banks have not been able to reach the same levels, although the non-bank capital inflows have increased significantly.

In order to explain this phenomenon of increased non-bank capital inflows, it may be necessary to discuss the different components of the capital inflows illustrated in Figure 2.12. Direct equity investment is essentially considered as Foreign Direct Investment (FDI), whereby the investor owns a large portion of a firm’s shares and has some degree of managerial control, while also involving the ownership of physical equipment and plants (Koepke, 2015:16). The drivers of these flows are generally considerations about the real economy as a whole, and are therefore not as sensitive to short-term financial fluctuations (Biglaiser & DeRouen, 2006:70; Addison & Heshmati, 2003:24). Portfolio equity flows are transactions that can theoretically be made very quickly. These flows will therefore be the ones adjusted most regularly in response to short-term fluctuations on financial markets and broader economic news (Koepke, 2015:16). The drivers of these flows include a number of financial variables, such as asset returns, exchange rate volatility, and other external financial volatility indicators indicating how risk averse investors are (Baek, 2006:372; Broner, Didier, Erce & Schmukler, 2013:132). As a result, the non-banks measure is the net external financing that is provided by all other private creditors, including flows from non-bank sources

into bonds markets, as well as deposits in local banks by non-residents other than banks (Koepke, 2014:7). These flows can also be classified as portfolio debt flows. The commercial banks inflow measure consists of net disbursements from commercial banks and therefore includes bond purchases by commercial banks (Koepke, 2014:7).

These banking flows have been shown to react positively to a decrease in global risk aversion – and vice versa (Herrmann & Mihaljek, 2013:501; Milesi-Ferretti & Tille, 2011:328). There is mixed evidence for the role of interest rates in developed economies on banking flows, with some showing a negative relationship (Ghosh, Qureshi & Sugawara, 2014:5) and others showing a positive relationship – with the negative relationship generally expected being explained by the term premium²⁸ (Cerutti, Claessens & Ratnovski, 2014:17). The evidence for a relationship between output growth of developed economies and banking flows is mixed and not particularly significant (Koepke, 2015:28). There is a strong relationship between domestic output growth and domestic return indicators in attracting banking flows to emerging markets (Herrmann & Mihaljek, 2013:501; Bruno & Shin, 2015:131), while country risk indicators also play a role (Bruno & Shin, 2015:131). Portfolio debt flows, or non-bank flows, have been shown to be strongly affected by increases in global risk aversion (Milesi-Ferretti & Tille, 2011:328; Broner *et al.*, 2013:132), as well as an increase in the external interest rate environment (Dahlhaus & Vasishtha, 2014:12).

It may be necessary to mention the types of capital flows that can take place, i.e. gross capital flows and net capital flows, due to the differing ways they respond to financial and economic changes. Gross capital flows reflect foreign inward investment and resident outward investment separately (the changes in assets in liabilities in the financial account), while net capital flows reflect the mirror image of the current account balance (a current account surplus would be shown by negative net capital flows) (Koepke, 2015:7). Obstfeld (2012:475) examines capital flows prior to the sub-prime crisis and found that capital flows rapidly increased, with net flows being far outpaced by gross capital flows – the conclusion being that gross capital flows may be the primary transmission channel of financial instability. Broner *et al.* (2013:132) found that gross capital flows have more volatility than net capital flows – particularly during economic downswings – and are also highly pro-cyclical. Milesi-Ferretti and Tille (2011:328) examined how the various components of capital flows contracted during the sub-prime crisis and found that banking flows contracted the most while FDI contracted the least.

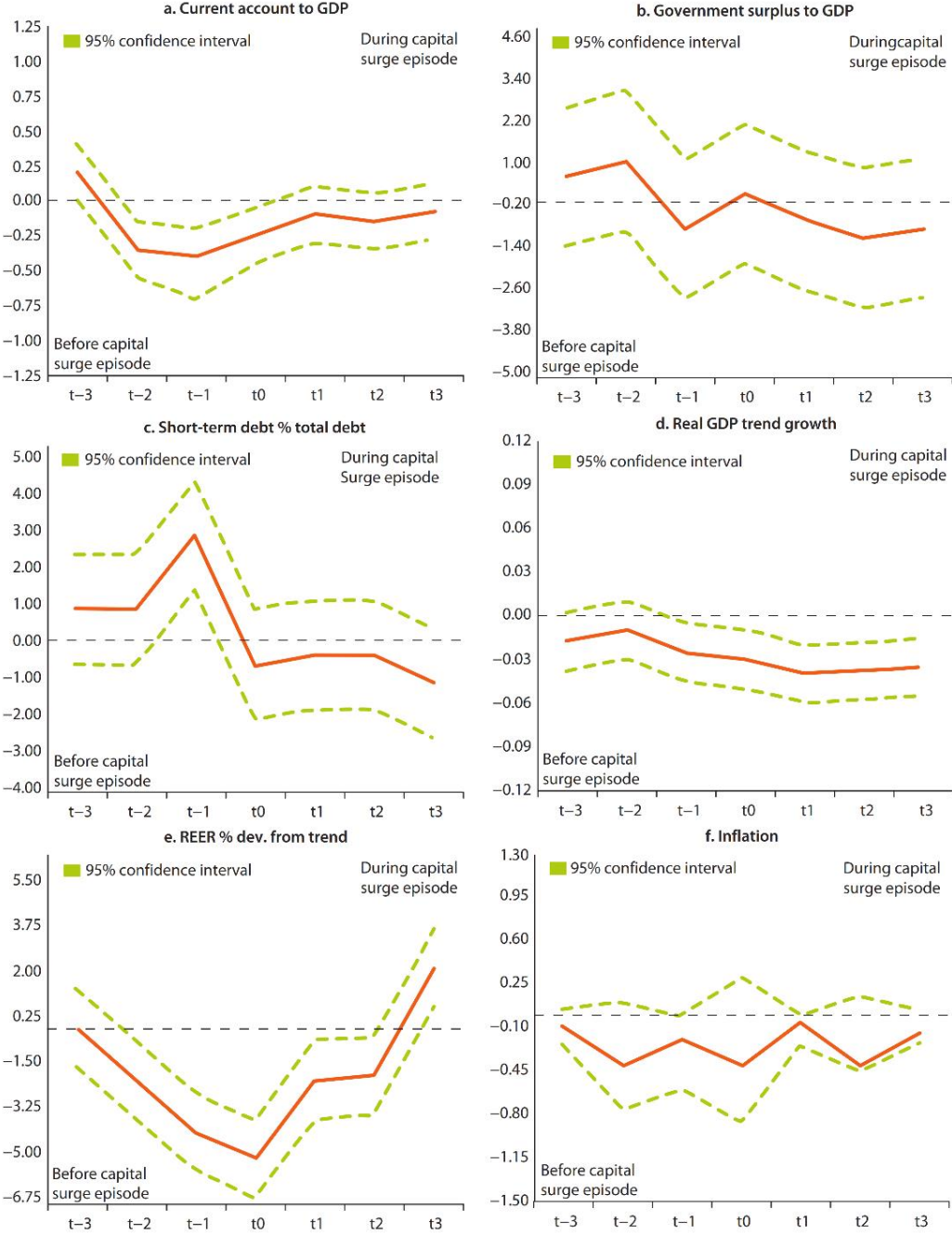
Capital flows are generally accepted as critical for emerging market economies (Acharya, 2013:64). The increase in global liquidity that occurred as a result of the sub-prime crisis, and the subsequent low interest rates in developed economies that followed, may have caused a large amount of capital to flow

28 The term premium (or risk premium) is the gap that exists between long-term yields and the average expected future short-term interest rate. This compensates risk-averse investors for potential capital losses that may occur if a long-term bond is sold before maturity or the risk of the bond's value decreasing because of inflation (Gürkaynak & Wright, 2012:339).

to emerging markets (Ghosh, 2010:1). These large surges in capital flows can be a source of systemic risk in emerging markets because if they are intermediated through the banking system they can cause rapid credit growth, and if they are intermediated through portfolio flows, they can cause rapid growth in asset prices and indirectly cause financial fragility (Claessens & Ghosh, 2012:15). Figure 2.13 below indicates how certain important macroeconomic variables were affected by surges in capital inflows.

Capital flows provide both advantages and disadvantages for the recipient emerging market. The emerging market can benefit through the accumulation of foreign assets during positive times, while those same assets will be depleted during bad times – therefore protecting against deteriorating living standards that may occur when a shock occurs to domestic income and production (Bernanke, 2005:1). The adverse consequences for the emerging market, however, can include inflationary pressures, widening current account deficits, exchange rate appreciation, and financial instability (Gossel & Biekpe, 2013:64). Capital flows combined with a too large degree of interconnectedness can have significant negative consequences for an economy – evidence of which could be seen in the banking sector of Iceland. The ratio of foreign assets to GDP of Iceland prior to the crisis grew to large levels because it had exhausted the banking sector in its domestic region and subsequently relied on its branches that operated abroad. These branches could only remain competitive if they offered higher interest rates than the local banks did, therefore when the banking sector began to crash; the entire Icelandic economy broke down (Acharya, 2013:64).

Figure 2.13: Capital inflow surges and indicators of macroeconomic vulnerability.



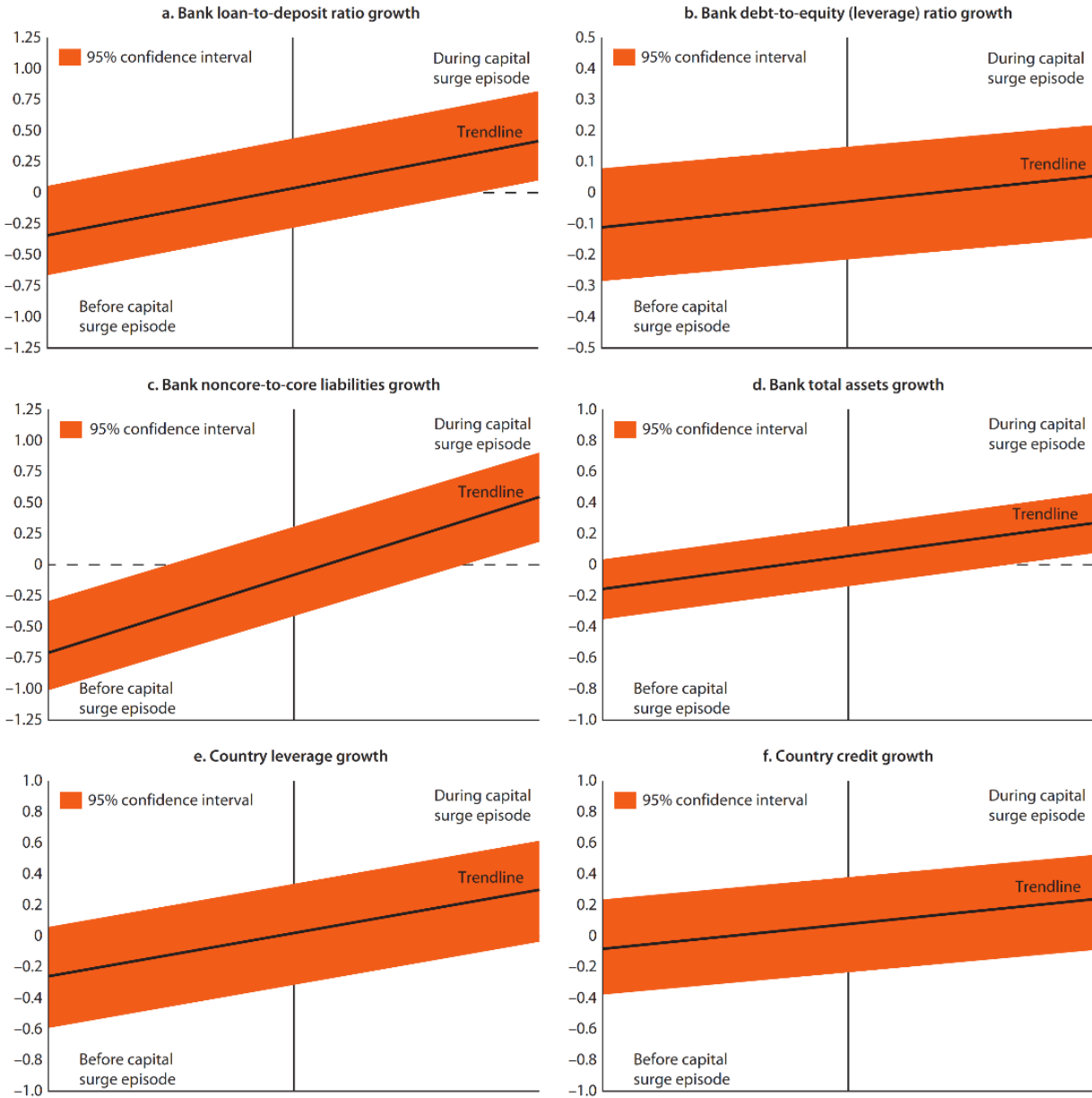
Source: Claessens and Ghosh (2013:110).

Figure 2.13 provides a comparison of the period before and after a surge of capital shows. As emerging markets experienced a surge in capital inflows, a number of key macroeconomic variables were affected. The fiscal deficits widened, growth rates slowed, the real effective exchange rate appreciated, current account deficits increased, and inflation rose. These occurrences are evidence of how capital flows, and their subsequent volatility, have the ability to amplify domestic cycles and increase the vulnerabilities of the financial sector because of mismatches in the balance sheets of banks and the lowered lending

standards. Shin (2013:31) explains this process as follows. The growth of retail deposits occurs in relation with the size of the economy and the wealth of the household sector, but banks will use non-core liabilities – some of which may be foreign – for funding when credit growth is quicker than retail deposits. The resulting increase in the balance sheets of banks leads to an increase in the ratios of non-core to core liabilities,²⁹ loan to deposit ratios, as well as the leverage ratios. If one considers that other financial institutions may have the same response, this cycle of asset price increases and credit growth will continue and increase the financial system's vulnerability even more. An example of how the financial sector can be affected by capital flow surges is shown in Figure 2.14 below.

29 Core liabilities refer to liabilities to the household sector such as demand and time deposits, while non-core liabilities refer liabilities to financial institutions such as demand deposits and short- to long-term payables to banks (Akdogan & Yildirim, 2014:5).

Figure 2.14: Capital inflow surges and indicators of financial sector vulnerability.



Source: Claessens and Ghosh (2013:111).

Figure 2.14 provides a comparison of the period before and after a surge of capital shows. It shows how during surge periods, the growth of banks’ non-core to core liabilities and bank loan to deposits increased significantly, while other measures of financial sector vulnerability – growth in bank assets, leverage ratios and overall credit – all illustrated an upward trend. The combination of increases in both macroeconomic indicators of vulnerability and financial sector indicators of vulnerability should be expected during the upturn of a normal domestic economic cycle. Due to this build-up during normal conditions, when a domestic cyclical downturn occurs or when a global shock that results in capital outflows takes place, these vulnerabilities can be significantly amplified (Claessens & Ghosh, 2013:112).

The evidence presented shows that although emerging markets initially avoided the effects of the sub-prime crisis, they were affected at a later stage and in a different manner. Emerging markets are inherently vulnerable to capital flows from developed economies, therefore a reversal of these capital flows, in response to a change that occurs in a developed economy, may have significant negative effects on an emerging market. This, combined with the tendency of emerging markets to have a greater degree of linkages between financial institutions, could result in shocks being transmitted more easily. It is important then to consider that since developed economies and emerging markets were affected differently by the sub-prime crisis, their policy responses may not necessarily be the same.

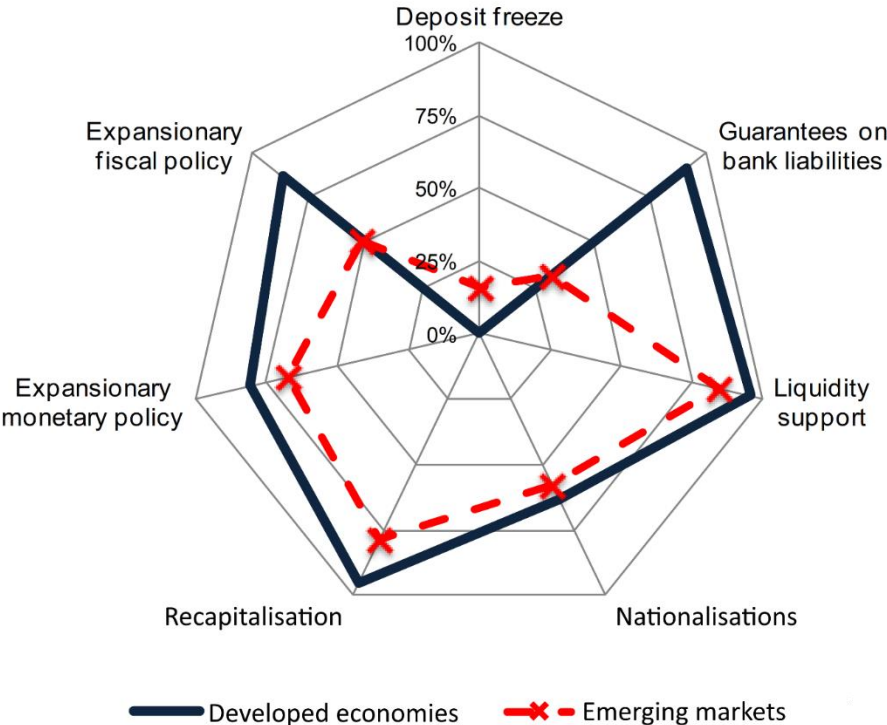
2.5.2 The differing policy responses for emerging markets

The macroeconomic policy responses that a country can undertake to a banking crisis differ for developed economies and emerging markets, with developed economies being more likely to use monetary and fiscal policies. Developed economies make these choices because when it comes to countercyclical fiscal policy, they have more financing options, and when it comes to monetary policy, they have more fiscal space through larger budgets. Given that emerging markets do not have these options, the occurrence of financial sector interventions such as bank recapitalisations with public funds are greater in emerging markets than in developed economies (Laeven & Valencia, 2013:226).

In past financial crises, the policy responses generally followed three distinct phases – as explained by Claessens, Pazarbasioglu, Laeven, Dobler, Valencia, Nedelescu and Seal (2011:7). The first is the containment phase which dealt with liquidity stress and the stabilisation of financial liabilities. The second is the resolution and balance sheet restructuring phase, with the aim of removing financial institutions which were insolvent and the subsequent recapitalisation of potentially viable institutions. The third phase is the use of asset management to rehabilitate non-performing loans and restructure operations. Ultimately, the goal is to restore profitability and financial stability to the institutions.

In order to examine why these particular policies are preferred by each set of economies, it may be necessary to consider what the cause of a specific banking crisis was, i.e. to consider whether the crisis was caused by macroeconomic conditions or a liquidity crisis, or whether it occurred because of a market disturbance. The different policy options that can be undertaken by developed economies and emerging markets are illustrated in Figure 2.15 below, where the percentage represents the frequency with which a policy option was used during crisis periods.

Figure 2.15: Differences in crisis policy responses for emerging markets and developed economies.



Source: Laeven and Valencia (2013:240).

These policy responses are defined by Laeven and Valencia (2013:230) as follows:

- I. Deposit freezes (and bank holidays) entail the freezing of deposits or the declaration of a bank holiday, meaning that no deposits can take place;
- II. Nationalisations (which are significant), when governments completely take over systemically important financial institutions, or take a majority position in the capital of systemically important financial institutions;
- III. Bank guarantees (which are significant), when a government guarantees a bank’s liabilities, with the implication that all the bank’s liabilities are protected, or when a government guarantee also extends to the bank’s non-deposit liabilities;³⁰
- IV. Liquidity support offered from central banks; and
- V. Bank restructuring costs, which is defined as the gross fiscal outlays required to restructure the financial sector. Through this process, the most important component is recapitalisation costs.

From Figure 2.15 it can be observed that deposit freezes were rarely used, and in the few cases that they were, these were mostly done by emerging markets. Developed economies tend to favour guarantees on bank liabilities. Guarantees on bank liabilities, along with liquidity and other support, are advantageous

³⁰ All other liabilities apart from deposits which have been placed in the bank by individuals/institutions.

because they do not require as much upfront fiscal outlays and reduce uncertainty for financial institutions, although they do end up imposing higher contingent fiscal costs (Claessens *et al.*, 2011:14). These forms of support and guarantees are used during the initial stages of the crisis, while recapitalisation programmes are used later to alleviate the real effects of the crisis. (Claessens *et al.*, 2011:7

Expansionary fiscal policy can indirectly support the financial sector by stimulating aggregate demand, which subsequently increases the demand for loans while lowering default risk on existing loans (Laeven & Valencia, 2013:226). It has, however, been argued that expansionary monetary policy may have been one of the causes of the sub-prime crisis, therefore the use of such policy in response to a crisis may not be applicable. The difference in the use of expansionary fiscal policy between emerging markets and developed economies may arise because developed economies are better able to finance large fiscal deficits, as well as having the ability to implement countercyclical discretionary fiscal packages (Laeven & Valencia, 2013:241). It should be remembered that emerging markets are faced with capital flows and currency depreciations during a crisis, and are therefore more likely to respond by using contractionary monetary policy (Laeven & Valencia, 2013:246). Claessens *et al.* (2011:16) argue that the reliance of developed economies on macroeconomic tools may explain why crises last longer there. The reasoning is that this reliance may discourage bank restructuring that would actually allow banks to recover quicker and renewed lending to take place.

While the reliance of developed economies on macroeconomic tools has remained relatively constant, the policy responses used by emerging markets have changed over the years. During the sub-prime crisis it was observed that instead of raising interest rates in order to contain capital outflows and depreciations in currency, emerging markets implemented countercyclical monetary policies, such as decreased interest rates. In terms of fiscal policy, an improvement in fiscal space by emerging markets during the 2000s allowed these economies to implement countercyclical fiscal policies, as opposed to the usual pro-cyclical fiscal policies used during the crises of the past (Didier *et al.*, 2012:2070).

The policy responses of emerging markets should perhaps be more aligned with managing the inherent pro-cyclicality of the business and financial cycles. The line of thought followed in this section is therefore that the vulnerability of emerging markets to capital flows can lead to amplifications in the business and financial cycles, where one reinforces the other, resulting in a high degree of pro-cyclicality. As mentioned above, this systemic risk due to pro-cyclicality then has the potential to interact with systemic risk due to interconnectedness and amplify existing vulnerabilities in the financial sector.

2.5.3 Section summary

The systemic risk that emerging markets experience is not necessarily the same as the systemic risk that developed economies experience. The evidence has shown that emerging markets are vulnerable to changes in capital flows and this can subsequently lead to amplifications in their business and financial cycles, where one can reinforce the other. This pro-cyclicality is a form of systemic risk that can interact with systemic risk due to interconnectedness, resulting in an amplification of vulnerabilities that may already be inherent in the financial sector.

2.6 CHAPTER SUMMARY

Although no single definition for systemic risk has been agreed upon in the literature, it is generally accepted to be an important concept for financial stability. Many definitions exist for systemic risk, with some authors focusing on systemic risk as a whole, while others focus on specific mechanisms within systemic risk. The differences between the conditions required for systemic risk, as well as the events that can trigger it, are also illustrated – the implication being that a financial system may have had a large degree of systemic risk, but no systemic event had taken place in order to cause the changes to the system. The most encompassing definition is given by the IMF, BIS and FStB where they set out criteria based on size, interconnectedness and substitutability, while acknowledging that other factors may increase its vulnerability, such as complexity and leverage. The difference between the two dimensions of systemic risk needs to be highlighted. The cross-sectional dimension of systemic risk refers to the structural characteristics of the financial system, such as common exposures and interconnections, while the time dimension refers to the pro-cyclicality of the business and financial cycles and how they reinforce each other, creating systemic risk endogenously. The clearest indication of systemic risk's importance could be observed during the sub-prime crisis when institutions were bailed out in order to avoid potential systemic risks.

During the sub-prime crisis it became clear that a combination of macroeconomic factors, such as an excessively loose monetary policy, allowed global imbalances to form, flooding the market with liquidity and facilitating a rapid credit expansion. The microeconomic factors – including a deregulation process that spanned over decades – worked in tandem with the macroeconomic conditions to allow the housing bubble to form. The use of a fair value accounting system – which requires that prices are readjusted according to their market values – may have been an important factor that worsened the effects of the sub-prime crisis, especially when one considers that the market may have been malfunctioning at the time. Other factors of a systemic nature include insufficient regulatory requirements and bank corrective actions, a dependence of institutions on a malfunctioning market, solvency issues, inadequate levels of liquidity and maturity mismatches.

The systemic developments that allowed the sub-prime crisis to translate into a global financial crisis would essentially manifest into three broad sources of systemic risk, namely contagion effects which cause cascades of defaults to take place; common shocks which can result in a number of institutions defaulting simultaneously; and informational spillovers where bad news from one bank negatively affects another bank. These three elements can interact with each other to amplify the negative effects that occur when a negative shock takes place. There may be a number of negative shocks that occur, but the failure of an institution that contributes a large degree of systemic risk to the financial sector may have the most negative effects.

Systemically important financial institutions are institutions that possess characteristics such as large size and a great degree of interconnectedness, which mean that their failure can have adverse effects on the financial system as well as the greater economy. The failure of Lehman Brothers and AIG, both systemically important financial institutions, during the sub-prime crisis illustrated how single financial institutions could cause contagion effects and common shocks to take place. The policy measures that can be implemented to facilitate systemically important financial institutions (in a decreasing order of feasibility) include the elimination of externalities which these institutions can generate; imposing financial penalties on the institution for potential externalities they produce; increasing the likelihood of the institution's survival; and the complete eradication of systemically important financial institutions. Before policy measures can be implemented, the identification of institutions which will be considered systemically important financial institutions should be undertaken. One of two approaches may be used. The first involves the marginal distress that the institution could impose on the system if it fails, while the second refers to the expected participation of the institution in a systemic event, and subsequent losses that may occur to its creditors. The policy objectives will therefore differ for the two approaches, with the contribution approach focusing on containing the systemic impact the institution may have if it fails, while also avoiding moral hazard in the build-up, and the participation approach focusing on ensuring that the institution survives a systemic event.

After the systemically important financial institutions have been identified, there are two approaches that can be used to quantify the amount of systemic risk they possess. The first is the indicator-based measurement approach. This is a transparent approach used by the BCBS which focuses on bank-level data through indicators such as the institution's size, interconnectedness, substitutability, cross-jurisdictional activity, and complexity. Although this method may be more robust, it can lead to a situation where institutions only control their exposures in these five indicators, and thus strengthening the argument that the systemic importance of an institution should be measured relative to the system as a whole. The second method is the market-based measurement approach. This makes use of market prices and financial modelling to attribute systemic risk to individual institutions in a portfolio context. The

market-based measures include additive measures which attribute system-wide risks to individual institutions, and non-additive measures which are based on the VaR or expected shortfall of an institution, conditional on the default of a particular institution. The conjecture regarding how to identify and measure systemically important financial institutions is likely to remain, but there is a universal agreement that they are an important part of the financial sector and that their failure can generate negative effects, not only for their domestic financial sectors, but also the financial sectors of other countries. An example of this could be seen during the sub-prime crisis where the failure of systemically important financial institutions in developed economies had negative effects in emerging markets that also had high levels of systemic risk.

The macro-financial conditions in emerging markets, namely the inherent pro-cyclicality of the real sector and the financial sector, and their subsequent reinforcing of each other, can lead to a build-up of systemic risk in the financial sector of emerging markets. This systemic risk due to pro-cyclicality has the potential to interact with systemic risk due to the interconnectedness of global financial markets and amplify existing vulnerabilities in the financial sector. Emerging markets were initially not severely affected by the sub-prime crisis. They were affected later on through the trade channel and the financial channel. Emerging markets are vulnerable to capital flows and a reversal of capital flows can occur even without any changes occurring in the domestic economy. Emerging markets also have a greater degree of interconnectedness between institutions and therefore shocks can be transmitted more easily. The policy responses used by emerging markets should perhaps then be more aligned with managing the pro-cyclicality of the business and financial cycles, and thus in turn, managing systemic risk.

Systemic risk, as with any other risk, is an inherent part of finance and financial systems. What sets systemic risk apart from other risks, however, is its complexity. It has been shown that systemic risk has no single definition, can be caused by a number of different factors, can be transferred in a number of different ways, and can also take different forms depending on the characteristics of its host. It is therefore important to understand that although systemic risk can never be removed completely, it should be regulated in such a way that it becomes a controlled risk that can be managed.

CHAPTER 3

THE REGULATION OF SYSTEMIC RISK

“Regulation needs to catch up with innovation.” – Henry Paulson

3.1 INTRODUCTION

A number of potentially significant lessons were learnt from the sub-prime crisis. These include the importance of increased financial stability, as well as the need for improvement of regulations and supervisions for financial institutions that keep up with increased financial innovations. Improvements and innovations also include a number of reforms in regulations, such as the measuring and regulating of systemic risk, along with the specific institutions that will be in charge of carrying out these objectives (Arnold, Borio, Ellis & Moshirian, 2012:3125). Chapter 2 illustrated the concept of systemic risk and the effects that it can have on financial and economic stability. Chapter 3 discusses the previous regulations and supervisory measures that were in place, as well as any future changes that may need to take place in order to regulate and mitigate systemic risk more effectively. It should, however, be remembered that regulations will change as the authorities’ understanding of the risk factors improves. Regulations and supervisory measures are vast, therefore in keeping with the subject of this study, the focus will remain on global regulations and measures that affect systemic risk, such as the Basel Accords, as well as country-specific regulations.

In line with this demarcation, Section 3.2 assesses the global framework for regulating and supervising banks – the Basel Accords – but with a specific focus on the regulations that may address systemic risk. As part of this assessment, certain shortfalls in the Basel Accords for assessing systemic risk will be highlighted. The assessment also points out that although Basel provides an adequate framework for financial institutions, individual countries may still have their own unique and independent approaches to regulations. In Chapter 2 it was illustrated that the US, as the origin of the sub-prime crisis, could best display the manifestation of systemic risk in a developed economy. For the case of emerging markets, the way in which they are affected by systemic risk is markedly different. Considering SA’s reliance on capital flows and high degree of global financial integration, it would provide an appropriate case study of an emerging market. Since these economies were affected by systemic risk in different ways, it would subsequently follow that the way in which they regulate systemic risk could also be different. Section 3.3 therefore undertakes an analysis of the respective regulatory approaches employed by the US and SA authorities and whether these regulatory approaches are successful in mitigating systemic risk and ensuring financial stability within their own financial sectors.

Subsequently, since the regulatory goals of supervisors should arguably be to ensure financial stability, it would be remiss if the macroprudential regulatory approach was not discussed – especially since its ultimate goal is to ensure the stability of the entire financial sector. The calls for a macroprudential approach to regulation have been reinforced by the role that the financial cycle plays in building up systemic risk through its inherent pro-cyclicality, among other factors. Section 3.4 discusses the macroprudential regulatory approach and its importance for regulating systemic risk, as well as the various challenges that may delay its implementation. It should be remembered that effective regulations may need to be based on a tangible measurement. Therefore, in order to design and implement appropriate policies to regulate systemic risk, an accurate measurement of systemic risk must be provided. As a result, Section 3.5 discusses the various quantitative measures of systemic risk.

3.2 BASEL: THE GLOBAL FRAMEWORK

The Basel Committee on Banking Supervision (BCBS) has its roots in systemic risk. It was established in 1974 by central bank governors of the Group of Ten (G10)³¹ in response to the failure of the small German bank Herstatt, and the subsequent systemic effects which occurred as a result of its failure (Acharya, 2012:9). Consultation and developments for Basel I began in 1988, although the regulations themselves only came into effect during December 1992. The objective of these regulations was to maintain capital adequacy within banks so that they could absorb losses and prevent systemic consequences, as well as to encourage more competitiveness among banks internationally. Although systemic risk – especially in the modern sense – only became an objective in Basel III, the first two Accords lay the foundation for many of these principles, thereby justifying a focused overview of both Basel I and Basel II. Section 3.2.1 conducts this overview, followed by an in-depth analysis of Basel III in Section 3.2.2. There has been conjecture surrounding the success of Basel III in mitigating systemic risk, therefore Section 3.2.3 discusses the areas in which Basel III may fall short in regulating systemic risk.

3.2.1 Basel I and II

The Basel Accords were initially mainly concerned with capital adequacy. This was later expanded in Basel II to three complementary pillars. Pillar 1 established minimum capital requirements for credit risk, market risk, and operational risk. Pillar 2 outlined the supervisory review process which was concerned with a bank's management of risks and capital, as well as the specific roles of supervisors. Pillar 3 focused on market discipline, specifically the public disclosure requirements of banks (BCBS, 2014:3). It should be

³¹ The G10 is comprised of eleven industrial countries, namely Belgium, Canada, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom, and the US. The finance ministers and central bank governors of these countries have meetings when necessary to discuss and cooperate on matters related to the economy, monetary policy and finance (BIS, 2015).

noted that the Basel Accords were implemented with the intention of evolving over time, implying that the initial foundations of Basel I would therefore be improved upon, expanded, and subsequently form the backbone of further Basel Accords (BCBS, 2014:2). This section therefore attempts to explain what these Accords entailed, and why they were implemented at that specific point in time.

Basel I categorised assets and assigned them a risk weighting from zero to 100 %. The risk-weighted assets are calculated by multiplying the sum of the assets in each category with that category's risk weight. The minimum ratio for capital to risk-weighted assets would then be a required 8 % (BCBS, 2014:2). Although this was meant to decrease the amount of risk taking banks could do, it may not have had the desired effect. Jackson (1999) noted that banks simply moved the required capital amounts between on-balance sheet assets with different weights, while also securitising assets and moving them off-balance sheet. Banks therefore continued undertaking risky activities and simply accumulated capital through these regulatory arbitrage methods. Essentially, banks were holding more than the required amount of capital while their riskiness increased significantly. The potential consequences of this would be that the amount of capital the banks were holding would not be able to cover their losses, should they occur.

In response to this regulatory arbitrage, Basel II was released in 2004. Overall, Basel II expanded the capital requirement rules of Basel I while implementing an internal risk assessment process. Basel II added more risk categories, allowed banks to use internal and more advanced risk models, as well as implementing capital charges based on a VaR approach (BCBS, 2004). Pillar 1 of the Basel II Accord – which focused on minimum capital requirements – is based on the calculation of total risk-weighted assets on weightings applied to credit risk, market risk, and operational risk (BCBS, 2004:12). Basel II effectively allowed banks to choose between a simpler calculation approach with fixed weights better suited to smaller banks, a more complex approach based on external ratings, and an internal ratings-based approach for larger banks (BCBS, 2004:15). The internal ratings-based approach essentially required that banks specify the probability of default for each individual credit, the loss-given-default and the exposure at default – all of which were determined by the financial modelling of the bank (BCBS, 2004:48).

These approaches arguably allowed banks to adjust their modelling to suit their own financial needs. This, along with a number of other problems in Pillar 1 of Basel II, was illustrated by Blundell-Wignall and Atkinson (2010). The first problem entailed the lack of a concentration penalty and the assumption that all portfolios were adequately diversified. This assumption was made because the model used for the risk-weightings formula included a restriction that the capital backing loans was only dependent on the risk of that particular loan, not the entire portfolio (Gordy, 2003:201). The dependence on a single systemic global risk factor may have understated the capital needed to support a specific region or lender, and therefore did not account for country-specific risk (Gordy, 2003:222). The capital weighting approach used was, however, undermined by complete credit markets, which were now possible as a result of credit

default swaps – since banks could now transform their risk buckets by using derivatives without the need for numerous trades on the underlying securities on primary markets. The theoretical implication of such a transformation is that ex ante risks would no longer exist in the particular bank (Blundell-Wignall & Atkinson, 2010:13). The reality, however, was illustrated by American Insurance Group (AIG) during the sub-prime crisis. Sjostrom (2009:978) explained that AIG was unable to finance the credit default swaps it had sold, ultimately resulting in a loss of protection for all the counterparties who had purchased them.

The next two problems are perhaps the most pertinent for this study since they involve contagion and pro-cyclicality. It was shown in Chapter 2 that banks' capital market activities were not supported by adequate capital, therefore allowing contagion and counterparty risk to manifest. If the Basel requirements are pro-cyclical – in that risks are underestimated during upswings and overestimated during downswings – and the leverage ratios are dependent on market values, the requirements should in retrospect be higher during upswings and lower during downswings. Other factors which reflect pro-cyclicality are bank risk measurements, and counterparty credit policies, as well as profit recognition and compensation schemes. The pro-cyclical effects of the factors are furthermore emphasised by the fact that the risk inputs that a bank uses are subjective, as is the intuitive derivation that banks will choose the input that allows them to hold the least amount of capital (Blundell-Wignall & Atkinson, 2010:14). Finally, the definition of what actually constitutes capital is unclear, therefore allowing the possibility of regulatory arbitrage to take place, with the result that a bank's loss-absorbing capacity during a crisis could be impeded.

As a result, the aims of Pillar 2 and 3 were essentially to capture the risks that Pillar 1 missed. Pillar 2 involves the supervisory process and the use of stress tests, requiring banks to hold capital for risks which were not captured under Pillar 1. Blundell-Wignall and Atkinson (2010:15) argued that the potential problem with this was that in order for supervisors to implement the additional buffers, they would need to keep up with changes in market structures, practices and complexity, while also predicting future asset prices and volatility. These objectives become challenging when it is considered that the staff of supervisory institutions may be smaller, less skilled and receive lesser remuneration than private bankers do. A practical example of this knowledge disparity between supervisory and private institutions could be viewed prior to the sub-prime crisis when the United Kingdom (UK) Financial Services Authority allowed Northern Rock to use the internal ratings-based approach, even though it would significantly reduce the amount of regulatory capital they would be required to hold (Blundell-Wignall & Atkinson, 2009:539).³²

³² Northern Rock subsequently experienced funding problems and sought liquidity support from the central bank, resulting in a depositor run (Shin, 2009a:102).

Similarly, it has been said that regulatory supervisors in the US were aware of the use of repo 105³³ to hide leverage in accounts, but they simply did not understand the effects that this could have (Sorkin, 2010).

Pillar 3 involves market discipline and disclosure requirements which could impede banks if they do not have adequate risk management practices. A large portion of this would, however, be dependent on the Efficient Market Hypothesis holding true (Wims, 2014:4). In the case of the sub-prime crisis, the housing bubble may have been an example of how informational efficiency was lacking in the market.³⁴ If the market were informationally efficient, a bubble in the housing market may not have occurred since appropriate housing prices would have been reflected and market participants would have reacted rationally. The intended functioning of Pillar 3 was arguably also hampered because business models³⁵ and the problem of too-big-to-fail institutions were not dealt with. As a result, failed strategies did not have any consequences if the counterparty position was held by banks that were too-big-to-fail. This essentially meant that risk-taking was under-priced, and although it directly affects the capital of banks, this was not yet an outright focus of the BCBS (Blundell-Wignall, Atkinson & Roulet, 2014:4). It was argued that the main idea behind Basel II was to reduce the probability of default for each individual bank, because this would theoretically ensure a stable and resilient banking sector (Lehar, 2005:2578), but ultimately ignored the developing fragility of bank liabilities such as uninsured wholesale deposit funding and the subsequent increase in risk taking and economic leverage (Acharya, 2012:10).

Further criticism was that Basel II could have actually provided incentives for banks to become larger and more interconnected. The reasoning behind this is that banks were encouraged to become more systemically risky, not only because of the increased profit making incentives, but also because of the increased probability that they would be bailed out during times of financial distress, effectively providing a subsidy to an institution when it causes negative externalities for other institutions (Brunnermeier, Crockett, Goodhart, Persaud & Shin, 2009:24). This argument was taken further by Schwerter (2011:339) in stating that Basel II also caused the propagation of systemic risk factors which could only be addressed by changing certain key areas. The case was made that there are seven systemic risk factors that regulations should address, namely size, maturity mismatch, idiosyncratic risk, leverage, pro-cyclicality,

33 A repurchase agreement (repo) is an agreement where one party transfers an asset or security to another party as collateral for a short-term borrowing of cash, while agreeing to repay the cash and reclaim the collateral at a certain point in time. On the maturity date, the borrower repays the funds plus the agreed interest and reclaims the collateral. Repo 105 transactions were similar to regular repo transactions; however, Lehman Brothers accounted for cash borrowings or financing transactions as “sales” due to overcollateralisation or a larger haircut than normal (Valukas, 2010:76).

34 A debate on the validity of the Efficient Market Hypothesis is beyond the scope of this study.

35 Business models refer to the intermediation activities and balance sheet structuring choices that banks make in order to achieve their business objectives. Banks will base their business model choices around the strengths of the organisation (Roengpitya, Tarashev & Tsatsaronis, 2014:55).

common risk exposure, and interconnectedness. A summary of the systemic risk factors is illustrated in Table 3.1.

Table 3.1: Systemic risk factors due to Basel II’s drawbacks.

Systemic risk factor	Areas lacking attention
Interconnectedness, pro-cyclicality, common risk exposure	Macroprudential view
All elements (Maturity mismatch, leverage)	Systemic risk (Systemic liquidity risk)
Pro-cyclicality, leverage	Pro-cyclicality
Size, interconnectedness, common risk exposure	Too-big-to-fail, too-many-to-fail, too-important-to-fail
Size, interconnectedness, common risk exposure,	International coordination
Size, interconnectedness, common risk exposure, leverage	Transparency
Idiosyncratic risk, pro-cyclicality, leverage, maturity mismatch	Sustainability

Source: Schwerter (2011:341).

The intricacies of these factors were explained by Schwerter (2011:341) as follows. A macroprudential approach is necessary because common risk exposures due to interconnectedness (both direct and indirect) between banks should be addressed, while pro-cyclicality should be addressed at a national economic level. Systemic liquidity risk is mainly caused by maturity mismatches and excess leverage. Banks which are highly leveraged have low equity levels or a large amount of risky assets (or both) and are therefore more susceptible to the effects of pro-cyclicality. The causes of pro-cyclicality in relation to the other systemic elements are therefore leverage and pro-cyclicality itself. Size, interconnectedness, and a common risk exposure are the main causes of the risk factors for too-big-to-fail, too-many-to-fail, and too-important-to-fail institutions, as well as for international coordination – since these factors transcend international borders and can lead to greater international financial integration. The case for transparency arises from the need for interconnectedness and common risk exposures to be assessed in order to determine a bank’s individual risk, while an increase in bank size increases the probability of merged bank structures, and therefore a lesser degree of transparency. Leverage measures, also partly due to interconnected and common risk exposures, should always be considered cautiously, since valuation techniques and accounting systems may report different leverage ratios. Finally, sustainability – whether a bank has a longer- or shorter-term orientation – is caused by idiosyncratic risk, pro-cyclicality, leverage and maturity mismatches. A greater degree of idiosyncratic risk is associated with individual bank failures while a longer-term orientation will be associated with less idiosyncratic risk. Other factors will subsequently be associated with a shorter-term orientation since a pursuit of short-term revenue may

involve greater risk-taking, a higher return on equity may involve more leverage, and a higher interest margin may involve interplay between long-term and short-term funding. The pro-cyclicality element may have greater impact on short-term oriented banks since accounting standards will result in the values having to be adjusted (Schwerter, 2011:342). Given the outlined areas in which Basel II falls short, it may be necessary to discuss the ways in which they can be addressed.

Brunnermeier *et al.* (2009:28) argued that in order for regulations to be successful, there should be no incentive for banks to avoid them, as was the case with Basel II. Goodhart (2010:24) predicted that bank innovations that attempt to avoid regulations will always be ahead of the regulations themselves. It may therefore be necessary to place greater emphasis on regulations that do not encourage banks (indirectly) to move their activities into the unregulated sector. The goal could perhaps be to fix the problems associated with Basel II, while providing incentives to encourage banks to obtain financial stability. The way to achieve this would be through implementing a macroprudential approach to regulation³⁶ aimed at achieving stability in the entire financial sector, as opposed to just individual institutions (Clement, 2010:65). The ultimate macroprudential goal is to avoid losses in real output, i.e. Gross Domestic Product (GDP) losses, by addressing potential episodes of financial distress through focusing on a top-down approach towards regulating endogenous systemic risk, while also addressing the linkages between financial stability and the stability of the real economy (Borio, 2003:2). Some degree of international cooperation may be necessary, given that banks are global, and a lack of international standards may lead to greater cross-border financial activity and therefore decrease the effectiveness of national macroprudential regulations (CGFS, 2010:7). A potential problem with an internationally coordinated implementation of macroprudential policies is that the policies themselves will depend on the economic cycle of the particular country (CGFS, 2010:7).

As a consequence, Basel III was introduced as an amendment to the existing rules of Basel II, essentially aiming to fix the shortcomings in Basel II (van Vuuren, 2012:309). These reforms were numerous and included the introduction of capital buffers, charges for counterparty credit risk, and a leverage ratio, while also incorporating amendments to the composition of regulatory capital and the capital required for the trading book (van Vuuren, 2012:310).

3.2.2 Basel III

For the most part, Basel I and II addressed solvency risk, with a lesser focus on liquidity risk. Basel III had a greater focus on liquidity risk, but it did not necessarily address how these risks could translate into

³⁶ The macroprudential regulatory approach will be discussed in detail in Section 3.4.

systemic risk. Basel III, however, recognised that there are three types of risks that could result in the failure of a financial institution (Acharya, 2012:10), namely:

- i. Solvency risk, which involves the market-valued assets of the firm declining below its obligations;
- ii. Liquidity risk, which involves a situation where asset markets have become illiquid, and as a result of this the firm is unable to convert its assets into cash and pay off its obligations;
- iii. Funding liquidity risk, which involves the inability of the firm’s maturing debt obligations to be rolled-over with immediacy at a point in the future.

It follows then that Basel III mostly addressed Pillar 1 of the Basel Accords (BCBS, 2011:61). Pillar 2 changes included an attempt to improve the powers of supervisory authorities to manage liquidity, concentration and off-balance sheet risk, as well as the implementation of stress tests that could assist in identifying systemic risk (Georg, 2011:4). Pillar 3 changes included an increase in market disclosure standards and an improvement in the transparency of the balance sheets of banks (BCBS, 2011:3). In order to address the probability of bank failure, the banks’ loss-absorption abilities would need to be increased. The largest and perhaps most significant changes that were to be implemented in Basel III were the addition of a non-risk based leverage ratio and two liquidity ratios. The non-risk based leverage ratio was introduced in an attempt to capture the effects of off-balance sheet leverage which was not captured by the risk based capital ratios, and subsequently restrain a deleveraging process which could have destabilising effects on the financial system and the greater economy. Regarding more stringent capital requirements, the Tier 1 capital requirements of Basel II – the ratio between core equity and risk-weighted assets – did not have the desired constraining effects on banks as they increased their leverage both on- and off-balance sheet while still maintaining strong Tier 1 ratios. In terms of their capital, banks would now have to hold an increased quantity – 4.5 % common equity instead of 2 % – as well as a higher quality, of capital, since the definition of common equity was adjusted, while the minimum Tier 1 ratio to un-weighted assets would be 3 % (BCBS, 2011:13). A summary of the capital requirements and their timeline for implementation is illustrated in Table 3.2.

Table 3.2: Capital adequacy standards for Basel III.

Capital Type	Year for final implementation	
	2013	2019
Minimum common equity capital ratio	3.5 %	4.5 %
Minimum Tier 1 Capital	4.5 %	6.0 %
Minimum Total capital plus conservation buffer	8.0 %	10.5 %

Source: BCBS (2011:69).
All ratios are a percentage of risk-weighted assets.

The argument for additional liquidity measures could be made because the sub-prime crisis demonstrated that banks with sufficient capital levels could still undergo financial difficulties due to liquidity shortages (BCBS, 2011:8). This argument was substantiated by the fact that the sub-prime crisis translated into a global crisis when Lehman Brothers failed and a subsequent run on investment banks and money market funds occurred (Acharya, 2012:12). In order to address the types of liquidity shortages of this nature, the liquidity coverage ratio and the net stable funding ratio were implemented in Basel III as additional liquidity measures. The liquidity coverage ratio is the ratio of the bank's liquid assets (which are of a high quality) to its net cash outflows over a 30-day period, during an acute system-wide stress. This would assess the bank's short-term ability to survive a stress test scenario for one month, and thereby encourage it to hold higher quality liquid assets (BCBS, 2011:9). The net stable funding ratio is the ratio of the current available stable funding of the bank to its required amount of stable funding. This provides the banks with long-term incentives to structure their assets and liabilities with a greater degree of sustainability and therefore avoid liquidity mismatches (BCBS, 2011:9).

In addition to increased liquidity support and the premise of stable funding, a number of other measures were proposed to address the inherent pro-cyclicality of the Basel regulations and ensure the build-up of greater capital buffers during upswings. These measures have the objective of dampening the excess cyclicality of the minimum capital requirements, the promotion of more forward looking provisions, and the conservation of capital in order to build up greater buffers for times of distress at both individual banks and the banking sector as a whole, while also achieving a broader macroprudential goal of protecting the entire banking sector from periods of excess credit growth (BCBS, 2011:5). Section 3.4 will discuss the macroprudential regulatory approach along with the countercyclical capital buffer in greater detail. Other ways in which excess cyclicality could be dampened include requiring the use of long-term data horizons to estimate probabilities of default, introducing downturn loss-given-default estimates, improving the calibration of risk functions which convert loss estimates into regulatory capital requirements, and requiring banks to conduct stress tests including widened credit spreads in recessionary scenarios (BCBS, 2015a:11).

Apart from addressing pro-cyclicality, the BCBS also promoted more forward-looking provisions and is in support of changing the accounting standards to an expected loss approach, which entails the capturing of actual losses more transparently and has less pro-cyclicality than the incurred loss approach (BCBS, 2011:6). In order to provide for losses that may occur from banks unwinding trading book assets in illiquid markets, an incremental risk charge is implemented. The incremental risk charge is equal to the estimated default and migration risk of an unsecuritised product over a one-year capital horizon and allows for credit default and migration risk in the trading books of the banks, since these losses are unable to be captured by short-term VaR modelling (BCBS, 2009:1). This essentially has the effect of adding to the risk-weighted

assets. Blundell-Wignall *et al.* (2014:22) described other measures in Basel III that were implemented to address interconnectedness and systemic risk (BCBS, 2011:3):

- i. A capital requirement for counterparty credit risk which uses stressed inputs. The counterparty credit risk requirement addresses the possibility that capital charges decrease during downturns and therefore remove pro-cyclicality which may arise when volatility-based risk inputs are used (BCBS, 2011:3). This would be based on three years of historical data, and includes actual credit spreads for a cross-section of the bank's counterparties or market-implied data. The adequacy of the stress testing models should be measured against benchmark portfolios that use similar data (BCBS, 2011:30);
- ii. A capital charge will be enforced on banks for any potential mark-to-market losses that occur as a result of a decrease in the creditworthiness of a counterparty, and would therefore address the risk associated with credit valuation adjustments. It should be noted that Basel II addressed the risk of a counterparty default, but not credit valuation adjustment risk which was the cause of more losses during the sub-prime crisis (BCBS, 2011:3). The calculation of this charge will be based on a bond-equivalent valuation, but the exact specifics of the calculation will be dependent on the bank (BCBS, 2011:33);
- iii. Counterparty credit risk standards are also being raised, with a focus on wrong-way risk. This entails situations where, as the exposure increases, the credit quality of the counterparty decreases, and therefore the probability of default increases (BCBS, 2011:4). Banks will be required to monitor this risk by analysing defined sectors and referring to specific transactions (BCBS, 2011:38);
- iv. In order to better regulate large financial institutions and mitigate the effects of their failure, an asset valuation correlation multiplier of 1.25 is applied to institutions that have assets of at least USD100 billion, as well as any unregulated financial institutions regardless of size. The asset valuation correlation multiplier will effectively increase the risk weights for these exposures (BCBS, 2011:39);
- v. The improvement of standards for collateral management and initial margining, which will be done through the application of longer margining periods as a basis for determining the regulatory capital requirements of banks with derivative exposures to a counterparty which are large and illiquid, as well as the adoption of additional standards to strengthen collateral and risk management practices (BCBS, 2011:3);
- vi. The use of central counterparties to establish higher standards for financial market infrastructures. The meeting of these enhanced standards by a bank's collateral and mark-to-market exposures to central counterparties is subject to a low risk weight, while default fund exposures to central counterparties will also be subject to capital requirements which are risk-sensitive. Systemic risk within the financial sector will further be addressed by increasing the risk weights on exposures to

financial institutions relative to non-financial corporate sector. This is because financial exposures have a higher degree of correlation than non-financial exposures do (BCBS, 2011:4).

Apart from these additional measurements, Basel III also initiated a shift towards a macroprudential approach to systemic risk considering that, based on evidence from the sub-prime crisis, microprudential regulations alone were insufficient in regulating systemic risks. A portion of these macroprudential regulations have to do with the regulation of systemically important financial institutions. Considering that the failure of global systemically important financial institutions played a large role in the sub-prime crisis, Basel III proposed a number of policies that could address potential problems with such institutions. The goal of these policies is to reduce the probability of failure of a global systemically important financial institution by increasing its going-concern loss absorbency, while also reducing the impact such a failure could have by improving the global recovery and resolution frameworks (BCBS, 2013:3). Using the twelve indicators for systemically important financial institutions explained in Figure 2.9 of Section 2.4.2, a score is calculated for each global systemically important financial institution in Equation 3.1:

$$S = \sum_{i=1}^{12} W_i I_i, \quad (3.1)$$

where W_i is the weight placed on the specific indicator I_i , and $i = 1, \dots, 12$. The scores obtained will classify a bank into one of five buckets, each with additional loss absorbency requirements. This is indicated in Table 3.3 below. These additional capital requirements are applicable to Tier 1 common equity as a percentage of risk-weighted assets, while the levels themselves are minimums and can be increased by national jurisdictions if deemed necessary. The movement of an institution to a higher bucket will mean that it will have to raise the additional required capital within one year, while scores equal to a boundary will be assigned to the higher bucket (BCBS, 2013:12). Twenty-nine global systemically important financial institutions have been identified so far, with the additional capital arrangements to be phased in between 2016 and 2018. The goal is for them to be fully implemented by 2019 (BCBS, 2013:15).

Table 3.3: The bucketing approach and additional capital requirements.

Bucket	Score range	Higher loss absorbency requirement (common equity as a percentage of risk-weighted assets)
5	D-E	3.5 %
4	C-D	2.5 %
3	B-C	2.0 %
2	A-B	1.5 %
1	Cutoff point-A	1.0 %

Source: BCBS (2013:12).

By introducing these changes, Basel III made an attempt to fix all the shortcomings of Basel II. Increased capital standards, a greater focus on systemic risk through a macroprudential approach, and the introduction of liquidity and solvency ratios were the main changes. This reiterates why Basel III is regarded as the global standard for banking regulations. However, despite these improvements, a number of oversights and problems still remain.

3.2.3 A critique of the Basel III Accord

Given these new elements introduced by Basel III, it is necessary to assess how banks will be encouraged to adopt them. A strengthening of the capital base of banks, as well as greater risk coverage, may result in banks being more critical of their investments and credit portfolios, while transparency and market discipline may arise due to the enhanced disclosure requirements. Furthermore, the increased conservation buffer could result in banks holding greater amounts of equity, since they do not want to be restricted in terms of distributions (Schwerter, 2011:343). The use of central counterparties may increase transparency in financial markets, since the BCBS has created incentives for banks to move their exposures to central counterparties. These incentives include increased standards for the institutions, higher risk weights for bilateral exposure, and a 0 % risk weight for exposures to central counterparties. This is required because negative externalities that each over-the-counter trade can impose on the financial system are not taken into account by bilateral margin requirements. Additionally, banks are incentivised to hedge credit valuation adjustment risks because, if these hedges reference the counterparty, they can be deducted from the capital requirements assessment basis, while an increased margin period of 20 business days has the potential to encourage an exposure reduction (Schwerter, 2011:343). The problem with this, however, is that subjective inputs will always remain and the institution-specific needs of financial and non-financial institutions for derivatives will not be appropriate for exchanges – since they are designed specifically for their individual needs (Blundell-Wignall & Atkinson, 2010:19).

Another questionable area of the Basel III Accord relates the asset valuation correlation factor. The proposed asset valuation correlation factor for larger financial institutions is a global factor, with the implication that the varying magnitudes of correlation for different assets will not be taken into account. Georg (2011:17) explained that this could be problematic because the correlation between, for example, interbank loans and corporate loans will be lower than the correlation between assets of the same class, leaving banks with no incentive to diversify their asset classes and can also lead to portfolio lumpiness – a significant source of systemic risk (Georg & Poschmann, 2010:21). The increase of the asset valuation correlation with a multiplier of 1.25 may, however, discourage banks from getting rated since the banks are now obligated to assess their exposures, regardless of the counterparty's rating (IIF, 2010:12). It is further suggested that the leverage ratio would be better suited as a Pillar 2 measure (IIF, 2010:13). Potential problems relating to capital buffers include the creation of incentives to invest in countries with lower capital buffers, as well as pressure from the political arena to increase a country's competitiveness by lowering the capital buffer (BCBS, 2010:5). In relation to the potential problem of interconnectedness between financial institutions and their subsequent systemic risk, no incentives are provided for financial institutions to address negative externalities which can arise (Schwerter, 2011:344). Conversely, the higher liquidity standards encouraged through the net stable funding ratio (which is the measure of long-term liquidity standards) incentivised structural changes in the liquidity profiles of banks towards more stable longer-term funding. Following on from the illustration of the incentives which Basel III creates for banks, it will be necessary to investigate the extent to which Basel III was able to correct some of the oversights in Basel II. A summary of this is illustrated in Table 3.4.

Table 3.4: Basel III’s response to oversights in Basel II.

Oversights	Basel III response
Macroprudential view	Conservation and countercyclical capital buffer
Systemic liquidity risk	(presumed) Liquidity standards
Pro-cyclicality	Build-up of additional capital buffer Avoid excessive credit growth Use of stressed data in the calculation of counterparty credit risk
Too-big-to-fail, too-many-to-fail, too-important-to-fail	None
International coordination	At least 27 members of the committee will implement the approach
Transparency	Intensified disclosure of capital and liquidity requirements Disclosure of the leverage ratio and national countercyclical capital buffer
Sustainability	Enhanced capital base Widened risk coverage Liquidity standards – net stable funding ratio

Source: Schwerter (2011:346).

It is clear from Table 3.4 that Basel III improved upon many of the oversights that occurred in Basel II; however, no direct proposals are made to address the potential problem of too-big-to-fail, too-many-to-fail, and too-important-to-fail institutions, while direct attention is only given to systemic liquidity risk. Schwerter (2011:347) argued that instead of directly addressing systemic risk, Basel III addresses other factors which cover the systemic risk factors created by Basel II that were illustrated earlier in Table 3.1. This is summarised in Table 3.5 below.

Table 3.5: Basel III’s systemic risk solutions.

Systemic risk factor	Basel III’s considered aspects
Idiosyncratic risk, pro-cyclicality	Equity Base
Interconnectedness, common risk exposure, idiosyncratic risk	Risk coverage
Pro-cyclicality, leverage, maturity mismatch	Leverage
Pro-cyclicality, idiosyncratic risk	Pro-cyclicality
Size, interconnectedness, common risk exposure	Systemic risk and interconnectedness
Maturity mismatch, leverage, systemic liquidity risk	Liquidity standards

Source: Schwerter (2011:347).

The aspects considered in Table 3.5 are explained as follows. A strengthening of the equity base will lead to less idiosyncratic risk, and along with the committee’s forward-looking provisions and attempts to decrease the cyclicity of the minimum requirements, may lead to less pro-cyclicality. Enhanced risk

coverage will include greater considerations of credit valuation adjustments, asset valuation correlations and counterparty credit risks, along with the utilisation of stressed input data, incentives to use central counterparties and longer margin periods, all of which could reduce common risk exposures, idiosyncratic risk, and risks associated with interconnectedness. By dampening the amount of borrowing with respect to risky assets, the risk factors of leverage, pro-cyclicality and maturity mismatch may all be addressed, while a focus on counter-cyclical measures can decrease pro-cyclicality and idiosyncratic risk. The aspects of systemic risk and interconnectedness are mostly addressed through capital surcharges, contingent capital and bail-in debt, while the introduction of two liquidity measures has the potential to address the problems of leverage and maturity mismatches as well as systemic liquidity risk (Schwerter, 2011:348).

In relation to the liquidity proposals, Blundell-Wignall and Atkinson (2010:27) raised a number of questions. Firstly, they argued that maturity transformation is an important function of the banking system and questions should be asked whether the liquidity proposals are not limiting this function unnecessarily. Secondly, the proposals had a propensity to show a bias towards government bonds, which in some countries can be riskier than others – meaning such a bias, could actually result in greater risk for the banks. Finally, the proposals encouraged liquidity which may occur at the expense of returns – resulting in excessive risk taking in other areas to make up for this.

From a holistic point of view, the proposal to address periods of excessive credit growth may be good in theory, but the practical implications of this are more challenging if one considers the structural changes that can be caused by financial innovation, as well as the inherent leads and lags in credit modelling (Blundell-Wignall & Atkinson, 2010:19). Since credit growth lags the economic cycle, the identification and subsequent provisioning of measures to counter it may actually be implemented when the economy has already entered a downswing, thereby further amplifying the cycle. While it is therefore clear that Basel III did address some of the systemic risk factors, it is arguable whether this will reduce the probability of a financial crisis in the future. Many of these shortcomings and systemic risk factors of Basel III are in fact remnants of those that occurred in Basel II.

The assumption of a perfectly diversified portfolio is one such shortcoming. Blundell-Wignall and Atkinson (2010:20) proposed the implementation of a quadratic penalty that could be applied if a portfolio deviates from a well-diversified benchmark portfolio. Another shortcoming is that the assumption of a single global risk factor does not take into account idiosyncratic risk associated with individual borrowers from different businesses and regions (Blundell-Wignall & Atkinson, 2010:20). This is in contrast to the findings of Schwerter (2011:348) who argued that idiosyncratic risk would be addressed through the measures focusing on pro-cyclicality, risk coverage, and the equity base. Further problems illustrated by Blundell-Wignall and Atkinson (2010:20) were that banks are able to transform risk through complete credit markets. These markets allowed them to shift their promises in accordance with their regulatory and tax

preferences, subsequently resulting in an unconstrained, increasing amount of leverage. This excess leverage was shown to play a large role during the sub-prime crisis, where a better Tier 1 capital ratio actually resulted in greater cumulative losses. The leverage ratio was shown to have a negative relationship with cumulative losses, possibly due to capital arbitrage which took place, or more risk being undertaken with taxpayer's money.

Expanding on the role of leverage in the sub-prime crisis, it is necessary to question whether the need for government bailouts was attributable to an insufficient quantity of quality capital held by banks and not necessarily the quality of capital alone. In response to this, Blundell-Wignall and Atkinson (2010:25) argued that the leverage ratio may need to be set at a level that ensures banks hold sufficient capital across all jurisdictions. The study also explained that the leverage ratio should not be thought of as a backstop measure, since it might not combine well with the risk-weighting approach. In order to explain this relationship, the equation for the minimum amount of capital when considering risk-weighted assets, and the equation for the minimum amount of capital when considering the liquidity ratio, are presented individually. The risk-weighting approach to capital is defined in Equation 3.2, while capital according to the leverage ratio is indicated in Equation 3.3:

$$\text{Min. CAP}(RWA) = 0.08 \times \{12.5(OR + MR) + \text{SUM}[w(i)A(i)]\} \quad (3.2)$$

$$\text{Min. CAP}(LR) = \beta \text{SUM}[A(i)]. \quad (3.3)$$

Min. CAP refers to the minimum capital required for *RWA* (the risk-weighted assets) and for the *LR* (leverage ratio). *OR* and *MR* represent operational risk and market risk, while *SUM* refers to the sum of the assets (*A*) adjusted for their weights (*w*). Therefore, regardless of the value for β , the leverage ratio is likely to be the factor that restricts capital since:

$$\text{Min. CAP}(RWA) \leq \text{Min. CAP}(LR). \quad (3.4)$$

Equation 3.4 essentially indicates that the leverage ratio could be set too high, resulting in the capital requirement being low and banks being incentivised to arbitrage the weights so that they do not hold excess capital. This may result in banks moving towards assets with a lower weighting and moving their promises outside the banking system – which could have negative consequences, such as the creation of bubbles. The implementation of a quadratic penalty, as referred to earlier in this section, may be able to deal with such a concentration of capital that arises due to such regulatory arbitrage. Georg (2011:16) questioned whether the main problem of the capital requirements could be due to their reliance on risk-weighted assets. The problem with risk-weighted assets is that they do not truly reflect the amount of risk inherent in these assets, and this actually encouraged banks to hold financial asset, such as interbank loans and derivatives with lower correlations, instead of real assets.

One way in which Basel III attempted to circumvent the regulatory arbitrage tendencies of large institutions was by imposing additional capital requirements for systemically important financial institutions that are based on their relative systemic importance. Georg (2011:16), however, argued that this categorisation is volatile and can change over time. Since banks are unable to obtain more capital overnight, they will always have to hold the amount of capital required, based on the time when it is in its most systemically important state, i.e. banks will be forced to always hold the maximum amount of capital. The goal of the capital requirements is essentially to discourage banks from becoming systemically important; however, this may only be truly effective if the costs of these capital requirements outweigh the potential benefits which banks could gain from bail-out guarantees (Akram & Christophersen, 2010:22). This raises the question as to what measures – apart from capital requirements – Basel III imposes in order to better regulate systemically important financial institutions.

Further interrogation of Basel III's systemic risk measures was undertaken in Georg (2011:16) where it was argued that in the Basel III Accord, the risk weights of assets, as well as the asset valuation correlation factor, do not adequately mitigate systemic risk. This is because banks do not have enough information regarding the financial system's network structure and can therefore not determine the correlation of their portfolios adequately. Furthermore, a macroprudential risk analysis will need to be undertaken in order to acquire an accurate map of the financial network – which can only be done by a supervisory authority. Additionally, the timing of when a supervisory authority needs to intervene in order to mitigate systemic risk build-up is a conundrum of sorts. The FStB (2010a:3) made the case that supervisors may need to deal proactively with systemic risk and intervene even before any tangible indicators of risk have emerged. This could, however, be difficult to persuade the directors of a firm to do when no clear risks exist yet. Since no current indicators of systemic risk are able to definitively measure systemic risk during its build-up phase, a pre-emptive intervention would therefore not necessarily be possible.

3.2.4 Section summary

The Basel Accords are the global standard for regulating financial institutions. Basel I was mostly concerned with decreasing the risk taking of banks by basing their capital requirements on their amount of risk-weighted assets. Basel II's main changes included an extension of the capital requirements and the implementation of an internal risk assessment process. It also allowed banks to use internal and more advanced risk models, in addition to using the VaR approach to calculate capital charges.

Basel III was introduced as an amendment to Basel II and therefore did not replace it. Basel II had a greater focus on solvency risk, with a limited focus on liquidity risk. Basel III had a greater focus on liquidity risk, with the introduction of capital buffers, counterparty credit risk charges, liquidity ratios and leverage ratios. The Basel approach, while being the global standard for regulating financial institutions, did not

provide significant improvements to current systemic risk regulations. Basel III's focus on systemic risk was mainly seen through a shift towards a macroprudential regulatory approach, including measures such as the countercyclical capital buffer. Basel III also outlined measures to regulate systemically important financial institutions through additional capital charges, based on the size of the systemically important financial institution. Although Basel III introduced a number of new regulations and aimed to fix some of the oversights from Basel II, whether these regulations have the desired effects would still need to be determined.

Such critical assessments have been carried out on the Basel Accords, specifically Basel III. Much of this criticism relates to how banks would be incentivised to adopt the Basel regulations. Furthermore, many of the oversights in Basel III were remnants of the previous Accords, such as whether the quality of capital is not perhaps more important than the quantity. Additionally, whether the Basel III Accord can adequately address systemic risk, and therefore ensure financial stability, is arguable. This will need to be combined with measures which can quantify systemic risk and identify it prior to its manifestation. In conclusion, the Basel III Accord is a global framework and the responsibility will remain with individual countries to implement them. As a result, individual countries are likely to implement their own country-specific regulations additionally, in order to ensure complete financial system stability.

3.3 COUNTRY-SPECIFIC REGULATIONS

The differences between developed economies and emerging markets, how they were affected by the sub-prime crisis, and systemic risk were explained throughout Chapter 2. The Basel III approach to systemic risk explained in Section 3.2 is focused on imposing additional capital charges on banks, but individual countries have begun to impose their own individual limitations on market-based activities. Considering the different characteristics of the US and SA economies and financial sectors, it would therefore follow that they could have vastly different regulatory approaches. The difference between the two approaches was briefly illustrated in Chapter 1, with the US being characterised by a great degree of complexity, while SA has a large amount of fragmentation. This will be expanded upon here. Section 3.3.1 discusses the US approach to regulating systemic risk and will mostly focus on the implementation and implications of the Dodd-Frank Act, as this was essentially the official regulatory response of the US to the sub-prime crisis. Section 3.3.2 describes the SA approach by making use of the failure of African Bank in 2014 as part of its explanation, in addition to explaining how the SA regulators tailored the Basel Accords to fit the characteristics of its economy.

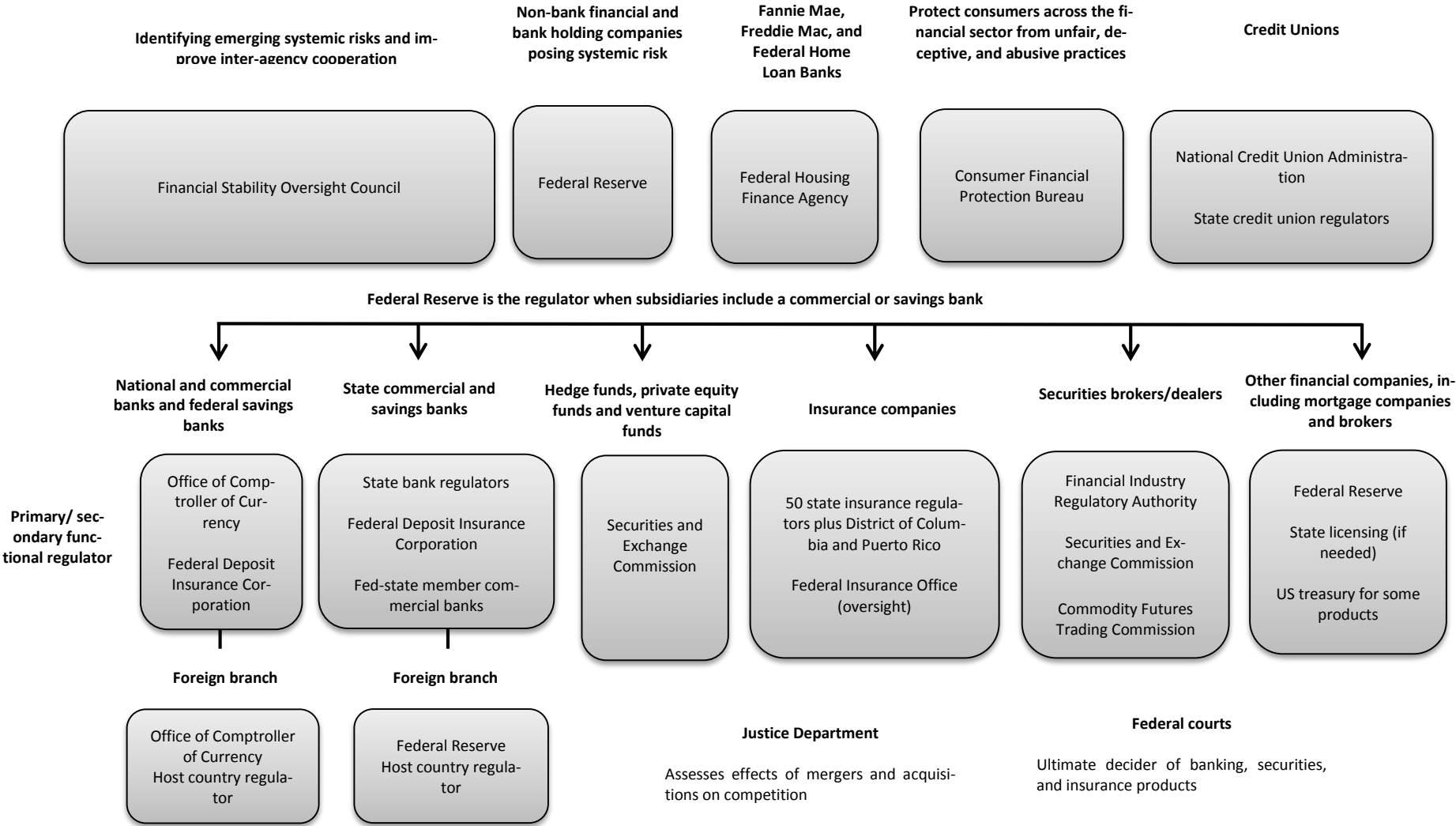
3.3.1 The US regulatory approach

The success of the Basel Accords in mitigating systemic risk is debatable – but this should not detract from its importance as a global standard for bank regulation. It should, however, be remembered that the Basel

Accords are not mandatory and need to be enforced by the relevant country's regulatory body. In Chapter 1, it was stated that the large number of regulators in the US structure, as well as the potential complexity of the regulatory structure, may be an inherent weakness. The regulatory structure under the Dodd-Frank Act³⁷ is illustrated in Figure 3.1 below.

37 The Dodd-Frank Act refers to the Dodd-Frank Wall Street Reform and Consumer Protection Act (United States, 2010).

Figure 3.1: The US regulatory structure.



Source: Barth, Prabha and Wihlborg (2014:4).

This section will focus on the country-specific measures that the regulatory entities are attempting to implement in order to regulate systemic risk, and not the regulatory entities themselves. The Dodd-Frank Act is essentially the official US regulatory response to the sub-prime crisis, thus this section draws extensively from this Act. The main features of the Act were highlighted by Acharya (2012:5) as follows:

- i. Identifying and regulating systemic risk;
- ii. Proposing an end to too-big-to-fail institutions;
- iii. Reinstating a limited form of the Glass-Steagall Act with the Volcker rule;
- iv. Expanding the responsibility and authority of the Fed;
- v. Restricting discretionary regulatory interventions; and
- vi. Regulation and transparency of derivatives.

Due to the enormous scope of the Dodd-Frank Act, delimitation needs to occur. This study will only focus on the first aspect of the report, with a limited focus on feature two and three. The other aspects are beyond the scope of this study. It should be noted that the Dodd-Frank Act only focuses on the endogenous form of systemic risk, such as the failure of a systemically important financial institution.

The goal of the Dodd-Frank Act was essentially to identify systemic risk before it could actually have an effect in the financial sector (for example, through a breakdown). One way in which this could be done would be with the conducting of stress tests. In 2009 the US Government conducted stress tests to determine the losses banks would suffer if certain aspects, such as GDP, unemployment, and house prices, were to worsen (Tarullo, 2010). The outcome was that 10 of the 19 banks tested were subsequently told that they would need to raise more equity capital. The Dodd-Frank Act requires annual stress tests to be undertaken, and places the responsibility for assessing the implications of such tests with the Financial Stability Oversight Council (FSOC). Krainer (2012:123) explained that the FSOC's main objectives were to identify financial institutions with the ability to create systemic risk, protect taxpayers from covering the losses of debt and equity investors in systemically important financial institutions, and address potential threats to US financial stability. In order to identify a financial institution which is likely to generate systemic risk, the Dodd-Frank Act recommends that factors, such as the institution's size, degree of market concentration, importance as a source of credit, interconnectedness, balance sheet exposure, leverage, and amount of risk-based capital of the institution, be considered. The FSOC can refer the identified institution to the Fed, who can then impose remedial actions such as requiring additional risk-based capital, contingent capital, and liquidity; limits on leverage, short-term debt and concentration; and the requirement of a living will or resolution plan, and implementing the resolution plan before actual bankruptcy takes place. The Dodd-Frank Act also established the Office of Financial Research which uses the fees imposed on systemically important financial institutions as financing to generate data and assist in general research for the FSOC. A significant power given to the FSOC is the ability to dissolve a financial

institution – prior to its actual breakdown – if two thirds of the council believe that it would assist in preserving financial stability. The Dodd-Frank Act further goes on to recommend a stock market-based measurement for a financial institution’s contribution to systemic risk, namely its Marginal Expected Shortfall (MES) – the measure which will be used in this study’s empirical section.

Once the institutions responsible for the build-up of systemic risk have been identified, the Dodd-Frank Act proposes that the institutions be then subjected to more stringent regulatory practices, based on the criteria mentioned in the previous paragraph for identifying the institutions. A significant measure which the Dodd-Frank Act proposes is the banning of bank holding companies from proprietary trading activities³⁸, as well as imposing a bank ownership limit of 3 % of bank equity capital in hedge funds and private equity funds. The objective of such measures is to prevent institutions from potentially going bankrupt, and if they do get into difficulty, the FSOC has the authority to liquidate the institution prior to its actual bankruptcy. An aspect of the Dodd-Frank Act that has received criticism is the fact that, if a financial institution is liquidated by the FSOC prior to its bankruptcy and losses remain, other surviving financial institutions will be charged to cover these losses. Acharya (2012:7) instead argued that rewarding the surviving institutions may be a more appropriate response since under the current proposal, banks will be encouraged to herd in order to avoid potential charges, thereby further increasing the amount of systemic risk present. Another criticism levelled at the Dodd-Frank Act is based on its propensity to focus on individual institutions, as opposed to institutions as a group. This relates to fire sales and the subsequent comovement of asset returns among systemically important financial institutions and other interconnected institutions (Krainer, 2012:124).

The potential threat that large, complex institutions pose to the financial sector and economy as a whole is therefore recognised by the Dodd-Frank Act. In addressing the advantages and disadvantages of these institutions, a number of proposals are made. It is proposed that financial companies cannot merge if the combined liabilities will exceed 10 % of the industry total. This could be a successful proposal since an institution accounting for 10 % of the industry’s liabilities will be systemic, but it does not address a number of smaller institutions which may also be systemic (Richardson, Smith & Walter, 2010:197). The FSOC also has the ability to break up an institution if it believes that it poses a threat to financial stability, or certain activities deemed to be the source of risk can be terminated. This is, however, subject to judicial review and must take into account the international competitiveness of the US financial services industry in comparison with the regulatory structures in other countries.

Since breaking up an institution is not always feasible, a more practical measure to regulate the activities of banks was put forth by the Volcker rule, which attempted to limit the speculative activities they could

38 With the exception of underwriting and market-making activities (Krainer, 2012:124).

undertake. The rule initially proposed that in exchange for the safety net of government guarantees, banks could undertake commercial and investment banking activities, but could not undertake non-banking activities such as proprietary trading, principal investing, commodity speculation, hedge fund management, and private equity fund management (Richardson *et al.*, 2010:198). This version of the rule did not pass Congress and instead a modified version remained in the Dodd-Frank Act, which imposed limitations on banks that undertook these activities, with the limitations spread out up to seven years in the future. The limitations entail the disallowing of proprietary trading and restriction of bank ownership in hedge funds and private equity funds to a maximum of 3 % of the bank's Tier 1 capital, and a maximum share of 3 % in the total ownership of hedge funds and private equity funds. Krainer (2012:127) argued that there is a grey area in relation to market-making activities in connection with securities underwriting, while the Dodd-Frank Act allows banks to undertake market-making activities in connection with their underwriting and not have limitations imposed. The practical implications are that it would be challenging to differentiate market-making trades from proprietary trades, while there is also no limit on securities traded on direct or indirect obligations of US, state, and local government securities. Although the version of the Volcker rule that was subsequently implemented was watered down to some extent, it could still potentially make a contribution towards financial stability (Richardson *et al.*, 2010:206).

In addition to the activities of banking institutions, the Dodd-Frank Act also addressed the activities of insurance companies. Government bailouts of insurance companies, such as the bailout of AIG that took place during the sub-prime crisis, will need to be avoided in the future. The Dodd-Frank Act proposes that this will be done through the creation of the Federal Insurance Office in the Treasury Department, which would be responsible for monitoring events that may cause financial instability. The specific details associated with this regulation are left up to the discretion of the FSOC. Expanding on this view, Acharya, Biggs, Le, Richardson, Ryan, Cooley and Walter (2010:241) argued that insurance on macro risks³⁹ should not be sold to begin with, and if they are, they should be subjected to appropriate capital and liquidity requirements.

A description of what constitutes appropriate requirements is not completely clear, since the US does not believe the Basel risk-weightings are sufficient, stating that they only create an illusion of capital adequacy (Norton, 2013). The Collins Amendment which was added to the Dodd-Frank Act removed trust-preferred securities from Tier 1 capital and established two floors for insured deposit institutions, bank and thrift holding companies, and systemically important non-bank financial companies. The first floor should not be less than the generally applicable risk-based capital leverage ratio requirements, while the second

39 Macro risks are exposures to changes in aggregate or fundamental economic factors that could affect financial markets, the banking sector, or the economy as a whole (Weithers, 2007:44).

should not be quantitatively lower than these requirements, since they were effectively for insured depository institutions from the date of the enactment of the bill (Blundell-Wignall *et al.*, 2013:4). Furthermore, in order for systemically important financial institutions to be considered as adequately capitalised, they would need to meet a 5 % leverage ratio, while insured depository institutions within these groups would need a 6 % ratio. This was proposed in a joint statement by the Fed, Federal Deposit Insurance Corporation, and Office of Comptroller of Currency in July 2013 (Federal Reserve, Federal Deposit Insurance Corporation and Office of the Comptroller of the Currency, 2013).

The US has also introduced an initiative referred to as the Comprehensive Capital Analysis and Review exercise which approves the capital plans put in place by 18 bank holding companies. Stress testing is used to determine capital requirements, which increased significantly from USD399 billion in 2008 to USD792 billion in 2012. Another rule was proposed in 2012 to regulate foreign bank organisations operating in the US, requiring them to create intermediate holding companies which consist of all US banking and non-banking operations, with the rules on leverage and separation of activities applying to these intermediate holding companies – the implication therefore being that these intermediate holding companies are subject to stricter regulations than in their home countries (Blundell-Wignall *et al.*, 2013:5).

It can be argued that while the Dodd-Frank Act does have many positive initiatives that will improve financial sector stability in some ways, it does not address the private incentives of individual financial institutions that contribute to financial instability, and therefore it may be out-dated in certain areas once finally implemented, and does not clearly outline how to deal with possible future economic crises (Acharya, 2012:9). There were reports stating that the problem may have been with corporate governance structures within countries. An Organisation for Economic Co-operation and Development report argued that the sub-prime crisis could be attributed to failures and weaknesses in corporate governance agreements, since these routines are meant to safeguard against excessive risk taking (Kirkpatrick, 2009:65). This argument was supported by the National Commission on the Causes of the Financial and Economic Crisis in the US, who indicated that failures in corporate governance in systemically important financial institutions were a significant cause of the crisis (The Financial Crisis Inquiry Report, 2011). Diamond and Rajan (2009:6) and Bebchuk and Spamann (2009:10) both confirmed this finding by stating that poor bank governance structures resulted in excessive risk taking which could lead to larger losses during a crisis.

The purpose of corporate governance is essentially to ensure that the institution operates in the interest of the shareholders. The shareholders subsequently control the institution through boards and, in the case of banks, incentivise managers through contracts. There are many challenges to the efficacy of corporate governance in banks. One such a challenge involves the limits imposed on the concentration of ownership and takeovers. In the US, for example, non-bank ownership of banks is limited to a maximum

of 10 % of the voting stock, while variations of the same limit exist in other countries (Caprio & Levine, 2002; Laeven, 2013:7). Another challenge relates to the propensity of banks to be highly leveraged. If the shareholders have aggressive risk preferences, this may not be in the interests of other stakeholders. Laeven and Levine (2009:273) showed that banks with shareholders who exercise more control take on more risk. The risks associated with bank trading activities may be challenging to control by either shareholders or management. This especially relates to the ability of banks to create hard to quantify tail risks which are inherently difficult to assess (Acharya *et al.*, 2010:311). The placing of blame on management for neglecting such risks may therefore be difficult. While corporate governance may be seen as an important part of a bank's management, it does not possess an exact measure.

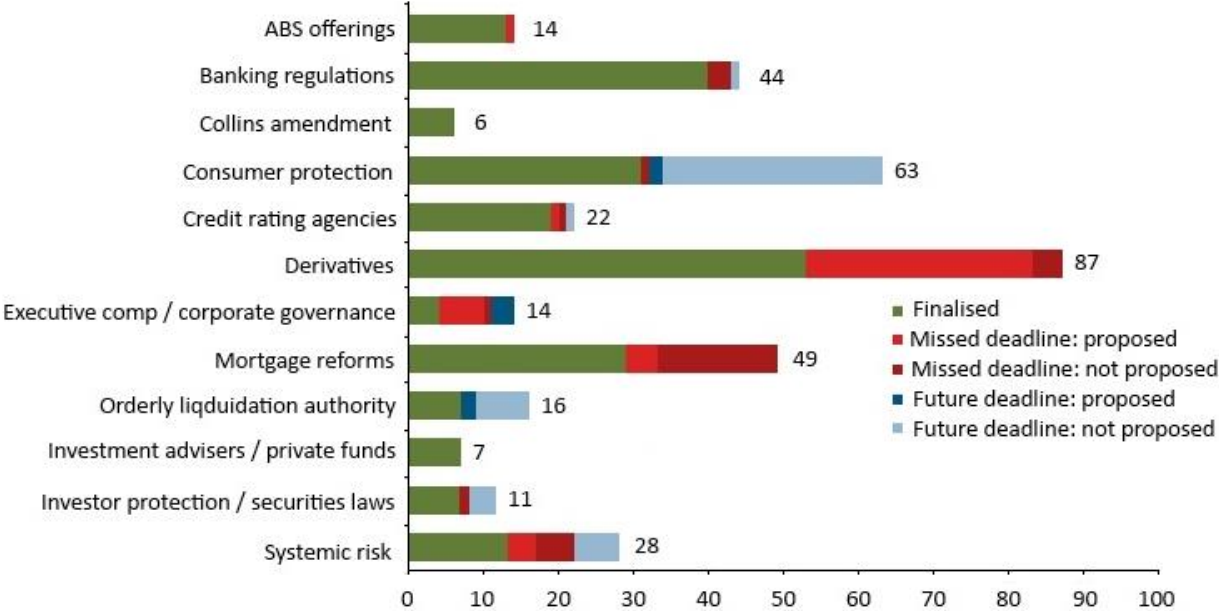
Beltratti and Stulz (2012:2) used two proxies to measure corporate governance. The first measure is the ownership of the controlling shareholder, and the second is whether the board of the bank was shareholder friendly. The study finds that banks with shareholder-friendly boards actually performed worse during the crisis. This is confirmed by a number of other studies such as Fahlenbrach and Stulz (2011:25) who found that banks with Chief Executive Officers who aligned their interests with those of shareholders performed worse during the sub-prime crisis, while higher option compensation for the Chief Executive Officer did not result in a bank performing worse. Erkens, Hung and Matos (2010:407) made use of a cross-country sample of financial institutions and found that institutions with greater board independence and higher institutional ownership experienced worse stock returns during the sub-prime crisis.

Despite the somewhat mixed nature of the evidence for the role of corporate governance, it may still be an important factor. It played a key role in the 2015 Democratic presidential primary debates in the US, with a number of senators proposing a reinstatement of many of the features of the original Glass-Steagall Banking Act discussed in Section 2.3.1.2 (Bloxham, 2015). Arguments were made that banks should not engage in securities trading, while non-bank financial institutions should not be able to use federally insured deposits to undertake transactions. A reinstatement of these features of the Glass-Steagall Act would effectively mean that investment banks, such as Morgan Stanley and Goldman Sachs, would no longer be classified as banks (Branson, 2014:31). The Volcker rule in its current form represents a middle ground between regulations prior to the sub-prime crisis, and regulations at present. It may be argued that individual corporate governance measures, such as the Sarbanes-Oxley Act,⁴⁰ if implemented correctly, could have had mitigating effects prior to and during the sub-prime crisis – but this argument is beyond the scope of this study.

⁴⁰ The Sarbanes-Oxley Act was implemented in order to improve corporate governance by modifying management's reporting responsibilities and overhauling the scope and specific responsibilities of the auditor (Zhang, 2007:75).

The success of the Dodd-Frank Act in ensuring financial stability so far remains mixed, especially since many of the measures have not yet been fully implemented, as indicated by Figure 3.2.

Figure 3.2: Dodd-Frank rulemaking progress in select categories (As of 15 July 2015).



Source: Davis Polk (2015:6).
 *Rulemaking counts are based on estimates and therefore require judgement.
 *Horizontal axis represents number of required rulemakings.

Figure 3.2 illustrates a significant variation in the number of rules finalised as a percentage of those required to still be finalised. This is especially clear in the systemic risk category, where approximately half still need to be finalised. Barth *et al.* (2013:30) described the Dodd-Frank Act’s regulatory reform as a band aid approach to financial regulation. Although it addresses all the potential causes of the crisis, it does not motivate the importance of these causes. It is furthermore argued that the Dodd-Frank Act, due to its complexity and scope, will result in significant regulatory burden. However, if the Act is successful in improving both the efficiency and stability of the financial system, it may justify the burden.

The response to the sub-prime crisis was bureaucratically comprehensive, but there is still much conjecture as to how successful the implemented measures have been so far, and potentially will be in the future. Based on the evidence presented in this section, it can be concluded in terms of the complexity of the US regulatory structure, not much has changed.

3.3.2 The SA regulatory approach

As an emerging market economy, the nature of systemic risk challenges that SA could experience may be different to those faced by the US. Chapter 1 illustrated the point that the SA financial sector is dominated by the five largest banks and that the sector is also characterised by a large degree of interconnectedness.

This section will expand upon that brief overview. Unfortunately, the literature relating to systemic risk and the regulation of it in the SA financial sector is rather limited, relying mostly on reports from the South African Reserve Bank (SARB) and the International Monetary Fund (IMF).

The SA financial sector consists of 31 banks, but is dominated by the four largest banks (ABSA, FirstRand, Nedbank, and Standard), one medium-sized bank (Investec), and two smaller banks who specialise in unsecured lending to low-income households (African Bank and Capitec) (IMF, 2014:10). The IMF (2014:10) has stated that the SA financial sector has a large degree of concentration and interconnectedness, due to the five largest banks accounting for 90.5 % of the banking assets. This characteristic also extends to the insurance and fund management sectors, where there is a significant amount of related party transactions between these financial institutions. The UK Barclays has a bank holding company in SA, Barclays Africa Group, which owns the majority stake of ABSA.⁴¹ Investec is dual listed on the Johannesburg Stock Exchange (JSE) and the London Stock Exchange, while the UK holding company is responsible for overseeing the non-African activities. Old Mutual in the UK indirectly owns Nedbank as well as a major SA insurance subsidiary. Standard Bank's holding company, the Standard Bank Group, owns majority shares in the Liberty Group which is one of the largest insurance companies in SA. The insurance companies that are associated with these banks are responsible for underwriting a large portion of assets for private pension funds, while some banks also own asset management companies that offer unit trusts (IMF, 2014:27). The SARB (2014:3) – which is responsible for maintaining financial stability – has stated that the growth of the non-bank financial institutions sector could pose potential systemic risks to the financial sector, as a result of it not being regulated as sufficiently as the banking sector is.

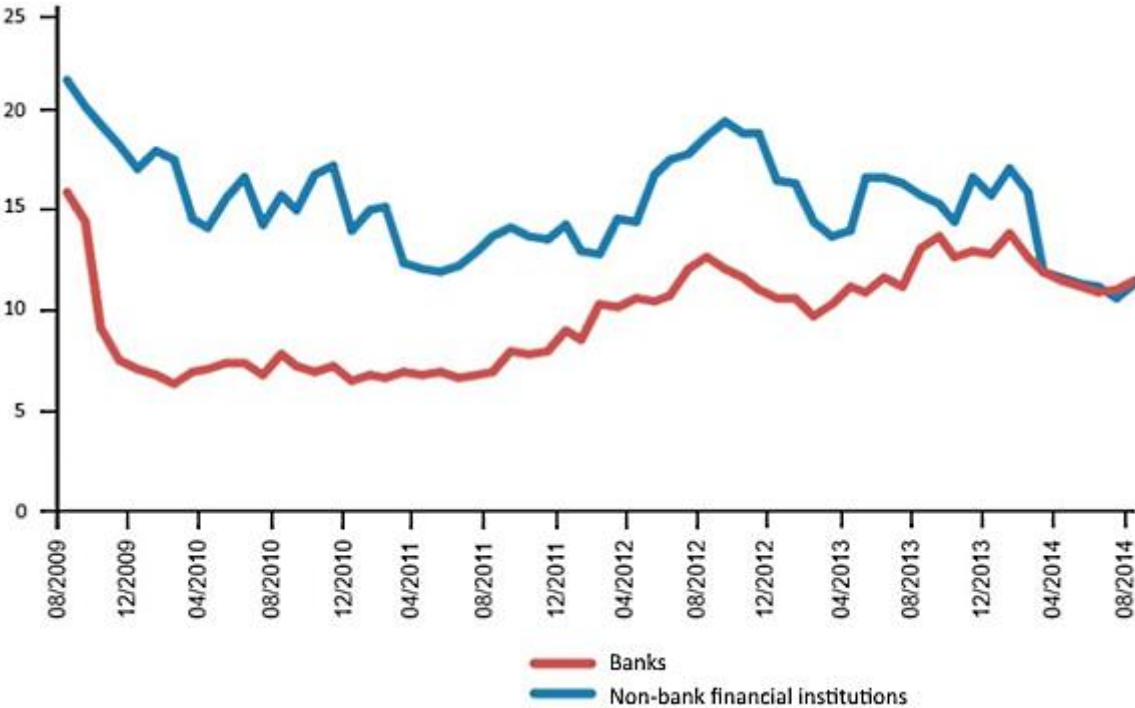
The failure of African Bank Limited (African Bank) in 2014 represents an important example of how the SA regulatory authorities mitigated a bank failure that could have had systemic effects, while simultaneously exposing the interconnectedness of the SA financial sector (SARB, 2014:18). The SARB (2014:6) explained that African Bank was placed under curatorship during August 2014 with assets amounting to ZAR58 billion, making up 1.44 % of the total banking sector assets. This curatorship was necessitated by a loss of confidence from shareholders and funders, and was also instituted to prevent contagion effects from African Bank's potential failure. The curatorship essentially entailed the splitting of the performing (good) assets from the non-performing (bad) assets, with the SARB being responsible for taking ownership of the bad assets. The good assets were transferred to a new good bank that was parented by a bank holding company capitalised with ZAR10 billion in share capital. The SARB (2014:17) explained that African Bank's

⁴¹ In 2016 it was announced that Barclays PLC (the UK Barclays) planned on selling this majority stake. In 2017 this sale had not yet been concluded (Saigal, 2016:60).

troubles began because shareholders and wholesale funders lost confidence in the bank's ability to generate earnings capable of maintaining business growth and returns on investment. This was characterised by the bank posting losses for three consecutive periods due to increased provisions against non-performing loans. During December 2013, the bank holding company of African Bank, African Bank Investments Limited (ABIL) was forced to raise ZAR5.5 billion in capital through a rights issue. This temporarily improved prospects, but March 2014 saw the share price and credit rating of ABIL falling when they increased provisions to ZAR2.5 billion, and posted losses of ZAR3.1 billion. August 2014 then saw additional credit impairments related to its more liberal unsecured lending portfolios, as compared with other banks. Finally, the bank posted expected headline losses of ZAR6.4 billion for September 2014 (SARB, 2014:17).

African Bank remained operational following the curatorship, although its loan advances had stricter lending criteria and reduced risk appetite. A run on retail deposits was absent due to a guarantee being provided on these deposits by the SARB, while no evidence of contagion on funding markets relating to retail or wholesale funding was observed. The success of the SARB in resolving the African Bank failure was due to its use of the key attributes of the effective resolutions regimes package outlined by the Financial Stability Board (FStB) (2014). The implementation of this package resulted in the continued operation of the bank and mitigation of contagion effects. Some spillover effects did, however, take place into bond markets, money market funds, and pension funds. Figure 3.3 below illustrates the vulnerability of a financial institution to spillover risks by measuring its conditional probability of default, given the default of another financial institution. A higher coefficient indicates a greater degree of spillover.

Figure 3.3: SA financial system spillover coefficients (%).



Source: IMF (2014:13).

African Bank’s debt accounted for 1.3 % of the assets held by 43 money market funds and caused a unit price fall in 10 of these funds, but the actions of the SARB played a role in limiting contagion, while the larger banks in general were mostly unaffected. The activities of non-bank financial institutions play an important role in financial intermediation in SA, and due to the level of interconnectedness they possess with other financial institutions, they have the potential to contribute to systemic risk (SARB, 2014:21).

The potential for risks to be amplified by the interconnectedness of the financial system is explained by the IMF (2014:16). Money market funds and other non-bank financial institutions invest a large amount of their assets in the largest banks through short-term instruments, such as deposits, which have the dual effect of exposing the non-bank financial institutions to counterparty risk and the banks to liquidity risk. This is because a large fund withdrawal could stress bank liquidity, while a bank failure could impact on the non-bank financial institutions’ asset quality. The additional interconnectedness of insurance companies with the major banks also poses a threat to financial stability. Apart from cross-ownerships and equity investments, SA banks obtain a large portion of funding from long-term insurers. The potential therefore exists for a shock to be transmitted from one of those sectors to another, and for it to become systemic in nature (IMF, 2014:72). This potential also exists because the regulation of such institutions – as explained in Chapter 1 – is fragmented. This could make regulations challenging, but the switch to a Twin Peaks regulatory structure in 2016 may improve this.

The Twin Peaks regulatory structure will essentially see an end to the fragmentation in the SA regulatory environment. Two authorities will take responsibility for the financial sector, the market conduct regulator in the Financial Services Board (FSeB), and the prudential regulator in the SARB. The FSeB will be responsible for the protection of consumers of financial services, and the promotion of confidence in the financial system. The SARB will be responsible for the safety and financial stability of regulated financial institutions. The SARB will also be the systemic regulatory authority of the financial system, including the prudential regulation and supervision of both banks and insurers. These responsibilities will also include the implementation of macroprudential regulations (National Treasury, 2011:11). As the prudential regulator, the SARB will have the potential to impact on the systemic risk of the SA financial sector in a significant way. The prudential standards that the SARB will be able to set include those related to liquidity, leverage, capital, and general risk management (National Treasury, 2014:56). If implemented correctly, the Twin Peaks regulatory structure has the potential to significantly improve the financial stability and oversight of the SA financial sector. This is because the SARB would be able to raise the requirement standards in accordance with its assessment of the financial sector and adjust these requirements in response to specific risks (National Treasury, 2014:56).

In terms of country-specific risks, the IMF (2014:16) explained that the SA economy remains vulnerable to capital flows, due to its dependence on external financing. This is, however, not necessarily due to banks being reliant on these flows themselves. Banks are affected by changes in the domestic funding market pricing – which is affected by the significant current account and fiscal deficits. Funding costs for banks can therefore increase due to changes in the demands of investors. The larger banks are also more likely to be affected by external shocks and global risk re-pricing due to their reliance on short-term wholesale funding, as well as their active trading in the over-the-counter derivatives market. These risks have been mitigated to an extent, as the economy has been buffered somewhat from capital flow volatility by the flexible exchange rate and capital controls, but the external position is still more vulnerable than fundamentals and policies would imply (IMF, 2014:16). This is shown by a number of key financial indicators in Table 3.6 below.

Table 3.6: Key financial indicators for SA financial sector on 30 June 2014.

Size of banking sector (ZAR trillions)	
Total assets of all banks operating in the jurisdiction	ZAR4.18
Total assets of all major locally incorporated banks	ZAR4.18
Total assets of all locally incorporated banks to which capital standards under the Basel framework are applied	ZAR4.18
Number of banks	
Number of banks operating in SA	31
Number of internationally active banks	31
Number of banks required to implement Basel standards (according to domestic rules)	31
Number of global systemically important financial institutions	0 (1 subsidiary of a global systemically important financial institution, 6 branches of foreign institutions regarded as global systemically important financial institutions)
Number of domestic systemically important financial institutions	0-2 (see discussion below)
Capital standards under the Basel framework	
Number of banks on internal ratings-based approach for credit risk	6
Number of banks on internal models approach for market risk	6
Number of banks on advanced measurement approaches for operational risk	4
Number of banks on internal model method for counterparty credit risk	0
Capital adequacy (internationally active banks) (ZAR trillions; %)	
Total capital	ZAR 0.32
Total Tier 1 capital	ZAR 0.26
Total common equity Tier 1 capital	ZAR 0.25
Total risk-weighted assets	ZAR2.02
Risk-weighted assets for credit risk (percentage of total risk-weighted assets)	82.3 %
Risk-weighted assets for counterparty credit risk (percentage of total risk-weighted assets)	2.9 %
Risk-weighted assets for market risk (percentage of total risk-weighted assets)	3.4 %
Risk-weighted assets for operational risk (percentage of total risk-weighted assets)	11.4 %
Total off-balance sheet bank assets	ZAR1.11
Capital adequacy ratio (weighted average)	14.8 %
Tier 1 ratio (weighted average)	11.9 %
Common equity Tier 1 ratio (weighted average)	11.4 %

Source: BCBS (2015b:32).

Two significant factors will be highlighted from among these indicators. It is important to note that all banking assets, and therefore all banks, are subjected to the Basel framework and are required to comply with it. The number of domestic systemically important financial institution is classified as 0-2 because different sources provide different reports. The BCBS (2015b:32) reported that the data are not yet available, therefore the number could not presently be confirmed, while the IMF (2014:57) reported that only two local banks which focus on retail banking are systemically important. The exact number of domestic systemically important financial institutions can therefore not yet be stated with certainty. Overall, the BCBS (2015b:4) found that the SA regulations for financial institutions were Basel compliant, which is an encouraging sign.

The current Basel requirements include a domestic systemically important financial institution capital requirement, conservation buffer, and countercyclical capital buffer which will be phased in during 2016 in order to replace the current 1 % systemic risk charge imposed on banks. Other requirements include a 4 % leverage ratio, while 2.5 % of total liabilities must be held in liquid assets (IMF, 2014:22). The liquidity coverage ratio was to be phased in during 2015, and will require banks to meet the minimum of 60 %, although banks which do not meet this will be supported by a Committed Liquidity Facility from the SARB (IMF, 2014:20).

The SARB, however, uses its own approach to identify domestic systemically important financial institutions, although it is largely based on the Basel method. The indicators and weightings were adjusted in order to reflect the characteristics of the SA financial sector. A comparison of the SA approach and Basel approach is provided in Table 3.7 below.

Table 3.7: SA and Basel domestic systemically important financial institution assessment methodology.

Indicator	SA’s domestic systemically important financial institution methodology indicators	Basel’s domestic systemically important financial institution methodology indicators
	Weighting (%)	Weighting (%)
Size	20	20
Global activity	10	20
Interconnectedness	20	20
Substitutability	20	20
Complexity	10	20
Impact on confidence within the financial sector/social impact	20	n/a

Source: SARB (2013:33).

The addition of a new indicator and the reduction in weighting of certain indicators is explained by the SARB (2013:33) as follows. The 'impact on confidence indicator' is unique to SA and represents the impact that the failure of a bank would have on financial inclusion and social considerations in the SA financial sector, i.e. whether the failure of a bank results in customers losing confidence in the banking sector as a whole, potentially resulting in spillover effects to other banks. In order to provide this indicator with a 20 % weighting, the complexity indicator was reduced, since SA banks' participation in complex activity is limited, while the global activity indicator was also reduced for the same reason.

Although no formal systemic protection authority, such as a framework for systemic liquidity provision exists, the SARB has intervened in cases where liquidity injections were needed to preserve financial stability (IMF, 2014:58). The shift towards a macroprudential approach can only fully take place once the Twin Peaks regulatory approach has been implemented. The SARB will be able to implement macroprudential tools in accordance with adequate systemic risk analysis. The IMF (2014:26) argued, however, that in order for the SARB to be an adequate systemic regulator, it should be given greater resources, such as the ability to assimilate more granular data, as well as conduct system-wide stress tests with a focus on systemically important financial institutions. Considering the role played by non-bank financial institutions in the SA financial sector, special attention should also be given to this area. It may, however, be argued that such attention is already paid through the high standards of corporate governance in SA (IMF, 2014:65).

The corporate governance approaches for the US and SA are markedly different. Corporate governance was blamed for having played a large role in the sub-prime crisis (although with unconvincing evidence). The SA case for corporate governance is, however, less prominent. The main corporate governance approach in SA is the Third Report on Governance in SA (King III), and is an important part of risk management in SA. King III focuses on the importance of annual reporting on the positive and negative effects the company has on the economic situation of the community in which it operates. Further emphasis is then placed on how the company plans to improve the positive effects, while also removing any negative effects during the year ahead (IODSA, 2012:4). King III addresses the role that corporate governance may have had in the sub-prime crisis, stating that problems in global financial architecture should not necessarily indicate a deficiency in the SA and UK corporate models, since they are more value-based and apply corporate governance in both form and substance (IODSA, 2012:8). Therefore, keeping in line with the limited evidence supporting the role of corporate governance during the sub-prime crisis, the King III report rejects a call for US-styled corporate governance in SA (IODSA, 2012:8).

3.3.3 Section summary

The US response to the sub-prime crisis was essentially provided by the Dodd-Frank Act. While it does make many sweeping and promising changes, the success of these changes is yet to be seen and in many cases, yet to be implemented. The main goal of the Dodd-Frank Act, in terms of systemic risk, is the identification before it has built-up. It suggests that stress tests be used and then the most systemically risky institutions be subjected to more stringent regulations. It is also argued that corporate governance played a large role in the sub-prime crisis, although the evidence supporting this is mixed. Consequentially, corporate governance measure such as the Glass-Steagall Act and Volcker rule still remain as relevant platforms upon which US politicians position their campaigning.

By comparison, the SA regulatory approach is less intricate than the US approach. The SA approach faced a significant test during 2014 with the failure of African Bank. The SARB was able to mitigate any systemic consequences and was subsequently praised by the IMF for its swift intervention (IMF, 2014:7). The SA regulatory structure is in the process of a shift towards a Twin Peaks regulatory model, with finalisation to take place in 2016. The reliance of SA on capital flows, as well as the interconnectedness of the financial sector, remains however as the potential main areas of concern. In terms of corporate governance, the King III report argues that large scale changes to corporate governance, similar to those made in the US, are unnecessary.

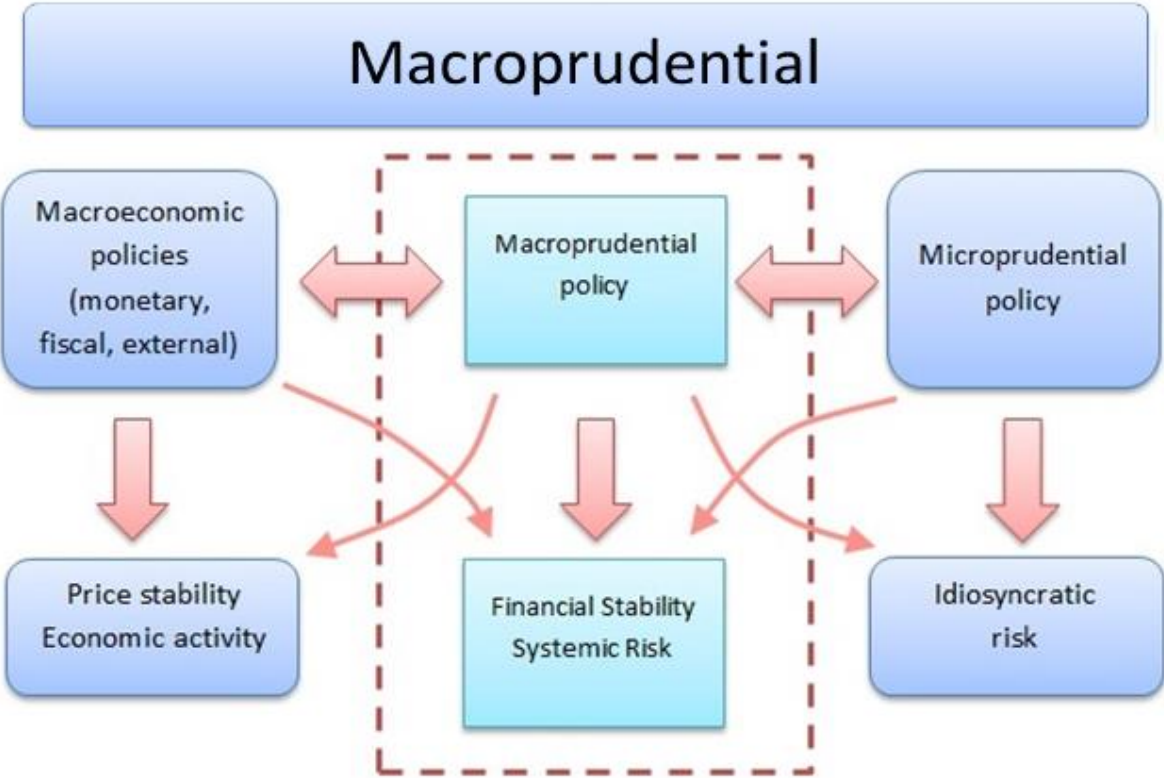
Although both countries are pursuing progressive changes to their regulations, a focus on the stability of the financial sector as a whole is not yet a priority. In order to ensure the stability of the macroeconomy, monetary and fiscal policies are used, while microprudential policies are used to mitigate idiosyncratic risk. Looking forward, a macroprudential policy approach may be used to bridge the gap between these two approaches.

3.4 MACROPRUDENTIAL REGULATIONS

The sub-prime crisis illustrated the fact that the use of microprudential tools focusing only on the risks of individual firms is inadequate in mitigating systemic risk (Georg, 2011:4). In response to this, Basel III began implementing more macroprudential policy tools, such as the conservation and countercyclical capital buffers. In addition to mitigating systemic risk and ensuring financial stability, macroprudential policies may be necessary because price stability alone will not ensure welfare maximisation (IMF, 2013:5). This is because imperfections in financial markets may distort individual behaviour, resulting in exaggerated ex ante risk taking and an amplification of the boom-bust cycle, as illustrated in Section 2.3.1. A bias in the composition of output can occur when the individual behaviour distortion varies over time or responds to certain economic conditions – resulting in one economic sector being more affected than another (Curdia & Woodford, 2009:32). Since financial instability is therefore indicative of instability in

the level or composition of output, it may be necessary to add financial stability as an intermediate policy goal in order to maximise welfare (IMF, 2013:5). A graphical depiction of how the macroprudential policy approach fits into the broader spectrum of policies and objectives following the sub-prime crisis is illustrated in Figure 3.4.

Figure 3.4: Policies and objectives after the sub-prime crisis.



Source: IMF (2013:6).

Based on Figure 3.4, it can be seen that macroprudential policies attempt to bridge the gap between existing macroeconomic and microprudential policy approaches. Borio (2003:2) described the difference between macroprudential and microprudential regulations as follows. Microprudential regulations are a bottom-up approach concerned with protecting the consumer and limiting the distress of individual institutions by focusing on exogenous risk. Macroprudential regulations are a top-down approach concerned with avoiding output (GDP) costs and limiting system-wide financial distress by focusing, in part, on endogenous risks, while also considering correlations and common exposures across institutions. Risks are endogenous if they are dependent on the collective actions of individual financial institutions, while exogenous risks are beyond the influence of individual institutions.

The use of macroprudential regulations may, however, not be entirely simple. Firstly, the implementation of a macroprudential approach may depend on the specific dimension of systemic risk which needs to be mitigated. Section 3.4.1 therefore discusses the macroprudential policies that could be implemented

depending on the systemic risk dimension being addressed. Secondly, since macroprudential regulations attempt to bridge the gap between macroeconomic and microprudential policy, some adverse reactions may occur as a result. Section 3.4.2 addresses the way in which monetary policy, in particular, interacts with macroprudential policies and how the two policies may affect each other. Monetary policy is singled out (rather than fiscal policy) due to the way in which it interacts with and could potential conflict with macroprudential policy. Since the financial cycle is seen as the main driving factor behind financial crises, an implementation of macroprudential policies requires a sound understanding of this cycle. Furthermore, a number of macroprudential policy tools are available and the correct implementation of these tools will be dependent on a few specific factors. Section 3.4.3 provides a brief overview of the financial cycle's key properties and how they relate to macroprudential policies, while further providing an overview of the various macroprudential policy tools the regulators have at their disposal.

3.4.1 Implementing a macroprudential regulatory approach

In order to effectively implement a macroprudential regulatory approach, it must be understood which dimension of systemic risk is being addressed. Clement (2010:64) pointed out that the macroprudential approach can have two dimensions. The first focuses on how risk evolves over time, specifically with reference to the financial cycle, and how it is reinforced by the real sector and vice versa, i.e. the procyclicality of the financial system. This aligns with the time dimension definition of systemic risk discussed in Section 2.2 and therefore encourages the building-up of capital buffers during upswings which can be drawn on during downswings. The second focuses on the similar exposures of institutions in the financial system and the interconnections between them, also referring to how risk is distributed at any given point in the financial system. This aligns with the cross-sectional dimension of systemic risk discussed in Section 2.2 and therefore makes use of policies focusing on the individual contribution that an institution makes to systemic risk. It is therefore clear that the objectives of macroprudential regulations are focused on mitigating systemic risk.

Borio (2010:5) examined how demanding a macroprudential regulatory approach should be to ensure systemic risk mitigation. In terms of the time dimension, considering that the objective is to build up the strength of the financial system for downturns, the capital and liquidity buffers should be large enough so that fire sales and credit restrictions can be avoided. Undertaking this buffer build-up during upswings makes logical sense, since it would be the most cost-effective time to do so. A more stringent form of the regulations could include control over the upswing, thereby limiting a build-up of risk during these good times. This could effectively be done by promoting the build-up of buffers for the downswing while also controlling credit expansion, asset price increases, and risk premium compression (Borio, 2010:6). The success of these regulations so far have been somewhat mixed. Borio and Shim (2008:19) found that

barriers of an analytical, institutional and political economy nature are hindering the rate at which macroprudential policies are being implemented. The Committee on the Global Financial System (CGFS) (2010) conducted a survey of central banks in a number of countries and reported that some authorities had stated that macroprudential instruments enhanced the resilience of their financial systems. The conclusion was, however, that it was still too early to say whether they would be successful in the long run.

In terms of macroprudential policies and small open economies, the findings so far have been encouraging. Section 2.5 illustrated the fact that emerging markets are vulnerable to capital flows, and many emerging markets – including SA – can be characterised as small open economies. It has been shown that capital flows in small open economies are driven by the differentials between domestic and global policies, where higher domestic rates encourage capital inflows, which in turn contributes to maturity and currency mismatches, and increased leverage (Hahm, Mishkin, Shin, H.S. & Shin, K., 2012:16). Macroprudential measures may be able to solve the problems arising from interactions between capital flows and monetary policy. A number of promising results were shown in Hahm *et al.* (2012). These include a levy applied to non-core foreign exchange liabilities, which has the effect of altering the composition of flows, thereby reducing financial instability associated capital flows. In order to counteract default risks associated with policy differentials which encourage borrowing in foreign exchange, higher risk weights, more stringent loan-to-value ratios,⁴² and limiting foreign exchange lending have all shown promise. A combination of higher capital and reserve requirements can manage sudden credit growths that occur due to capital flows – thereby working in tandem with policy rate changes and encouraging increased policy independence. Considering this evidence, the use of targeted macroprudential measures to mitigate the systemic risk associated with capital flows is promising (IMF, 2013:18).

The interaction between macroprudential policies and monetary policy alluded to above is especially important when it is considered that monetary policy can only be successful if the financial system is stable (Borio & Shim, 2008:4). Since both macroprudential policies and monetary policy attempt to moderate fluctuations in the financial cycle, it may be inevitable that they could either conflict or reinforce each other in some way (Angelini, Neri & Panetta, 2011:3).

3.4.2 The interaction of macroprudential policy and monetary policy

The way in which monetary policy and macroprudential policies interact could potentially be one of the most significant challenges facing the successful implementation of a macroprudential regulatory approach. Conventional monetary policy measures are not well-suited to mitigating systemic risk, and

⁴² Loan-to-value is the ratio of a loan's value in relation to the value of an asset purchased. Maximum loan-to-value ratios on mortgages have been adopted by some countries as a macroprudential policy instrument (Wong, Fong, Li & Choi, 2011:3).

price stability does not necessarily coincide with financial stability (Tressel & Zhou, 2013:385). The argument made in Section 2.3 was that loose monetary policy and low interest rates played a key role in allowing the sub-prime crisis to develop by fuelling the upswing in the credit and asset price cycle, while also providing excess liquidity to financial intermediaries during a downswing (Tressel & Zhou, 2013:385). Since macroprudential and monetary policies share some transmission channels, they may interact and conflict with each other – even if they have different objectives (IMF, 2013:10). When macroprudential instruments are constrained, monetary policy will have to respond to systemic risk, while the effectiveness and possible side effects of macroprudential policies are still uncertain (Tressel & Zhou, 2013:385). Ingves (2011:23) further explained that macroprudential policies can have an effect on price stability by using simplified, stylised views of the monetary policy transmission mechanism in Equations 3.5 and 3.6.

$$i_t^{lending} = i_t + \delta_t. \quad (3.5)$$

Equation 3.5 illustrates the lending rates of banks ($i_t^{lending}$) as a function of the policy rates of the central bank (i_t) plus the interest rate margin (δ_t). The interest rate margin will be determined by factors such as the administrative costs, capital costs, risk premiums and bank profit margins. During a crisis period, a divergence between the policy rate and market rate may occur due to credit risk uncertainty. Macroprudential policy will essentially render the bank lending rate a function of bank regulations (Ingves, 2011:23).

$$i_t^{lending} = i_t + \delta_t(z_t). \quad (3.6)$$

Equation 3.6 adds variable z_t to illustrate the regulations which affect the interest rate margin. This may represent macroprudential instruments that have a once-off effect on the interest rate margin, such as capital or reserve requirements, or an on-going effect through instruments such as a time-varying countercyclical capital buffer. It should, however, be noted that the overlapping of the two policy approaches does not imply perfect substitutability (Bean, Paustian, Penalver & Taylor, 2010:23). It may instead be necessary to coordinate their uses and construct a situation where they work in tandem to achieve policy objectives and to avoid conflicts that may exacerbate conditions. In order to thoroughly explain the overlap that occurs between macroprudential policy and monetary policy, it will be prudent to sufficiently analyse the challenges which form part of such a process.

Ingves (2011:25) explained that the analysis of this overlap may be challenging for three reasons. Firstly, the introduction of financial instabilities in central bank models is difficult because the financial sector cannot be adequately modelled. Secondly, psychology is an occasional driver of financial market developments, but is a difficult characteristic to model with rational agents. Thirdly, the risk of a crisis has to be modelled as an extra channel in the transmission mechanism, as opposed to the regular way. Lastly,

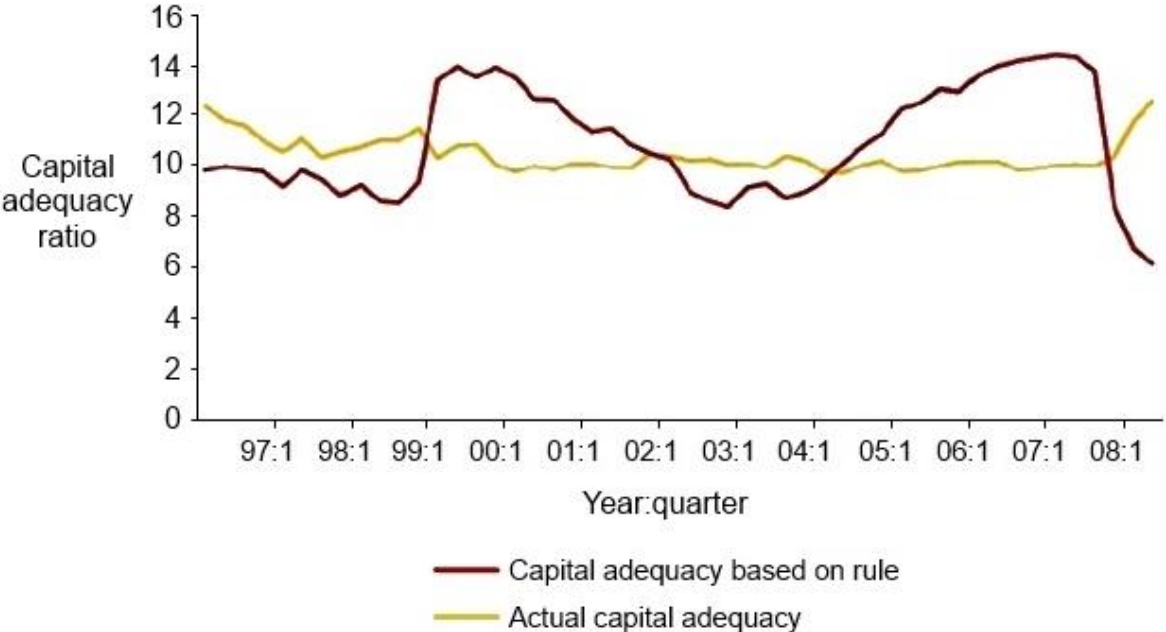
it is difficult to provide policymakers with models that guide them on when to act. Two potential approaches can be undertaken. The first was proposed by Woodford (2012:12), who describes a new Keynesian model with a normal credit spread state and an elevated state during a crisis. The case made is that leverage is responsible for financial instability as opposed to asset prices. A regular New Keynesian model would have the optimal policy goal of a constant output-gap adjusted price level (Ingves, 2011:25). In this adjusted model, however, since leverage increases the probability of a crisis, a factor should be included that increases the marginal expected losses from a crisis for every unit increase in leverage. A balance between financial stability, inflation and output objectives can then take place. The second approach that was proposed by Ingves (2010:10) uses two forms of the Taylor rule. The first is the normal Taylor rule used for monetary policy, while the other describes that regulations can vary based on the assessment of a factor such as credit growth. These two versions will be connected via the monetary transmission mechanism described by Equation 3.6 previously. The Taylor rule for monetary policy determines the policy rate (i_t) while the interest rate margin (δ_t) is affected by the regulation measures (z_t) which in turn is influenced by the non-time-varying regulations (\bar{z}), the credit gap ($I_t - \bar{I}_t$), and the output gap ($y_t - \bar{y}_t$).⁴³ This proposes Equation 3.7.

$$z_t = z(\bar{z}, I_t - \bar{I}_t, y_t - \bar{y}_t, \dots). \tag{3.7}$$

Equation 3.7 therefore illustrates the relationship between monetary policy and macroprudential policy by combining the Taylor rule for monetary policy with the Taylor rule for regulations. It should be noted that this is only a loose concept used for illustrative purposes (Ingves, 2010:10). As an example of such an application, Figure 3.5 demonstrates the effect of a theoretical countercyclical capital buffer on the capital adequacy of Sweden’s banks.

⁴³ The credit gap and output gap are both measured as the actual credit volume and actual output volume in relation to a level seen as sustainable over the long term (Ingves, 2011:26).

Figure 3.5: The effect of a countercyclical capital buffer on capital adequacy.



Source: Ingves (2011:26).

Figure 3.5 uses a simplified version of the rule explained above, where capital adequacy for the four largest banks in Sweden is a function of the long-run capital adequacy ratio, the output gap, and the credit gap (Ingves, 2010:26). The key finding from this figure is that the rule would have increased the banks’ capital prior to the sub-prime crisis and decreased it afterwards, in accordance with the financial cycle.⁴⁴

The countercyclical capital buffer depicted above is just one of a number of macroprudential policy tools that exist. Macroprudential policy tools are essentially policy instruments that can be used to mitigate the causes of systemic risk and to reduce the externalities that may contribute to adverse financial sector developments (Claessens *et al.*, 2013:155). The selection and implementation of the correct tools are, however, conditional on a number of factors.

3.4.3 Macroprudential policy tools

Under macroprudential policies, the financial cycle is seen as the main systematic factor driving all the other idiosyncratic factors, i.e. the financial cycle underlies large financial crises (Arnold *et al.*, 2012:3127). The focus of macroprudential policies would therefore be on improving the systemic regulation and supervisory frameworks, as opposed to focusing on individual institutions. Since the financial cycle plays a key role in macroprudential policy implementation, a brief analysis of its key properties may be necessary. Arnold *et al.* (2012:3128) provided a succinct summary as follows:

⁴⁴ Further discussions on how monetary policy and macroprudential policy should potentially be separated were provided by Ingves (2014).

- i. The financial cycle is best described in terms of the behaviour of private-sector credit and property prices. Equity prices are not included because they illustrate shorter cycles and respond more to short-term changes;
- ii. The frequency of the financial cycle is lower than the business cycle's, with a length of up to 8 years, compared with approximately 16 to 20 years. The implication is that the financial cycle is categorised as a medium-term event;
- iii. Peaks in the financial cycle and periods of financial distress coincide with each other;
- iv. The few crises that do not occur at domestic financial cycle peaks are in turn due to exposures to financial cycles in other countries;
- v. Real-time indicators of banking crises that provide a two- to four-year signal can be constructed. Indicators of this nature tend to be based on private sector credit-to-GDP and asset prices jointly exceeding a threshold level. These indicators are essentially proxy measures for the build-up of financial imbalances; and
- vi. The regime employed will affect the amplitude and length of a financial cycle, with three factors having supporting influences. Firstly, the weakening of financial constraints through financial liberalisation. Secondly, lower resistance to a build-up of financial imbalances as a result of stable levels of low inflation – facilitated through a monetary policy approach targeting short-term inflation control. Lastly, positive supply-side developments, such as the globalisation of the real economy, which exert downward pressure on inflation and reinforce the financial boom.

The countercyclical capital buffer briefly discussed in Section 3.2.2 is an example of a policy recommendation which takes into account the six aspects mentioned above. The objective of the countercyclical capital buffer is essentially to build up a capital buffer during the financial cycle's boom period, and then to use those buffers during the financial cycle's downturn period, with the added benefit of constraining activity during the boom period (Drehmann, Borio & Tsatsaronis, 2011:197). In order for the accurate implementation of a countercyclical capital buffer, however, an accurate leading indicator may be needed which can provide early indications for both the build-up phase and the release phase (Drehmann *et al.*, 2011:198). The BCBS (2010:3) identified the credit-to-GDP gap as the measure for the build-up phase. An appropriate variable has not yet been identified for the release phase, but other variables such as credit spreads and bank losses may be used to indicate the arrival of a financial downturn (BCBS, 2010:25). Two challenges for the countercyclical capital buffer may arise. The first concerns the political resistance to the implementation of the countercyclical capital buffer, since the use of the credit-to-GDP measure is only a guideline for when its implementation should take place (Drehmann *et al.*, 2011:199). The second refers to conjecture surrounding cross-border exposures such as how to address exposures influenced by the financial cycles in other countries, or how the impact of international lending

can be offset. The answers to these challenges are that the countercyclical capital buffer will be calculated relative to the weighted average of the bank's exposures to a number of jurisdictions, while cooperative arrangements will also take place where the countercyclical capital buffer is activated by the host authority as opposed to the home authority (Drehmann *et al.*, 2011:224). The countercyclical capital buffer is therefore a promising policy recommendation for countries that need greater regulation during their financial cycles. The case for other macroprudential policies will largely be dependent on determining if they are necessary for a particular country, based on the country's specific characteristics.

Macro stress tests could be seen as an important factor in determining macroprudential regulations because they focus on stressing the entire financial system as opposed to individual institutions within it (Borio, Drehmann & Tsatsaronis, 2014:3). The success of these tests is arguable, especially when it is considered that they failed to provide any significant warnings prior to the sub-prime crisis (Arnold *et al.*, 2012:3128). Borio *et al.* (2014:4) explained that a macro stress test involves a set of risk exposures subjected to exogenous shocks from some scenario, while a model maps and traces the impact of the shocks onto an outcome which is subsequently measured. Borio *et al.* (2014:8) argued that the current challenge with macro stress tests is that the model element cannot capture the intricacies of financial distress accurately. Adjusting the size of the exogenous shock does not provide the same effect, since the objective of the test is to model financial instability – which entails a normal-sized shock causing a financial system collapse. Another challenge relates to the interpretation of certain indicators, such as credit growth, asset prices, leverage, volatility, and risk premiums. All of these indicators may illustrate a strong financial system even though risk had been building up during a boom phase (Borio *et al.*, 2014:8). Considering these challenges, macro stress tests may be better suited in identifying additional capital needs and, due to current designs, are not necessarily appropriate as an early warning indicator (Arnold *et al.*, 2012:3129).

Given the unsuitability of macro stress tests in highlighting potential areas of weakness, the implementation of a macroprudential policy approach will need to be calibrated in a certain way in order to reflect a particular measure of financial instability, or in the case of this study, systemic risk. The two different dimensions of systemic risk may play a role here. Borio (2010:7) explained that the ideal measure for the time dimension of systemic risk would be a leading indicator of financial distress which provides at least a year's warning. Such a leading indicator could allow an inflation targeting type of approach, whereby the measure is gauged and calibrated in advance. This coincides with the countercyclical capital buffer approach outlined above. The ideal measure for the cross-sectional dimension of systemic risk would be a vigorous quantitative measure of each institution's contribution to systemic risk as a whole, which was briefly reviewed in Section 2.5. These measures rely on market prices and essentially characterise the financial system as a portfolio of financial institutions. It will be important that the correct

indicators are used for the appropriate dimension of systemic risk, because an indicator for the cross-sectional dimension of systemic risk may not provide accurate signals when applied to the time dimension. In addition, a number of macroprudential policies are available to choose from.

The various macroprudential policies available are summarised in Table 3.8 below. The columns represent the goals of the various policies, while the rows represent the intermediate targets. The first two rows address the cyclical financial risks that may occur. Their focus will therefore be on either a dampening of the expansionary phase or increasing the resilience of the financial sector to a contractionary phase. The third row focuses on the risks that may arise due to interconnectedness, such as contagion or the effects of common shocks. The columns classify the policies according to their intended target and the method undertaken. Claessens, Ghosh and Mihet (2013:157) explained these classifications as follows:

- i. Quantitative restrictions imposed on borrowers, instruments, or activities;
- ii. Capital and provisioning requirements;
- iii. Other quantitative restrictions imposed on financial institutions' balance sheets;
- iv. Taxation/levies imposed on activities or balance sheet composition; and
- v. Other more institutional-oriented measures, including accounting and compensation changes.

The classifications also line up with specific objectives, such as (i) attempting to decrease the demand for financing, while all the other factors affect financing from the supply side. More specifically, tools in (ii) attempt to improve financial sector resilience, while (iii) and (iv) attempt to dampen the effects of the financial cycle. A specific measure under each classification can also be used to address particular fundamental factors which may cause externalities and market failures, or to address policy factors – such as pro-cyclicality – which can negatively affect the financial sector. In the list above, classifications (i) to (iv) should also be viewed as time-varying, institution-varying, or state-varying, while classification (v) addresses structural factors. Many of the policy tools are used to achieve microprudential objectives, but by calibrating them to vary according to time, institution or state, they can be used for macroprudential objectives. The tools can also be classified as being either broad based or targeted, as well as either rule based or discretionary (Claessens *et al.*, 2013:157). An accurate classification is challenging to illustrate simply, but Table 3.8 provides the best attempt. A simplified classification is provided here through the columns, rows, and the colour guide.

Table 3.8: The macroprudential policy toolkit.

Policy Tool					
	Restrictions related to borrower, instrument or activity	Capital requirements, provisioning, surcharges	Restrictions on financial sector balance sheet (assets, liabilities)	Taxation, levies	Other (including institutional infrastructure)
Expansionary phase	Time-varying caps/limits/rules on: <ul style="list-style-type: none"> • Debt-to-income, loan-to-income, loan-to-value • Margins, haircuts • Lending to sectors • Credit growth 	Countercyclical capital requirements, leverage restrictions, general (dynamic) provisioning	Time-varying caps/limits on: <ul style="list-style-type: none"> • Mismatches (Foreign Exchange, interest) • Reserve requirements 	Levy/tax on specific assets and/or liabilities.	<ul style="list-style-type: none"> • Accounting (e.g. varying rules on mark-to-market) • Changes to compensation, market discipline.
Contractionary Phase: fire sales, credit crunch	Adjustment to specific loan-loss provisioning, margins or haircuts (e.g. through the cycle, dynamic)	Countercyclical capital requirements, general (dynamic) provisioning	Liquidity limits (e.g. net stable funding ratio, liquidity coverage ratio)	Levy/tax (e.g. on non-core liabilities)	<ul style="list-style-type: none"> • Standardised products • Over-the-counter vs on exchange • Safety net (Central Bank/Treasury liquidity, fiscal support)
Contagion, or shock propagation from systemically important financial institutions or networks	Varying restrictions on asset composition activities (e.g. Volcker, Vickers)	Capital surcharges linked to systemic risk	Institution specific limits on (bilateral) financial exposures, other balance sheet measures	Tax/levy varying by externality (size, network)	<ul style="list-style-type: none"> • Institutional infrastructure (e.g. central counterparties) • Resolution (e.g. living wills) • Varying information, disclosure
		Enhancing resilience			
		Dampening the cycle			
		Dispelling gestation of cycle			

Source: Claessens *et al.* (2013:156).

The specific macroprudential policy tool that should be implemented will depend on the identification of the source of a particular externality. This links up with the definition of systemic risk proposed in Section 2.2.1 by De Nìcolo *et al.* (2012:5) relating to externalities which take place in three broad categories. To briefly review this, externalities are said to be related to strategic complementarities, fire sales and credit crunches, as well as interconnectedness. This can then be further classified under the two dimensions of

systemic risk. Externalities related to strategic complementarities, fire sales and credit crunches fall under the time-dimension of systemic risk since they can cause pro-cyclicality, while externalities related to interconnectedness are in the cross-sectional dimension of systemic risk. Claessens *et al.* (2013:158) provided an explanation that the use of macroprudential policies will also be dependent on a number of country-specific factors including the country’s exposure to shocks and risks, as well as characteristics of a structural and institutional nature. The characteristics of the financial market will also play a role since this may affect the financial and business cycle – thereby influencing the effectiveness of the policy. The availability and effectiveness of fiscal, monetary, and macroprudential policies may also play a role, since, for example, countercyclical policies would not be an option for countries with high debt. Some countries (such as the US and European Union) may prefer stress tests, which are more forward looking than macroprudential policies, although these stress tests could to some extent complement or substitute macroprudential policies depending on how they are calibrated. Finally, institutional factors, such as the political economy, data availability, supervisory agencies, and country specific regulations (e.g. the Volcker rule) may affect a country’s willingness to adopt macroprudential policies. Evidence for the actual use and success of macroprudential policies is limited, but some data are available and are presented in Table 3.9.

Table 3.9: Overall use of macroprudential instruments.

Type of Instrument	Total Countries	Frequency of use (%)	Emerging markets	Developed economies	Frequency of Emerging markets-year (%)	Frequency of Developed economies -year (%)
Loan-to-value	24	44	15	9	35	74
Debt-to-income	7	9	5	2	8	11
Credit growth	6	8	5	1	10	1
Foreign lending	8	8	7	1	10	3
Reserve requirements	5	5	5	0	7	0
Dynamic provisioning	9	9	8	1	9	11
Countercyclical requirements	2	1	2	0	2	0
Profits redistribution	6	3	6	0	4	0
Other	13	12	12	1	15	1

Source: Claessens et al. (2013:161).

The instruments included are classified according to their use in specific markets, although they can also be classified according to their intended targets. The tools include measures aimed at *borrowers* (caps on loan-to-value and debt-to-income ratios); measures aimed at *financial institutions* (credit growth limits,

foreign lending limits); measures aimed at *liabilities* (reserve requirements); and measures aimed at *increasing buffers* (dynamic provisioning, countercyclical requirements and limits on profit redistribution). In general, emerging markets make greater use of macroprudential policies, which is understandable given their vulnerability to external shocks, such as capital flow volatility, as well as the ownership of less sophisticated financial systems (Claessens, 2014:15).

An extensive review of the literature regarding the experience of macroprudential policies in a number of countries was provided in Claessens (2014). The brief findings indicate that increased capital requirements through the countercyclical capital buffer and capital surcharges in general can increase the resilience of the financial system, while ratio caps on loan-to-value and debt-to-income ratios may limit the positive feedback mechanisms created between a growth in credit and increased asset prices, while also reducing the risk of fire sales. Cerutti, Claessens and Laeven (2015) documented the use of macroprudential policies in a large sample of countries and found that emerging markets make greater use of macroprudential policies, specifically foreign exchange related policies, while developed economies make greater use of borrower-based policies. In general, macroprudential policies are shown to significantly affect credit developments, while their effectiveness is country and instrument specific, with policy circumvention still remaining a challenge (Cerutti *et al.*, 2015:16).

A final caveat relating to macroprudential policy tool implementation was outlined by Tarashev *et al.* (2010:4). It is explained that certain aspects of the instruments at policymakers' disposal are constructed at the firm level. This applies to measures implemented for systemic risk ex ante, such as capital and liquidity requirements, as well as systemic risk ex post, such as central bank interventions to contain externalities. Therefore, an adequate measurement and attribution of systemic risk to the individual institution could ensure that the correct policy measures are appropriately designed and implemented.

3.4.4 Section summary

Macroprudential policies attempt to bridge the gap between existing macroeconomic policies and monetary policy by focusing on financial stability and the mitigation of systemic risk. In order to accurately implement macroprudential policies, the correct dimension of systemic risk needs to be identified, followed by a selection of the appropriate measures for the identified dimension. Since macroprudential policies and monetary policy both address cyclical fluctuations, they may either clash or reinforce each other at some point in time. This could represent a potential challenge to the successful implementation of macroprudential policies. Therefore, in order for macroprudential policies to be successful, they will need to work in tandem with monetary policy. Furthermore, since a large number of macroprudential policy tools exist, the correct tool for the particular risk factor will need to be identified. Macro stress tests may not have been successful as early warning indicators for systemic risk, but they do provide a means

of quantifying systemic risk, and this could potentially be used as an identification mechanism when deciding which tools should be implemented. It would therefore follow that the production of an accurate, quantitative measure for systemic risk could be just as important as the actual regulations for systemic risk.

3.5 QUANTIFICATION MEASURES FOR SYSTEMIC RISK

The production of a quantitative measure for systemic risk has been undertaken by a large number of research groups – largely due to the ambition of the Dodd-Frank Act and other measures undertaken in Europe in response to the sub-prime crisis (Hansen, 2012:3). In order to adequately regulate systemic risk, an accurate measurement is needed. A review of 31 quantitative systemic risk measures was undertaken by Bisias *et al.* (2012), but this section only discusses a limited number of measures for systemic risk. It should be noted that most of the measures discussed are applicable to the cross-sectional dimension of systemic risk, and therefore are aligned with our objective of measuring the systemic risk of the financial sector and the individual institutions within the sector.

3.5.1 Conditional Value-at-Risk (CoVaR)

The first way of defining the individual contribution that a financial institution makes to the systemic risk of the entire financial sector is with the conditional value-at-risk (CoVaR) measure. Adrian and Brunnermeier (2011:2) explained that the CoVaR measure is defined as the VaR of the market returns conditional on the financial institution's distress. This essentially means that the 5% quantile of the conditional distribution of daily market returns are conditional on the equity return of the market being at its VaR. The "Co" prefix stands for conditional, contagion, or comovement. The difference between CoVaR in the distressed state and CoVaR in the normal state is represented by the indicator ΔCoVaR .

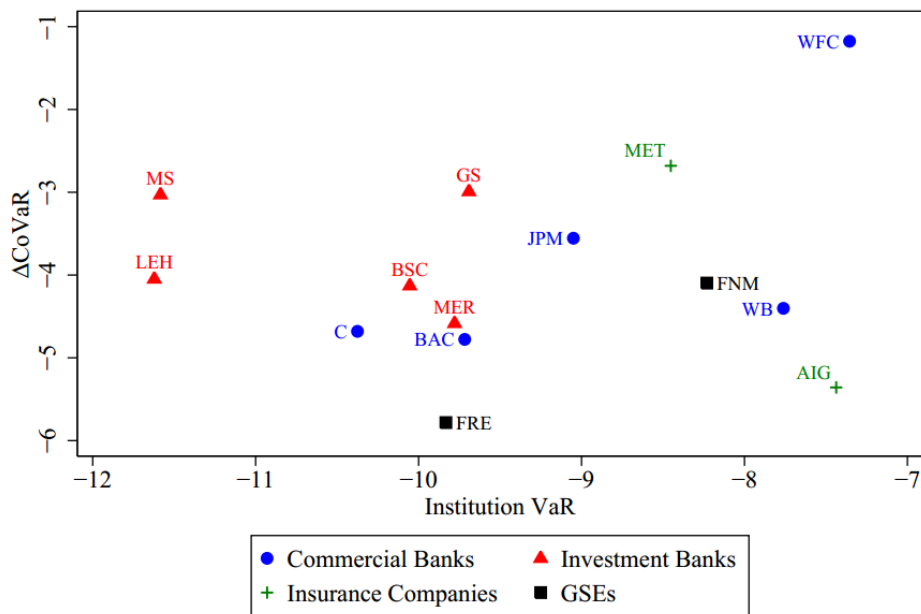
Traditional risk measures tend to only focus on the individual risk of an institution, and regulations based on this alone may lead to excessive risk-taking across systemic risk dimensions. The ΔCoVaR measure attempts to correct this. If two institutions A and B have the same VaR, they would be considered to possess the same amount of risk. If they have differing ΔCoVaR values, say A = zero and B = high, it would follow that B contributes more systemic risk to the financial sector than A does. The implication of this is that B might have a higher risk premium due to its associated systemic risk, and therefore outperform A. The imposition of stringent regulatory requirements based on the systemic risk contribution would, however, attempt to control this generation of systemic risk.

The ΔCoVaR measure also has the ability to model a financial network and the spillovers within it from one institution to another. Consider the measure $\Delta\text{CoVaR}_{i|j}$ which models the increase in risk of i

conditional on j being under distress, thereby capturing the spillover effects of i on j . It should however be noted that $\Delta CoVaR_{i|j}$ does not necessarily imply that $\Delta CoVaR_{j|i}$. The CoVaR measure therefore also has the ability to measure the negative spillover effects of smaller institutions that are systemic due to their herding behaviour.

Similarly, the $\Delta CoVaR$ measure of one institution does not empirically relate to its VaR measure, as illustrated by Figure 3.6.

Figure 3.6: $\Delta CoVaR$ vs VaR.



Source: Adrian and Brunnermeier (2011:3).
GSEs refers to Government Sponsored Entities.

Figure 3.6 shows a scatter plot of the institutions' isolated risk (VaR) versus the institutions' contribution to systemic risk (CoVaR). VaR is the 1% quantile of institution returns, while CoVaR is the percentage point change in the 1% VaR of the financial system when an individual institution realises its own 1% VaR (Adrian & Brunnermeier, 2011:3). The simple implication of this is that an increase in an institution's isolated risk does not necessarily mean that its contribution to systemic risk will increase. If this were the case, a straight trend line could be drawn across the institutions in Figure 3.4 above.

The VaR of institution i at the q percentile is defined by Adrian and Brunnermeier (2011:7) as:

$$\Pr(X^i \leq VaR_q^i) = q, \tag{3.8}$$

with X^i representing the asset return market value of i and VaR_q^i generally being a negative number, although in practice the sign may be switched. Term j represents either another financial institution or the entire financial system. The VaR of j conditional on the event $\{X^i = VaR_q^i\}$ is represented by $CoVaR_q^{j|i}$ where q is the quantile:

$$\Pr(X^j \leq CoVaR_q^{j|i} | X^i = VaR_q^i) = q, \quad (3.9)$$

while i 's contribution to j 's risk is calculated by:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|i} - CoVaR_{50\%}^{j|i}, \quad (3.10)$$

with $CoVaR_{50\%}^{j|i}$ representing the VaR of j 's market value asset returns when i 's returns are the median/50th percentile. If the j term is representing the financial system, the return of all financial institutions will be at their VaR level. Following on from this, the subscript j is removed and subsequently $\Delta CoVaR^i$ illustrates the difference between the financial system's VaR conditional on i 's distress, and the financial system's VaR conditional on the median state of i , therefore measuring how much i contributes to the overall systemic risk of the financial system.

Adrian and Brunnermeier (2011:11) explained that the market value of asset returns for the financial institutions must be estimated before the actual CoVaR can be estimated. In the following equation, ME_t^i represents i 's market value of total equity, while LEV_t^i is the ratio of total book assets to book equity. The market-to-book equity ratio is then applied to book-valued assets to essentially transform them in to market valued total assets. The growth rate of market valued total assets is given in Equation 3.11:

$$X_t^i = \frac{ME_t^i \cdot LEV_t^i - ME_{t-1}^i \cdot LEV_{t-1}^i}{ME_{t-1}^i \cdot LEV_{t-1}^i} = \frac{A_t^i - A_{t-1}^i}{A_{t-1}^i}. \quad (3.11)$$

The time variation in the joint distribution of X^i and X^{system} is captured by estimating the conditional distribution as a function of state variables with two quantile regression run on weekly data, with M_t representing a vector of state variables (Adrian & Brunnermeier, 2011:14):

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \epsilon_t^i \quad (3.12)$$

$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \epsilon_t^{system|i}. \quad (3.13)$$

The state variables used in M_t were summarised in a table by Bisias *et al.* (2012:107). The quantile regression for Equation 3.12 consists of an optimised modified function shown below:

$$\min_{\alpha_q, \beta_q, \gamma_q} \sum_t \begin{cases} q |X_t^i - \alpha_q - M_{t-1} \gamma_q| & \text{if } (X_t^i - \alpha_q - M_{t-1} \gamma_q) \geq 0 \\ (1 - q) |X_t^i - \alpha_q - M_{t-1} \gamma_q| & \text{if } (X_t^i - \alpha_q - M_{t-1} \gamma_q) \leq 0 \end{cases} \quad (3.14)$$

An analogous quantile regression function is provided for Equation 3.13. Once the quantile regression parameters have been estimated, the predicted values for VaR and CoVaR are denoted by Equations 3.15 and 3.16:

$$VaR_t^i = \alpha^i + \gamma^i M_{t-1} \quad (3.15)$$

$$CoVaR_t^i = \alpha^{system|i} + \beta^{system|i} VaR_t^i + \gamma^{system|i} M_{t-1}. \quad (3.16)$$

The $\Delta CoVaR_t^i$ for each institution is then calculated (Adrian & Brunnermeier, 2011:15):

$$\begin{aligned} \Delta CoVaR_t^i(q) &= CoVaR_t^i(q) - CoVaR_t^i(50\%) \\ &= \beta^{system|i} (VaR_t^i(q) - VaR_t^i(50\%)). \end{aligned} \quad (3.17)$$

In order to estimate $\Delta CoVaR_t^i$, the quantile regressions must be run for both the desired q as well as for $q = 0.5$.

Through the use of the *CoVaR* measures, Adrian and Brunnermeier (2011:18) found that the link between an institution's VaR and its CoVaR is weak, with the implication that regulations based solely on individual risk will not be sufficient in mitigating systemic risk. Furthermore, they found that firm characteristics, such as increased leverage, size, and maturity mismatches, are associated with a larger degree of systemic risk contribution (Adrian & Brunnermeier, 2011:20). The use of these variables to predict a forward measure of $\Delta CoVaR$ makes the finding that the forward measure is negatively related to contemporaneous CoVaR measure. Macroprudential regulations based on the forward $\Delta CoVaR$ will therefore be countercyclical (Adrian & Brunnermeier, 2011:24).

A number of studies have been conducted using the CoVaR method. Girardi and Ergun (2013:3170) conducted a CoVaR analysis but modify the definition of financial distress in order to model a greater degree of distress, as well as to improve the consistency of their parameter. The definition of financial distress changes from an institution being *exactly* at its VaR to being *at most* at its VaR. They further use a multivariate generalised autoregressive conditional heteroskedasticity (GARCH) model in order to capture the time-varying systemic risk exposure of an individual institution. They also make a contradictory finding to the original study, where the relationship between VaR and CoVaR is found to be weak in both the time series and cross-sectional dimension (Girardi & Ergun, 2013:3170). The original study found the relationship between VaR and CoVaR to be weak in the cross-section but strong in the time-dimension (Adrian & Brunnermeier, 2011:18).

The original CoVaR uses equity returns as the input measures, but other authors have used credit default swap spreads to measure systemic risk. Huang, Zhou and Zhu (2009:9) estimated the expected probability

of default of a financial institution in a risk-neutral sense through the proposition of the distressed insurance premium as the systemic risk measure, while also using the equity returns to model the simultaneous defaults of a number of institutions. In terms of performance, systemic risk measures based on credit default swap spreads are shown to outperform those based on equity returns, although this may only apply in the US sector where the trading volume of credit default swaps is sufficiently high (Rodriguez-Moreno & Pena, 2013:1830).

The advantage that expected loss-based measures provide over VaR based measures is that they take into account extreme tail risk, specifically low probability, large impact losses. This is a significant characteristic that was illustrated by the sub-prime crisis (Gray & Jobst, 2011:83). Furthermore, the VaR and CoVaR measures have not yet been shown to have backing of explicit economic theory, as the Marginal Expected Shortfall does.

3.5.2 Marginal Expected Shortfall (MES)

Marginal Expected Shortfall (MES) is another way of defining the contribution that an individual financial institution makes to the systemic risk of the entire financial sector, conditional on it being under distress. The MES measure has its roots in a definition of the systemic risk of a firm, illustrated by Acharya *et al.* (2010) and subsequently refined by Acharya *et al.* (2012:60). The banks, in their model, choose their leverage levels and asset positions in an economic environment, with systemic risk emerging when aggregate bank capital falls below a certain threshold level. They show that the systemic risk of the individual firm is the product of three components:

$$\begin{aligned}
 & \textit{Real systemic risk of a firm} \\
 &= \textit{Real social costs of a crisis per dollar of capital shortage} \\
 &\times \textit{Probability of a crisis (i.e. an aggregate capital shortfall)} \\
 &\quad \times \textit{Expected capital shortfall of the institution in a crisis.}
 \end{aligned}$$

The argument made by Acharya *et al.* (2010:13) was that a financial institution's system risk contribution can be based on its Systemic Expected Shortfall (SES), which is essentially the institution's degree of undercapitalisation when the financial system as a whole is undercapitalised. The SES is proxied by three measures (Acharya *et al.*, 2010:18). Firstly, the amount of capital that stress tests recommend it should raise. Secondly, the equity valuation declines of the large financial institutions during the sub-prime crisis, measured by the cumulative equity returns for July 2007 to December 2008. Lastly, the broadening of credit default swap spreads of the large financial institutions for the same period. Two leading indicators

are then constructed from these proxies, namely the MES and leverage (LVG).⁴⁵ LVG is calculated in Equation 3.23.

MES is based on a standard risk management practice approach, the Expected Shortfall (ES) of an institution, explained by Acharya *et al.* (2012:6) as follows:

$$ES_{\alpha} = -E[R|R \leq -VaR_{\alpha}]. \quad (3.18)$$

with $\alpha = 5\%$, implying that VaR is the maximum loss of the bank with 95% confidence. The expected shortfall is essentially the expected loss, given that the loss is greater than the VaR. Similarly, the expected shortfall is the average return on days when the portfolio's loss is greater than its VaR limit. When dealing with tasks such as risk management, transfer pricing and strategic capital allocation, banks break down losses that are firm-wide into contributions that originate from individual groups or trading desks. This is done by deconstructing the bank's return R into the sum of each group's return r_i . Therefore:

$$R = \sum_i y_i r_i, \quad (3.19)$$

with y_i representing the weight of group i in the portfolio. Based on the definition of expected shortfall above, it can be represented in Equation 3.20:

$$ES_{\alpha} = \sum_i y_i E[r_i | R \leq -VaR_{\alpha}]. \quad (3.20)$$

Deriving from Equation 3.20, the overall risk sensitivity to exposure y_i to each group i is represented as follows:

$$\frac{\partial ES_{\alpha}}{\partial y_i} = -E[r_i | R \leq -VaR_{\alpha}] \equiv MES_{\alpha}^i. \quad (3.21)$$

MES^i represents group i 's Marginal Expected Shortfall, which is how the risk taking of group i contributes to the overall risk of the bank. Therefore MES is measured by calculating group i 's losses when the entire bank is performing badly. The use of MES can then be extended to a financial system, where each institution contributes to the return of the aggregate banking sector R . The MES of each bank is therefore its contribution to the risk of an expected shortfall for the entire financial sector.

The MES of an institution is defined as its average equity return (R_b) during the worst 5% of days in the overall market return (R_m). This is represented by Equation 3.22:

⁴⁵ The abbreviation LVG is only used when referring to the leading indicator constructed in this sense, and not the broader concept of leverage.

$$MES_b = \frac{1}{\text{number of days}} \sum_{\{t:\text{system is in its 5\% tail}\}} R_{bt}. \quad (3.22)$$

The LVG measure is based on an approximation, since it is challenging to measure true leverage as a result of limited market data, especially regarding off- and on-balance sheet funding (Acharya *et al.*, 2010:17):

$$\begin{aligned} LVG_b &= \frac{\text{quasi market value of assets}}{\text{market value of equity}} \\ &= \frac{\text{book assets} - \text{book equity} + \text{market equity}}{\text{market value of equity}}. \end{aligned} \quad (3.23)$$

A cross-sectional regression analysis of firms' MES, SES, LVG is then run as follows:

$$SES_i = a + bMES_i + cLVG_i + \epsilon_i, \quad (3.24)$$

where (a, b, c) are then estimated for a specific metric of SES in order to estimate a systemic risk indicator. An example of this would be the use of June 2006 to June 2007 returns data to estimate the MES, and the use of balance sheet data from June 2007 to estimate the LVG. Each firm's SES is then proxied by its cumulative equity return for the period July 2007 to December 2008. Once this is input into Equation 3.24 above, the systemic risk of the firm i is calculated by Equation 3.25:

$$\text{Systemic risk of firm } i = \frac{\hat{b}}{\hat{b} + \hat{c}} MES_i^t + \frac{\hat{c}}{\hat{b} + \hat{c}} LVG_i^t. \quad (3.25)$$

Two variants of the measure were also introduced. The first is F-MES, which substitutes the worst 5 % of days of the overall market for the worst 5 % of days for returns of the financial industry. The results returned were, however, the same results as the MES measures (Acharya *et al.*, 2010:25). The second variant uses the credit default swap data of 40 financial institutions that traded credit default swaps on their debt. The credit default swap MES is modelled by using the worst 5 % days for an equally weighted portfolio of all the credit default swap returns and then calculating the average credit default swap returns of the firm for these days. The credit default swap MES is found to be useful in predicting the start of a crisis (Acharya *et al.*, 2010:25).

The general empirical findings were as follows. The regression analyses which were done to determine the predictability of MES and LVG returned relatively high R-squared values of between 20 and 60 %. The study found that insurance firms are the least systemically risky institutions, which is contradictory to the

findings of Adrian and Brunnermeier (2011:42) and Billio *et al.* (2012:555). Securities broker/dealers are found to be the most risky, most likely due to the amount of leverage they undertake (Acharya *et al.*, 2010:22).

The relevance and applicability of MES can therefore not be overstated, since it lays the foundation for the empirical analysis of this study. The complete implementation and mathematical background will be explained in Chapter 4. MES also forms part of another proposed measure in the form of the Systemic Risk Index (SRISK) which measures the capital shortfall of an individual institution. Brownlees and Engle (2012:3) explain that the capital shortfall of an institution is dependent on the degree of its leverage and the loss of equity that occurs during a crisis. The degree of leverage which an institution has can be measured, while the loss of equity can be predicted. SRISK is therefore calculated using both MES and LVG.

3.5.3 Systemic Risk Index (SRISK)

SRISK measures the contribution that an institution would make to market undercapitalisation during a financial crisis, and therefore how systemically risky it is. Intuitively, a higher value indicates a greater contribution to market undercapitalisation and a higher degree of systemic risk. In terms of its forecasting success, SRISK shows promise. An example being that 18 months prior to the failure of Lehman Brothers, eight of the top ten institutions, according to their SRISK, were financially troubled (Brownlees & Engle, 2012:4). The calculation is conceptually similar to stress tests which are done on financial institutions, therefore making it an appealing empirical measure for this study. This section will explain the broader theoretical and mathematical derivations of the measure, while Section 4.3 will focus on its implementation and precise specifications.

Brownlees and Engle (2012:5) explained a simplified version of the model used by Acharya *et al.* (2010). A two-period model is used where a financial institution i chooses in Period 1 how much capital to raise from risky debt F_i , guaranteed debt G_i , and initial capital W_i . This is invested in J amount of assets by taking exposures $X_{i1} \dots, X_{ij}$. A discount rate of B_1 is used to price the risky debt, while the guaranteed debt is priced at par. The exposures pay a total return of r_1, \dots, r_j in Period 2 while repayment of the debt must be at face value. There may be additional costs during Period 2, due to bankruptcy costs and capital shortage costs in general. The budget constraint in Period 1 is therefore calculated as follows:

$$W_{i1} + F_{i1}B_1 + G_{i1} = \sum_{j=1}^J X_{ij}. \quad (3.26)$$

The institution in Period 1 chooses investments in X and borrows F from long-term capital markets, while additional funds may be obtained from negative X 's, indicative of short-term rollover financing. Based on

the distribution of equity values during the second period, the institution will choose leverage to maximise its returns. The net worth of the institution will therefore be equal to:

$$W_{i2} = \sum_{j=1}^J X_{ij}r_j - G_{i1} - F_{i1} - \phi. \quad (3.27)$$

The cost of distress is indicated by ϕ and could be a bankruptcy or the abandonment of plans due to a shortage of capital, but in general it will be a function of the state variables. If a situation arises where W_{i2} is smaller than zero, the institution would be insolvent, while a small positive value would indicate a shortage of capital and potential inability to function. The key implications that Brownlees and Engle (2012:7) based their model on were the following: a shortage of capital by an individual firm will result in external costs for the real economy if they occur during a period of financial system distress, and will as a result need to be taken up by taxpayers offering the guarantee G_{i1} . Externalities are also included and will be worse during a period of constrained capital. An institution's bankruptcy will not be absorbed by a stronger competitor when the economy is in a downswing, resulting in an impairment of the functions of the financial sector and the subsequent spreading of obligations through the financial sector and real economy. An undercapitalisation of the financial system will result in a halting of credit supply for businesses and will negatively affect the economy, therefore the undercapitalisation of one firm is also dangerous for the entire economy if it occurs when the entire system is undercapitalised. It should be noted that the negative externality costs that an institution generates during a crisis are not taken into account by the objective function. The implication being that a large degree of leverage can be undertaken by the institution if regulatory interventions are absent. For example, if the returns have a low volatility, the risk will be low, and the optimal leverage level would be high (Brownlees & Engle, 2012:7).

In order to measure the capital shortfall of an institution during a crisis, a prudential ratio⁴⁶ of assets to equity k is set, with the institution's capital buffer at the end of period 1 is equal to:

$$k(B_1F_{i1} + G_{i1} + W_{i1}) - W_{i1}. \quad (3.28)$$

A positive value in Equation 3.28 is indicative of a capital shortage. Following on from this, the expected loss of equity during a crisis, and the subsequent capital shortfall, must be calculated. A crisis is defined as a decline below a specific threshold value C , referred to as the systemic event. The expected capital shortfall CS_{i1} in Period 2 is estimated during Period 1 as follows:

$$CS_{i1} = E_1(k(F_{i1} + G_{i1} + W_{i2}) - (W_{i2}|Crisis)) - k(E_1(F_{i1} + G_{i1}) - (1 - b)E_1(W_{i1}|Crisis)) \quad (3.29)$$

⁴⁶ The prudential ratio refers to the minimum amount of capital that the Basel Committee requires each bank to hold. This is set at 8% (BCBS, 2011:27).

$$\begin{aligned}
&= k(F_{i1} + G_{i1}) - (1 - k)W_{i1}E_1(R_{i2}|R_{m2} < C) \\
&= k(F_{i1} + G_{i1}) - (1 - k)W_{i1}MES_{i1}.
\end{aligned}$$

R_{i2} and R_{m2} represent the bank and market returns in Period 2 while MES represents the tail expectation of the institution, conditional on the market being in its left tail, i.e. a financial crisis situation. Brownlees and Engle (2015:6) used capital shortfall as the basis of their SRISK equation where:

$$\begin{aligned}
CS_{i,t} &= kA_{i,t} - W_{i,t} \\
&= k(D_{i,t} + W_{i,t}) - W_{i,t},
\end{aligned} \tag{3.30}$$

with $W_{i,t}$ representing the market value of equity, $D_{i,t}$ the book value of debt, $A_{i,t}$ the value of quasi-assets, and k the prudential capital ratio.⁴⁷ In this case, a systemic event is defined as a market decline below a certain threshold level C over a time horizon h (Acharya *et al.*, 2010:14). The systemic event is defined as $\{R_{m,t+1:t+h} < C\}$, while the arithmetic multi-period market return between period $t + 1$ and $t + h$ is defined as $R_{m,t+1:t+h}$. SRISK is therefore defined as the expected capital shortfall conditional on a systemic event:

$$\begin{aligned}
SRISK &= E_t(CS_{i,t+h}|R_{m,t+1:t+h} < C) \\
&= kE_t(D_{i,t+h}|R_{m,t+1:t+h} < C) - (1 - k)E_t(W_{i,t+h}|R_{m,t+1:t+h} < C).
\end{aligned} \tag{3.31}$$

The assumption is made that debt cannot be renegotiated in the case of a systemic event, with the implication therefore being that $E_t(D_{i,t+h}|R_{m,t+1:t+h} < C) = D_{i,t}$. It will follow that:

$$\begin{aligned}
SRISK &= kD_{i,t} - (1 - k)W_{i,t}(1 + LRMES) \\
&= W_{i,t}[kLVG_{i,t} - (1 - k)LRMES_{i,t} - 1],
\end{aligned} \tag{3.32}$$

with $LVG_{i,t}$ representing the leverage ratio $(D_{i,t} + W_{i,t})/W_{i,t}$ and $LRMES_{i,t}$ representing the expected multi-period return of the institution conditional on a systemic event:

$$LRMES_{i,t} = E_t(R_{i,t+1:t+h}|R_{m,t+1:t+h} < C). \tag{3.33}$$

$R_{i,t+1:t+h}$ indicates the multi-period equity return of the institution between period $t + 1$ and $t + h$. Equation 3.32 therefore shows that SRISK is a function of the institution's size, its degree of leverage, and the expected devaluation of its equity conditional on a market decline. It will follow that the SRISK measure will be higher for larger institutions with a greater degree of leverage and higher tail dependence.

⁴⁷ The book value of debt will be measured by total liabilities.

In order to retain simplicity, the dependence on the prudential ratio k , the threshold C , and the time horizon h is implicit in the SRISK notation. The SRISK measure in Equation 3.32 therefore provides a prediction of the level of capital shortfall a financial institution would experience at a particular point in time, if a systemic event occurred.

The $1 - \alpha$ conditional capital shortfall prediction interval can be defined as follows:

$$\left(CS_{i,t+h|t}^{\frac{\alpha}{2}}, CS_{i,t+h|t}^{1-\frac{\alpha}{2}} \right), \quad (3.34)$$

with:

$$CS_{i,t+h|t}^q = W_{i,t} [kLVG_{i,t} - (1 - k)F_{i,t+1:t+h|t}^{-1}(q) - 1], \quad (3.35)$$

where $F_{i,t+1:t+h|t}(x)$ represents the distribution function of the institution's multi-period returns conditional on the systemic event. Since the return distribution will imply uncertainty, the prediction intervals incorporate this and therefore may prove useful. The $SRISK_{i,t}$ index across all institutions is used to construct a financial distress index that is system wide, with the total amount of systemic risk in the entire financial sector being measured as:

$$SRISK_t = \sum_{i=1}^N (SRISK_{i,t})_+, \quad (3.36)$$

with $(x)_+$ representing $\max(x, 0)$. The total amount of capital that the government would need to provide in order to bail out the financial system, conditional on the occurrence of a systemic event, is therefore represented by aggregate $SRISK_t$. The contribution of negative capital shortfalls (capital surpluses) is ignored because surplus capital is unlikely to be mobilised easily during a crisis through mergers or loans – therefore providing no support to failing institutions. The SRISK measure can also be illustrated in percentage form, indicating the systemic risk share an institution possesses as follows:

$$SRISK\%_{i,t} = \frac{SRISK_{i,t}}{SRISK_t} \text{ if } SRISK_{i,t} > 0, \quad (3.37)$$

if $K_{i,t} \leq 0$, then the $SRISK\%_{i,t} = 0$.

If we recall the argument made earlier by Brownlees and Engle (2012:8) that a large capital shortfall in the financial sector would cause a real crisis, and the institutions contributing the most to the capital shortfalls (and therefore the crisis) would be the most systemically risky – a conclusion can be made that significant capital shortages during a crisis also capture systemic risk in addition to individual firm risk.

In practice, however, there may be different determinants for SRISK. For example, if the size of the institution increases and the leverage ratio is constant, the capital shortfall will be larger and therefore systemic risk will also be greater. Increased debt will make the institution's capital buffer higher, therefore also increasing systemic risk. Similarly, the systemic risk of the institution will also increase if it has a greater downside exposure to systematic shocks in the economy.

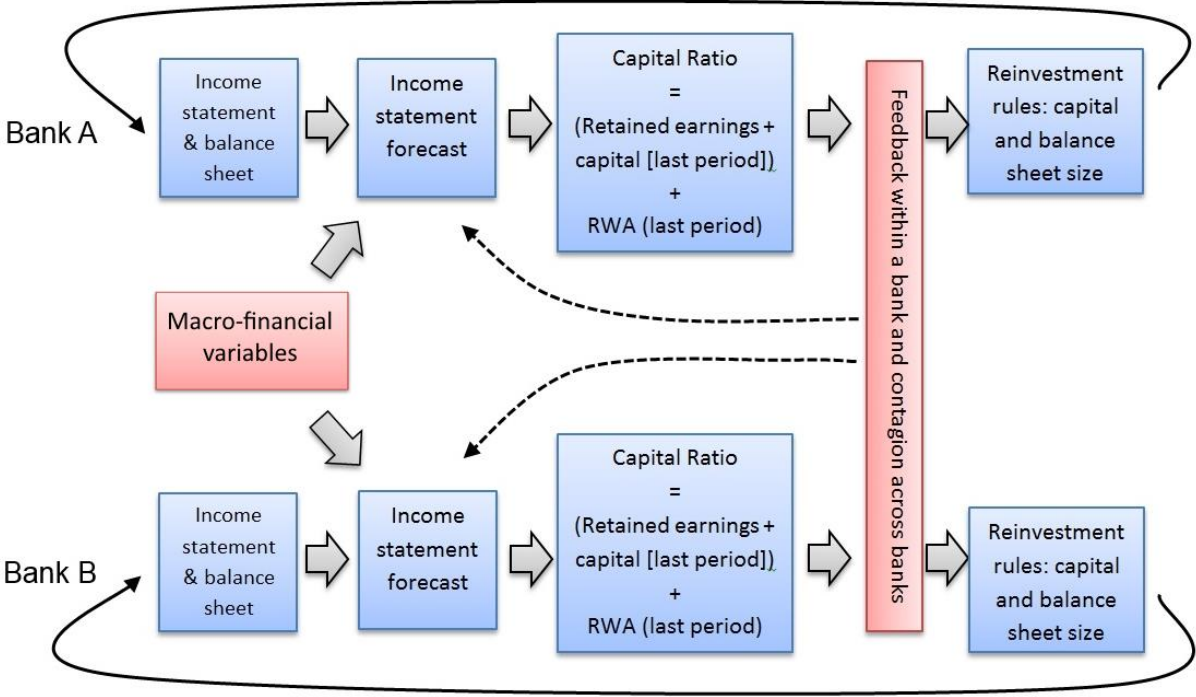
Another noteworthy characteristic of this measurement approach used is that it combines market-related information (equity returns) with balance sheet data to predict the conditional capital shortfall. By including market-related information, it provides a prediction of the future value of the bank, which could be different from the accounting value. The reason for this is that market values are more forward looking and may consider factors that have yet to occur (Brownlees & Engle, 2015:9).

In conclusion, SRISK, MES and CoVaR represent cross-sectional measures of systemic risk. That is, they measure systemic risk at a particular point in time by classifying banks as assets in the greater portfolio that is the financial sector. This is useful for quantifying systemic risk at a particular point in time, but may not necessarily be an accurate representation of the entire systemic risk process. The applicability to the time-dimension of systemic risk may therefore be lacking and could be modelled by another approach.

3.5.4 Risk Assessment Model of Systemic Institutions (RAMSI)

The RAMSI is a top-down approach developed by the Bank of England to assess the solvency and liquidity of the UK banking sector as a whole, as well as of individual institutions (Burrows, Learmonth, McKeown & Williams, 2012:204). It does not explicitly measure systemic risk, but rather models the entire systemic risk process. Considering that the RAMSI is a highly regarded and unique approach, it is worth discussing. Projections for macroeconomic and financial variables, such as GDP and interest rates are estimated by a set of equations and mapped into profiles for each bank's income statement. The inputs for these equations include data from the balance sheet of each bank and projections for macro-financial variables. Figure 3.7 below illustrates an overview of RAMSI.

Figure 3.7: RAMSI overview.



Source: Burrows *et al.* (2012:205).

An in-depth analysis of the empirical measures used in RAMSI has been provided by Alessandri, Gai, Kapadia, Mora and Pühr (2009). In this illustration, only two banks are included, although the actual model will include more. The income statements and balance sheets of banks A and B, as well as the forecasted macro-financial variables, are the first set of inputs. These are then combined with the estimated equations to generate forecasts for each item in the bank’s income statements, thereby producing a forecasted income statement for each bank. In order to estimate changes in the market value of the banks’ assets as a result of changes in equity prices, market interest rates, or credit risk premia – an asset pricing model is used. The banks’ capital ratios are then calculated from the forecasted retained earnings. Feedback effects within and across banks can now begin to take place. A worsening in forecasted bank fundamentals such as solvency and profitability can cause higher funding costs for banks in RAMSI, and if these fundamentals fall below a threshold level, banks can be cut off from certain funding markets. An example of a feedback effect would be that if a bank is cut off from funding, other similar banks will have an increased probability of also being cut off.

RAMSI also models contagion effects (Burrows *et al.*, 2012:206). If a bank experiences severe losses and its capital ratio declines below a threshold level, representing a failure, then a feedback loop will take place, causing other banks to experience losses. This will be caused by externalities that can produce systemic risk, such as counterparty credit risk and asset fire sales. The retained earnings that remain will then update the balance sheets of the bank and subsequently the top-down models will have to decide

what banks do with the retained earnings. They can either be used to increase the amount of risk-weighted assets held, and use the rest as capital. Alternatively, if a capital target exists, risk-weighted assets will only be increased if the capital target is met. Once the reinvestment of earnings has taken place, the next period begins with updated balance sheets and variables (Burrows *et al.*, 2012:206).

RAMSI, as stated above, is not concerned with providing an empirical measure of systemic risk, but rather with testing the resilience of the entire financial system. It involves top-down stress testing which can include different macroeconomic scenarios. Through this stress-testing scenario, the Bank of England can identify and address any financial system vulnerabilities which may be revealed.

3.5.5 Other measures

The measures illustrated above thus far, such as MES and CoVaR, are categorised as institution-specific risk. Other means of quantifying systemic risk may include comovement and contagion measures (Absorption Ratio, Dynamic Causality Index and the International Spillover Index), and volatility or instability measures (Herfindahl Index and Turbulence measure).

The comovement and contagion measures are based on the quantification of the equity return dependence among financial institutions. Kritzman, Li, Page and Rigobon (2010:8) constructed the absorption ratio as an indicator for systemic risk. Equation 3.38 illustrates the fraction of total variance of a set of assets that is explained or absorbed by a finite set of eigenvectors:

$$AR(K) = \frac{\sum_{i=1}^n \sigma_{E_i}^2}{\sum_{j=1}^N \sigma_{A_j}^2}, \quad (3.38)$$

where AR represents the absorption ratio, N is the number of assets, n is the number of eigenvectors used to calculate the absorption ratio, $\sigma_{E_i}^2$ represents the variance of the i -th eigenvector or the eigen portfolio, and $\sigma_{A_j}^2$ is the variance of the j -th asset. A large value for the absorption ratio will represent more unified sources of risk, and therefore a higher level of systemic risk. Conversely, a low ratio will represent more disparate sources of risk, and therefore a lower level of systemic risk.

Another measure is the Dynamic Causality Index, constructed by Billio *et al.* (2012:540). This measure attempts to model the interconnectedness of a set of financial institutions by calculating the fraction of significant Granger-causality relationships between their returns, are illustrated by Equation 3.39.

$$DCI_t = \frac{\text{Number of significant GC relations}}{\text{Number of relations}}. \quad (3.39)$$

A Granger-causality relationship is significant if the p-value is under 0.05. The measure is created using the 20 largest financial institutions' daily returns over a 36-month rolling window.

Moving from a discussion of causality to comovement, Diebold and Yilmaz (2009:170) developed the International Spillover Index to measure the comovement in macroeconomic variables between countries. This measure aggregates the contribution that each variable makes to the forecast error variance of other variables across a number of return series, thereby modelling the total extent of spillover that occurs across the considered series. The total extent of spillover is a measure of interdependence.

Since systemic risk has been shown to be closely related to times of volatility and instability, Giglio, Kelly and Pruitt (2015:6) calculated the average equity volatility of the 20 largest financial institutions, as well as the aggregate book leverage, market leverage, size, concentration in the financial industry, and financial sector turbulence. The individual volatility series is calculated by using the monthly standard deviation of daily returns. The aggregate volatility is then determined by taking the average of the individual volatility of the 20 largest institutions (Giglio *et al.*, 2015:A9). The potential for instability and shock propagation among the 20 largest financial institutions that may occur when they have large degrees of leverage is modelled by aggregate book leverage and the aggregate market leverage.⁴⁸ To measure size concentration, the Herfindahl Index is constructed to measure size distribution among financial firms, illustrated in Equation 3.40.

$$Herfindahl_t = N \frac{\sum_{i=1}^N ME_i^2}{\left(\sum_{i=1}^N ME_i\right)^2}. \quad (3.40)$$

The numerator represents the sum of the squared market equity returns of each firm, while the denominator represents the squared value of the sum of market equity returns for each firm. The concentration index attempts to capture the effect that the threat of default of the largest institutions could have on stability. By multiplying the measure of dispersion by the number of firms, the index corrects for the changing number of firms, in this case the largest 100. The discussion surrounding measures of volatility and instability is concluded with the explanation of the Turbulence measure proposed by Kritzman and Li (2010:31), whereby they measured excess volatility by comparing the realised squared returns and historical volatility of financial institutions, represented by Equation 3.41.

$$Turbulence_t = (r_t - \mu)' \sum^{-1} (r_t - \mu). \quad (3.41)$$

Variable r_t represents the vector of financial institutions' returns, while μ is the historical mean and \sum is the variance-covariance matrix. This effectively measures the turbulence in financial markets.

⁴⁸ Book leverage refers to debt divided by assets, while market leverage refers to debt divided by market equity (Giglio *et al.*, 2015:A9).

3.5.6 Section summary

The empirical measures outlined represent the way in which the systemic risk of the entire financial sector is measured, and then in some cases attributed to individual institutions. CoVaR measures the risk increase of an institution, conditional on the entire financial sector being under distress. The significant drawback of this measure is that it does not take extreme tail risk into account. One measure which does capture extreme tail risk is MES. This represents the average equity return of the institution falling below a particular level when the financial sector is under distress. The SRISK measure expands upon this and measures the contribution that each institution makes to the undercapitalisation of the entire financial sector during a period of financial distress. An alternative approach is undertaken by RAMSI, whereby the entire systemic risk process is modelled. This does not provide a particular empirical measure of systemic risk, but rather a quantitative illustration of how banks are affected by the systemic risk process. The other measures discussed analyse comovement and contagion, interconnectedness, volatility, concentration and financial sector turbulence.

3.6 CHAPTER SUMMARY

An analysis and discussion of the Basel Accords as the global framework for banking supervision was introduced in Chapter 3. Basel I presented the concept of risk-weighted assets, where banks would hold capital in accordance with their risks. Basel II then expanded upon these requirements by introducing more in-depth risk assessment procedures and risk weight categories, as well as VaR-based capital charges. A number of oversights in the Basel II Accord were identified, in particular relating to systemic risk. One such finding was that the Basel requirements are pro-cyclical in nature. The implication was that the requirements would be lower during downswings, which is precisely when the largest buffers are needed. The summated drawback of Basel II is essentially that it attempted to ensure a stable financial system by focusing on the stability of each bank individually. The introduction of Basel III was meant to improve the liquidity risk associated with banks and implemented additional ratios and buffers to ensure this. A number of authors found, however, that there was still not a significant enough focus on the mitigation of systemic risk. Basel's main regulatory measures for systemic risk would be through a shift towards a macroprudential regulatory approach and additional capital charges for systemically important financial institutions. From a critical point of view, several authors mentioned the lack of incentives for banks to adopt the new suggested measures, while the ability of Basel III to address systemic risk remained a contentious issue.

As a result of the potential oversights in the Basel Accords, individual countries are likely to implement their own country-specific regulation additionally. The Dodd-Frank Act in the US was the de facto response to the financial crisis. The main goal of the Dodd-Frank Act was to identify systemic risk before it could

actually have an effect on the financial sector. The identification of systemic risk and the institutions responsible for causing it would be done by conducting annual stress tests. The responsible institutions would then be subjected to more stringent regulations, such as additional capital charges. The Volcker rule was also a significant part of the Dodd-Frank Act. It essentially barred proprietary trading by banks and restricted bank ownership in hedge funds and private equity funds. Some authors point out that the Dodd-Frank Act does not sufficiently address the contribution to financial instability that the private incentives of individual institutions' may have made. The case is also made for the role of corporate governance in causing the sub-prime crisis, although the empirical evidence supporting this is weak. Subsequently, the reinstatement of corporate governance measures remains a campaign angle for US politicians. SA by comparison had its own potential systemic risk crisis during 2014 with the failure of African Bank. The actions of the SARB mitigated any systemic effects of the failure and were largely praised by the IMF. Nevertheless, the main areas of concern and potential sources of systemic risk are the large degree of interconnectedness in the financial sector and the reliance on capital flows. As a result, any large-scale changes to corporate governance in future King reports are unlikely to take place.

One of the most significant lessons learnt from the sub-prime crisis was that focusing on the risks of individual firms would not ensure the stability of the entire financial sector. Consequently, a middle ground between microprudential policies, which focus on idiosyncratic risk, and macroprudential policies, which focus on economic activity, would need to be found. Macroprudential policies would focus on ensuring financial stability and mitigating systemic risk. Considering that systemic risk has both a time dimension and cross-sectional dimension, macroprudential policies would also focus on both dimensions. The time dimension would include measures to mitigate systemic risks that build up over time (pro-cyclicality), while the cross-sectional dimension will include measures to mitigate the contributions of individual institutions to systemic risk. In general, the evidence supporting macroprudential policies so far has been mixed, but for small, open economies that are vulnerable to capital flows, the evidence has been encouraging. These economies can use targeted macroprudential policies to mitigate the systemic risk which is associated with capital flows. The way macroprudential policies interact with monetary policy may be a potential challenge to its success, since both policies share a transmission channel. Furthermore, while conventional monetary policy is focused on price stability and macroprudential policy is focused on financial stability, there may be some overlap and conflict. The two approaches will need to be effectively combined and managed to ensure that they do not undermine each other's objectives.

Further success of macroprudential policies will also be dependent on their calibration in response to a particular factor. A large toolkit of macroprudential policies exists and in the context of this study, the type of systemic risk the macroprudential policy is responding to will need to be identified, as well as country- and institution-specific factors. Macro stress tests will play a role in this identification, although

whether they can adequately serve as an early warning indicator is still arguable. These stress tests will, however, be able to provide a quantification of systemic risk.

In addition to these regulatory measures, corporate governance institution and management models, as well as the broader spectrum of macroprudential policies, another response to the sub-prime crisis has been the attempts to identify an accurate measurement for systemic risk – since this will allow more effective regulation. In order to expand on this discussion regarding the measurement of systemic risk, a number of measures were discussed which quantify the systemic risk contributions that a portfolio of financial institutions make to the financial sector as a whole. CoVaR measures the increase in risk of an institution, conditional on the entire financial sector being in a state of financial distress. This measure does not, however, take into account tail risk, especially low probability, large impact losses, something that was significant during the sub-prime crisis. The MES measure fills this void. MES explains the contribution that individual institutions make to the systemic risk of the entire financial sector, conditional on it being under financial distress. The SRISK measure then builds on this framework to combine the MES with the degree of leverage an institution possesses. This combination produces the SRISK, which measures the contribution that an individual institution makes to the undercapitalisation of the financial sector during a financial crisis. The final quantitative measure is not a measure per se, but rather a systemic risk modelling framework. This framework, referred to as RAMSI, is a top-down approach used to model the entire systemic risk process. It essentially simulates a stress test scenario for banks, and then models the feedback effects in order to project future income statements and balance sheets for these banks. While this does not produce an absolute quantifiable measure for systemic risk, it does represent a quantitative framework for the entire systemic risk process.

A number of other measures may also be used to measure systemic risk from a different context. Equity return dependencies among financial institutions can be modelled by the Absorption Ratio, while the interconnectedness of financial institutions can be measured by calculating the number of Granger-causality relationships between them. The International Spillover Index measures the comovement in macroeconomic variables between countries, while other measures such as equity volatility combined with leverage, and financial sector turbulence are also used to model systemic risk.

Considering that systemic risk is such a complex phenomenon, it would follow that the regulation of systemic risk would be just as complex. The Basel Accords provide a decent framework upon which individual countries can base their own regulatory measures, calibrated in accordance with their specific characteristics. The reality is, however, that a macroprudential regulatory approach which focuses on financial stability is likely to be the most effective way of mitigating systemic risk. Subsequently, in order to identify the correct policy to implement, the measurement of systemic risk in the entire financial sector becomes important.

CHAPTER 4

THE MEASURING OF SYSTEMIC RISK: METHODOLOGY

4.1 INTRODUCTION

Chapter 2 explained the concept of systemic risk and the various ways in which it can manifest, while Chapter 3 illustrated the point that in order to ensure financial and economic stability, the mitigation and regulation of systemic risk should be a priority for central banks. One of the reasons for this, as illustrated by the sub-prime crisis, is that an undercapitalisation of the largest financial institutions can result in negative externalities for the entire economy (Brownlees & Engle, 2015:2). It follows that if the entire financial sector is undercapitalised and the economy is in a downswing, the bankruptcy of one institution cannot be absorbed by another institution, resulting in the liabilities of the failed institution spreading through the entire financial sector and economy. Along with the function of the financial sector to act as intermediary, the supplying of credit will also be hindered. The undercapitalisation of an institution is therefore not only potentially dangerous for the individual institution, but also for the entire economy – if the financial sector as a whole is also undercapitalised (Acharya *et al.*, 2012:59). It may therefore be valuable to know how much systemic risk is present in the financial sector, as well as its causes. This chapter therefore explains the methodology that will be followed in order to measure systemic risk in the SA and US financial sectors.

The first step will be to produce a quantifiable measure of systemic risk. Section 4.2 explains the process undertaken to construct the Systemic Risk Index (SRISK). A key input into SRISK is the Marginal Expected Shortfall (MES). This is an intricate measure which requires the calculation of conditional volatilities (Section 4.2.1), Dynamic Conditional Correlations (Section 4.2.2), and tail expectations (Section 4.2.3). Once these three components have been obtained, they are used as inputs into the MES measure (Section 4.2.4). Given that SRISK can also be calculated by using MES over a longer period, this equation will be used as an alternative. An approximation equation can be used to calculate long-run MES. Additionally, Section 4.2.5 describes the simulation procedure which can be used to calculate long-run MES. The simulation procedure takes into account the conditional volatilities and correlations over a six month period,⁴⁹ and produces forecasts of long-run MES in a hypothetical crisis scenario.

Given the interconnectedness of global financial markets, the manner in which systemic risk can be transferred between different sectors needs to be examined. A situation may exist where systemic risk in

⁴⁹ A six month period is used as this is considered the length of a crisis period (Acharya *et al.*, 2012:60).

the SA financial sector is caused by factors in a foreign country. Section 4.3 therefore explains the different methods that will be used to first identify if a transfer took place, and then to measure the size of the transfer. Section 4.3.1 uses the Glosten-Jagannathan-Runkle Generalised Autoregressive Conditional Heteroskedasticity (GJR-GARCH) and Dynamic Conditional Correlation (DCC) models to measure the correlation between the SA and US financial sectors and determine whether a contagion effect may exist. Additionally, Section 4.3.2 uses an Exponential GARCH (EGARCH) model to determine if a volatility spillover effect from the US to SA is present and also what the size of such a spillover would be. Subsequently, Section 4.3.3 measures the effect of a financial crisis scenario in the US on the SA financial sector by using the MES measure. In this situation, the SA equity market is used as a hypothetical bank within the US equity market. This will effectively measure the effect of a decline in the US sector on the SA sector and provide an indication of the systemic response of the SA market to the US market.

Once the broad SRISK measure and systemic risk transfers have been calculated, the determinants of SRISK within individual banks will be investigated, i.e. the individual characteristics that affect how much SRISK a bank produces. In order to inspect this, Section 4.4 undertakes a panel regression analysis. Considering the different ways in which systemic risk is characterised in emerging markets and developed economies, this analysis will contribute a new perspective on the individual determinants of SRISK within these different economies. Section 4.5 summarises the empirical methodology undertaken and attempts made to provide a simplified overview of a complicated process.

4.2 SYSTEMIC RISK INDEX (SRISK)

A financial institution is characterised as systemically risky if it is likely to experience a significant capital shortfall when the entire financial sector is experiencing financial distress. The SRISK measure therefore empirically reflects this propensity of an institution to be undercapitalised when the entire financial sector is undercapitalised (Laeven *et al.*, 2014:15).⁵⁰ Two different equations can be used to calculate SRISK. The first is set out in Equation 4.1 (Brownlees & Engle, 2015:7):

$$\begin{aligned} SRISK &= kD_{i,t} - (1 - k)W_{i,t}(1 + LRMES) \\ &= W_{i,t}[kLVG_{i,t} - (1 - k)LRMES_{i,t} - 1], \end{aligned} \tag{4.1}$$

with $LVG_{i,t}$ representing the leverage ratio $(D_{i,t} + W_{i,t})/W_{i,t}$, k the prudential capital ratio, and $LRMES$ the long-run MES. The LVG measure represents a combination of market and balance sheet data. $(D_{i,t} + W_{i,t})$ is the quasi-market value of the bank's assets, defined as the sum of the book value of its debt ($D_{i,t}$) and the market capitalisation of the bank ($W_{i,t}$). The LRMES measure is calculated using either an approximation equation or a simulation procedure. Following the example of Acharya *et al.* (2012:60), a

⁵⁰ The SRISK measure was explained in detail in Section 3.5.3.

40 % decline over 180 days is considered a crisis period. In addition to Equation 4.1, an alternative SRISK equation is also specified which uses MES instead of LRMES as the input. This is presented in Equation 4.2:

$$SRISK_{i,t} = kD_{i,t} - (1 - k) \cdot E_{i,t} \{1 - MES_{i,t+h|t}(C_{t+h|t})\}. \quad (4.2)$$

In Equation 4.2, SRISK is calculated by taking into account the prudential capital ratio (k), the bank's total liabilities (D), the market capitalisation of the bank (E), and the one-day MES at a certain threshold value (in this case -2 %). The key differences between the two measures are therefore the choice of MES or LRMES.

The $SRISK_{i,t}$ index across all institutions is then used to construct a financial distress index that is system wide, with the total amount of systemic risk in the entire financial sector being measured as:

$$SRISK_t = \sum_{i=1}^N (SRISK_{i,t})_+, \quad (4.3)$$

with $(x)_+$ representing $\max(x, 0)$. The total amount of capital that the government would need to provide in order to bail out the financial system, conditional on the occurrence of a systemic event, is therefore represented by aggregate $SRISK_t$. The contribution of negative capital shortfalls (capital surpluses) is ignored because surplus capital is unlikely to be mobilised easily during a crisis through mergers or loans – therefore providing no support to failing institutions.

The SRISK measure can also be illustrated in percentage form, indicating the systemic risk share an institution possesses, as follows:

$$SRISK\%_{i,t} = \frac{SRISK_{i,t}}{SRISK_t} \text{ if } SRISK_{i,t} > 0, \quad (4.4)$$

if $SRISK_{i,t} \leq 0$, then the $SRISK\%_{i,t} = 0$

In order to calculate the SRISK for both the bank and the market, the dynamic time-varying volatilities will need to be calculated (Section 4.2.1), followed by the Dynamic Conditional Correlations (Section 4.2.2), and finally the tail expectations will also need to be captured (Section 4.2.3). These three components will then be used in Section 4.2.4 to produce the MES for a threshold value of -2 %, i.e. the daily equity return of the firm given that the market as a whole has fallen below the -2 % threshold level.⁵¹ The LRMES can then be obtained by using the following approximation equation (Acharya *et al.*, 2012:60):

$$LRMES_{i,t} = 1 - \exp\{-18 \times MES_{i,t+1|t}\}. \quad (4.5)$$

⁵¹ The choice of threshold value is explained in Section 1.6.2.

An alternative to Equation 4.5 is a dynamic simulation procedure explained in Section 4.2.5 which takes into account the conditional volatilities and correlations of returns (Brownlees & Engle, 2015:7).

In order to calculate the firm and market compound returns, a dynamic time series model is used. The return pair has an unspecified distribution D with a mean of zero and time-varying covariance which is conditional on the information set F_{t-1} which is available to time $t - 1$. This is represented by Equation 4.6:

$$\begin{bmatrix} r_{i,t} \\ r_{m,t} \end{bmatrix} | F_{t-1} \sim D \left(0, \begin{bmatrix} \sigma_{i,t}^2 & \rho_{i,t} \sigma_{i,t} \sigma_{m,t} \\ \rho_{i,t} \sigma_{i,t} \sigma_{m,t} & \sigma_{m,t}^2 \end{bmatrix} \right). \quad (4.6)$$

σ_i and σ_m represent the volatility of the institution and the market, while ρ_i represents the correlation. In order to use this approach, the evolution of time-varying volatilities and correlations will need to be specified with equations. The threshold generalised autoregressive conditional heteroskedasticity (TGARCH) volatility model (Rabemananjara & Zakoian, 1993) and Dynamic Conditional Correlation (DCC) model (Engle, 2002) will be used.

4.2.1 Conditional volatility

The use of a TGARCH model is encouraged because standard GARCH models make the assumption that positive and negative error terms will have a symmetric effect on volatility. Put another way, this implies that stock price volatility will be affected in the same way by both good and bad news. Black (1976:181), however, proved the existence of the leverage effect, i.e. that a decrease in the firm's value will cause negative stock returns, and usually increased leverage of the stock.⁵² Subsequently, an increase in the debt-equity ratio will then increase the volatility of the stock. The practical implications of this theory are that negative return shocks have a greater effect on stock volatility than positive return shocks do, even if they are of the same magnitude. New research has however shown that the channel for leverage alone to cause this effect is too small, but the principle remains (V-Lab, 2015a). Two extensions of the GARCH model can be used to capture this effect, the exponential GARCH (EGARCH) and the TGARCH. For the estimation of conditional volatility, we focus on the TGARCH model given its reputation of being successful in terms of forecasting (Brownlees & Engle, 2012:12).

The TGARCH model divides the distribution of the innovations into disjoint intervals, followed by an approximation of a piecewise linear function for the conditional standard deviation and the conditional variance (Glosten, Jagannathan & Runkle, 1993:1787). This model is also referred to as a Glosten-

⁵² Further research has, however, disputed whether the leverage effect is actually due to financial leverage (Hasanhodzic & Lo, 2011:14).

Jagannathan-Runkle (GJR) GARCH model. A GJR-GARCH model assumes a specific form of the conditional heteroskedasticity, where $\varepsilon_t = \sigma_t z_t$ with z_t being standard Gaussian⁵³ and:

$$\sigma_t^2 = \omega + (\alpha + \gamma I_{t-1})\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2, \quad (4.7)$$

with:

$$I_{t-1} = \begin{cases} 0 & \text{if } r_{t-1} \geq \mu \\ 1 & \text{if } r_{t-1} < \mu \end{cases} \quad (4.8)$$

Even though it is assumed that z_t is Gaussian, it does not mean that the returns will be Gaussian. The unconditional distribution will actually present fat tails even though the conditional distribution is Gaussian. The assumption of a Gaussian conditional distribution is therefore not that restrictive. This is because the quasi-maximum likelihood estimator will still be consistent under mild regularity conditions, even if the true distribution is different.⁵⁴ This assumption and the concept of likelihood estimation require an explanation.

The approach used by the New York University Stern Volatility Laboratory (V-Lab) (2015a) estimates the parameters $(\mu, \omega, \alpha, \gamma, \beta)$ simultaneously by maximising the log likelihood. Maximum likelihood estimation refers to the selection of values for the parameters that maximise the likelihood of data occurring (Hull, 2012:504). If a variable's variance (X) is estimated from a certain number of observations (m) of X when the distribution is normal with a mean of zero. The assumption is made that the observations are u_1, u_2, \dots, u_m and the variance is (v), then the probability density function for X when $X = u_i$ will define the likelihood of observing u_i , illustrated as:

$$\frac{1}{\sqrt{2\pi v}} \exp\left(\frac{-u_i^2}{2v}\right). \quad (4.9)$$

The likelihood of m observations then occurring in their order of observation is shown as:

$$\prod_{i=1}^m \left[\frac{1}{\sqrt{2\pi v}} \exp\left(\frac{-u_i^2}{2v}\right) \right]. \quad (4.10)$$

According to the maximum likelihood method, the value that maximises the expression will be the best estimate of v . Since the maximisation of an expression is the same as the maximisation of the logarithm of the expression, Equation 4.10 can be rewritten in log form by ignoring constant multiplicative factors:

53 Gaussian is simply another term for normally distributed.

54 Mild regularity conditions are assumptions regarding the behaviour of the distribution, which are largely expected to hold in practice. Consistency is the tendency of the estimator to converge to the true value when the number of observations is large (Christoffersen, 2011:75).

$$\sum_i^m \left[-\ln(v) - \frac{u_i^2}{v} \right]. \quad (4.11)$$

Equation 4.11 is therefore the log likelihood equation which we will maximise in order to obtain the parameter estimates (Hull, 2012:505). Maximum likelihood estimation can be criticised by arguing that the conditional normal distribution for the returns is not normal. However, even if this is the case, maximum likelihood estimation will still return variance and mean parameters estimates which converge to the true parameters when the sample size approaches infinity, on the condition that both mean and variance functions have the correct specifications. Quasi-maximum likelihood estimation is the use of maximum likelihood estimation even when the normal distribution assumption is not true. A caveat with this is that the quasi-maximum likelihood estimates may be less precise than those obtained using maximum likelihood estimation are (Christoffersen, 2011:75).

The GJR-GARCH model provides the advantage of capturing leptokurtic returns, as well as volatility clustering – both of which are characteristic of financial time series data. Volatility clustering is the propensity of volatility to be higher at time t if it was also high in the previous period $t - 1$. Similarly, a shock at time $t - 1$ still has an effect on the volatility at time t . The volatility may however, be mean reverting and fluctuate around the square root of the unconditional variance σ if $\alpha + \frac{\gamma}{2} + \beta < 1$. That is:

$$\sigma^2 = \text{Var}(r_t) = \frac{\omega}{1 - \alpha - \frac{\gamma}{2} - \beta}, \quad (4.12)$$

where $\frac{\gamma}{2}$ occurs because z_t is assumed to be normally distributed, as well as the assumption of symmetrical conditional distribution of returns around μ . The following assumption applies to parameters $\omega, \alpha, \gamma, \beta > 0$.

The V-Lab (2015a) explains the prediction as follows. Variable r_t is the last observation in the sample.

$\hat{\omega}, \hat{\alpha}, \hat{\gamma},$ and $\hat{\beta}$ are the quasi-maximum likelihood estimators of the parameters $\omega, \alpha, \gamma,$ and β .

The forecast of the conditional variance at time $T + h$ is then implied by the GJR-GARCH model as:

$$\hat{\sigma}_{T+h}^2 = \hat{\omega} + \left(\hat{\alpha} + \frac{\hat{\gamma}}{2} + \hat{\beta} \right) \hat{\sigma}_{T+h-1}^2. \quad (4.13)$$

This formula is applied iteratively in order to forecast the conditional variance for any time horizon h . The forecast of the compound volatility at time $T + h$ is therefore:

$$\hat{\sigma}_{T+1:T+h} = \sqrt{\sum_{i=1}^h \hat{\sigma}_{T+i}^2}. \quad (4.14)$$

If the value of h is large, the compound volatility forecast will converge to:

$$\sqrt{h} \sqrt{\frac{\hat{\omega}}{1 - \hat{\alpha} - \frac{\hat{\gamma}}{2} - \hat{\beta}}} \quad (4.15)$$

Equation 4.15 uses the square root law to scale over the forecast horizon, multiplied by the unconditional volatility estimate implied by the GJR-GARCH model. The $\frac{\hat{\gamma}}{2}$ term occurs because returns are assumed to be symmetrically and conditionally distributed.

In order to account for more lags in the conditional variance, A TGARCH model of order q or GJR-GARCH(p,q) model is defined as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^p \alpha_i \varepsilon_{t-1}^2 + \sum_{i=1}^p \gamma_i s_{t-1} \varepsilon_{t-1}^2 + \sum_{j=1}^q b_j \sigma_{t-j}^2, \quad (4.16)$$

with:

$$s_{t-1} = \begin{cases} 1 & \text{if } \varepsilon_{t-1} < 0 \\ 0 & \text{if } \varepsilon_{t-1} \geq 0 \end{cases} \quad (4.17)$$

The implications of Equation 4.16 are that the conditional variance σ_t^2 will be affected differently by ε_{t-1}^2 depending on whether ε_{t-1} is above or below the threshold value of zero.

If ε_{t-1} is positive, the total effects will be explained by $\alpha_i \varepsilon_{t-1}^2$ and when ε_{t-1} is negative, the total effects will be explained by $(\alpha_i + \gamma_i) \varepsilon_{t-1}^2$. It therefore follows that in the event of bad news, γ_i will be positive and have larger impacts.

The TGARCH model used by Rabemananjara and Zakoian (1993) is an extension of the standard TGARCH model but includes the lagged conditional standard deviations and variances as a regressor. The TGARCH model equations for the dynamics of volatility are as follows:

$$\sigma_{m,t}^2 = \omega_{m,G} + \alpha_{m,G} r_{m,t-1}^2 + \gamma_{m,G} r_{m,t-1}^2 I_{m,t-1}^- + \beta_{m,G} \sigma_{m,t-1}^2 \quad (4.18)$$

$$\sigma_{i,t}^2 = \omega_{i,G} + \alpha_{i,G} r_{i,t-1}^2 + \gamma_{i,G} r_{i,t-1}^2 I_{i,t-1}^- + \beta_{i,G} \sigma_{i,t-1}^2. \quad (4.19)$$

In the Equations 4.18 and 4.19, $I_{m,t}^- = 1$ if $\{r_{m,t} < 0\}$ and $I_{i,t}^- = 1$ if $\{r_{i,t} < 0\}$. This is essentially the same variance equation as the one explained by the GJR-GARCH model in Equation 4.7. To summarise, the volatility is therefore calculated by maximising the log likelihood function for both the bank and market's data series, using the GJR-GARCH Equation 4.7. The returns are then adjusted by dividing with these volatilities in order to produce standardised returns for use in the DCC model.

4.2.2 Dynamic Conditional Correlation (DCC)

The second step in the calculation of MES involves the computation of the DCC estimates. DCC estimators have the flexibility of univariate GARCH estimates, but not the complexity of conventional multivariate GARCH estimates. Furthermore, the number of parameters to be estimated in the DCC model is independent of the number of series to be correlated, therefore allowing the estimation of large correlation matrices (Engle, 2002:3).

The DCC model can be described as a generalisation of the constant conditional correlation estimator explained by Bollerslev (1990). If:

$$H_t = D_t R D_t, \quad (4.20)$$

where $D_t = \text{diag}\{\sqrt{h_{i,t}}\}$ and R is a correlation matrix consisting of the conditional correlations. This is also shown by rewriting Equation 4.20 as:

$$E_{t-1}(\varepsilon_t \varepsilon_t') = D_t^{-1} H_t D_t^{-1} = R, \quad (4.21)$$

since $\varepsilon_t = D_t^{-1} r_t$. The values for h may be univariate GARCH models, or functions of variables in the system as predetermined, or exogenous variables. Bollerslev (1990:499) used the unconditional correlation matrix of the standardised residuals as the estimate of R . Engle (2002:8) proposed the DCC as the estimator, which modified the equation to:

$$H_t = D_t R_t D_t, \quad (4.22)$$

where R is allowed to be time-varying. Parameterising R would have the same requirements as H , but the conditional variances must be unity, while the matrix of R_t would still be the correlation matrix. The approach used by Brownlees and Engle (2015:13) to construct a DCC model uses the volatility adjusted returns as follows:

$$\varepsilon_{i,t} = \frac{r_{i,t}}{\sigma_{i,t}} \quad \text{and} \quad \varepsilon_{m,t} = \frac{r_{m,t}}{\sigma_{m,t}}. \quad (4.23)$$

to model the correlation as:

$$\text{Cor} \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{m,t} \end{pmatrix} = R_t = \begin{bmatrix} 1 & \rho_{i,t} \\ \rho_{i,t} & 1 \end{bmatrix} = \text{diag}(Q_{i,t})^{-\frac{1}{2}} Q_{i,t} \text{diag}(Q_{i,t})^{-1/2}. \quad (4.24)$$

Variable R_t represents the matrix of time-varying conditional correlations with the diagonal elements equal to one, while $Q_{i,t}$ represents the pseudo-correlation matrix, the dynamics of which are specified by the DCC model as:

$$Q_{i,t} = (1 - \alpha_C - \beta_C) S_i + \alpha_C \begin{bmatrix} \varepsilon_{i,t-1} \\ \varepsilon_{m,t-1} \end{bmatrix} \begin{bmatrix} \varepsilon_{i,t-1} \\ \varepsilon_{m,t-1} \end{bmatrix}' + \beta_C Q_{i,t-1}, \quad (4.25)$$

with S_i representing the unconditional correlation matrix of the firm and market adjusted returns. A two-step quasi-maximum likelihood procedure is used to estimate the model. The V-Lab (2015b) explains this process as follows: If D_t is a diagonal matrix with the conditional volatilities calculated earlier using the GJR-GARCH model, $D_t^{i,j} = \sigma_t^i$ and if $i \neq j, D_t^{i,j} = 0$, the standardised residuals will then have to be illustrated with unit conditional volatility:

$$v_t = D_t^{-1}(r_t - \mu). \quad (4.26)$$

The matrix, which is also the Bollerslev's Constant Conditional Correlation estimator, is then defined:

$$\bar{R} = \frac{1}{T} \sum_{t=1}^T v_t v_t'. \quad (4.27)$$

In order to capture the dynamics in the correlation, Bollerslev's Constant Conditional Correlation will need to be generalised. The DCCs are then defined as:

$$Q_t = \bar{R} + \alpha(v_{t-1}v_{t-1}' - \bar{R}) + \beta(Q_{t-1} - \bar{R}). \quad (4.28)$$

The $Q_t^{i,j}$ will therefore represent the correlation between r_t^i and r_t^j at time t .

Estimation of the DCCs will then take place as follows. The parameters α and β will both be estimated simultaneously by maximising the log likelihood. The standardised residuals are assumed to be jointly Gaussian. The V-Lab (2015b) then proposes the use of a composite likelihood technique which eases the computation cost of estimating a vast dimensional time-varying correlation model, but we do not use this approach since only two data series are used.

The DCC model provides the advantage of taking into account the correlation clustering characteristic of financial time series data, which is similar in nature to the volatility clustering property. In this case, the correlation is more likely to be high at time t if it was also high at time $t - 1$. Similarly, a shock that occurs at time $t - 1$ will still have an impact on the correlation at time t . The correlation itself may however be mean reverting if $\alpha + \beta < 1$ and fluctuate around the unconditional correlation \bar{R} . The parameters are restricted to $\alpha, \beta > 0$ but if the conditional correlation is an integrated process, then $\alpha + \beta = 1$ (V-Lab, 2015b).

It is worth explaining that the DCC model uses variance targeting to simplify the modelling of vast dimensional time-varying covariance or correlation models. Variance targeting involves setting the long-run variance σ^2 equal to the sample variance, which is estimated as:

$$\sigma^2 = \frac{1}{T} \sum_{t=1}^T R_t^2. \quad (4.29)$$

Recalling the equation for a simple GARCH model:

$$\begin{aligned}\sigma_{t+1}^2 &= \omega + \alpha R_t^2 + \beta \sigma_t^2 \\ &= (1 - \alpha - \beta)\sigma^2 + \alpha R_t^2 + \beta \sigma_t^2.\end{aligned}\tag{4.30}$$

It can be seen that variance targeting eases the computation cost by reducing the number of parameters that need to be estimated by one (Christoffersen, 2011:75). The DCC model can be written similarly to the GARCH model:

$$Q_t = \Omega + \alpha v_{t-1} v'_{t-1} + \beta Q_{t-1}.\tag{4.31}$$

In this case, the Ω matrix would also have to be estimated. The implication being that $2 + n \frac{n+1}{2}$ parameters would need to be estimated as opposed to just two parameters, giving the unconditional correlation as:

$$\bar{R} = \frac{\Omega}{1 - \alpha - \beta}.\tag{4.32}$$

By substituting Ω for $\bar{R}(1 - \alpha - \beta)$ in the DCC formula, the model is written in more parsimonious way. In order to account for more lags, a DCC(p,q) model can be generalised as:

$$Q_t = \bar{R} + \sum_{i=1}^p \alpha_i (v_{t-i} v'_{t-i} - \bar{R}) + \sum_{j=1}^q \beta_j (Q_{t-j} - \bar{R}).\tag{4.33}$$

The procedure used in this study is based on the above methodology, but adapted as follows. A mean-reverting DCC model is constructed based on the work of Christoffersen (2011:159). Firstly, the correlation is defined in terms of the covariance $\sigma_{i,j}$ and volatilities as:

$$\rho_{ij,t+1} = \frac{\sigma_{ij,t+1}}{\sigma_{i,t+1} \sigma_{j,t+1}}.\tag{4.34}$$

A decomposition of covariance into volatility and correlation can then be illustrated:

$$\sigma_{ij,t+1} = \sigma_{i,t+1} \sigma_{j,t+1} \rho_{i,j,t+1},\tag{4.35}$$

and in matrix notation:

$$\begin{aligned}\sum_{t+1} &= D_{t+1} Y_{t+1} D_{t+1} \\ &= \begin{bmatrix} \sigma_{1,t+1}^2 & \sigma_{12,t+1} \\ \sigma_{12,t+1} & \sigma_{2,t+1}^2 \end{bmatrix} \\ &= \begin{bmatrix} \sigma_{1,t+1} & 0 \\ 0 & \sigma_{2,t+1} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12,t+1} \\ \rho_{12,t+1} & 1 \end{bmatrix} \begin{bmatrix} \sigma_{1,t+1} & 0 \\ 0 & \sigma_{2,t+1} \end{bmatrix}.\end{aligned}\tag{4.36}$$

The volatility adjusted returns are then created using the volatilities calculated earlier in the GJR-GARCH model, illustrated as:

$$z_{i,t+1} = \frac{R_{i,t+1}}{\sigma_{i,t+1}}, \quad i = 1, 2, \dots, n. \quad (4.37)$$

Dividing the returns by their conditional volatilities creates the volatility adjusted return variables $z_{i,t+1}$ which has a conditional volatility of one for all i . Furthermore, the conditional covariance of the volatility adjusted returns is then equal to the conditional correlation of the non-volatility adjusted returns, proven in:

$$\begin{aligned} E_t(z_{i,t+1}z_{j,t+1}) &= E_t \left[\left(\frac{R_{i,t+1}}{\sigma_{i,t+1}} \right) \left(\frac{R_{j,t+1}}{\sigma_{j,t+1}} \right) \right] \\ &= E_t \frac{(R_{i,t+1}R_{j,t+1})}{(\sigma_{i,t+1}\sigma_{j,t+1})} \\ &= \frac{\sigma_{ij,t+1}}{\sigma_{i,t+1}\sigma_{j,t+1}} \\ &= \rho_{ij,t+1} \quad \text{for all } i, j. \end{aligned} \quad (4.38)$$

The implication of this is that a model for the conditional covariance of volatility adjusted returns is the same as a model for the conditional correlation of non-volatility adjusted returns (Christoffersen, 2011:160).

A mean-reverting correlation model allows the correlations to revert to the average long-run correlation $\rho_{ij} = E(z_{i,t}z_{j,t})$. In the equations that follow, the correlation dynamics are driven by the variable q_{ij} which gets updated by the cross product of the volatility adjusted returns. By using correlation targeting and setting the initial unconditional correlation seed point $\bar{\rho}_{ij} = \frac{1}{T} \sum_{t=1}^T z_{i,t}z_{j,t}$, a specification in the form of a GARCH(1,1) model can be illustrated as:

$$q_{ij,t+1} = \bar{\rho}_{ij} + \alpha(z_{i,t}z_{j,t} - \bar{\rho}_{ij}) + \beta(q_{ij,t} - \bar{\rho}_{ij}). \quad (4.39)$$

The conditional correlations for the two entities are then obtained by normalising $q_{ij,t+1}$ as:

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t}q_{22,t}}} \quad (4.40)$$

where:

$$\begin{aligned} q_{11,t+1} &= 1 = \alpha(z_{1,t}^2 - 1) + \beta(q_{11,t} - 1) \\ q_{12,t+1} &= \bar{\rho}_{12} + \alpha(z_{1,t}z_{2,t} - \bar{\rho}_{12}) + \beta(q_{12,t} - \bar{\rho}_{12}) \\ q_{22,t+1} &= 1 = \alpha(z_{2,t}^2 - 1) + \beta(q_{22,t} - 1). \end{aligned} \quad (4.41)$$

The same quasi-maximum likelihood method used for the volatilities is then used to find the persistence parameters α and β with the dynamics initialised by setting $q_{11,0} = 1, q_{22} = 1$ and $q_{12,0} = \bar{\rho}_{12}$. It should

be recalled from Section 4.2.1 that this quasi-maximum likelihood method provides constant, inefficient estimates, but remains the best choice in order to avoid numerical optimisation in high dimensions (Christoffersen, 2011:164).

The log likelihood equation which will be maximised is illustrated using the bivariate normal distribution function for $z_{1,t}$ and $z_{2,t}$ as:

$$\ln(L_{c,12}) = -\frac{1}{2} \sum_{t=1}^T \left(\ln(1 - \rho_{12,t}^2) + \frac{(z_{1,t}^2 + z_{2,t}^2 - 2\rho_{12,t}z_{1,t}z_{2,t})}{(1 - \rho_{12,t}^2)} \right). \quad (4.42)$$

An important feature to note about this model is the persistence parameters will be constant between the two entities. The implication of this is that the level of correlation will change over time, but the persistence will not. The persistence in correlation is also different to the persistence in volatility. The DCC model can be written in matrix notation as:

$$\begin{aligned} Q_{t+1} &= \begin{bmatrix} q_{11,t+1} & q_{12,t+1} \\ q_{12,t+1} & q_{22,t+1} \end{bmatrix} \\ &= \begin{bmatrix} 1 & \rho_{12} \\ \rho_{12} & 1 \end{bmatrix} (1 - \alpha - \beta) + \alpha \begin{bmatrix} z_{1,t}^2 & z_{1,t}z_{2,t} \\ z_{1,t}z_{2,t} & z_{2,t}^2 \end{bmatrix} + \beta \begin{bmatrix} q_{11,t+1} & q_{12,t+1} \\ q_{12,t+1} & q_{22,t+1} \end{bmatrix}, \end{aligned} \quad (4.43)$$

where Q_{t+1} is a positive semi-definite matrix because it is a weighted average of positive definite and positive semi-definite matrices, which will cause the correlation matrix and covariance matrix to also be semi-definite.

In conclusion, the DCC model estimation occurs as follows. First, the volatilities are calculated using the GJR-GARCH model explained in Section 4.2.1. Then, the returns are adjusted using these volatilities, and the unconditional correlation matrix is calculated. Finally, the correlation persistence parameters α and β are estimated in order to obtain the DCCs.

4.2.3 Tail expectations

Since both the volatilities and the correlations have now been modelled, the final step in calculating MES involves the estimation of the tail expectations. Given that we are concerned with capturing the losses a bank will experience in its tail, this will ensure that the MES measures take into account the unique tail distributions that occur when the market is under distress. Two approaches can be used to model these expectations, an approach using non-parametric tail expectation estimators (Section 4.2.3.1), and a parametric approach using extreme value theory (Section 4.2.3.2).

4.2.3.1 Non-parametric tail expectation estimators

Brownlees and Engle (2012:15) implement an approach using non-parametric tail expectation estimators.

The tail expectations can be defined as:

$$E(\epsilon_{m,t} | \epsilon_{m,t} < K) \quad \text{and} \quad E(\epsilon_{i,t} | \epsilon_{m,t} < K), \quad (4.44)$$

where K represents a threshold level. By observing the average of the two residuals in all cases satisfying the condition $\epsilon_{m,t} < K$, the expectations can be estimated for a specific value of the variances ($\sigma_{m,t}^2, \sigma_{i,t}^2$) and the conditional correlation ρ_t . It should be noted that since there are only a few observations, the estimator will be unstable when $-K$ is large. In order to improve the efficiency of the estimators, a non-parametric kernel estimation approach can be implemented:

$$K_h(t) = \int_{-\infty}^{t/h} k(u) du. \quad (4.45)$$

The term $k(u)$ represents a kernel function and h represents a positive bandwidth. This will then result in the following for the market:

$$\hat{E}_h(\epsilon_{m,t} | \epsilon_{m,t} < K) = \frac{\sum_{i=1}^n \epsilon_{m,t} K_h(\epsilon_{m,t} - K)}{(n\hat{p}_h)}, \quad (4.46)$$

and for the bank:

$$\hat{E}_h(\epsilon_{i,t} | \epsilon_{m,t} < K) = \frac{\sum_{i=1}^n \epsilon_{i,t} K_h(\epsilon_{m,t} - K)}{(n\hat{p}_h)}, \quad (4.47)$$

with:

$$\hat{p}_h = \frac{\sum_{i=1}^n K_h(\epsilon_{m,t} - K)}{n}. \quad (4.48)$$

The non-parametric estimators in Equations 4.46 and 4.47 provide the advantage of being smooth estimates of the short-term MES, as a function of K . This is because they are smooth functions of the cut-off point K . However, since this method is non-parametric, it makes the assumption that the data does not come from any particular distribution, which may lead to inaccurate modelling of the tail distribution (Nadarajah, Zhang & Chan, 2014:284; Skoglund & Chen, 2015:104). Another drawback of the kernel-based method is that smoothing of the data may lead to increased bias and a subsequent increase in the mean square error of the kernel estimator, therefore rendering the entire process of smoothing counterproductive (Chen, 2008:93). These drawbacks may therefore warrant the investigation of an alternative approach.

4.2.3.2 Extreme value theory

This study uses a previously unused parametric approach based on extreme value theory to model the tail expectations in MES. Extreme value theory can be viewed as a way of smoothing and extrapolating the tails of an empirical distribution (Hull, 2015:290). Put another way, extreme value theory shifts the focus from modelling the entire distribution to modelling the tail behaviour alone, and as a result requires fewer degrees of freedom (Skoglund & Chen, 2015:104). A potential problem with extreme value theory explained by Christoffersen (2011:138) is that all returns are assumed to be independent and identically distributed (i.i.d.). It is further explained that since asset returns approach a normal distribution over a long time horizon, extreme value theory will be more useful over a shorter horizon, such as daily periods (Christoffersen, 2011:138). As a result of the time-varying variance patterns that take place over short time periods, the i.i.d. assumption does not hold. Therefore, if we want to apply extreme value theory, the variance dynamics have to be removed. Conveniently, the volatility adjusted returns we constructed earlier in Equation 4.23 can be defined as:

$$z_{t+1} = \sim i.i.d. D(0,1). \quad (4.49)$$

Since the assumption of i.i.d. can be made regarding the volatility adjusted returns, extreme value theory can be applied to them. Extreme value theory in this situation is concerned with modelling the tail distribution of returns, with the tail defined by the user (Christoffersen, 2011:138). In this case, the work of Brownlees and Engle (2012:11) is followed, and the threshold value (u) is selected as -2 % for the market. One of the key points in extreme value theory is that any observations (y) that go beyond the threshold value (u) will converge to the Generalised Pareto Distribution (GPD):

$$GPD(y; \xi, \beta) = \begin{cases} 1 - \left(1 + \frac{\xi y}{\beta}\right)^{-\frac{1}{\xi}} & \text{if } \xi > 0 \\ 1 - \exp\left(-\frac{y}{\beta}\right) & \text{if } \xi = 0 \end{cases}, \quad (4.50)$$

where $\beta > 0$ and $y \geq u$. The tail index parameter ξ is responsible for the shape of the distribution and the speed with which it approaches zero as y approaches infinity. The assumption is made that the tail index parameter is positive, since this is the case when return distributions have fat tails, therefore allowing the use of the Hill estimator to approximate the GPD. The Hill estimator (Hill, 1975:1164) and its approximation of the GPD are explained by Christoffersen (2011:139) as follows:

$$F(y) = 1 - cy^{-\frac{1}{\xi}} \approx 1 - \left(1 + \frac{\xi y}{\beta}\right)^{-\frac{1}{\xi}} = GPD(y; \xi; \beta), \quad (4.51)$$

for $y > u$ and $\xi > 0$. Considering the conditional distribution:

$$f(y|y > u) = \frac{f(y)}{\Pr(y > u)} = \frac{f(y)}{1 - F(u)}, \quad (4.52)$$

for $y > u$. From the definition of $F(y)$ above, it can be shown that:

$$F(u) = 1 - cu^{-\frac{1}{\xi}} \quad (4.53)$$

As well as the density function of y :

$$f(y) = \frac{\partial F(y)}{\partial y} = \frac{1}{\xi} cy^{-\frac{1}{\xi}-1}. \quad (4.54)$$

Using this information, the likelihood function for all y values larger than the threshold value can be calculated as:

$$L = \prod_{i=1}^{T_u} \frac{f(y_i)}{1 - F(u)} = \frac{\prod_{i=1}^{T_u} \frac{1}{\xi} cy_i^{-\frac{1}{\xi}-1}}{(cu^{-\frac{1}{\xi}})}, \quad (4.55)$$

where T_u represents the number of observations that are beyond the threshold value. The log likelihood function is therefore illustrated as:

$$\ln L = \sum_{i=1}^{T_u} \left(-\ln(\xi) - \left(\frac{1}{\xi} + 1 \right) \ln(y_i) + \frac{1}{\xi} \ln(u) \right). \quad (4.56)$$

The Hill estimator of the tail index parameter is then obtained by taking the derivative of ξ and setting it to zero:

$$\xi = \frac{1}{T_u} \sum_{i=1}^{T_u} \ln\left(\frac{y_i}{u}\right). \quad (4.57)$$

One assumption that may be challenged, is whether the tail parameter is positive, but this is a common assumption in risk management and making the assumption leads to the convenient derivation of the Hill estimator. Relaxing the condition of a positive tail parameter implies incoherent measures which contradict empirical evidence, so this is not an unusual or incorrect assumption (Scarrott & MacDonald, 2012:45).

Subsequently, by ensuring that the number of observations beyond the threshold value is correctly captured by the density in:

$$F(u) = 1 - cu^{-\frac{1}{\xi}} = 1 - \frac{T_u}{T} \left(\frac{y}{u} \right)^{-\frac{1}{\xi}}. \quad (4.58)$$

Solving for c then gives the estimate:

$$c = \frac{T_u}{T} u^{\frac{1}{\xi}}. \quad (4.59)$$

Therefore, for all values smaller than the threshold value, the cumulative density function is:

$$F(y) = 1 - cy^{-\frac{1}{\xi}} = 1 - \frac{T_u}{T} \left(\frac{y}{u}\right)^{-\frac{1}{\xi}}. \quad (4.60)$$

Since this study is concerned with extreme losses as opposed to extreme gains, the methodology will only be applied to the negative of returns. Using the Hill estimator, the expected shortfall (ES) can then be calculated as:

$$ES_{t+1}^p = \sigma_{PF,t+1} ES_{EVT}(p), \quad (4.61)$$

where:

$$ES_{EVT}(p) = -\frac{u}{\xi - 1} \left[\frac{p}{\left(\frac{T_u}{T}\right)} \right]^{-\xi}, \quad (4.62)$$

when $\xi < 1$ (Christoffersen, 2011:143). By using the Hill estimator, the daily expected shortfall, given that that the returns are below the threshold value of -2 %, is calculated, i.e. the tail distribution of the market.

Alternatives to the Hill estimator include the Pickands (1975) tail index estimator and the ratio estimator (Goldie & Smith, 1987). The Hill estimator was chosen above these models and the restricted Pareto model because it enjoys a simple structure which facilitates the verification of mathematical results (Reiss & Cornmann, 2008:211). The main drawback of using the Hill estimator lies in the choice of the threshold, u , as a trade-off exists between bias and variance. A larger threshold will result in a tail consisting of fewer observations, and therefore estimates of the tail parameter ξ will be noisy. Conversely, a smaller threshold value could result in the extreme value theory not holding. The implications of this are that the data to the right of the threshold value do not conform to the GPD in order to generate estimates of ξ which are unbiased (Nuyts, 2010: 4; Scarrott & MacDonald, 2012:44). Simulation studies have shown that for daily asset return data, a threshold value, u , which results in the number of observations that are beyond the threshold value, T_u , being at least 50 is adequate (McNeil, & Frey, 2000). The T_u values in this study are 86 for SA and 108 for the US.

It is necessary to clarify that existence of both the upper and lower bounds in the above discussion, and but the existence of an upper bound merely changes the power law from

$$p_{k_{\min}, k_{\max}}(k; \gamma) = \frac{k^{-\gamma}}{\zeta(\gamma, k_{\min}, k_{\max})}, \quad (4.63)$$

to:

$$p_{k_{\min}}(k; \gamma) = \frac{k^{-\gamma}}{\zeta(\gamma, k_{\min})}, \quad (4.64)$$

where the variables are defined by Bauke (2007:170). This applies for $k \in \mathbb{N}$ and $k_{\min} \leq k < k_{\max}$ in the former case and this changes to the condition that $k \in \mathbb{N}$ and $k \leq k_{\min}$ in the latter (as done in this study). Including or excluding this, however, does not change the outcome of any of the analysis. It is standard practice to only include the lower bound when using the Hill estimator – indeed, once the assumption of positivity has been made, the upper bound becomes redundant.

However, clarification regarding the selection of the threshold value u is necessary, since this will determine where the tail begins (Skoglund & Chen, 2015:105). For the market, the value of -2 % is selected. The choice of u for the bank is, however, not made, instead shifting the focus to the number of observations below the threshold value T_u . When applying this to the bank, the T_u value is set to the same number as was determined for the market, i.e. if the market breached the threshold value 20 times, the T_u value will also be set to 20 for the bank. This will model the tail distribution for the 20 largest losses of the bank, given that the market breached the threshold value on 20 occasions. It should be noted that the 20 largest losses of the bank will not necessarily occur on the exact same dates as the market. Therefore, symmetry is ensured by modelling the tail distribution for the same number of values for both the market and the bank. It should be reiterated that this step only involves modelling the shape of the tail distribution of the returns. This is then combined with the correlations and volatilities when the final MES measure is calculated in Section 4.2.4.

4.2.4 Marginal Expected Shortfall (MES)

Considering that the volatilities, correlations, and tail expectations have been estimated, the final step is now to use the three calculated components to obtain the MES by using Equation 4.65 (Brownlees & Engle, 2012:10):

$$\begin{aligned} MES_{i,t-1}^1(C) &= E_{t-1}(r_{i,t} | r_m < C) \\ &= \sigma_{i,t} E_{t-1} \left(\epsilon_{i,t} \middle| \epsilon_{m,t} < \frac{\mu}{\sigma_{m,t}} \right) \\ &= \sigma_{i,t} E_{t-1} \left(\rho_t \epsilon_{m,t} + \sqrt{1 - \rho_t^2} \epsilon_{i,t} \middle| \epsilon_{m,t} < \frac{C}{\sigma_{m,t}} \right) \\ &= \sigma_{i,t} \rho_t E_{t-1} \left(\epsilon_{m,t} \middle| \epsilon_{m,t} < \frac{C}{\sigma_{m,t}} \right) + \sigma_{i,t} \sqrt{1 - \rho_t^2} E_{t-1} \left(\epsilon_{i,t} \middle| \epsilon_{m,t} < \frac{C}{\sigma_{m,t}} \right), \end{aligned} \quad (4.65)$$

where $\sigma_{i,t}$ is the bank's volatility, $\sigma_{m,t}$ is the market's volatility, ρ_t is the conditional correlation, the term $\left(\epsilon_{m,t} \left| \epsilon_{m,t} < \frac{C}{\sigma_{m,t}} \right.\right)$ is the tail expectation of the market, and the term $\left(\epsilon_{i,t} \left| \epsilon_{m,t} < \frac{C}{\sigma_{m,t}} \right.\right)$ is the tail expectation of the bank.

Brownlees and Engle (2012:10) explained certain characteristics of Equation 4.65 as follows. The assumption is made that the bank and the market are positively dependent on each other. MES is therefore an increasing function of the bank's volatility. If the correlation is high, the MES formula assigns a greater weighting to the tail expectation of the standardised market residual. If the correlation is low, the MES formula assigns a greater weighting to the tail expectation of standardised idiosyncratic firm residual. The second term in Equation 4.65 (i.e. the error term) is present because the assumption is made that $\epsilon_{m,t}$ and $\epsilon_{i,t}$ has a non-linear dependence. If the dependence were to be captured by the correlation alone, it would be zero. This is a standard market assumption. Furthermore, since MES relates to the capital asset pricing model and the systematic risk of the beta, the data generated by a one-factor model will show that MES would be calculated as the systematic risk multiplied by the expected shortfall of the market.

The approach undertaken here allows for greater flexibility in that it permits for time-varying moments and an emphasis on downside exposure. The C variable indicates the conditioning systemic event. VaR and expected shortfall are typically expressed in conditional terms, meaning that the conditioning event is a quantile from the conditional return distribution; however, in this model the conditioning event is unconditional. The contrast is then that in a conventional approach, the probability of observing the conditioning event is constant, whereas in this model, the probability is time-varying in the sense that a larger volatility would result in a greater probability of observing a loss above a given threshold. It is important to note that since the log of returns and not arithmetic returns would be used, an approximation error will be present in Equation 4.65.

Since this study applied a new technique for measuring the tail expectations of MES for the bank and market, it will follow that the MES equation will need to be adjusted as follows:

$$\begin{aligned}
 MES_{i,t-1}^1(C) &= E_{t-1}(r_{i,t} | r_m < C) \\
 &= \sigma_{i,t} \rho_t E_{t-1} \left(ES_{t+1}^m \left| \epsilon_{m,t} < \frac{C}{\sigma_{m,t}} \right. \right) \\
 &\quad + \sigma_{i,t} \sqrt{1 - \rho_t^2} E_{t-1} \left(ES_{t+1}^i \left| \epsilon_{m,t} < \frac{C}{\sigma_{m,t}} \right. \right),
 \end{aligned} \tag{4.66}$$

where $\left(ES_{t+1}^m \mid \epsilon_{m,t} < \frac{c}{\sigma_{m,t}}\right)$ represents the expected shortfall of the market beyond the threshold value of -2%, while $\left(ES_{t+1}^i \mid \epsilon_{m,t} < \frac{c}{\sigma_{m,t}}\right)$ represents the expected shortfall of the bank on the number of occasions when the market breached its threshold value.

In addition to the MES values, we also use a simulation procedure to construct hypothetical values of MES over a longer time period, which take into account the historical volatilities and correlations.

4.2.5 Simulations for long-run Marginal Expected Shortfall (LRMES)

If LRMES is not approximated using Equation 4.6, a simulation-based procedure is implemented to extract the LRMES predictions. Brownlees and Engle (2015:30) explained that this process entails the simulation of a random sample of the arithmetic firm and market returns during the h -period, conditional in the information set available on day t .

$$\begin{bmatrix} R_{i,t+1:t+h}^S \\ R_{m,t+1:t+h}^S \end{bmatrix} \mid F_t \quad s = 1, \dots, S, \quad (4.67)$$

with S representing the number of simulations. The GARCH-DCC standardised innovations are constructed for each $t = 1, \dots, T$.

$$\epsilon_{m,t} = \frac{r_{m,t}}{\sigma_{m,t}} \quad \text{and} \quad \epsilon_{i,t} = \left(\frac{r_{i,t}}{\sigma_{i,t}} - \rho_{i,t} \frac{r_{m,t}}{\sigma_{m,t}} \right) / \sqrt{1 - \rho_{i,t}^2}. \quad (4.68)$$

Both $\epsilon_{m,t}$ and $\epsilon_{i,t}$ have means of zero, unit variance, and are cross-sectionally and serially uncorrelated. Replacement $S \times h$ pairs of standardised innovations $[\epsilon_{m,t}, \epsilon_{i,t}]'$ are sampled, and then used to construct S pseudo sample of GARCH-DCC innovations from period $T + 1$ to period $T + h$ as follows:

$$\begin{bmatrix} \epsilon_m^S T + t \\ \epsilon_i^S T + t \end{bmatrix}_{t=1, \dots, h} \quad s = 1, \dots, S. \quad (4.69)$$

The pseudo sample of the GARCH-DCC innovations are then fed into the DCC and GARCH filters using the last values of the conditional correlation ρ_{iT} and variances σ_{mT}^2 and σ_{iT}^2 as the initial conditions. This delivers S pseudo samples of GARCH-DCC returns from period $T + 1$ to period $T + h$ conditional on the realised process up to time T . Symbolically:

$$\begin{bmatrix} r_m^S T + t \\ r_i^S T + t \end{bmatrix}_{t=1, \dots, h} \mid F_T \quad s = 1, \dots, S. \quad (4.70)$$

The multi-period ahead arithmetic firm return of each pseudo sample is then constructed:

$$R_{iT+1:T+h}^S = \exp \left\{ \sum_{t=1}^h r_{iT+t}^S \right\} - 1, \quad (4.71)$$

and the multi-period arithmetic market return $R_{m,T+1:T+h}^s$ is calculated analogously. The LRMES is then calculated as the average of the simulated multi-period returns, conditional on the systemic event:

$$LRMES_{i,T} = \frac{\sum_{s=1}^S R_{i,t+1:t+h}^s I\{R_{m,t+1:t+h}^s < C\}}{\sum_{s=1}^S I\{R_{m,t+1:t+h}^s < C\}}. \quad (4.72)$$

The process we follow in this study is a new contribution which uses the Monte Carlo simulation procedure and Cholesky decomposition to simulate returns that preserve the volatilities and correlations of returns over a specific time period. Since this studies approach involves simulating returns for a crisis period, the sub-prime crisis provides the appropriate sample period. The exact time period used will be 1 July 2007 to 31 December 2008 (Laeven *et al.*, 2014:28).

The average returns for the bank μ_b and the market μ_m , and the volatilities σ_b and σ_m are calculated over the specified period. The covariance matrix for the bank and market over this period is also constructed:

$$COV_{b,m} = \begin{bmatrix} \sigma_b^2 & \sigma_b \sigma_m \rho_{bm} \\ \sigma_b \sigma_m \rho_{bm} & \sigma_m^2 \end{bmatrix}, \quad (4.73)$$

where ρ_{bm} is the average of the conditional correlation values over the specified period. Two sets of uncorrelated, normally distributed random variables z_b^u and z_m^u are drawn for 180 days (to represent six months). Since these are uncorrelated, we need to correlate the random variables so that their correlation matrix can be illustrated as:

$$\rho = \begin{bmatrix} 1 & \rho_{bm} \\ \rho_{bm} & 1 \end{bmatrix}. \quad (4.74)$$

In order to obtain this result, we use the Cholesky decomposition of the correlation matrix:

$$Y = \begin{bmatrix} \sigma_b & \frac{\sigma_b \sigma_m \rho_{bm}}{\sigma_b} \\ 0 & \sqrt{\sigma_m^2 - \left(\frac{\sigma_b \sigma_m \rho_{bm}}{\sigma_b}\right)^2} \end{bmatrix}, \quad (4.75)$$

and then the transpose of the Cholesky matrix:

$$Y^{\frac{1}{2}} = \begin{bmatrix} \sigma_b & 0 \\ \frac{\sigma_b \sigma_m \rho_{bm}}{\sigma_b} & \sqrt{\sigma_m^2 - \left(\frac{\sigma_b \sigma_m \rho_{bm}}{\sigma_b}\right)^2} \end{bmatrix}. \quad (4.76)$$

The correlated variables are then created by using the above as:

$$z_b^c = \mu_b + (\sigma_b z_1^u + 0 z_2^u) \quad (4.77)$$

$$z_m^c = \mu_m + \left[\frac{\sigma_b \sigma_m \rho_{bm}}{\sigma_b} z_1^u + \sqrt{\sigma_m^2 - \left(\frac{\sigma_b \sigma_m \rho_{bm}}{\sigma_b} \right)^2} z_2^u \right].$$

The sum of the values over 180 days is calculated to arrive at the cumulative return. Following the example of Acharya *et al.* (2012:60), a 40 % decline over 180 days is considered a crisis period. The LRMES is then calculated as:

$$LRMES_{b,t} = \frac{\sum_{z=1}^Z z_{i,t+1:t+180}^c I\{z_{m,t+1:t+180}^c < C\}}{\sum_{z=1}^Z I\{z_{m,t+1:t+180}^c < C\}}, \quad (4.78)$$

where I is an indicator function:

$$\begin{cases} I = 1 & \text{if } z_m^c < -40 \\ I = 0 & \text{if } z_m^c \geq -40 \end{cases} \quad (4.79)$$

A crisis scenario where the market return falls below -40 % is rare, with only three such falls ever to have taken place. The first was in 1929 (Black Tuesday), the second in 2000 (Dotcom bubble), and the third in 2008 (Sub-prime crisis). In order to account for this scarcity, 50 000 draws will take place, with Equation 4.78 representing one draw. The average of these draws, which return a result, will then be calculated, giving the final LRMES as:

$$LRMES_b = \sum_{i=1}^{50\,000} \left(\frac{\sum_{z=1}^Z z_{i,t+1:t+180}^c I\{z_{m,t+1:t+180}^c < -40\}}{\sum_{z=1}^Z I\{z_{m,t+1:t+180}^c < -40\}} \right). \quad (4.80)$$

The final LRMES is then used as an input into the alternative SRISK equation. The LRMES may provide an advantage in that it offers a prediction over a longer, hypothetical crisis period. It is therefore likely to represent more of a 'worst case scenario' for banks. The LRMES value will also be constant for the entire period 2001 to 2013. The reason for keeping the LRMES constant is because this will allow the estimation of SRISK values using the balance sheet data for the current period while investigating the effect that sub-prime crisis volatilities and tail dependence would have had in that period.

4.2.6 Section summary

This section outlined the various components that must be calculated in order to produce the SRISK measure. Firstly, the conditional volatilities for the banks and market are calculated using a GJR-GARCH model. These volatilities are then used as part of a DCC model which produces daily conditional correlation values between the banks and market. Next, the tail expectations of the bank and market are calculated using a new contribution, based on extreme value theory. The three components are then combined to produce the MES of the banks. Since the SRISK measure can also be represented using an alternate equation which considers LRMES, a simulation procedure is undertaken to produce these values. This

approach to the simulation process is a new contribution as it combines the Monte Carlo simulation procedure and Cholesky decomposition to simulate returns which preserve the original volatilities and correlations over a certain time period.

4.3 SYSTEMIC RISK TRANSFER

Section 2.2.3 discussed the various ways in which systemic risk could be transferred from one financial sector to another. In order to investigate the evidence of a systemic risk from the US to SA, three different approaches will be used. Section 4.3.1 considers the possible contagion effects that may take place from the US sector to SA by estimating a DCC model and examining the correlations between the two markets. Following on from this it will be necessary to investigate if volatility is transferred from the US to SA. Section 4.3.2 includes the estimation of an exponential GARCH (EGARCH) model in order to investigate if volatility in the US sector may be transferred to the SA sector. Finally, Section 4.3.3 analyses the MES of the SA equity sector conditional on a decline in the US equity sector.

4.3.1 Contagion

In order to model contagion numerically, a strict definition will need to be applied. Section 2.2.3.1 discussed contagion in depth and noted the narrow definition proposed by Forbes and Rigobon (2002:2224), which this study will use. They define contagion as a significant increase in cross-market linkages following a shock to a single or group of countries. The implication of this is that contagion is only evidenced when the correlations between the two countries increase during a crisis period. As a result, correlation during periods of stability is not necessarily indicative of contagion (Forbes & Rigobon, 2002:2224).

The use of unconditional correlations to examine the presence of spillover effects and subsequently the possibility of systemic risk is characterised with biases. That is, during periods of high market volatility, correlation coefficients will increase and be biased upwards (Forbes & Rigobon, 2002:2225). In order to overcome these biases, a DCC model is used. A DCC model analyses the comovement between the markets by using the correlations of changes in the stock returns market, and provides the advantage of taking time-varying volatility into account, while also addressing feedback effects by not assuming unidirectionality (Frank & Hesse, 2009:3). The DCC model was discussed in depth in Section 4.2.2.

Contagion between financial markets is one measure of how systemic risks can be transferred between financial markets. While the DCC model takes the volatilities into account, it does not explicitly investigate the presence of a volatility spillover effect. That is, whether volatility in one market (good and bad) is transferred to another.

4.3.2 Volatility spillovers

In order to model the volatility spillover effect between the S&P 500 and the ALSI,⁵⁵ we use an EGARCH model for the sample period 2001 to 2013. The EGARCH model is the most appropriate model to use when examining volatility spillover effects between stock markets, as evidenced by a number of studies, such as Kanas (1998), Miyakoshi (2003), Rivas, Verma, Rodriguez and Verma (2008), and Liebenberg (2012).

The advantages and drawbacks of GARCH models were discussed in Section 4.2.1. The GJR-GARCH and EGARCH models are similar, with the main differences being that the EGARCH model produces a guaranteed non-negative form of variance and provides a greater weighting to more recent returns. The EGARCH model was first proposed by Nelson (1991) with the conditional variance illustrated as:

$$\ln(h_t) = \omega + \sum_{j=1}^q \psi_j \left| \frac{u_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^q \xi_j \frac{u_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^p \delta_i \ln(h_{t-1}), \quad (4.81)$$

where ω , ψ , ξ , and δ are the parameters that need to be estimated. Since the variance is taken in logarithmic form, the leverage effect will be exponential as opposed to quadratic. The parameter ξ is important when testing for asymmetries in that $\xi_1 = \xi_2 = \dots = 0$ would imply that the model is symmetric. The constraint $\xi < 0$ implies that the positive shocks result in less volatility than negative shocks (Asteriou & Hall, 2011:308). Variable ψ measures the impact of innovation on the conditional variance at time t , while δ is the shock persistence parameter. This study is not concerned with examining the returns, therefore the return equation is not reported.

In order to estimate an EGARCH model, certain requirements must still be met. An ordinary least squares regression model has the requirement that the variables being regressed on each other must be stationary, i.e. they must not contain a unit root. That is, if non-stationary variables are regressed on each other, a spurious regression will result (Gujarati, 2003:822). Unit root tests are conducted to ensure that this is not the case.

4.3.2.1 *Time series unit root testing*

The basic unit root theory for time series considers the following AR(1) model (Asteriou & Hall, 2011:335):

$$y_t = \phi y_{t-1} + u_t, \quad (4.82)$$

with u_t representing a white noise process and the stationarity condition being $|\phi| < 1$. Three possible situations may occur:

⁵⁵ S&P 500 refers to the Standard and Poor's 500. ALSI refers to the FTSE/JSE All-Share Index.

- $|\phi| < 1$ which implies that the series is stationary,
- $|\phi| > 1$ which represents an exploding series, and
- $\phi = 1$ which implies that the series contains a unit root and is therefore non-stationary.

The Dickey-Fuller test modifies the AR(1) model to:

$$\Delta y_t = \phi y_{t-1} + u_t, \quad (4.83)$$

where $\phi = (\phi - 1)$ with the null hypothesis $H_0: \phi = 0$ and the alternative hypothesis $H_1: \phi < 0$. The implication being that if $\phi = 0$ then y_t follows a random walk.

Since it is unlikely that the error term will be white noise, and in order to avoid autocorrelation, the Augmented Dickey-Fuller (ADF) test is used which includes additional lagged terms of the dependent variables, the length of which are determined by the Akaike information criterion or the Schwartz Bayesian criterion. The ADF test can be represented in three different forms (Asteriou & Hall, 2011:344):

$$\Delta y_t = \phi y_{t-1} + \sum_{i=1}^p \beta_i \Delta y_{t-1} + u_t, \quad (4.84)$$

where if $\phi = 0$ it will mean that y_t is a random-walk model. The second form includes a constant in the random walk process:

$$\Delta y_t = \alpha_0 + \phi y_{t-1} + \sum_{i=1}^p \beta_i \Delta y_{t-1} + u_t, \quad (4.85)$$

where in such cases a definite trend will be present when $\phi = 0$. The third form includes a non-stochastic time trend:

$$\Delta y_t = \alpha_0 + \phi y_{t-1} + a_2 t + \sum_{i=1}^p \beta_i \Delta y_{t-1} + u_t. \quad (4.86)$$

In all forms, the focus is on testing if $\phi = 0$. The ADF test statistic is the t-statistic for the lagged dependent variables.⁵⁶ The null hypothesis is rejected when the ADF test statistic is smaller than the critical value. If the null hypothesis of a unit root is rejected, it can be concluded that y_t is stationary. If the series are found to be non-stationary, the next step involves testing for potential cointegration.

4.3.2.2 Time series cointegration testing

Stationary time series are a requirement if sensible regression results are to be obtained. However, if the error term is stationary, the regression of a non-stationary series on another non-stationary series may

⁵⁶ The critical values for the ADF test can be found in Asteriou & Hall (2011:343).

cancel out the stochastic trends. The implication is then that the two series are cointegrated (Gujarati, 2003:822). If the series contains a unit root, and are both integrated of the same order, e.g. both are $I(1)$ or both are $I(2)$, then a cointegration test should be conducted. The result is that if a cointegrating relationship exists between the two series, the use of these series would not lead to spurious regression (Asteriou & Hall, 2011:356). If the series are already determined to be stationary, it can be concluded that there are no cointegrating relationships between the variables (Asteriou & Hall, 2011:365). In order to test for cointegration, the Engle-Granger approach and the Johansen approach will be used, as this is the standard approach in the literature (Asteriou & Hall, 2011:365)

Engle and Granger (1987) developed a test which checks for the existence of cointegration (long-run equilibrium) between two non-stationary processes. The first step involves testing the order of integration of the variables. Next, the long-run relationship is estimated and the residuals saved:

$$Y_t = \beta_1 + \beta_2 X_t + e_t. \quad (4.87)$$

If no cointegration is present, the results will be spurious, but if cointegration is present, the ordinary least squares regression will have highly consistent estimators for β_2 , the cointegrating parameter. If the variables are cointegrated, the estimated residual sequence \hat{e}_t is obtained from the equation. If this is found to be stationary, then X_t and Y_t are cointegrated. A modified form of the Dickey-Fuller test is conducted on the residual series to test for stationarity.

The Johansen approach is used when there are more than two variables in the model, and therefore the potential for more than one cointegrating relationship exists. The first step once again is testing the order of integration of the variables. Next, the appropriate lag length of the model is selected as well as model specification in terms of deterministic components such as an intercept, or trends in the multivariate system. In order to determine the number of cointegrating vectors, two methods can be used, both involving the estimation of a $k \times k$ matrix with rank r . Once the number of cointegrating relationships is determined, a test for weak exogeneity is conducted. If a variable is found to be weakly exogenous, it can be removed as an endogenous part of the system. The final step then involves testing the linear restrictions in the cointegrating vectors (Asteriou & Hall, 2011:375). Given that there are only two variables in the model, the Johansen procedure will not be used.

Once the testing for cointegration and the presence of a unit root has been completed, thereby ensuring that spurious results will not be obtained, the estimation of the EGARCH model can take place. If a volatility spillover effect is found, the variance of the model will be generated and illustrated graphically. This will allow an examination of whether this effect has changed over time and how it reacted around the sub-prime crisis period. The final measure of potential cross-market contamination will then take this

volatility spillover effect into account, as well as the potential contagion by considering the decline in the equity market of SA, given that the equity market of the US declined by a specified margin.

4.3.3 Marginal Expected Shortfall (MES) of the SA market

Recalling the discussion of MES in Section 4.2, MES is concerned with predicting the expected decline in equity value of a bank, given that the market as a whole declined by a specified margin. It was stated in Section 1.6.2 that MES refers to the one-day decline in the equity value of the bank, given that the equity market as a whole has declined by 2%. This is widely accepted to be representative of a one-day systemic event (Brownlees & Engle, 2012:10; Laeven et al., 2014:28). This study proposes that the measurement of the ALSI relative to the S&P 500 could provide an indication of the systemic response of the SA market to the US market. This will take into account the time-varying conditional volatilities and the DCCs, as well as the tail expectations of both markets, to provide a measure of the decline in equity value of the ALSI conditional on a decline in the S&P 500 by 2%. Additionally, the simulation procedure outlined in Section 4.2.5 will also be used to produce LRMES values for a hypothetical crisis period. A further analysis is then conducted with an alternate set of inputs, although the same procedure outlined above is followed. In order to better isolate the financial sectors of the SA and US markets, the Johannesburg Stock Exchange (JSE) Bank Index is specified as a hypothetical bank in the US financial sector, proxied by the Financial Select Sector Standard & Poor's Depository Receipts (SPDR) exchange traded fund.⁵⁷ These specifications of the SA equity market as a hypothetical bank in the US equity market, and the subsequent assessment of a potential systemic response represents a new contribution to the field.

4.3.4 Section summary

Three approaches will be used to examine potential cross-market contaminations. The first will be the investigation of potential contagion using a DCC model. Secondly, an EGARCH model will be used to determine if a volatility spillover effect is present from the US to the SA market. Finally, the MES procedure outlined in Section 4.2 will be used to measure the expected decline in value of the SA equity market conditional on a decline in the US equity market, as well as the decline of SA banks on the decline of the US financial sector. While these three approaches will illustrate potential linkages between the two markets, they may also provide a link to the systemic risk produced by specific banks within these sectors. The logical next question to investigate then would be the cause of systemic risk within these individual banks. This involves an investigation into which individual characteristics of a bank result in it having a specific amount of systemic risk.

⁵⁷ The Financial Select Sector SPDR exchange traded fund tracks an index of S&P 500 financial stocks and is weighted by market cap.

4.4 THE DETERMINANTS OF SRISK

The calculation of the SRISK measure represented the completion of the first part of the empirical analysis. It will now be used as the dependent variable in a multivariate panel regression model. This regression model will assist in identifying the individual determinants of systemic risk for each individual bank, as well as the size of the effect that individual determinants have on systemic risk. The regression analysis draws on the work of Beltratti and Stulz (2012) and Laeven *et al.* (2014). The choice of independent variables for inclusion in the model is based loosely on the work carried out in both studies, with data constraints also limiting the choice of variables. This study contributes new variables for SA based on the theory associated with systemic risk for emerging markets and SA in particular.

It should also be noted that our analysis is conducted using publicly available data. The determinants of systemic risk will therefore not be the same as those used by Basel or other regulatory authorities. Given the unique characteristics of the two economies, it will also follow that the determinants may not be the same for both. Considering that significantly more US banks are included in the study, compared with SA banks, only the US banks with the five highest SRISK rankings will be included in the regression. Additionally, the SRISK of SA banks may be affected by factors outside of the SA financial sector. One such factor could be the potential volatility spillover effect and contagion from the US market to the SA market. This measure would be proxied by the variance produced by the EGARCH model in Section 4.3.2. Since SA is an emerging market, and Section 2.5.1 showed that systemic risk in emerging markets is affected by volatile capital flows, the presence of capital flows may be a determinant of systemic risk in SA. This measure would be proxied by the portfolio investment liabilities for SA.

The regression analysis in Section 4.4.1 outlines the panel regression approach, as well as the benefits and disadvantages associated with this procedure. Section 4.4.2 and Section 4.4.3 discuss the various tests that need to be undertaken in order to ensure that the data meet the necessary requirements for all the econometric models.

4.4.1 Panel regression model

Panel data will be used in order to provide estimation and information that is more efficient, while also capturing the dynamic behaviour of the variables. Panel data models also provide a number of advantages over cross-section and time series models. These include increasing the number of data points and therefore the degrees of freedom, while also reducing collinearity among explanatory variables (Hsiao, 2014:3). Panel data also provide the advantage of controlling for heterogeneity, offering data that have more variability and information, while also allowing the inference of the dynamics of adjustment. By combining both cross-section and time series data, panel data allow the identification and measuring of effects that are only detectable when these two series are combined (Baltagi, 2001:7).

Panel data modelling includes three methods. The simplest method is the common constant or pooled ordinary least squares method. This method essentially assumes that there are no differences among the data of the different cross-sectional dimensions. This means that a common constant will exist for all the cross-sections, and this is useful when analysing cross-sections that are expected to be homogenous (Asteriou & Hall, 2011:417). Since bank sizes display some variation, it is unlikely that the common constant method will be a good fit.

The random effects method is a method of estimation which treats the constants for each cross-section unit as a random parameter, as opposed to a fixed parameter. The intercepts for each cross-section are therefore assumed to come from a common intercept α which does not change over cross-sections or through time, in addition to a random variable ϵ_i , which stays constant over time but does change cross-sectionally. Variable ϵ_i therefore measures the random deviations that occur for each cross-section's intercept term from the global intercept term represented by α . The random effects model can thus be illustrated by Equation 4.88 (Asteriou & Hall, 2011:420):

$$y_{it} = \alpha + \beta x_{it} + \omega_{it}, \quad (4.88)$$

where:

$$\omega_{it} = \epsilon_i + v_{it} \quad \text{and} \quad \epsilon_i \sim IN(0, \sigma^2). \quad (4.89)$$

Term x_{it} represents a $l \times k$ vector of independent variables. The heterogeneity in the cross-sectional dimension is captured by the ϵ_i terms. Furthermore, instead of using an ordinary least square, the generalised least square method is used and the α and β vectors are estimated consistently.

The next method that can be used is the fixed effects method. In this case, the one-way fixed effect model will be used – as the constant is assumed to be cross-section specific, therefore allowing each cross-section to have a different constant. The one-way fixed effects model can be illustrated by Equation 4.90 (Asteriou & Hall, 2011:418):

$$y_{it} = \alpha + \beta' x_{it} + e_{it}, \quad (4.90)$$

with:

$$e_{it} \sim IN(0, \sigma^2). \quad (4.91)$$

The fixed effects can also be referred to as the least squares dummy variables estimators, since the model now includes dummy variables that take into account heterogeneity in the cross-sectional dimension.

The difference between the fixed effects and random effects method is essentially that the fixed effect method assumes that each cross-section differs in the intercept term, whereas the random effects method assumes this difference to be in the error term (Asteriou & Hall, 2011:420). The choice of the

most appropriate method is likely to be dependent on the balance of the panel. Asteriou and Hall (2011:20) state that generally if the panel contains all the existing cross-sectional data, the fixed effects method would be the better choice. Conversely, if the panel contains fewer observations of cross-sectional units, then the random effects method would be better. In order to choose between the two methods, the Hausman test will be conducted. The test compares the fixed effects and random effects under the null hypothesis of no correlation between the individual effects and other regressors in the model (Hausman, 1978:1268). Simply put, it tests the null hypothesis, whether the random effects are consistent and efficient, against the alternative hypothesis, whether the random effects are inconsistent (Asteriou & Hall, 2011:421). If we reject the null hypothesis, then the fixed effects model will be used, and if not, the random effects model will be used.

A panel regression model is used because we are limited to 13 observations per bank and such a limited number of observations may be problematic in a normal time series model. The main aim of the regression model is to determine the significant determinants of SRISK. The regression equation is represented in the following form:

$$SRISK_{i,t} = \alpha + \beta_1 SIZE_{i,t} + \beta_2 CAP_{i,t} + \beta_3 FUND_{i,t} + \beta_4 ACT_{i,t} + \beta_5 LVG_{i,t} + \varepsilon_{i,t}. \quad (4.92)$$

The variables in Equation 4.92 are based on the work of Laeven *et al.* (2014:13) and are represented as follows:

- α – Constant.
- $SIZE_{i,t}$ – Bank size for bank i at time t . Measured using the total value of bank assets.
- $CAP_{i,t}$ – Bank capitalisation for bank i at time t with two alternative measures. The Tier 1 capital ratio, which represent a bank's core capital (BCBS, 2011:2) – and a simple leverage ratio. The leverage ratio is mostly underreported for SA banks, therefore only the Tier 1 capital ratio will be used to measure CAP .
- $FUND$ – Bank funding structure for bank i at time t with two alternative measures. The share of depository funding, and an index of funding fragility. The funding fragility index is defined as deposits from other banks, other deposits, and short-term borrowing as a fraction of total deposits, plus money market and short-term funding (Laeven *et al.*, 2014:10). Due to data constraints, FUND will only use the funding fragility index. This measure is calculated as follows:

$$Funding\ fragility\ index = \frac{deposits\ from\ other\ banks + other\ deposits\ and\ short-term\ borrowings}{total\ deposits, money\ market\ and\ short-term\ funding}. \quad (4.93)$$

- $ACT_{i,t}$ – Bank activities of bank i at time t . Two alternative measures are used – the share of loans in total assets, and the share of non-interest income in total income. The share of loans is proxied by gross loans, the share of non-interest income is proxied by total non-interest operating income, and total income is proxied by the gross income (gross interest and dividend income plus total non-interest operating income).
- $LVG_{i,t}$ – The leverage of the bank i at time t measured as (total liabilities + market capitalisation)/market capitalisation.
- ε – Error over time t .

Large banks are integral in the interbank market for two main reasons. Firstly, they provide liquidity to smaller banks, and secondly, the activities they undertake rely on economies of scale and scope, and therefore cannot be replicated by smaller banks (Laeven *et al.*, 2014:15). The undercapitalisation of the financial sector is therefore likely to be greatest when a large bank fails. It is expected then that the size of a bank will potentially to be the most significant determinant of systemic risk.

Given the characteristics of banks in emerging markets, we contribute new variables to the SRISK equation for SA banks. It was shown in Section 2.5.1 that systemic risk in emerging markets was largely affected by the volatility of capital flows to the country. In order to take this into account, the portfolio investment liabilities for SA are used as a proxy for capital inflows. FDI flows are not included, since these are typically invested in real economic activity and have been shown to be less volatile (De Beer, 2015:2). Additionally, based on the literature discussed in Section 2.5, this study proposes that the volatility spillover from the US market to the SA market may also be a potential determinant of systemic risk for SA banks. The EGARCH model discussed in Section 4.4.2 produces a conditional variance series which will be used as a proxy for the volatility spillover. A new regression equation is then constructed, which includes the volatility spillover from the US market to the SA market, as well as capital inflows to SA:

$$SRISK_{i,t} = \alpha + \beta_1 SIZE_{i,t} + \beta_2 CAP_{i,t} + \beta_3 FUND_{i,t} + \beta_4 ACT_{i,t} + \beta_5 LVG_{i,t} + \beta_5 VOL_{i,t} + \beta_6 FLOW_{i,t} + \varepsilon_{i,t}, \quad (4.94)$$

where $VOL_{i,t}$ is the volatility spillover between the S&P 500 and the ALSI, and $FLOW_{i,t}$ is the capital inflows to SA. The conducting of either time series or panel regression analysis first requires that the data meet certain econometric requirements. This was explained for time series analysis in Section 4.3.2.1 and Section 4.3.2.2. The testing procedures for panel data differ from time series data, and therefore require a separate explanation. Section 4.4.2 describes the panel unit root testing procedure, while Section 4.4.3 explains the panel cointegration procedure.

4.4.2 Panel unit root testing

Panel data unit root theory considers the following AR(1) model:

$$y_{i,t} = \rho_i y_{i,t-1} + X_{i,t} \delta_i + \epsilon_{i,t}, \quad (4.95)$$

where $i = 1, 2, \dots, N$ cross-section units observed over $t = 1, 2, \dots, T_i$ periods. $X_{i,t}$ is the exogenous variables in the model (including fixed effects or individual trends), while ρ_i are the autoregressive coefficients. $\epsilon_{i,t}$ are assumed as mutually independent idiosyncratic disturbances. y_i is weakly stationary if $|\rho_i| < 1$, and contains a unit root if $|\rho_i| = 1$

When testing for unit roots in panel data, two assumption regarding ρ_i are made. The first is that $\rho_i = \rho$ for all i , implying that the persistence parameters are the same for all the cross-sections. The second is that ρ_i varies for each cross-section.

In order to test for the common unit root process, the Levin, Lin and Chu (2002), Breitung (2000), and Hadri (2000) test can be used. The Levin-Lin-Chu (LLC) and Breitung tests consider the basic ADF specification:

$$\Delta y_{i,t} = \alpha y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{i,j} \Delta y_{i,t-j} + X'_{i,t} \delta + \epsilon_{i,t}, \quad (4.96)$$

where a common $\alpha = \rho - 1$ is assumed and a variable lag order for the difference terms p_i is allowed for the cross-sections. The null hypothesis is therefore that $H_0: \alpha = 0$ (the data contains a unit root) while the alternative hypothesis is that $H_1: \alpha < 0$ (the data does not contain a unit root). The Hadri test is based on the residuals obtained from individual ordinary least squares regressions of $y_{i,t}$ on a constant, or a constant and a trend (Hadri, 2000:151). It has a null hypothesis of no unit root in any of the series in the panel. The results from the Hadri test will need to be evaluated with care, since it has a tendency to over reject the null hypothesis (QMS, 2013:491).

When testing for individual unit root processes ρ_i that vary for each cross-section, the Im, Pesaran and Shin (2003) test, and the Fisher-ADF and Fisher-Philips Perron tests, are used (QMS, 2013:491). The Im-Pesaran-Shin (IPS) test specifies an ADF regression for each cross-section as:

$$\Delta y_{i,t} = \alpha y_{i,t-1} + \sum_{j=1}^{p_i} \beta_{i,j} \Delta y_{i,t-j} + X'_{i,t} \delta + \epsilon_{i,t}. \quad (4.97)$$

The null hypothesis is then that $H_0: \alpha_i = 0$ for all i , while the alternative hypothesis can be illustrated as:

$$H_1: \begin{cases} \alpha_i = 0 & \text{for } i = 1, 2, \dots, N_1 \\ \alpha_i < 0 & \text{for } i = N + 1, N + 2, \dots, N \end{cases} \quad (4.98)$$

The average of the t-statistics for α_i from the individual ADF regressions is then adjusted as follows to obtain the desired test statistic:

$$\overline{t_{NT}} = \left(\sum_{i=1}^N t_{iTi}(p_i) \right) / N. \quad (4.99)$$

The Fisher-ADF and Fisher-PP use the results of Fisher (1932) to derive tests combining the p-values of the individual unit root tests. Both versions of the Fisher test will require the selection of whether to include individual constants, individual constants and trend terms, or no exogenous variables (QMS, 2013:493).

A useful summary of the panel unit root tests used is provided by the EViews™ 8 user guide in Table 4.1 below.

Table 4.1: Summary of available panel unit root tests.

Test	Null	Alternative	Possible deterministic component	Autocorrelation correction method
Levin, Lin and Chu	Unit root	No unit root	None, F, T	Lags
Breitung	Unit root	No unit root	None, F, T	Lags
IPS	Unit root	Some cross-sections without unit root	F, T	Lags
Fisher-ADF	Unit root	Some cross-sections without unit root	None, F, T	Lags
Fisher-PP	Unit root	Some cross-sections without unit root	None, F, T	Kernel
Hadri	No unit root	Unit root	F, T	Kernel

Source: QMS (2013:494).

None – no exogenous variables; F – fixed effect; T – individual effect and individual trend.

Following on from the concept of time series cointegration introduced earlier, the same situation may arise in panel data, namely that the regression of two non-stationary series may cancel out the stochastic trends if the error term is stationary (Gujarati, 2003:822). The result is that if both the series are non-stationary and have a cointegrating relationship, the use of these series would not lead to spurious regression (Asteriou & Hall, 2011:356). For our panel, considering the short time period, it is expected that no cointegrating relationships will be present; however, the tests will be conducted in any case.

4.4.3 Panel cointegration testing

Once it has been determined whether unit roots are present in some of the data series, the next step involves investigating if these series display cointegrating relationships. The cointegration tests will

investigate two possible scenarios. First, if $Y_{i,t}$ and $X_{i,t}$ are integrated of the same order and the residuals $u_{i,t}$ obtained through regression have a stochastic trend. Alternatively, if $Y_{i,t}$ and $X_{i,t}$ are integrated of the same order and the residuals $u_{i,t}$ are stationary. To resolve the first scenario, the variables can simply be transformed into first differences, while the second scenario indicates that the variables are clearly cointegrated (Asteriou & Hall, 2011:447).

Both the Pedroni (2004) and the Kao (1999) tests are extensions of the Engle and Granger (1987) framework. The Engle-Granger test for cointegration examined the residuals of a spurious regression estimated using variables which were $I(1)$. If the variables were cointegrated, then the residuals would be $I(0)$, and if not, they would be $I(1)$ (QMS, 2013:865). The Pedroni test allows for heterogeneity in the intercepts and trend coefficients for each cross-section, as well as multiple regressors, such that:

$$Y_{i,t} = \alpha_i + \delta_t + \sum_{m=1}^M \beta_{mi} X_{mi,t} + u_{i,t}. \quad (4.100)$$

Eleven different statistics with differing properties, such as size and power for different numbers of cross-sections and number of observations, are generated. The null hypothesis is that there is no cointegration. A disadvantage of this test is the a priori assumption of a unique cointegrating vector, which is restrictive (Asteriou & Hall, 2011:451; QMS, 2013:865). The Kao test is similar to the Pedroni test with the exception that it assigns intercepts that are cross-section specific and coefficients which are homogenous for the first stage regressors. The null hypothesis is that there is cointegration. A disadvantage of this test is that if more than one cointegrating vector is present, it does not address its identification (Asteriou & Hall, 2011:449; QMS, 2013:865). The final test is the Fisher-Johansen test, which was described by Maddala and Wu (1999). They used the idea of Fisher (1932) to combine the results from individual Johansen tests from individual cross-sections in order to obtain a panel test statistic. The null hypothesis for the Fisher-Johansen will be that the variables have either none, at most one, at most two, or more, depending on how many variables are being tested. This study will use the Kao, Pedroni, and the Fisher-Johansen tests.

4.4.4 Section summary

The individual determinants of SRISK within each individual bank will be investigated through the use of a panel regression model in order to assist in identifying the individual determinants of systemic risk for each individual bank, as well as the size of the effect that individual determinants have on systemic risk. Considering the short time period of our data and the collinearity of the variables, regular time series analysis is likely to be characterised with problems. A panel data analysis allows us to overcome many of these problems by increasing the number of data points and reducing collinearity. However, in order to estimate a panel data model, the data first have to be tested for stationarity and cointegration to ensure that the regressions are not spurious.

In order to take into account the unique characteristics of systemic risk associated with an emerging market such as SA, the variables used for the SA sector will differ slightly from those used for the US sector. The independent variables for the SA sector will take into account the volatility spillover from the US market, as well as the volatility of capital flows. The regression analyses therefore include a culmination of all the data used in the study.

4.5 CHAPTER SUMMARY

Chapter 4 started out by defining what the SRISK measure is, as well as the various components it is made up of. SRISK is a composite measure which includes both balance sheet data and market data. The MES measure, representing the decline in equity value of a bank given a specified decline in the market, is a function of three components. All three were calculated individually for the banks and the market. First, the conditional volatilities were calculated for the market and the individual banks. The GJR-GARCH model assigned a greater weighting to negative shocks and calculated the time-varying volatilities of the returns data. The original returns were then divided by these volatilities to obtain standardised returns. Subsequently, the returns were used in a DCC model to calculate time-varying correlations. Finally, the tail expectations were modelled. The conventional way of modelling tail expectations would be by calculating non-parametric estimators. Given the potential disadvantages associated with this method, this study used a parametric approach based on extreme value theory. This approach uses the Hill estimator to calculate the expected shortfall of the banks and the market below a certain threshold level. The use of such an approach to model the tail expectations of MES, represents a new contribution to the field. The three components are then combined to produce the MES of the bank, given a decline of 2 % in the market. An alternative SRISK equation can also be implemented, which required the use of LRMES as opposed to MES. Two methods exist for calculating LRMES. The first method is a simple approximation equation using MES, while the second is a more complicated simulation procedure. This study contributes a new method for the simulation of LRMES, which uses the Monte Carlo simulation technique and Cholesky decomposition to simulate returns that preserve the original volatilities and correlations over the crisis period 1 July 2007 to 31 December 2008. By using all these components, three different SRISK measures were calculated, each using a different MES or LRMES input.

Considering the degree of global financial integration, as well as the standing of the US financial sector in the global financial network, an investigation of possible systemic risk transfer from the US to SA was investigated using three approaches. First, the potential contagion from the US market to the SA market was investigated by implementing the same GJR-GARCH and DCC models that were used to calculate MES. The GJR-GARCH model calculated the time-varying volatilities of the ALSI and S&P 500 over the period 2001 to 2014. The returns series were then divided by the volatilities to produce the standardised returns.

The standardised returns were then used in the DCC model to calculate the correlations. An investigation of the DCCs will indicate if a contagion effect is present because an increased correlation during a crisis period is indicative of contagion. The second approach involved investigating the volatility spillover effect from the US to SA. In order to determine if an effect was present, an EGARCH model was used which – similar to the GJR-GARCH model – assigned a greater weighting to negative returns shocks. The EGARCH model also indicated whether volatility was affected more by negative or positive return shocks. The model also produced the conditional variance series for use as an additional independent variable in the regression model for SA. The final approach then made use of the MES model to measure a decline in equity value of the SA sector, given a decline in the US sector. That is, the ALSI was specified as a theoretical bank in the US equity market and the effects of a 2 % decline in the S&P 500 were investigated. Additionally, by specifying the JSE Bank Index as a hypothetical bank in the US financial sector, the effect of a 2 % decline in the US financial sector on the equity value of SA banks were investigated.

The final empirical investigation then focused on the individual determinants of systemic risk within each individual bank. Given the differing characteristics of the two economies, SA as an emerging market and the US as a developed economy, and the differing ways in which systemic risk can manifest in these financial sectors, it was necessary to investigate the different determinants of systemic risk within each individual bank. A panel regression model was used to conduct this investigation. The panel model was selected over a normal time series model because the short time period and high collinearity among variables was likely to prove problematic. A panel model would overcome these problems. Different variables will be used for the two economies. The US model will include factors that are mostly internal to the US financial sector, such as bank size and bank capitalisation, while the SA model will include external factors such as capital inflows and the volatility spillover effect calculated earlier. A number of tests will need to be conducted in order to ensure that the data comply with the necessary econometric requirements. Stationarity of the variables was examined through a number of unit root tests, and if the variables exhibited non-stationarity, cointegration tests were also conducted to determine if these series could still be used.

CHAPTER 5

THE MEASURING OF SYSTEMIC RISK: EMPIRICAL RESULTS

“It’s a wrong perception to believe that you can eliminate risk because you can measure it.”

– Myron Scholes

5.1 INTRODUCTION

Chapter 4 explained in depth the empirical methodology that will be used to measure systemic risk and its associated phenomena. Given the highly complex nature of systemic risk and the number of origins it may have, as well as its propensity to spread between entities, various factors were investigated. In light of the numerous models that are constructed and the analyses that are conducted, a large amount of data are needed. Section 5.2 describes the properties of the data, such as their source and the format they are reported in. Additionally, it discloses the banks included in the study and highlights the process used to select these banks. Naturally, since the empirical study is effectively split into three parts, namely the estimation of the Systemic Risk Index (SRISK) (Section 4.2), the calculation of a systemic risk transfer (Section 4.3) and the identification of the individual determinants of systemic risk (Section 4.4) – the results will repeat this pattern.

Section 5.3 measures the amount of systemic risk in the financial sector and the contribution that each bank makes to this amount. This amount is indicated by the SRISK values, which represent the capital shortfall of the financial sector during a financial crisis. In other words, it is the amount of capital a government would need to bail out the entire financial system during a crisis. This measure is then decomposed to determine the individual contribution that banks make to the total financial sector SRISK, and therefore the amount of capital a government would need to bail out the individual bank. Section 5.3.1 reports the results for SA, followed by the US results in Section 5.3.2. In order to provide some insight into the phenomena of systemic risk in a developed economy versus that in an emerging market, Section 5.3.3 compares the results and discusses their implications.

Given the importance of the US economy and the role it plays in the world financial market, it would be prudent to investigate whether turmoil in the US market has an adverse effect on the SA market. Section 5.4 explores the potential transfer of systemic risk from the US sector to the SA sector. Section 5.4.1 firstly assesses whether the correlation between the two markets increases during a crisis, thereby indicating a contagion effect from the US to SA. Following on from this, Section 5.4.2 analyses a possible volatility

spillover effect, which determines if volatility from the US sector is transferred to the SA sector, as well as the size of this transfer. Considering the evidence put forth by these two analyses, Section 5.4.3 measures the effect that a financial crisis scenario in the US would have on the SA market. In order to do this, we make a new contribution to the field by using the MES model with the specification of the SA equity market as the hypothetical bank in the US equity market.

Finally, Section 5.5 narrows the focus to individual banks and reports the results of the panel regression models. These models investigated the individual determinants of systemic risk for each individual bank, as well as the size of the effect that individual determinants have on systemic risk. Information acquired in Section 5.4, such as the volatility spillover effect, is used in the SA regression model. Section 5.5.1 presents the results for SA which, as an emerging market, may be affected by factors outside of its own financial sector. This is indicated by the volatility spillover effect and capital inflows variables. The use of these measures as independent variables in a panel regression model for SA represents a new contribution to the field. Subsequently, Section 5.5.2 presents the US results using the more traditional, inherent determinants of systemic risk. Once again, Section 5.4.3 compares and discusses the results in order to provide comparative insights. Section 5.6 then attempts to provide a brief summation of a voluminous amount of results and in doing so, determine if the various new objectives investigated in this study have any merit, namely (i) the SRISK values produced when a different, previously unused technique is used to model the tail distribution component of the MES measure; (ii) the worst case scenario SRISK values which used simulated LRMES values; (iii) the investigation of a systemic risk transfer from the US sector to the SA sector using the MES model; and (iv) the validity of our newly contributed variables to the panel regression model for SA.

5.2 DATA

As discussed in Section 3.5.3, the SRISK measure combines balance sheet data with market data in order to produce values that may be more forward looking than balance sheet data alone. It will follow then that this study uses a large amount of data from a number of different sources, for a number of different banks. Section 5.2.1 outlines the balance sheet data used, while Section 5.2.2 discusses the market data. Section 5.2.3 then explains how the banks were chosen for inclusion in the study.

5.2.1 Balance sheet data

All balance sheet data were acquired from Fitch Ratings agency in the UK. The data cover the period 2001 to 2013. Fitch data are reported in US Dollars (USD), therefore in the case of SA banks, the values are

converted using the exchange rate⁵⁸ at the end of the reporting period of that particular year to arrive at the South African Rand (ZAR) value. A mention needs to be made regarding the financial statement dates for SA banks. Two of the banks' statements are dated for the year ended March and June, respectively. It is not expected that this had any significant impact on the results.

Another caveat concerns the accounting technique used to record the data. In order to ensure consistency in the selection process, the following was involved. For the SA banks, the International Financial Reporting Standards amounts are preferred, but if these are not available, the local Generally Accepted Accounting Principles amounts are used. For US banks, the local Generally Accepted Accounting Principles amounts are preferred, but if these are not available, the regulatory amounts are used.

5.2.2 Market data

The equity returns and market capitalisation data for SA are acquired from the INET BFA Dataset (2015). US equity returns and market capitalisation data are retrieved from Bloomberg (2015). Daily stock market returns data are used for the period 2001 to 2013. Considering that the equity returns data are an integral part of the study, the entity selected for participation in the study will be conditional on its listing on a stock market.

For the SA market, the FTSE/JSE All-Share Index (ALSI) will be used, while the S&P 500 will be used for the US market. The EGARCH model will use equity returns data for the sample period 2001 to 2013 and the same proxies for the overall SA and US markets. The data for the JSE Bank Index were and the Financial Select Sector Standard & Poor's Depository Receipts (SPDR) exchange traded fund were obtained from INET BFA Dataset (2015).

5.2.3 Bank selection

The listing of an individual bank on a stock market is rare. For example, ABSA bank, as referred to in the literature in Section 3.3.2, should be analysed in the study, but it is not listed on the JSE. ABSA forms part of Barclays Africa Group Limited, which is listed on the JSE. Therefore, the bank holding company Barclays Africa Group Limited will be the analysed entity in this study and not ABSA bank individually. This matchup process was conducted for all the other participating banks. Banks that did not have data available for the period considered are eliminated from the analysis.

Five banks are studied in SA, while 47 are studied in the US. Although it may be argued that the other SA banks are relevant to this study, data availability was a limiting factor. Financial data are only available for the five largest banks, and as shown in Section 3.3.2, these banks account for 90.5 % of banking assets in

58 As provided by Fitch Ratings agency.

SA (IMF, 2014:10). Considering that bank size is a significant input for both the SRISK measure and the regression analysis, it may be argued that even if data were available, the results for these banks, given their relatively small size, would be insignificant by comparison. The list of banks is summarised in Tables 5.1 and 5.2.

Table 5.1: SA Banks included in the study.

SA Banks	
Barclays Africa Group Limited	(JSE:BGA)
FirstRand Bank Limited	(JSE:FSR)
Investec Limited	(JSE:INL)
Nedbank Group Limited	(JSE:SBK)
Standard Bank Group Limited	(JSE:NED)

Source: Compiled by the Author.

Table 5.2: US banks included in the study.

US Banks			
American Express Company	(NYSE:AXP)	Huntington Bancshares Inc.	(NASDAQ:HBAN)
Astoria Financial Corp	(NYSE:AF)	Independent Bank Corp	(NASDAQ:INDB)
BB&T Corporation	(NYSE:BBT)	JPMorgan Chase & Co.	(NYSE:JPM)
BOK Financial Corporation	(NASDAQ:BOKF)	KeyCorp	(NYSE:KEY)
Bank of America Corp	(NYSE:BAC)	M&T Bank Corporation	(NYSE:MTB)
CVB Financial Corp.	(NASDAQ:CVBF)	Morgan Stanley	(NYSE:MS)
Capital One Financial Corp.	(NYSE:COF)	New York Community Bancorp, Inc.	(NYSE:NYCB)
Cathay General Bancorp	(NASDAQ:CATY)	Northern Trust Corporation	(NASDAQ:NTRS)
Central Pacific Financial Corp.	(NYSE:CPF)	PNC Financial Services Group Inc.	(NYSE:PNC)
Citigroup Inc.	(NYSE:C)	Popular Inc.	(NASDAQ:BPOP)
City National Corp	(NYSE:CYN)	Regions Financial Corp	(NYSE:RF)
Comerica Incorporated	(NYSE:CMA)	State Street Corp	(NYSE:STT)
Community Bank System, Inc.	(NYSE:CBU)	Stifel Financial Corp	(NYSE:SF)
Dime Community Bancshares, Inc.	(NASDAQ:DCOM)	SunTrust Banks, Inc.	(NYSE:STI)
East West Bancorp, Inc.	(NASDAQ:EWBC)	Synovus Financial Corp.	(NYSE:SNV)
Fifth Third Bancorp	(NASDAQ:FITB)	TCF Financial Corporation	(NYSE:TCB)
First Bancorp	(NYSE:FBP)	Trustmark Corp	(NASDAQ:TRMK)
First Commonwealth Financial	(NYSE:FCF)	U.S. Bancorp	(NYSE:USB)
First Horizon National Corp	(NYSE:FHN)	UMB Financial Corp	(NASDAQ:UMBF)
First Midwest Bancorp Inc.	(NASDAQ:FMBI)	Webster Financial Corporation	(NYSE:WBS)
First Niagara Financial Group Inc.	(NASDAQ:FNFG)	Wells Fargo & Co	(NYSE:WFC)
Fulton Financial Corp	(NASDAQ:FULT)	Wintrust Financial Corp	(NASDAQ:WTFC)
Goldman Sachs Group Inc.	(NYSE:GS)	Zions Bancorporation	(NYSE:ZION)
HSBC Holdings plc (ADR)	(NYSE:HSBC)		

Source: Compiled by the Author.

The modelling of SRISK is done using Microsoft Excel™ (2013), while the preparation of data for the regression model, as well as the subsequent estimation of the model itself, will be conducted using EViews™ 8 econometrics software (QMS, 2013).

5.2.4 Section summary

The data used in this study are combined from a number of sources. Balance sheet data are sourced from Fitch Ratings and covers the period 2001 to 2013. Market data are acquired from INET BFA and Bloomberg, respectively, and cover the period 2001 to 2014. The selection of a bank for inclusion in the study was based on both data availability and significance.

5.3 SRISK

Before undertaking the analysis, it should be recalled what SRISK actually measures. SRISK is the expected capital shortfall of a bank if there is another financial crisis. That is, the amount of capital that would be needed during a crisis for banks to maintain a capital to asset ratio of 8%.⁵⁹ Negative values for SRISK represent capital surpluses, which simply means banks would have more than the required amount of capital during a crisis scenario. The SRISK (%) contribution measures the bank's percentage of total financial sector capital shortfall. Put another way, the banks with the highest percentage of SRISK are not only the most vulnerable during a crisis, but are also the most responsible for causing the crisis.

The SRISK results for SA are discussed in Section 5.3.1, followed by the results for the US in Section 5.3.2. Following on from the results, Section 5.3.3 analyses similarities and contradictions observed for the two sectors, and additionally discusses the broader implications of these results.

5.3.1 SA

The total financial sector SRISK in SA, using three different Marginal Expected Shortfall (MES) or long-run MES (LRMES) methods, is reported in Table 5.3. The use of three different methods allows comparisons between the methods and provides this study with a larger MES sample. The amounts are reported in ZAR billions.

⁵⁹ The 8% ratio is the minimum amount of capital that Basel III requires banks to hold (BCBS, 2011:27).

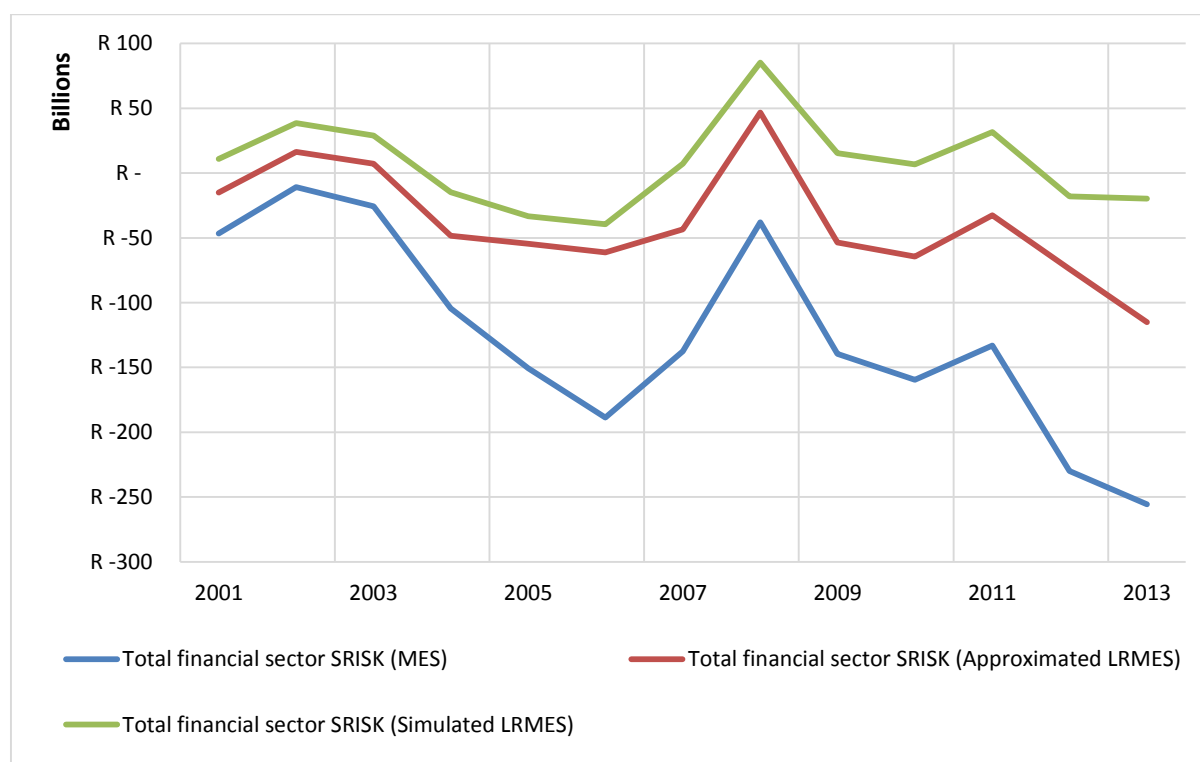
Table 5.3: SRISK of the SA financial sector.

	SRISK		
	MES	LRMES approximation	LRMES simulated
2001	-47 billion	-15 billion	11 billion
2002	-11 billion	16 billion	39 billion
2003	-26 billion	7 billion	29 billion
2004	-105 billion	-48 billion	-15 billion
2005	-151 billion	-54 billion	-33 billion
2006	-189 billion	-61 billion	-40 billion
2007	-138 billion	-43 billion	7 billion
2008	-38 billion	47 billion	85 billion
2009	-139 billion	-54 billion	15 billion
2010	-160 billion	-64 billion	7 billion
2011	-133 billion	-32 billion	32 billion
2012	-230 billion	-74 billion	-18 billion
2013	-256 billion	-115 billion	-20 billion

Source: Compiled by the Author.

Total SRISK in the entire SA financial sector is presented in Figure 5.1 below.

Figure 5.1: SRISK of the SA financial sector.



Source: Compiled by the Author.

From Table 5.3 and Figure 5.1, it is clear that using the daily MES value resulted in the smallest SRISK value, while both LRMES values produced significantly larger SRISK values. Since they took into account a longer period, and year-end accounting data were being used, it would make more sense to use the LRMES values. If daily or monthly accounting data were being used, it would be more appropriate to use the daily MES values. Henceforth, only SRISK values using the approximated LRMES and simulated LRMES measures as inputs are reported, as these are both yearly measures and therefore match the period of the accounting data.

The SRISK values in Figure 5.1 illustrate a peak in systemic risk levels during the stock market crash in 2002, followed by a steady decline and another subsequent peak during the sub-prime crisis. A similar pattern is then exhibited after the sub-prime crisis, when another decline in systemic risk levels occurs. This is followed by a relatively small spike during the European sovereign debt crisis before systemic risk levels tail off. An initial conclusion drawn from these results is that systemic risk in SA seems to spike during financial crises and times of significant market turmoil in foreign countries. The SRISK results for each bank are summarised in Tables 5.4 and 5.5. This is the capital shortfall that each bank will contribute to the entire financial sector as a whole.

Table 5.4: SRISK of each SA bank using approximated LRMES as input.

	Barclays	FirstRand	Investec	Nedbank	Standard
2001	-2 billion	-17 billion	5 billion	-1 billion	-1 billion
2002	4 billion	-11 billion	21 billion	4 billion	-0.3 billion
2003	1 billion	-14 billion	4 billion	12 billion	4 billion
2004	-12 billion	-30 billion	4 billion	4 billion	-15 billion
2005	-11 billion	-41 billion	4 billion	-0.1 billion	-6 billion
2006	-14 billion	-43 billion	4 billion	-3 billion	-5 billion
2007	-4 billion	-38 billion	7 billion	-5 billion	-3 billion
2008	8 billion	-15 billion	12 billion	13 billion	28 billion
2009	-15 billion	-30 billion	10 billion	-1 billion	-18 billion
2010	-19 billion	-35 billion	12 billion	-0.1 billion	-22 billion
2011	-13 billion	-36 billion	16 billion	-0.1 billion	-1 billion
2012	-7 billion	-65 billion	18 billion	-10 billion	-9 billion
2013	-6 billion	-85 billion	17 billion	-17 billion	-24 billion

Source: Compiled by the Author.

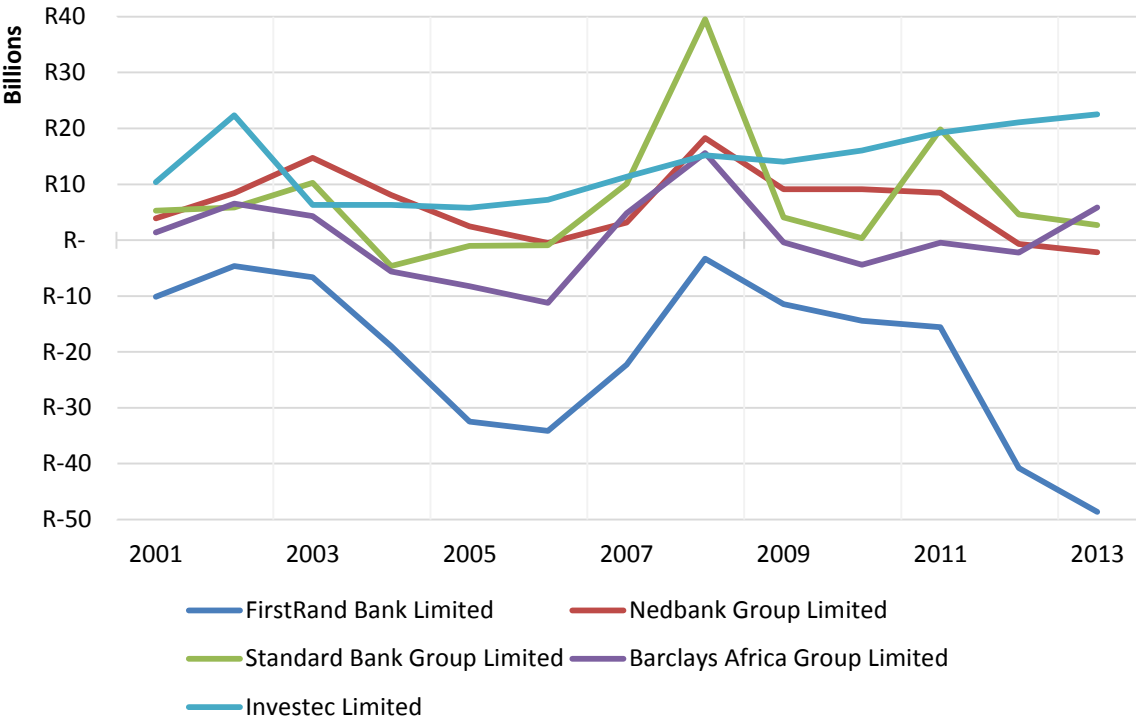
Table 5.5: SRISK of each SA bank using simulated LRMES as input.

	Barclays	FirstRand	Investec	Nedbank	Standard
2001	1 billion	-10 billion	10 billion	4 billion	5 billion
2002	7 billion	-5 billion	22 billion	8 billion	6 billion
2003	4 billion	-7 billion	6 billion	15 billion	10 billion
2004	-6 billion	-19 billion	6 billion	8 billion	-5 billion
2005	-8 billion	-32 billion	6 billion	2 billion	-1 billion
2006	-11 billion	-34 billion	7 billion	-.5 billion	-1 billion
2007	5 billion	-22 billion	11 billion	3 billion	10 billion
2008	16 billion	-3 billion	15 billion	18 billion	40 billion
2009	-0.4 billion	-11 billion	14 billion	9 billion	4 billion
2010	-4 billion	-14 billion	16 billion	9 billion	0.3 billion
2011	-0.4 billion	-16 billion	19 billion	8 billion	20 billion
2012	-2 billion	-41 billion	21 billion	-1 billion	5 billion
2013	6 billion	-49 billion	23 billion	-2 billion	3 billion

Source: Compiled by the Author.

The differences between the two measures are explained as follows. The simulated LRMES measure takes into account the volatility and correlation over the sub-prime crisis period of 1 July 2007 to 31 December 2008 and therefore inflates the tail dependence of the banks. The reason for this is that it represents the period of greatest market volatility and is therefore likely to present the worst case scenario of a very low probability. Furthermore, since we use the same simulated LRMES value for every year, the SRISK values are amplified to an even greater degree. This provides an interesting comparison because it illustrates the SRISK values of banks over the sample period, given that they had the volatility and tail dependence shown during the sub-prime crisis. The result, however, is not a hugely significant increase in SRISK over the period. The peaks are not significantly higher, while the troughs are only marginally lower. Overall the slope remains mostly the same while only shifting upwards. Henceforth, to represent a more adequate balance between probability and worst-case scenario analysis, only the SRISK measure using the approximated LRMES as in input measure will be reported. Figure 5.2 presents the amounts of SRISK each individual bank was responsible for producing:

Figure 5.2: SRISK of each SA bank.



Source: Compiled by the Author.

Figure 5.2 illustrates some interesting characteristics. FirstRand Bank displayed large capital surpluses (negative SRISK values). Therefore, when considering the total SRISK of the entire financial sector, these negative SRISK values offset much of the positive SRISK values that the rest of the banks were responsible for producing. All the banks showed increased SRISK measures over the period 2002 to 2003 when the stock market crash took place, as well as during the sub-prime crisis. Following that, the levels of SRISK have generally decreased, with the exception of Investec which displayed a steady upward trend. Standard Bank contributed a large amount of SRISK during the sub-prime crisis period but was only responsible for small contributions during the rest of the period. In general, SA banks seem to have increased SRISK levels during and following crisis scenarios in foreign countries. This coincides with the literature discussed in Section 2.5.1 which showed that systemic risk in emerging markets manifests as a result of volatile capital flows (Claessens & Ghosh, 2012:15; Claessens & Ghosh, 2013:112). A spike of this nature (reported in Figure 5.2) may raise questions about the role of capital flows in contributing to systemic risk in SA and emerging markets in general. That is, a build-up of foreign capital may have taken place, then once a crisis occurred, the capital could have been withdrawn and left the bank undercapitalised. This proposition will be investigated by the regression in Section 5.5.

Another conclusion that can be made is that the SA financial sector as a whole generally displays low levels of systemic risk, with many banks in fact displaying large capital surpluses. The only years in which the

sector as a whole had a positive amount of SRISK were 2002 to 2003, and 2008. During a crisis scenario, however, capital surpluses may be misleading, as discussed in Section 4.2. Brownlees and Engle (2015:8) argued that surplus capital held by other banks during a financial crisis is unlikely to be easily mobilised and used to bail out partnering banks. In order to negate the effects of surplus capital, for the rest of this section we report SRISK as:

$$SRISK_t = \sum_{i=1}^N (SRISK_{i,t})_+, \tag{5.1}$$

thereby assuming low market liquidity and examining the worst case scenario.⁶⁰ Considering this assumption, SRISK is reported according to Equation 5.1. The percentage SRISK contribution of each bank is simply the bank’s SRISK calculated according to Equation 5.1, divided by the total financial sector SRISK. This is presented in Table 5.6 and Figure 5.3 below.

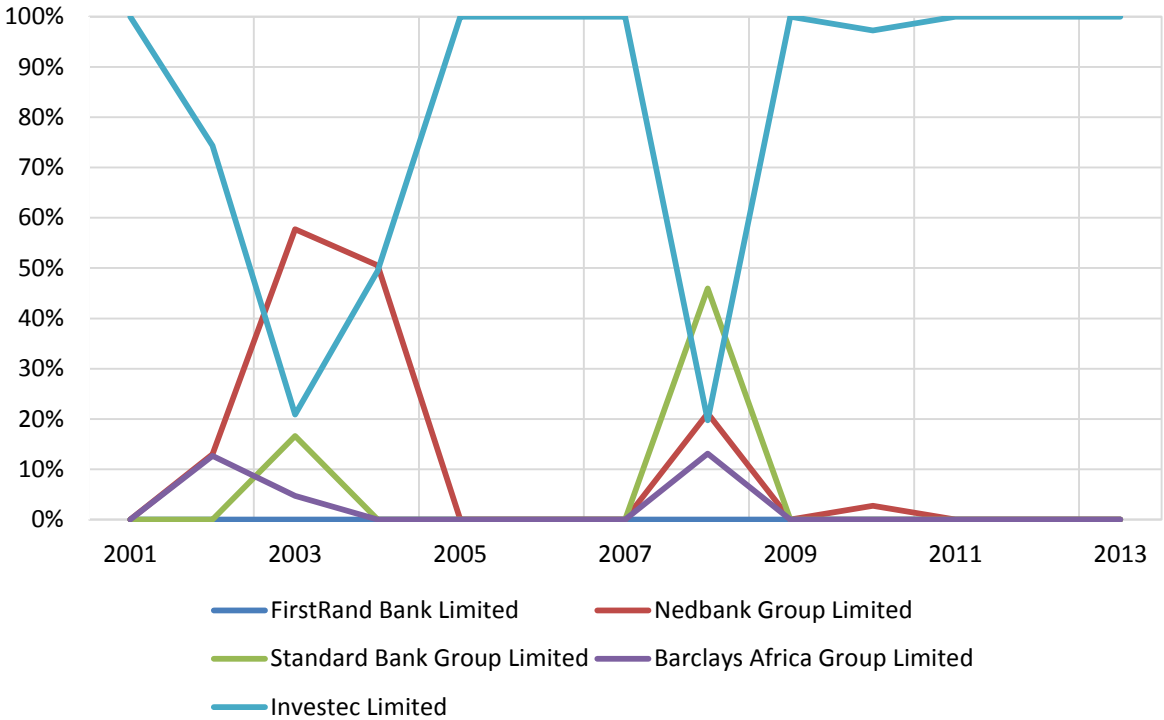
Table 5.6: SRISK contribution (%) of each SA bank.

	Barclays	FirstRand	Investec	Nedbank	Standard
2001	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %
2002	12.67 %	0.00 %	74.32 %	13.01 %	0.00 %
2003	4.71 %	0.00 %	20.90 %	57.76 %	16.62 %
2004	0.00 %	0.00 %	49.48 %	50.52 %	0.00 %
2005	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %
2006	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %
2007	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %
2008	13.14 %	0.00 %	19.75 %	21.14 %	45.96 %
2009	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %
2010	0.00 %	0.00 %	97.28 %	2.72 %	0.00 %
2011	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %
2012	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %
2013	0.00 %	0.00 %	100.00 %	0.00 %	0.00 %

Source: Compiled by the Author.

60 When the regression analysis is conducted in Section 5.4, however, the negative representations will be included so that accurate inferences can be made.

Figure 5.3: SRISK contribution (%) of each SA bank.



Source: Compiled by the Author.

In Figure 5.3, the effect of crisis periods on SA banks can be seen. Practically, a 0 % contribution indicates that those specific banks contributed no systemic risk. During both crisis periods, the SRISK contribution of Investec dropped rapidly as other banks increased their contribution. An investigation of the balance sheet data for Investec shows that during the periods when it contributed systemic risk, its market capitalisation dropped markedly while its assets and liabilities continued on an upward trend. During 2002, Nedbank took over as the leading contributor, while during the sub-prime crisis, Standard Bank contributed the most. Standard Bank was the largest bank in terms of total assets and market cap, followed by Nedbank. Both banks also had a leverage ratio near 3 % higher than the other banks. FirstRand was clearly the least systemically risky, with no contributions ever being above zero. Given that the literature has shown that Investec could be classified as the most systemically risky, since it was responsible for 100 % of the systemic risk at most points during the sample period. Critically, however, these were points when there was less market turmoil.

The analysis of Figure 5.3 and the spikes that coincide with periods of financial turmoil in foreign countries may also raise the question regarding the significance of external factors, rather than the internal characteristics of the SA banks. The spikes displayed by other banks as soon as a crisis takes place in another economy may make a ranking based on SRISK contentious. The argument could therefore be made that a ranking would only be sensible during the crisis periods, as the levels of SRISK appear flat

during periods of less turmoil. Nevertheless, the SRISK measure is used in Table 5.7 to rank, from left to right, the most to least systemically risky banks in SA during a particular year.

Table 5.7: SRISK ranking of SA Banks.

	Most to least systemically risky				
2001	Investec	Barclays / FirstRand / Nedbank / Standard			
2002	Investec	Nedbank	Barclays	FirstRand / Standard	
2003	Nedbank	Investec	Standard	Barclays	FirstRand
2004	Nedbank	Investec	Barclays / FirstRand / Standard		
2005	Investec	Barclays / FirstRand / Nedbank / Standard			
2006	Investec	Barclays / FirstRand / Nedbank / Standard			
2007	Investec	Barclays / FirstRand / Nedbank / Standard			
2008	Standard	Nedbank	Investec	Barclays	FirstRand
2009	Investec	Barclays / FirstRand / Nedbank / Standard			
2010	Investec	Nedbank	Barclays / FirstRand / Standard		
2011	Investec	Barclays / FirstRand / Nedbank / Standard			
2012	Investec	Barclays / FirstRand / Nedbank / Standard			
2013	Investec	Barclays / FirstRand / Nedbank / Standard			

Source: Compiled by the Author.

Interestingly, Standard Bank was the most risky during the sub-prime crisis (2008), and Nedbank was the most risky following the stock market crash (2002 to 2003). Given the absence of crises, however, Investec was clearly the most systemically risky bank in SA over the rest of the sample period. The reasons for Investec’s large contribution of systemic risk can be investigated by looking at some of the components used in the SRISK equation, namely the leverage ratio (Table 5.8 below) and approximated LRMES (Table 5.9 below):

Table 5.8: Leverage of each SA bank.

	Leverage				
	Barclays	FirstRand	Investec	Nedbank	Standard
2001	8.90	4.46	13.17	9.24	9.79
2002	12.13	6.14	69.19	11.14	10.00
2003	10.10	5.87	18.72	18.44	10.63
2004	6.74	4.34	14.68	10.93	7.54
2005	6.62	3.66	10.75	8.33	8.06
2006	6.48	4.17	9.28	7.53	8.10
2007	8.94	5.08	14.05	8.26	9.11
2008	10.80	7.13	21.90	12.73	12.09
2009	8.09	6.19	17.01	9.47	8.51
2010	7.60	5.94	17.87	9.33	8.21
2011	8.09	5.91	24.57	9.07	9.77
2012	7.91	4.66	20.82	7.54	8.49
2013	8.80	4.58	18.12	7.38	8.35

Source: Compiled by the Author.

Table 5.9: Approximated LRMES of each SA bank.

	LRMES				
	Barclays	FirstRand	Investec	Nedbank	Standard
2001	23.62 %	24.43 %	32.42 %	24.38 %	21.48 %
2002	21.99 %	24.20 %	29.01 %	25.05 %	20.87 %
2003	24.84 %	26.11 %	32.51 %	27.41 %	23.62 %
2004	24.31 %	26.97 %	34.53 %	27.83 %	24.76 %
2005	32.83 %	33.74 %	48.28 %	35.86 %	32.73 %
2006	34.61 %	34.76 %	49.21 %	37.52 %	34.08 %
2007	25.16 %	27.91 %	34.68 %	27.54 %	26.88 %
2008	26.81 %	28.66 %	38.05 %	29.74 %	27.92 %
2009	20.67 %	23.57 %	34.41 %	25.30 %	22.42 %
2010	22.24 %	21.96 %	36.31 %	28.09 %	23.15 %
2011	24.89 %	24.20 %	41.10 %	29.67 %	23.33 %
2012	33.12 %	27.86 %	44.20 %	31.39 %	29.66 %
2013	26.25 %	22.96 %	39.97 %	27.71 %	23.60 %

Source: Compiled by the Author.

Based on the components, it is clear that Investec has significantly higher leverage ratios, and in many cases more than double those of the other banks. This was largely due to the fact that it has a low market

capitalisation relative to its liabilities. Additionally, the LRMES is also higher, indicating that it has greater tail dependence. In other words, when the ALSI declines, Investec shares are more affected by this than the other banks are. FirstRand, by comparison, has the lowest levels of SRISK in the SA financial sector. An investigation of the components shows that it has low leverage ratios and LRMES values, indicating that even though it has the highest market capitalisation of all the banks, its comparatively lower amounts of liabilities offset the potential effects of this. Its LRMES values also show that FirstRand had lesser tail dependence and was therefore not as significantly affected by an ALSI decline.

Although Investec contributes the most systemic risk, the actual amount of systemic risk in the sector may appear as if it is not uncontrollably high – since most other banks display capital surpluses. However, in a crisis scenario when liquidity dries up, there may be systemic implications even before taking into account factors related to interconnectedness. The result is that during a crisis period, surplus capital held by less systemically risky banks cannot be used to bail out more systemically risky banks. The responsibility would then fall solely to the regulators if a capital injection or bailout were to occur. Additionally, the change in SRISK contributions during the period following the stock market crash and sub-prime crisis period may be indicative of vulnerabilities in the economy following upswing periods (Claessens *et al.*, 2013:157). This further strengthens the argument of a different manifestation of systemic risk in SA, whereby a large portion of systemic risk is due to the amount of capital inflows in the economy and the regional source of these capital flows. This is different to the way in which systemic risk manifests in developed markets such as the US.

5.3.2 US

The same analysis procedure is now followed for the US sector. The total financial sector SRISK in the US, using three different MES methods, is reported in Table 5.10. The amounts are reported in USD billions.

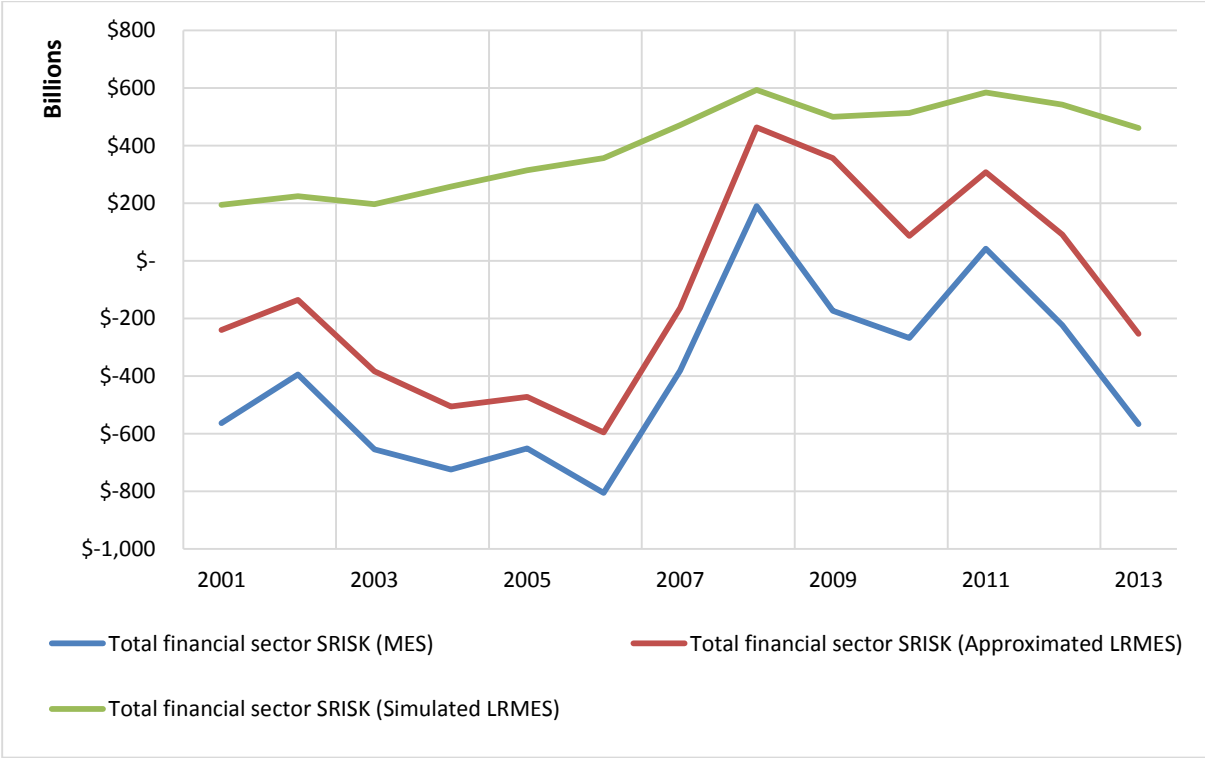
Table 5.10: SRISK of the US financial sector.

	SRISK		
	MES	LRMES approximation	LRMES simulated
2001	-564 billion	-240 billion	195 billion
2002	-394 billion	-136 billion	225 billion
2003	-654 billion	-383 billion	196 billion
2004	-724 billion	-506 billion	258 billion
2005	-652 billion	-473 billion	315 billion
2006	-806 billion	-596 billion	356 billion
2007	-382 billion	-163 billion	472 billion
2008	191 billion	464 billion	594 billion
2009	-173 billion	357 billion	500 billion
2010	-268 billion	87 billion	514 billion
2011	42 billion	308 billion	585 billion
2012	-224 billion	92 billion	543 billion
2013	-567 billion	-254 billion	461 billion

Source: Compiled by the Author.

A graphical depiction of the total SRISK in the US financial sector is presented in Figure 5.4 below.

Figure 5.4: SRISK of the US financial sector.



Source: Compiled by the Author.

From Table 5.10 and Figure 5.4, it is clear that using the simulated LRMES values resulted in the greatest SRISK value. The simulated LRMES measure clearly results in heightened SRISK values since it assumed that every period consisted of the same volatility and tail dependence from the sub-prime crisis. This provides an interesting contradiction to the results shown for the SA financial sector in Section 5.3.1, where the use of simulated LRMES resulted in the graph shape remaining mostly similar. For the case of the US, using the extremely heightened volatilities of the sub-prime crisis significantly inflated the SRISK values. Furthermore, the approximated LRMES produced marginally larger SRISK values than the MES values. The choice of which MES measure to use going forward once again follows the same logic used for the SA sector. Since the SRISK measure took into account a longer period, and year-end accounting data were being used, it would make more sense to use the LRMES values. If daily or monthly accounting data were being used, it would be more appropriate to use the daily MES values. Henceforth only SRISK values using the approximated LRMES and simulated LRMES measures as inputs will be reported, and only six banks will be examined. The reason for only reporting the results of six banks is that the next largest contribution to SRISK was only 2.18 % in 2008 and 0.56 % in 2013. The complete SRISK results for 2008 and 2013 are reported in Appendix A.

The SRISK values shown in Figure 5.4 illustrate a spike in systemic risk during the stock market crash of 2002, followed by a steady decline up to a point where a large capital surplus was held by the financial sector as a whole. Leading up to the sub-prime crisis, the SRISK values increased dramatically before reaching their peak in 2008. SRISK values began declining but another spike took place in 2011 as a result of the European sovereign debt crisis. Following this, it appears as if SRISK levels have declined rapidly and that the SRISK of the financial sector as a whole is approaching levels last seen prior to the sub-prime crisis. In order to investigate the validity of these indications, the results of each US bank need to be analysed. The SRISK results for each bank are summarised in Tables 5.11 and 5.12 below. This is the capital shortfall that each US bank will contribute to the entire financial sector as a whole.

Table 5.11: SRISK of each US bank using approximated LRMES as input.

	Bank of America	Citigroup	Goldman Sachs	JP Morgan	Morgan Stanley	Wells Fargo
2001	-11 billion	-77 billion	-1 billion	14 billion	17 billion	-29 billion
2002	-17 billion	-12 billion	7 billion	35 billion	22 billion	-32 billion
2003	-31 billion	-69 billion	-2 billion	14 billion	12 billion	-48 billion
2004	-66 billion	-77 billion	3 billion	-17 billion	21 billion	-54 billion
2005	-51 billion	-83 billion	9 billion	-20 billion	28 billion	-51 billion
2006	-85 billion	-74 billion	-3 billion	-29 billion	26 billion	-64 billion
2007	-14 billion	61 billion	20 billion	9 billion	45 billion	-36 billion
2008	99 billion	129 billion	45 billion	107 billion	43 billion	39 billion
2009	109 billion	111 billion	16 billion	78 billion	43 billion	35 billion
2010	83 billion	67 billion	7 billion	50 billion	36 billion	-15 billion
2011	122 billion	95 billion	38 billion	88 billion	40 billion	2 billion
2012	90 billion	71 billion	28 billion	66 billion	37 billion	-27 billion
2013	40 billion	31 billion	7 billion	18 billion	23 billion	-75 billion

Source: Compiled by the Author.

Table 5.12: SRISK of each US bank using simulated LRMES as input.

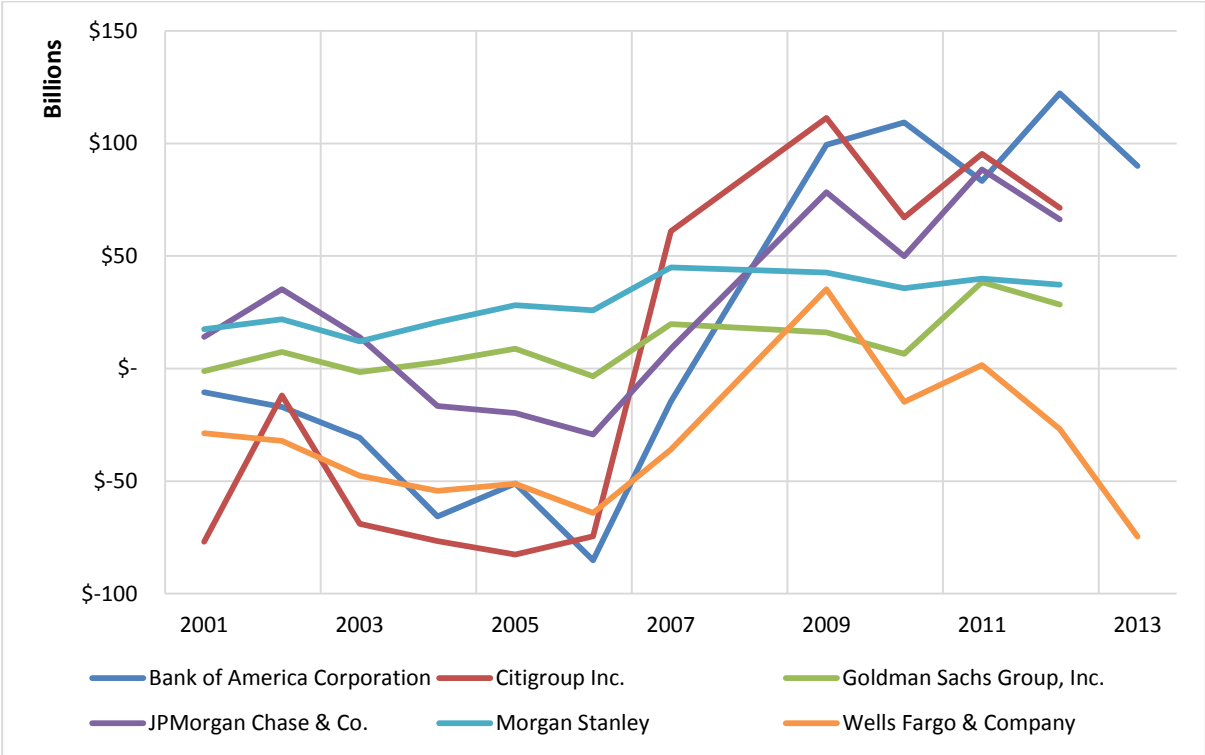
	Bank of America	Citigroup	Goldman Sachs	JP Morgan	Morgan Stanley	Wells Fargo
2001	35 billion	137 billion	14 billion	24 billion	37 billion	-14 billion
2002	37 billion	121 billion	20 billion	38 billion	40 billion	-14 billion
2003	41 billion	151 billion	21 billion	29 billion	46 billion	-21 billion
2004	60 billion	168 billion	30 billion	30 billion	60 billion	-20 billion
2005	75 billion	167 billion	42 billion	33 billion	69 billion	-16 billion
2006	80 billion	204 billion	45 billion	33 billion	87 billion	-24 billion
2007	106 billion	199 billion	67 billion	58 billion	81 billion	-7 billion
2008	124 billion	152 billion	57 billion	115 billion	49 billion	42 billion
2009	141 billion	156 billion	44 billion	81 billion	57 billion	21 billion
2010	146 billion	170 billion	48 billion	89 billion	59 billion	9 billion
2011	145 billion	152 billion	58 billion	116 billion	54 billion	22 billion
2012	144 billion	160 billion	56 billion	106 billion	56 billion	13 billion
2013	131 billion	170 billion	50 billion	90 billion	61 billion	-9 billion

Source: Compiled by the Author.

The differences between the approximated LRMES and simulated LRMES input measures are quite large. Once again, the reasoning is that the simulated LRMES measure took into account the sub-prime crisis

period when volatility and tail dependence were highest and therefore produced the largest SRISK values. While not inaccurate, these values are inflated since they represent a worst case scenario of a very low probability. However, if the regulators were solely concerned with financial system stability, the consideration of low probability, high impact scenarios may be appropriate. Nevertheless, the approximated LRMES values present a more adequate balance between probability and worst-case scenario analysis. Henceforth, only the SRISK values using approximated LRMES values will be reported. The SRISK of individual US banks are illustrated in Figure 5.5.

Figure 5.5: SRISK of each US bank.



Source: Compiled by the Author.

Figure 5.5 shows that, in general, the change in SRISK could largely be attributed to the three largest banks, namely Bank of America, Citigroup, and JPMorgan. Goldman Sachs and Morgan Stanley showed levels of SRISK that steadily increased over time, but did not fluctuate as much as the other three banks did. Wells Fargo exhibited a similar pattern to the three largest banks, but to a lesser degree – and mostly had a capital surplus. Around the time of the stock market crash in 2002, only Citigroup and JPMorgan showed noticeably increased SRISK levels. An interesting observation is that prior to the sub-prime crisis at the beginning of 2006, the top three banks and Wells Fargo showed large capital surpluses. An examination of the banks’ financial sheets provides an explanation for this. The top three banks’ market capitalisations reached a peak in 2006. In the following years, their total liabilities increased substantially

while their market capitalisation decreased. The result is that the amount of capital which banks were required to hold increased, while their leverage also increased. Wells Fargo's market capitalisation continued to increase after 2006, but its liabilities increased by more than 100 % from 2007 to 2008. Furthermore, a number of acquisitions were made by banks, leading up to the peak values of SRISK in 2008.

JP Morgan, Bank of America and Wells Fargo all increased their assets and liabilities considerably through the acquisition of other financial institutions. JP Morgan merged with Bank One in 2004, and purchased both Bear Sterns and Washington Mutual in 2008. Bank of America purchased Countrywide Financial in 2007, and Merrill Lynch in 2008, while Wells Fargo purchased Wachovia in 2008. Since this increased the banks' assets and liabilities considerably, it would make sense that they would subsequently be responsible for the largest amount of SRISK, due to size alone (Laeven *et al.*, 2014:23). The most worrying indication from Figure 5.5 is that Bank of America's SRISK levels were higher in 2013 than they were during the sub-prime crisis. This was as a result of a significant increase in total assets and liabilities, in conjunction with a decline in market capitalisation. This raises the question of government guarantees and the moral hazard associated with them, if banks are still being allowed to increase to the point where they become too-big-to-fail, especially in the wake of the sub-prime crisis.

In order to examine the percentage contributions of the individual banks to systemic risk,⁶¹ only the positive contributions to the financial sector's total SRISK are considered, as explained in Section 5.3.1. The SRISK contribution in percentage form, i.e. the percentage contribution each bank makes to the SRISK of the entire financial sector, is illustrated in Table 5.13:

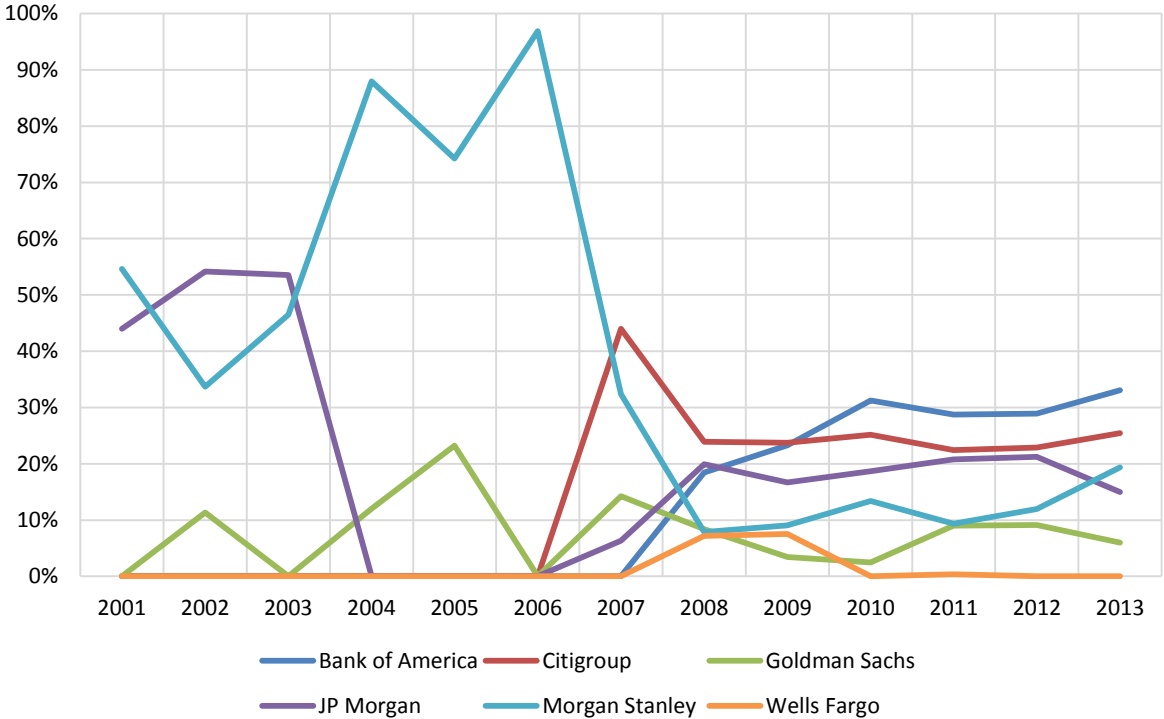
61 This is simply calculated as the SRISK contribution of the bank divided by the total financial sector SRISK.

Table 5.13: SRISK contribution (%) of each US bank.

	Bank of America	Citigroup	Goldman Sachs	JP Morgan	Morgan Stanley	Wells Fargo
2001	0.00 %	0.00 %	0.00 %	43.97 %	54.61 %	0.00 %
2002	0.00 %	0.00 %	11.37 %	54.15 %	33.70 %	0.00 %
2003	0.00 %	0.00 %	0.00 %	53.53 %	46.47 %	0.00 %
2004	0.00 %	0.00 %	12.04 %	0.00 %	87.96 %	0.00 %
2005	0.00 %	0.00 %	23.20 %	0.00 %	74.26 %	0.00 %
2006	0.00 %	0.00 %	0.00 %	0.00 %	96.88 %	0.00 %
2007	0.00 %	44.01 %	14.26 %	6.33 %	32.41 %	0.00 %
2008	18.43 %	23.89 %	8.36 %	19.92 %	7.89 %	7.18 %
2009	23.30 %	23.72 %	3.43 %	16.68 %	9.09 %	7.51 %
2010	31.25 %	25.16 %	2.45 %	18.69 %	13.39 %	0.00 %
2011	28.74 %	22.42 %	9.00 %	20.78 %	9.37 %	0.37 %
2012	28.89 %	22.91 %	9.15 %	21.25 %	11.96 %	0.00 %
2013	33.04 %	25.45 %	6.00 %	14.98 %	19.34 %	0.00 %

Source: Compiled by the Author.

Figure 5.6: SRISK contribution (%) of each US bank.



Source: Compiled by the Author.

A number of conclusions can be made from Figure 5.6. Wells Fargo was responsible for some systemic risk during the sub-prime crisis, but prior to and following that, it displayed no contribution. All other

banks were at most responsible for contributing 2 % or less risk and are therefore not reported. The full SRISK contributions for 2008 and 2013 are presented in Appendix A. The SRISK index is then used in Table 5.14 below to rank, from left to right, the most to least systemically risky banks in the US.

Table 5.14: SRISK ranking of US banks.

	Most to least systemically risky					
2001	Morgan Stanley	JP Morgan	Bank of America / Citigroup / Goldman Sachs / Wells Fargo			
2002	JP Morgan	Morgan Stanley	Goldman Sachs	Bank of America / Citigroup / Wells Fargo		
2003	JP Morgan	Morgan Stanley	Bank of America / Citigroup / Goldman Sachs / Wells Fargo			
2004	Morgan Stanley	Goldman Sachs	Bank of America / Citigroup / JP Morgan / Wells Fargo			
2005	Morgan Stanley	Goldman Sachs	Bank of America / Citigroup / JP Morgan / Wells Fargo			
2006	Morgan Stanley	Bank of America / Citigroup / Goldman Sachs/ JP Morgan / Wells Fargo				
2007	Citigroup	Morgan Stanley	Goldman Sachs	JP Morgan	Bank of America / Wells Fargo	
2008	Citigroup	JP Morgan	Bank of America	Goldman Sachs	Morgan Stanley	Wells Fargo
2009	Citigroup	Bank of America	JP Morgan	Morgan Stanley	Wells Fargo	Goldman Sachs
2010	Bank of America	Citigroup	JP Morgan	Morgan Stanley	Goldman Sachs	Wells Fargo
2011	Bank of America	Citigroup	JP Morgan	Morgan Stanley	Goldman Sachs	Wells Fargo
2012	Bank of America	Citigroup	JP Morgan	Morgan Stanley	Goldman Sachs	Wells Fargo
2013	Bank of America	Citigroup	Morgan Stanley	JP Morgan	Goldman Sachs	Wells Fargo

Source: Compiled by the Author.

The SRISK rankings show that the sector is largely dominated by the top three banks, Citigroup, JP Morgan, and Bank of America, with each bank accounting for approximately 20 % of the SRISK. These three banks interchanged their positions over the sample period, with Citigroup ostensibly declining in riskiness throughout and after the sub-prime crisis. The contributions of Morgan Stanley in the earlier sample years 2001 to 2006 are interesting and can best be explained by examining the leverage ratio (Table 5.15 below) and LRMES (Table 5.16 below) of the banks.

Table 5.15: Leverage of each US bank.

	Leverage					
	Bank of America	Citigroup	Goldman Sachs	JP Morgan	Morgan Stanley	Wells Fargo
2001	6.73	4.70	7.29	10.03	8.53	4.77
2002	6.80	6.63	10.97	15.84	12.73	4.98
2003	6.71	5.62	8.77	10.67	10.16	4.51
2004	6.33	6.49	10.75	8.56	13.38	4.71
2005	7.44	6.62	12.16	8.85	15.48	5.20
2006	6.54	7.44	9.64	8.36	13.71	4.63
2007	9.58	15.11	12.15	10.81	18.99	6.21
2008	24.26	50.07	21.01	18.05	37.18	11.80
2009	14.14	18.98	9.44	11.79	18.65	9.04
2010	15.91	13.59	9.94	12.58	18.91	7.83
2011	34.48	22.82	19.30	17.31	24.15	9.02
2012	16.71	15.34	14.88	13.83	19.71	8.00
2013	12.23	11.57	10.95	11.00	13.40	6.66

Source: Compiled by the Author.

Table 5.16: Approximated LRMES of each US bank.

	LRMES					
	Bank of America	Citigroup	Goldman Sachs	JP Morgan	Morgan Stanley	Wells Fargo
2001	38.64 %	35.59 %	42.71 %	42.84 %	65.57 %	24.90 %
2002	31.73 %	43.70 %	37.10 %	50.83 %	53.16 %	21.23 %
2003	22.39 %	29.88 %	28.89 %	36.10 %	41.22 %	17.61 %
2004	16.04 %	18.91 %	21.13 %	21.25 %	29.51 %	11.63 %
2005	14.12 %	14.54 %	18.75 %	16.22 %	25.05 %	10.53 %
2006	13.23 %	14.45 %	20.91 %	17.03 %	22.41 %	10.35 %
2007	16.68 %	22.53 %	25.41 %	21.22 %	30.14 %	16.01 %
2008	50.56 %	56.12 %	45.80 %	50.87 %	60.64 %	43.72 %
2009	65.15 %	72.99 %	45.73 %	55.89 %	61.86 %	57.81 %
2010	37.74 %	43.61 %	29.96 %	31.97 %	38.56 %	30.69 %
2011	44.74 %	45.13 %	31.00 %	34.27 %	47.43 %	31.49 %
2012	41.53 %	42.18 %	29.36 %	31.51 %	44.56 %	22.87 %
2013	28.53 %	29.28 %	22.97 %	21.99 %	33.72 %	16.86 %

Source: Compiled by the Author.

Morgan Stanley had a high leverage ratio over the sample period, but relative to the other banks in the sample up to 2007, it was among the highest. Additionally, its LRMES values throughout the entire period were also among the highest. The LRMES value is interesting because it would suggest that Morgan Stanley had greater tail dependence and was more affected by a decline in the S&P 500. Furthermore, Morgan Stanley's SRISK increase coincided largely with the period between the stock market crash and the sub-prime crisis, possibly due to its role in technology investment banking. For example, Morgan Stanley was responsible for underwriting the IPOs of large technology firms such as Google, Atheros, and VMWare (Hibbard, 2005:56).

Another noteworthy characteristic of the US sector is that following the sub-prime crisis, no single bank was completely dominant of the sector in terms of its SRISK contribution. Bank of America and Citigroup contribute between 20 and 30 % each, JPMorgan and Morgan Stanley between 10 and 20 %, while Goldman Sachs, Wells Fargo and the remaining 41 banks account for the rest. The situation before the sub-prime crisis is very different, with Morgan Stanley contributing the majority of, but during the sub-prime crisis this contribution decreased significantly. This illustrates that the SRISK indicator, although useful for historical measurement, may not serve as an accurate leading indicator of future financial crises.

5.3.3 Comparisons and implications

There were not many similarities between the SRISK results of the SA and US sectors, which may be confirmation of the evidence that systemic risk in developed economies and emerging markets manifest in different ways. Systemic risk in the US is clearly caused by the largest banks, while in SA, Investec was the smallest of the big five banks, yet it contributed the most systemic risk. However, as illustrated in Figure 5.2, when financial crises or turmoil occurred in foreign countries, the systemic risk levels of the sector increased. This may lead to an argument regarding the success of regulatory measures in mitigating systemic risk. Based on the results, SA's regulatory approach was successfully mitigating systemic risk, but came under more pressure when crises occurred in foreign countries. It is therefore likely that a future financial crisis in areas such as China or Europe could have a similar or even larger effect. It is also worrisome that no prediction could be made as to which bank would be the most affected prior to a crash or crisis.

While the US regulatory approach did not allow systemic risk to increase significantly following the sub-prime crisis, it did not decrease significantly either. Cumulatively, the total financial sector SRISK decreased, but the largest banks' contributions increased. It may therefore have been a situation where the smaller banks compensated for the increased contributions of the bigger banks. This is why the SRISK contribution under the assumption of low liquidity was analysed, and based on this alone, the systemic

risk levels of the US financial sector did not decrease significantly. The question may then be asked whether the levels were being controlled, or simply just being constrained.

Furthermore, the Dodd-Frank Act had been implemented (or mostly implemented) but its success in reducing systemic risk was not yet shown. The same argument may be made for Basel III in 2013, with all the large banks displaying high Tier 1 ratios, yet still producing large amounts of SRISK. It may be possible that the total financial sector SRISK will always increase as the size of the financial sector increases (Laeven *et al.*, 2014:23). That is, as banks undertake more liabilities, it will follow that the amount of SRISK increases. As discussed in Section 2.3.1.3, increases in market capitalisation will, however, not offset these increases since the market may malfunction during a crisis (Hellwig, 2009:133). A tentative proposal could be the limiting of the size of individual banks, or breaking them up into smaller constituents once they surpass a certain threshold. This will, however, decrease the economies of scale and scope associated with larger banks, and limit the activities they can undertake. Consequentially, a convincing solution has not yet been found.

A final conclusion is that all financial sectors are not the same when it comes to systemic risk and the determinants may differ for various countries. Similarly, individual banks may also produce SRISK as a result of different activities. While the causes of SRISK for the US are largely inherent, i.e. they are within the US financial sector, the SA sector may be affected by factors outside of its own financial sector. That is, systemic risk may be transferred from another market to the SA market. The next two sections are focused on investigating this theory.

5.3.4 Section summary

Contrasting results were observed for SA and the US. SA was not characterised by a large degree of systemic risk throughout the sample period, with significant levels only being shown after the stock market crash and during the sub-prime crisis period. This relatively low levels of systemic risk and spikes during foreign crises may support the theory of systemic risk due to volatile capital flows. The US by comparison showed increasing levels of systemic risk up to the sub-prime crisis which was then followed by a decrease. An analysis of the relative contributions to systemic risk, however, showed that the largest banks all increased their levels of systemic risk. It may therefore be argued that the smaller banks are compensating for the bigger banks increased systemic risk levels by decreasing theirs. Subsequently, an assessment of systemic risk should assume low levels of liquidity and ignore capital surpluses. Based on these results, it is also arguable whether regulatory measures are successfully mitigating systemic risk in the US, given that the contributions of the large banks had not declined significantly. Similarly, on the surface, the SA regulatory measures seem to have successfully mitigated systemic risk, but the spike

following the stock market crash and during the sub-prime crisis may provide new evidence regarding the effect of financial turmoil in foreign countries. As a result, the possibility of a systemic risk transfer from the US sector to the SA sector will need to be investigated.

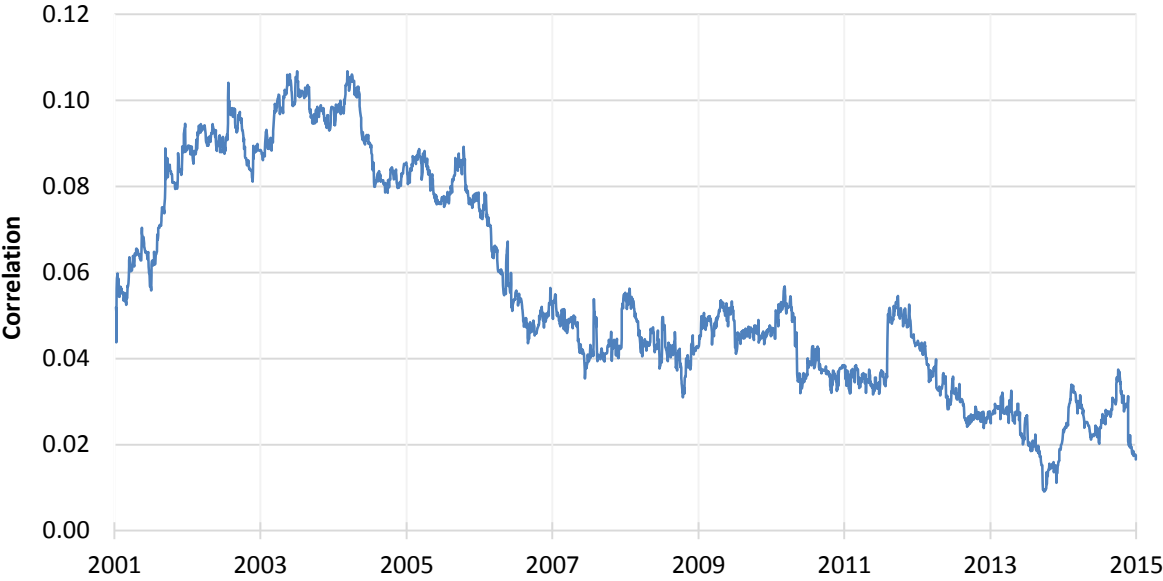
5.4 SYSTEMIC RISK TRANSFER

Three approaches were used to examine the possible systemic risk transfer and cross-market contaminations from the US to SA. Firstly, the potential contagion between the markets was investigated through the use of a DCC model. Secondly, the existence of a volatility spillover effect was determined using an EGARCH model. Finally, the MES of the SA market, given a crisis scenario in the US market. This entailed specifying the ALSI as a hypothetical bank within the US equity market in order to measure the systemic response the SA market could potentially have to a decline in the US equity market. The ALSI and S&P 500 are used in all three specifications as they represent the equity market, and a decline in the equity market is representative of a systemic event (Brownlees & Engle, 2012:10; Laeven *et al.*, 2014:28).

5.4.1 Contagion

In order to determine the potential contagion effects that may take place from the US to the SA market, a DCC model was used. This mathematical explanation of the DCC model was done in Section 4.2.2, while the use of this model in measuring contagion was discussed in Section 4.3.1. The DCC model measures the correlation between the ALSI and S&P 500. The graph of the DCCs is presented in Figure 5.7 below.

Figure 5.7: DCCs between the S&P 500 and the ALSI.



Source: Compiled by the Author.

Figure 5.7 illustrates some degree of correlation between the ALSI and the S&P 500. Interestingly, the correlation between the markets increased steadily throughout 2009 to 2012 before tapering off. The correlations clearly decreased during the crisis period and continued decreasing steadily since then. Recalling the theory outlined in Section 4.3.1, it was argued that a contagion effect is only present if the DCCs increased during a crisis period (Forbes & Rigobon, 2002:2225). Based on the evidence above, the implication is that during the sample period, there were no contagion effects that took place between the US market and the SA market. Nevertheless, the absence of contagion does not necessarily rule out a potential volatility spillover effect.

5.4.2 Volatility spillovers

To determine the presence of a spillover effect, the EGARCH model explained in Section 4.4.2 is used. Before an EGARCH model can be estimated, the variables are transformed using logs and tested for stationarity using the ADF test. The results are presented in Tables 5.17 and 5.18 below.

Table 5.17: Unit root tests (level form).

		t-Statistic	Probability
ALSI	ADF test statistic	-2.10	0.54
	1 % level	-4.01	
	5 % level	-3.44	
	10 % level	-3.14	
S&P 500	ADF test statistic	-2.00	0.60
	1 % level	-4.01	
	5 % level	-3.43	
	10 % level	-3.14	

Source: Compiled by the Author.

Model assumption: A trend and intercept is included in the ADF equation

Table 5.18: Unit root tests (first differences form).

		t-Statistic	Probability
ALSI	ADF test statistic	-9.65	0.00
	1 % level	-4.01	
	5 % level	-3.44	
	10 % level	-3.14	
S&P 500	ADF test statistic	-10.01	0.00
	1 % level	-4.01	
	5 % level	-3.44	
	10 % level	-3.14	

Source: Compiled by the Author.

Model assumption: A trend and intercept is included in the ADF equation

The tests indicate that both series are only stationary when they are in first differences form, i.e. I(1). Therefore, in order to ensure stationarity, the variables were transformed into first differences form before the EGARCH model was estimated. In order to test for the correct specification of the EGARCH (p, q) model in terms of the p^{th} order autoregressive GARCH term, as well as the q^{th} order moving average ARCH term, a number of different EGARCH specifications were tested and examined using the Akaike Information Criterion (AIC) and the Schwarz Criterion (SIC).⁶² The data patterns are expressed most accurately in the model with the lowest AIC and SBC (QMS, 2007:1027). Both information criteria indicate that the EGARCH (1,1) model was the best fitting model.⁶³ The EGARCH model is presented in Table 5.19 below.

62 The AIC and SIC are explained in detail in the EViews™ 8 user guide (QMS, 2007:1027).

63 The various models tested are reported in the Appendix B.

Table 5.19: EGARCH (1,1) model output.

Variance Equation			
Variable	Coefficient	z-Statistic	Probability
ω	-0.06	-46.58	0.00
ψ	-0.07	-204.31	0.00
ξ	0.03	1.77	0.08
δ	0.99	2094.88	0.00
Descriptive Statistics			
Durbin-Watson		1.41	
AIC		-4.35	
SIC		-4.24	
R²		0.54	
Adjusted R²		0.54	

Source: Compiled by the Author.

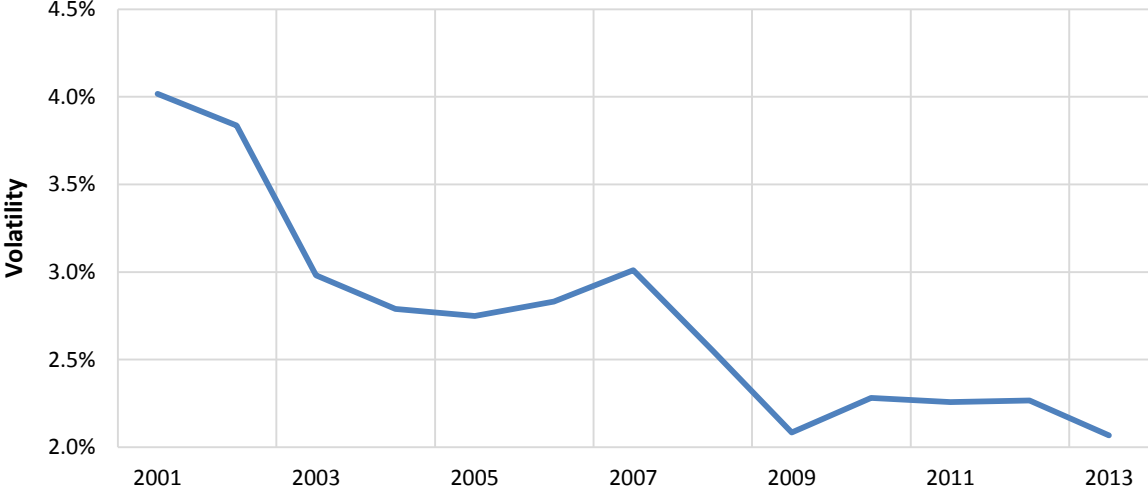
Model assumption: Asymmetric order of one.

The EGARCH model reports that variable ψ which measures the impact of innovation on the conditional variance is significant. The implication of this is that there was a clear volatility spillover effect from the S&P 500 to the ALSI. Since the shock persistence parameter ξ is positive, positive shocks will have a greater effect on volatility than negative effects do, i.e. the volatility of the ALSI has a greater reaction to good news from the S&P 500 than from bad news. A similar result was found in China by Moon and Yu (2010:147) where positive effects from the US had a greater effect on volatility in the Chinese stock market. The argument made to substantiate this was that good news in the US would attract global capital away from the Chinese stock market and therefore increase volatility. A similar situation could be occurring for SA, especially given its reliance on capital flows. The shock persistence parameter δ is close to one, meaning that the volatility in the ALSI will be present for a longer period and will converge to the steady state at a slower pace.

Additionally, the Lagrange Multiplier (LM) test was applied to the residuals of the EGARCH model in order to determine if any ARCH effects remained (QMS, 2007:107). The null hypothesis of homoskedasticity was not rejected, therefore implying that no ARCH effects remained. The Augmented Dickey-Fuller (ADF) test was then conducted. The null hypothesis of a unit root was rejected, therefore implying that the residual series does not contain a unit root. Additionally, the null hypothesis of a normal distribution was not rejected, indicating that the residuals are normally distributed. The results of all tests are reported in

Appendix B. Additionally, the EGARCH model produces a conditional variance series which is presented in Figure 5.8 below.

Figure 5.8: Volatility spillover effect from the S&P 500 to the ALSI.



Source: Compiled by the Author.

There was a clear decrease in the volatility spillover effect between the S&P 500 and ALSI over time, with it essentially being cut in half since 2001. Whether this will affect the SRISK of SA banks is unclear at this point. In order to investigate this possibility, the conditional variance series will be used as an additional independent variable in the regression model for SA to assist in determining the magnitude of the effect. However, given the decrease over time, it would not be surprising to observe a relationship that is not statistically significant.

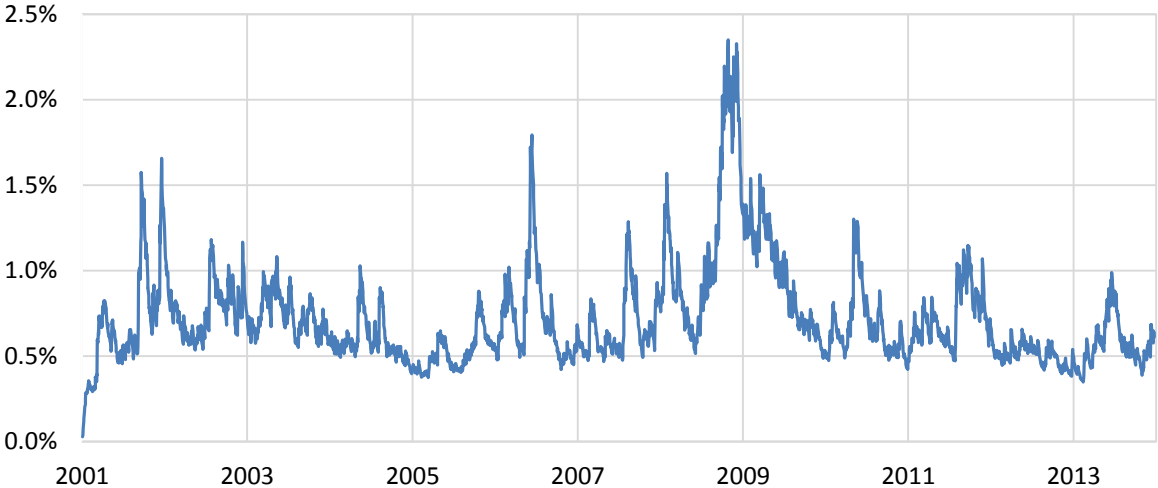
Considering the correlation between the S&P 500 and the ALSI (although weak), and the presence of a volatility spillover effect, the analysis can be taken further. The next step involves measuring how a financial crisis scenario in the US would affect the SA market. That is, a measurement of the potential decline in the SA equity market, given a decline in the US equity market. This will be done by measuring the MES of the SA equity market relative to the US equity market.

5.4.3 Marginal Expected Shortfall (MES) of the SA market

The MES model is used to measure the decline in the equity value of the ALSI, given a decline in the S&P 500. This represents a decline in the SA equity market, given a financial crisis scenario in the US sector. An exploration like this is similar to the analysis undertaken with banks in Section 5.2, where typically the MES of a bank would be measured relative to a market index. In this iteration, the ALSI is now specified

as a theoretical 'bank' in the market which is the S&P 500. The MES of the ALSI is reported in Figure 5.9 below.

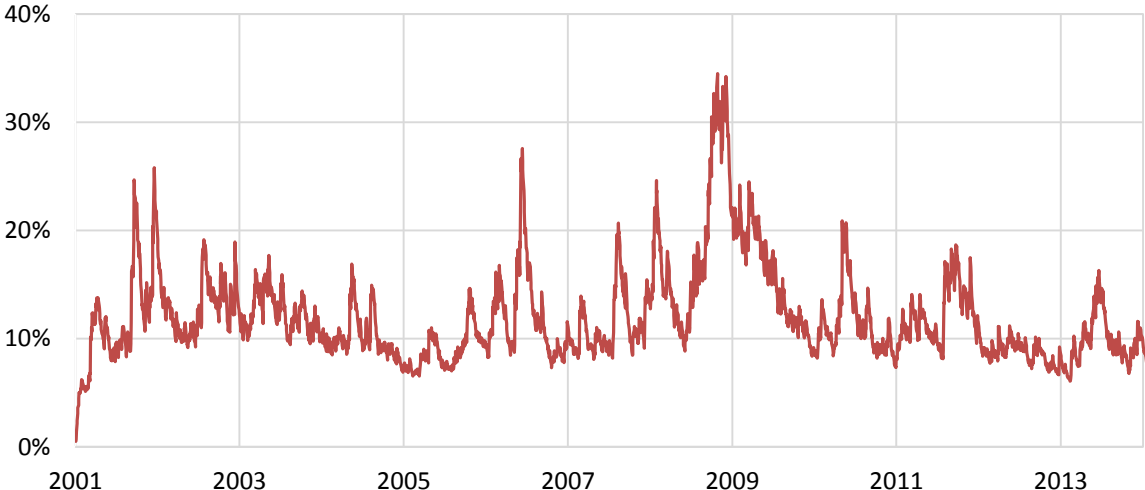
Figure 5.9: MES of ALSI in S&P 500 portfolio.



Source: Compiled by the Author.

The results show a relatively weak effect on the SA market. Given a decline of 2 % on the S&P 500, the SA market would only decline at worst by almost 2.5 %. The analysis can be extended to a longer time period. The approximated LRMES values are presented in Figure 5.10 below.

Figure 5.10: LRMES of ALSI in S&P 500 portfolio.



Source: Compiled by the Author.

It should be remembered that the LRMES values in this iteration represent a crisis scenario of six months and a decline of 40 % for the S&P 500 over that period.⁶⁴ Therefore, the LRMES values represent the equity

⁶⁴ The work of Acharya *et al.* (2012:60) is followed in specifying a crisis scenario as a decline of 40 % over a period of six months.

value decline of the ALSI if the S&P 500 declined by 40 % over a six-month window. The yearly averages produced from this analysis, including the LRMES values from the simulation procedure outlined in Section 4.2.4, are presented in Table 5.20 below.

Table 5.20: MES of ALSI in S&P 500 portfolio.

	MES	LRMES approximation	LRMES simulated
2001	0.66 %	11.11 %	17.06 %
2002	0.79 %	13.20 %	17.06 %
2003	0.74 %	12.45 %	17.06 %
2004	0.60 %	10.16 %	17.06 %
2005	0.52 %	8.88 %	17.06 %
2006	0.74 %	12.36 %	17.06 %
2007	0.66 %	11.17 %	17.06 %
2008	1.19 %	18.91 %	17.06 %
2009	0.97 %	15.87 %	17.06 %
2010	0.68 %	11.45 %	17.06 %
2011	0.73 %	12.27 %	17.06 %
2012	0.51 %	8.80 %	17.06 %
2013	0.57 %	9.65 %	17.06 %

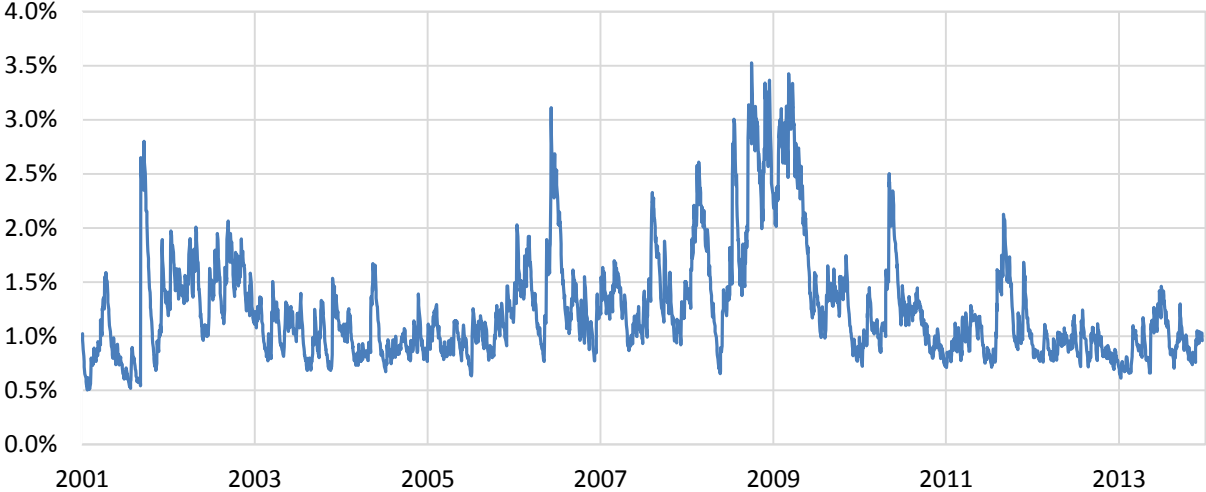
Source: Compiled by the Author.

None of the MES values were particularly high. In fact, the simulated LRMES value, which represents the period of greatest volatility and therefore the worst-possible market conditions, did not rise significantly. An examination of the approximated LRMES values provides more context. A slight decrease occurs in 2005, before this reaches its peak in 2008. An MES value of 1.19 % is not particularly high, nor is the LRMES of 18.91 %. These results line up with the results of the DCC model (Section 5.4.1) which showed no contagion, and the EGARCH model (Section 5.4.2) which showed a decreasing volatility spillover effect. The conclusion that can be made from these results is that the SA market was not significantly affected by market turbulence and crisis periods in the US sector.

Another iteration of the MES model is conducted in order to determine if an isolation of the financial sectors of the SA and US markets would yield different results. In order to conduct this analysis, the same procedure is followed as outlined above, however the inputs are modified. In this iteration, the SA financial sector is proxied by the Johannesburg Stock Exchange (JSE) Bank Index and is specified as a

hypothetical bank in the US financial sector, proxied by the Financial Select Sector SPDR exchange traded fund.⁶⁵ The MES of the JSE Bank Index is reported in Figure 5.11.

Figure 5.11: MES of JSE Bank Index in Financial Select Sector SPDR exchange traded fund portfolio.

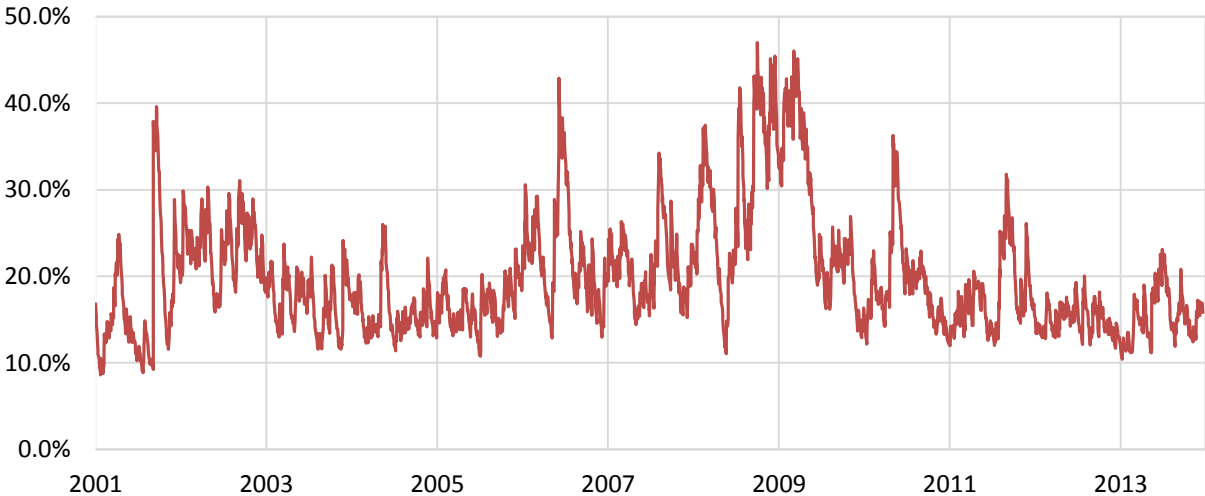


Source: Compiled by the Author.

The results show a similar, yet slightly magnified effect as the shape of the graph is mostly retained while only shifting up slightly. Figure 5.11 shows that a decline of 2 % in the value of the US financial sector would cause at worst single day decline of just over 3 % in the value of SA banks. The analysis can be extended to a longer time period and the approximated LRMES values are presented in Figure 5.12 below.

65 The Financial Select Sector SPDR exchange traded fund tracks an index of S&P 500 financial stocks and is weighted by market capitalisation.

Figure 5.12: MES of JSE Bank Index in Financial Select Sector SPDR exchange traded fund portfolio.



Source: Compiled by the Author

The LRMES values presented in Figure 5.12 represent the equity value decline of SA Banks conditional on the US financial sector declining by 40 % over a six-month window. As above, the yearly averages produced from this analysis and the LRMES values from the simulation are presented in Table 5.21 below.

Table 5.21: MES of JSE Bank Index in Financial Select Sector SPDR exchange traded fund portfolio.

	MES	LRMES approximation	LRMES simulated
2001	1.01%	16.27%	17.38 %
2002	1.50%	23.53%	17.38 %
2003	1.05%	17.11%	17.38 %
2004	0.96%	15.82%	17.38 %
2005	1.00%	16.49%	17.38 %
2006	1.43%	22.47%	17.38 %
2007	1.32%	21.08%	17.38 %
2008	2.00%	29.65%	17.38 %
2009	1.82%	27.32%	17.38 %
2010	1.20%	19.32%	17.38 %
2011	1.10%	17.92%	17.38 %
2012	0.90%	14.99%	17.38 %
2013	0.94%	15.47%	17.38 %

Source: Compiled by the Author.

Although the MES values have been magnified slightly, the MES values are still not particularly high. In fact, the simulated LRMES value, which represents the period of greatest volatility and therefore the worst-possible market conditions, only rose by 0.38 %. An examination of the approximated LRMES values

provides the approximately the same results as the previous analysis. A slight decrease occurs in 2004, before this reaches its peak in 2008. An MES value of 2 % is still not particularly high, nor is the LRMES of 29.65 %. Subsequently, these results serve to confirm the earlier conclusion that that the SA market was not significantly affected by market turbulence and crisis periods in the US sector.

5.4.4 Section summary

In order to determine whether a contagion effect took place from the US to the SA sector, a DCC model was used. The DCC model showed that the correlation between the two sectors decreased during the crisis, therefore indicating that contagion did not take place. Next, the potential volatility spillover effect from the US to SA was investigated with an EGARCH model. The model illustrated a volatility spillover effect which was more responsive to positive shocks, but also showed that the effect had been weakening over time. Finally, the effects of a decline in the US equity markets on the SA equity markets, as well as the effects of a decline in the US financial sector on SA banks were investigated. By measuring the MES of the SA sector and the MES of SA banks, potential systemic effects could be observed. The MES analysis showed a relatively small decline for both specifications. Based on these analyses, the overall evidence for systemic risk transfer from the US to SA is weak.

It is important to note that this does not necessarily imply that systemic risk transfer does not take place between the two sectors, but in terms of direct transfer between the sectors; the evidence is unconvincing. As shown in Section 5.3.1 and illustrated by the increased levels of systemic risk in Figure 5.2, there was a systemic response in SA to crisis scenarios in foreign countries. The implication is therefore that the systemic risk transfer may simply be taking a different form. One such form could be in the volatility of capital flows, and this will subsequently be investigated in the next section as part of a regression model.

5.5 PANEL REGRESSION MODEL

Section 5.3 measured the amount of SRISK that the US and SA financial sectors possessed, as well as the amount of SRISK each bank contributed to this total. Section 5.4 then investigated whether there was any meaningful systemic risk transfer between the two sectors. The next step is to identify the individual determinants of SRISK within each individual bank. Additionally, the size of the effect that changes in these determinants have on the bank's SRISK will also be examined. In order to conduct this identification and measurement, a panel regression analysis⁶⁶ is undertaken.

5.5.1 SA

A large number of variables were included for SA in order to account for the external factors associated with systemic risk transfer from other countries. The descriptive statistics and correlation matrix are presented in Tables 5.22 and 5.23 below.

⁶⁶ As discussed in Section 4.4.1, a panel regression model is used to overcome problems associated with the short time period, and takes into account the assumed homogeneity of the banks.

Table 5.22: Descriptive statistics for SA variables.

	SRISK	Bank Size	Bank Capitalisation	Bank Activities Measure 1	Bank Activities Measure 2	Volatility spillover	Funding Fragility Index	Capital inflows (log)	Leverage
Mean	-7.6 billion	560 billion	10.21	0.29	0.59	0.0008	0.19	6.59	10.73
Median	-3.3 billion	480 billion	10.80	0.28	0.65	0.0008	0.15	6.69	8.80
Maximum	28.4 billion	1.7 trillion	14.10	0.44	0.85	0.0016	0.61	7.64	69.19
Minimum	-86.5 billion	103 billion	5.00	0.15	0.18	0.0004	0.00	5.73	3.66
Std. Dev.	19.6 billion	379 billion	2.37	0.07	0.16	0.0004	0.13	0.65	8.61
Skewness	-1.42	1.30	-0.44	0.29	-0.54	1.20	0.97	-0.01	5.03
Kurtosis	6.26	4.16	2.26	2.32	2.17	3.38	4.09	1.73	33.95
Jarque-Bera Probability	50.52	21.89	3.55	2.14	4.98	15.94	13.48	4.39	2869.05
	0.00	0.00	0.17	0.34	0.08	0.00	0.00	0.11	0.00
Observations	65	65	65	65	65	65	65	65	65

Source: Compiled by the Author.

Table 5.23: Correlation matrix for SA variables.

	SRISK	Bank Size	Bank Capitalisation	Bank Activities Measure 1	Bank Activities Measure 2	Funding Fragility Index	Capital inflows (log)	Volatility spillover	Leverage
SRISK	1.00								
Bank Size	-0.18	1.00							
Bank Capitalisation	-0.26	0.50	1.00						
Bank Activities Measure 1	-0.35	0.43	0.33	1.00					
Bank Activities Measure 2	-0.41	-0.09	0.01	-0.43	1.00				
Funding Fragility Index	0.19	-0.34	-0.33	-0.13	-0.22	1.00			
Capital inflows (log)	-0.26	0.58	0.76	0.25	0.05	-0.31	1.00		
Volatility spillover	0.22	-0.47	-0.70	-0.22	-0.09	0.32	-0.78	1.00	
Leverage	0.52	-0.20	-0.26	-0.07	-0.54	0.41	-0.14	0.18	1.00

Source: Compiled by the Author.

The correlation matrix shows a few instances of correlation between dependent variables, but none of these are particularly high (greater than 0.8), and only three cases exist where values are greater than 0.7. The panel nature of the regression model should account for any potential problems and it is not expected that all the variables displaying high degrees of collinearity will be included in the final model, although cognisance of multicollinearity problems will be taken if they occur. Before the panel regression analysis is undertaken, the variables are first tested to ensure that they are stationary using the process outlined in Section 4.4.2.3. Since the data are yearly and exist for 13 years, the assumption is made that one lag would be the most appropriate test specification (Wooldridge, 2015:577). The capital flows variable is logged in order to remove the influence of scale and increase the likelihood of stationarity. The results of the unit root tests are summarised in Table 5.24 below.

Table 5.24: Summary of SA panel unit root test results.

	SRISK	Bank Size	Bank Capitalisation	Bank Activities 1	Bank Activities 2	Volatility spillover	Funding Fragility Index	Capital inflows (log)	Leverage
Levin	I(0)*	I(0)*	I(0)*	I(0)*	I(0)**	I(0)*	I(0)*	I(0)*	I(0)*
IPS	I(0)**	I(0)*	I(0)*	I(0)***	I(2)***	I(0)*	I(0)*	I(0)*	I(0)*
Breitung	I(1)*	I(1)***	I(0)**	I(0)*	I(1)*	I(1)*	I(0)*	I(0)*	I(0)**
Fisher – ADF	I(0)**	I(0)*	I(0)*	I(0)***	I(2)*	I(0)*	I(0)*	I(0)*	I(0)*
Fisher – PP	I(1)*	I(1)*	I(0)*	I(1)*	I(1)*	I(0)*	I(0)*	I(1)***	I(0)**
Hadri	N.S.*	N.S.*	S.*	N.S.*	N.S.*	N.S.*	S.*	S.*	N.S.*
Consensus	I(0)	I(0)	I(0)	I(0)	I(2)	I(0)	I(0)	I(0)	I(0)

Source: Compiled by the Author.

*Significant at 1 % level

**Significant at 5 % level

***Significant at 10 % level

N.S. indicates non-stationary; S. indicates stationary.

Based on the results of the unit root tests, all the variables are I(0) except the Bank Activities 2 measure. Since an alternate measure exists for Bank Activities, the Bank Activities 2 variable is henceforth left out. The variable used for Bank Activities is therefore the share of non-interest income in total income. Furthermore, considering that all the variables are stationary, it follows that there are no cointegrating relationships, and therefore testing for this is unnecessary. A panel regression model with fixed effects, specifying SRISK as the dependent variable and including all the variables is first estimated and illustrated in Table 5.25 below.

Table 5.25: Panel regression model with fixed effects for SA.

Variable	Coefficient	Standard error	t-Statistic	Probability
Bank size	0.01	0.01	1.08	0.29
Bank Capitalisation	-6.6 million	1.1 billion	-0.01	0.99
Bank Activities Measure	-98.1 billion	28.1 billion	-3.49	0.00
Volatility	570 billion	6.4 trillion	0.09	0.93
Funding Fragility Index	-5.8 billion	15.8 billion	-0.37	0.71
Capital inflows	-9.0 billion	5.9 billion	-1.53	0.13
Leverage	281 million	218 million	1.29	0.20
Constant	71.3 billion	33.2 billion	2.15	0.04
Bank fixed effects				
FirstRand Bank	-22.8 billion		Adjusted R ²	0.71
Nedbank Group	1.5 billion			
Standard Bank Group	2.8 billion			
Barclays Africa Group	-1.9 billion			
Investec Limited	20.4 billion			

Source: Compiled by the Author.

The likelihood ratio test is conducted to determine if the fixed effects are redundant, with the conclusion that they are indeed necessary.⁶⁷ The implication is that the fixed effects model is preferred to the common constant model. In order to investigate the potential suitability of a random effects model, a Hausman test will need to be conducted. This first requires the estimation of a random effects model, but given that the current model has more independent variables than cross-sections, this would not be possible. An analysis of the model shows that the volatility spillover from the S&P 500 to the ALSI is not a significant determinant of SRISK. Considering Figure 5.8 in Section 5.4, which showed a decline in the spillover effect over time as well as a relatively low correlation value in Section 5.4.1, this makes sense. We therefore remove the insignificant variables – the volatility spillover, bank capitalisation, the funding fragility index, and bank size. The removal of these variables subsequently allows the estimation of a random effects model, reported in Table 5.26 below. The Hausman test is then conducted, which

⁶⁷ The results of the likelihood ratio test are reported in Appendix B.

concludes that a random effects model is a better fit than a fixed effects model is.⁶⁸ The final regression model is presented in Table 5.26.

Table 5.26: Final panel regression model with random effects for SA.

Variable	Coefficient	Standard error	t-Statistic	Probability
Bank Activities Measure	-91.8 billion	25.6 billion	-3.58	0.00
Capital inflows	-4.7 billion	2.1 billion	-2.19	0.04
Leverage	4.0 million	1.9 million	2.11	0.04
Constant	45.8 billion	15.4 billion	2.97	0.00
Bank random effects				
FirstRand Bank	-22.6 billion	(ω_1)	Adjusted R ²	0.32
Nedbank Group	1.6 billion	(ω_2)		
Standard Bank Group	8.7 billion	(ω_3)		
Barclays Africa Group	-1.5 billion	(ω_4)		
Investec Limited	13.8 billion	(ω_5)		
			Effects specification	Rho
			Cross-section random	0.61
			Idiosyncratic random	0.39

Source: Compiled by the Author.

The regression equation therefore takes the form:

$$SRISK_{i,t} = \alpha_i + \beta_1 ACT_{i,t} + \beta_2 Flow_{i,t} + \beta_3 LVG_{i,t} + \omega_i, \tag{5.2}$$

where ω_i specified in Table 5.26 varies for each bank, but is constant over time. The results illustrated in Table 5.26 show that the conventional determinants of SRISK in developed economies do not necessarily apply to emerging markets. For SA, the most significant determinants were the bank activities, capital inflows and leverage. As expected, an increase in the leverage ratio will result in an increased measure of SRISK, while an increase in the bank activities measure would actually decrease SRISK. This implies that an increase in market activities undertaken by banks resulted in less SRISK. The capital inflows measure provides particular interest and must be interpreted with care. The regression model shows that an increase in capital inflows decreases the amount of SRISK in the SA financial sector. The volatility of these flows should be considered, since a reversal of flows during a crisis will subsequently increase the SRISK by the same amount. The results presented above therefore illustrate interesting comparisons, which in some cases do not line up with the usual expected determinants of SRISK. The implication is therefore a

68 The results of the Hausman test are reported in Appendix B.

further strengthening of the case that systemic risk in SA manifests differently and is caused by different factors when compared to the US.

5.5.2 US

Since fewer variables are used for the US regression model, as the capital flows and volatility spillover effects variables were unique to SA, the initial data examination is simpler than for the SA sector. The descriptive statistics and correlation matrix for the US variables are presented in Tables 5.27 and 5.28 below.

Table 5.27: Descriptive statistics for US variables.

	SRISK	Bank Size	Bank Capitalisation	Bank Activities Measure	Funding Fragility Index	Leverage
Mean	21.9 billion	1.3 trillion	12.18	0.44	0.54	13.73
Median	20.6 billion	1.1 trillion	11.71	0.43	0.37	12.15
Maximum	129 billion	2.4 trillion	34.93	0.84	1.00	50.07
Minimum	-85.1 billion	312 billion	6.87	-0.01	0.16	4.70
Std. Dev.	52.1 billion	614 billion	4.92	0.17	0.32	7.76
Skewness	-0.12	0.37	2.56	0.59	0.48	2.30
Kurtosis	2.73	1.76	11.57	3.57	1.48	10.12
Jarque-Bera	0.36	5.65	269.72	4.65	8.73	194.42
Probability	0.84	0.06	0.00	0.10	0.01	0.00
Observations	65	65	65	65	65	65

Source: Compiled by the Author.

Table 5.28: Correlation matrix for US variables.

	SRISK	Bank Size	Bank Capitalisation	Bank Activities Measure	Funding Fragility Index	Leverage
SRISK	1.00					
Bank Size	0.43	1.00				
Bank Capitalisation	0.20	-0.27	1.00			
Bank Activities Measure	-0.08	-0.41	0.38	1.00		
Funding Fragility Index	-0.05	-0.68	0.50	0.44	1.00	
Leverage	0.71	0.22	0.11	-0.16	0.08	1.00

Source: Compiled by the Author.

Once again, the correlation matrix indicates a few instances of correlation among dependent variables, but none that should cause any problems. The same process used in Section 5.5.1 for SA is followed here. That is, the variables are tested to ensure stationarity, with the unit root test results summarised in Table 5.29 below.

Table 5.29: Summary of US panel unit root test results.

	SRISK	Bank Size	Bank Capitalisation	Bank Activities 1	Funding Fragility Index	Leverage
Levin	I(1)*	I(1)*	I(0)*	I(0)***	I(0)*	I(0)*
IPS	I(1)**	I(1)***	-	-	I(1)*	I(0)**
Breitung	I(1)***	I(1)*	I(2)**	I(0)*	I(2)**	I(1)*
Fisher – ADF	I(1)**	I(1)***	I(2)***	I(2)**	I(2)*	I(0)*
Fisher – PP	I(1)***	I(1)*	I(0)*	I(0)*	I(1)*	I(0)**
Hadri	S.*	N.S.*	N.S.*	N.S.*	N.S.*	N.S.*
Consensus	I(1)	I(1)	I(0)	I(1)	I(1)	I(0)

Source: Compiled by the Author.

*Significant at 1 % level

**Significant at 5 % level

***Significant at 10 % level

N.S. indicates non-stationary; S. indicates stationary.

The non-stationary variables are transformed as necessary to achieve stationarity. Alternatively, considering that a number of the variables are I(1), it will be necessary to test for cointegration. If a cointegrating relationship is found, a different model specification, such as the error-correction model,

can be used which allows the use of non-stationary variables.⁶⁹ A summary of the cointegration test results are shown in Table 5.30, while the full results are presented in Appendix B.

Table 5.30: Summary of cointegration test results.

Test	Consensus
Kao	Cointegration present*
Pedroni	Mixed, mostly no cointegration
Fisher -Johansen	No cointegration*

Source: Compiled by the Author.

*Significant at 1 % level

The Kao (1999) panel cointegration test has the null hypothesis of no cointegration. With the inclusion of one lag, the null hypothesis is rejected. The inclusion of further lags, as well as the use of automatic lag selection, confirms this rejection. A limitation of the Kao test is that it assumes that the autoregressive coefficients are homogenous. The Pedroni (2004) test attempts to take this into account. The null hypothesis of the Pedroni test is that there is no cointegration and further allows the specification of a deterministic trend and individual intercepts, individual intercept alone, or none. In this case, automatic lag selection is used. The test is conducted under all specifications. Under the specification of no intercept or trend, and with an intercept and no trend, the null hypothesis cannot be rejected for all test statistics. With the specification of both an intercept and trend, some of the test statistics reject the null hypothesis, meaning that there may be cointegrating relationships for some of the cross-sectional units. Another approach is taken by the Fisher-Johansen test which pools individual Johansen test results. The test can be run under five assumptions. The Fisher-Johansen test reports that there are no cointegrating relationships, under all the assumptions. The majority consensus is therefore that there is no cointegration present. The results of the cointegration tests are reported in Appendix B. Recalling the theory surrounding cointegration testing discussed in Section 4.3.2.2, if the series contains a unit root, and are both integrated of the same order, e.g. both are $I(1)$ or both are $I(2)$, then a cointegration test should be conducted. The result is that if a cointegrating relationship exists between the two series, the use of these series would not lead to spurious regression (Asteriou & Hall, 2011:356). The result that no cointegration is present means that the variables transformed using first differences will be used in the regression model.

A panel regression model with fixed effects is first estimated and illustrated in Table 5.31.

69 See Asteriou and Hall (2011:359).

Table 5.31: Panel regression model with fixed effects for US.

Variable	Coefficient	Standard error	t-Statistic	Probability
Bank size – I(1)	0.12	0.03	3.82	0.00
Bank Capitalisation	1.4 billion	1.2 billion	-1.12	0.27
Bank Activities Measure – I(1)	-56 billion	47.5 billion	-1.18	0.24
Funding Fragility Index – I(1)	53.8 billion	88.8 billion	0.61	0.55
Leverage	3.2 billion	696 million	4.58	0.00
Constant	-34.2 billion	18.7 billion	-1.82	0.07
Bank fixed effects				
Bank fixed effects	Coefficient		Adjusted R ²	0.35
Bank of America	-5.2 billion			
Citigroup	2.0 billion			
Goldman Sachs	11.2 billion			
JPMorgan	-6.3 billion			
Morgan Stanley	-1.8 billion			

Source: Compiled by the Author.

A likelihood ratio test is conducted to determine if the fixed effects are redundant, with the conclusion that they are indeed necessary.⁷⁰ The implication is that the fixed effects model is preferred to the common constant model. In order to investigate the potential suitability of a random effects model, a Hausman test will need to be conducted. This first requires the estimation of a random effects model, but given that the current model has the same number of independent variables as cross-sections, this would not be possible. We therefore remove the least significant variables – bank capitalisation and the bank activities measure – which subsequently allows the estimation of a random effects model, reported in Table 5.32 below. The Hausman test is then conducted, which concludes that a random effects model would not be a better fit than a fixed effects model.⁷¹ The final regression model is presented in Table 5.32.

⁷⁰ The results of the likelihood ratio test are reported in Appendix B.

⁷¹ The results of the Hausman test are reported in Appendix B.

Table 5.32: Final panel regression model with fixed effects for the US.

Variable	Coefficient	Standard error	t-Statistic	Probability
Bank Size – I(1)	0.13	0.03	4.55	0.00
Funding Fragility Index – I(1)	122 billion	69 billion	1.77	0.09
Leverage	3.4 billion	603 million	5.60	0.00
Constant	-54.3 billion	10.6 billion	-5.10	0.00
Bank fixed effects				
Bank fixed effects	Coefficient			
Bank of America	-3.5 billion	(ω_1)	Adjusted R ²	0.36
Citigroup	4.9 billion	(ω_2)		
Goldman Sachs	9.2 billion	(ω_3)		
JPMorgan	-3.9 billion	(ω_4)		
Morgan Stanley	-6.7 billion	(ω_5)		

Source: Compiled by the Author.

The regression equation therefore takes the form:

$$\Delta SRISK_{i,t} = \alpha_i + \beta_1 \Delta Size_{i,t} + \beta_2 \Delta Fund_{i,t} + \beta_3 LVG_{i,t} + \omega_{it}, \quad (5.2)$$

where ω_i specified in Table 5.32 above varies for each bank, but is constant over time. The results show the expected outcomes for SRISK in developed economies. The transformations that were applied to the variables to achieve stationarity should be considered when interpreting the regression results. The change in SRISK shows a positive relationship with the change in bank size, the change in the funding fragility index, and the leverage ratio. The implications are that as banks grow larger, they will produce more SRISK. Similarly, funding that becomes more unstable (of a non-depository nature) also results in increasing SRISK values. Finally, increased leverage, as shown with SA, also resulted in increases in the SRISK values of US banks. The results therefore illustrate mostly the expected relationships, although bank capitalisation and the bank activities measure, which were expected to play a role are shown to not have a statistically significant relationship.

5.5.3 Comparisons and implications

The results illustrate that the systemic risk produced by both SA and US banks occurred as a result of the leverage position of the individual banks. Therefore, the greater the leverage of the bank, the more systemic risk it would produce. It is important to remember that the leverage ratio in this study uses the quasi-market value of assets in the leverage ratio. The leverage ratio is subsequently defined as:

$$\begin{aligned}
 LVG &= \frac{\textit{Quasi market value of assets}}{\textit{Market capitalisation}} \\
 &= \frac{\textit{Market capitalisation} + \textit{Total liabilities}}{\textit{Market capitalisation}}.
 \end{aligned}
 \tag{5.3}$$

A higher leverage ratio is therefore a function of increased liabilities and is not offset by an increased market capitalisation. In fact, an increased market capitalisation actually decreases the leverage ratio. The only way to decrease this form of the leverage ratio is to decrease the total liabilities. The reasoning behind this is that market capitalisation can erode quickly during crisis periods, thereby leaving the bank undercapitalised (Engle, Jondeau & Rockinger, 2015:170). This increased market equity value may give the banks a false sense of financial security. It would therefore make sense that higher leverage ratios are significant determinants of systemic risk for banks in all economies.

The difference in the determinants of systemic risk for the two countries emerged when external and internal factors were considered. Additionally, the SA results showed systemic risk to have a negative relationship with some variables, while the US only showed positive relationships. The SA results illustrated the point that the external factors were more significant determinants of systemic risk than internal, bank specific factors were. SA banks' systemic risk displayed a significant but negative relationship with bank activities. Therefore, an increase in market-based activities resulted in decreased systemic risk. The implication of this is that market-based activities in the SA financial sector were not perceived to be particularly risky and may in fact be less systemically risky than activities of a direct nature. This may be an indication of the safety of the SA financial sector as a whole, since activities undertaken in the market do not produce more systemic risk. Additionally, market-based activities may be more transparent to regulators and are therefore easier to monitor and control. Finally, the capital inflows were shown to have a negative relationship with systemic risk. That is, inflows would decrease systemic risk, but similarly, it can be argued that outflows would reverse this effect. This keeps in line with the theory of volatile capital flows being one of the main causes of systemic risk in emerging markets (Claessens & Ghosh, 2013:92). This may also explain why the systemic risk of some banks increased following the stock market crash and during the sub-prime crisis, as capital flows decreased. The regulatory implications of this are that SA should essentially be in a constant state of preparation for a systemic crisis, given that such crises may occur when no actual change takes place in any of the economic fundamentals or bank characteristics. It would therefore also be worth investigating internal factors which could affect capital flows into the country in the future, such as the domestic interest rates and the credit ratings. The US results, by comparison, focus more on internal bank characteristics and are generally in line with the expectations of Laeven *et al.* (2014:18), finding that larger banks, and banks with more unstable sources of funding were responsible for producing more systemic risk.

In light of these results, the best way to decrease systemic risk in SA would be to encourage banks to decrease leverage and increase market-based activities. The newly contributed measure for capital inflows (portfolio investment liabilities for SA) provides the most pertinent results. Although capital flows initially decrease systemic risk, their volatile nature should be considered when interpreting this analysis. For the US financial sector, the best way to decrease systemic risk would be to decrease the leverage of banks, decrease their size, and encourage more stable sources of funding.

5.5.4 Section summary

The regression results show that the only significant determinants that SA and the US had in common were the leverage of individual banks. For each sector individually, the determinants were different. The SA results illustrated that an increased undertaking of market-based activities would decrease systemic risk, while an increase in capital inflows would have the same effect. The capital inflows should be interpreted with care, as their volatile nature means that a reversal could lead to rapid increases in systemic risk. The US results focused on internal bank characteristics, such as the size of the bank, as well as the stability of the bank's funding source. Both these variables were found to have a positive relationship with systemic risk.

5.6 CHAPTER SUMMARY

Chapter 5 presented the results of the empirical analysis outlined in Chapter 4. Before the results were presented, the data used in the study were described in Section 5.2. The balance sheet data needed to be selected according to specific accounting standards, as well as transformed into local currency amounts. The market data consisted of equity returns and the market capitalisation of banks. It would therefore follow that if a bank were to be included in the study, it would need to be listed on a stock exchange. All financial modelling was conducted in Microsoft Excel™ (2013), while the regression modelling was done in EViews™ 8 econometrics software (QMS, 2013).

Following the structure laid out in the previous chapter, Chapter 5 separated the results into three sections. Section 5.3 provided the results of the SRISK analysis. That is, it provided an empirical representation of systemic risk for both SA and the US. This study used a parametric approach based on extreme value theory and used the Hill estimator to calculate the expected shortfall of the banks and the market below a certain threshold level. The use of such an approach to model of the tail expectations of MES represents a new contribution to the field. Furthermore, a Monte Carlo simulation procedure and Cholesky decomposition were used to simulate returns that preserved the sub-prime crisis period volatilities and correlations. This was used as an additional input to the SRISK measure. For both countries, the SRISK measure using the approximated LRMES input was found to be the most appropriate measure.

The simulated LRMES results provided interesting comparisons on the effect of sub-prime crisis volatilities combined with balance sheet data from non-crisis periods. Section 5.3.1 presented the results for SA which show that the levels of SRISK were not particularly high, although an increase was seen following the stock market crash and during the sub-prime crisis period. Although most of the banks display capital surpluses, when the assumption of low liquidity during crisis scenarios was made and only positive contributions to SRISK were considered, the results provided more insight. Investec was shown to be the largest contributor to SRISK, in many cases accounting for 100 % of the amount. Interestingly, following the stock market crash and during the sub-prime crisis, this contribution dropped below those of the other banks, supporting the idea that systemic risk in the SA sector manifests in a different way. The US results showed that it was mostly dominated by the top three banks (Bank of America, Citigroup, and JPMorgan) who interchanged their positions throughout much of the sample period. Morgan Stanley also featured largely in the period between the stock market crash and sub-prime crisis, but fell away afterwards. Additionally, the total financial sector SRISK increased, but the largest banks either increased their SRISK or decreased it only slightly. This raises the question as to whether the smaller banks are compensating for the increased SRISK of larger banks by holding capital surpluses. Furthermore, given these SRISK values, questions regarding the regulatory measures may arise. The SRISK contributions of the largest banks have not declined significantly in the US following the sub-prime crisis, even though Basel III and the Dodd-Frank Act had been implemented. In SA, SRISK was low for the majority of the period but the spike around crisis periods, especially from banks that initially display capital surpluses, could provide a mild warning that fragilities may exist and that external factors need to be considered.

The potential transfer of systemic risk from the US to the SA market was examined in Section 5.4 using three different approaches. Section 5.4.1 explored the existence of a contagion effect. By using the DCC model, an increase in correlation during the sub-prime crisis was not observed and therefore the possibility of contagion was rejected. Section 5.4.2 then tested for a potential volatility spillover effect from the US sector to the SA sector with an EGARCH model. The model showed that a volatility spillover effect existed but that this volatility increased more from positive return shocks than negative return shocks, and the effect decreased over the sample period. Finally, this study made a new contribution to the field by measuring the MES of the ALSI. This is accomplished by setting the ALSI as a hypothetical 'bank' in the equity market represented by the S&P 500. The results showed a relatively weak effect on the ALSI with a peak daily decline of only 2.5 %, while the longer-run values and simulations also illustrated modest declines. An additional iteration of the MES analysis was conducted in order to isolate the financial sectors of the SA and US markets. The SA banking sector, proxied by the JSE Bank Index was set as a hypothetical bank in the US financial sector, proxied by the Financial Select Sector SPDR exchange traded

fund. The results from this iteration were analogous to those for the equity market. Considering these three analyses, the evidence for systemic risk transfer from the US to SA was relatively weak.

Section 5.5 conducted a panel regression analysis to identify the determinants of systemic risk within individual banks and took into account factors that may be unique to either SA or the US. This study made a novel contribution by specifying new variables for emerging markets which were based on the appropriate systemic risk literature, and would therefore be more relevant than the traditional variables. Section 5.5.1 presented the results for SA which found that the leverage of individual banks had a positive relationship with systemic risk. Additionally, it also found that increased market-based bank activities and greater capital inflows had a negative relationship with systemic risk. The newly contributed variable, the capital inflows measure, is of particular interest given its volatility. The implication is that capital inflows could reverse relatively quickly and therefore cause an increase in systemic risk. The US results, by comparison, showed one similar result in that the leverage of the banks had a positive relationship with systemic risk. Additionally, internal bank characteristics, such as the size of the bank and the stability of its funding source, had positive relationships with systemic risk.

In conclusion, this study provided an all-encompassing, top-down measurement of systemic risk while traditional approaches would typically only investigate one of the approaches presented in this study. The contribution made is therefore not only that systemic risk was measured on an institutional level but that the factors to which this systemic risk could be attributed were also identified. In the case of SA, systemic risk levels were found to be manageable to an extent, but during crisis periods these levels increased dramatically.

CHAPTER 6

SUMMARY, CONCLUSIONS AND SUGGESTIONS FOR FUTURE WORK

6.1 SUMMARY

The sub-prime crisis sparked a renewed interest in systemic risk, which is arguably one of the least understood, yet most important risks. It may therefore be perplexing that a single definition for systemic risk cannot be agreed on. A general definition refers to the risk of a financial system collapse, but part of the problem in identifying systemic risk may relate to its manifestation within different economies and countries. In order to measure this, Systemic Risk Index (SRISK) analysis which takes into account Marginal Expected Shortfall (MES) was used.

This study used a parametric approach based on extreme value theory and the Hill estimator to calculate the expected shortfall of the banks and the market below a certain threshold level. This method (discussed in Section 4.2.3.2) has the advantage of shifting the focus to modelling the tail behaviour of the distribution alone and therefore requires fewer degrees of freedom. It also does not suffer the disadvantages of the alternative method (discussed in Section 4.2.3.1). These disadvantages includes the assumption that the data do not come from any particular distribution, therefore potentially leading to inaccurate modelling of the tail distribution (Nadarajah *et al.*, 2014:284; Skoglund & Chen, 2015:104). Additionally, it also does not suffer from the negative effects of smoothing associated with the kernel based-method, which could result in increased bias and a subsequent increase in the mean-squared error of the kernel estimator – the result of which renders the entire process of smoothing counterproductive (Chen, 2008:93). The use of such an approach to model the tail expectations of MES, represents a new contribution to the field. Furthermore, a novel technique for long-run MES (LRMES) was employed, whereby a Monte Carlo simulation procedure and Cholesky decomposition were used to simulate returns that preserve the sub-prime crisis period volatilities and correlations.

The sub-prime crisis showed that systemic risk in developed economies, such as the US occurred as a result of large, highly leveraged banks undertaking complex activities that left them undercapitalised (Section 2.3.1). Given the inherent interconnected nature of these banks (and financial institutions), systemic effects can also rapidly transfer between these institutions. Emerging markets, by comparison, were affected both differently and belatedly through third-party effects (Section 2.5). Interestingly, none of the economic fundamentals of emerging markets, such as SA changed, yet they were still affected by a crisis in another country. This illustrates the global impact that a large enough level of systemic risk could have. In order to determine if systemic risk was transferred from the US market to the SA market. An MES model was used which specified the ALSI as a hypothetical ‘bank’ within the US market. MES refers to the

one-day decline in the equity value of the bank, given that the equity market as a whole has declined by 2 %. This is widely accepted to be representative of a one-day systemic event (Brownlees & Engle, 2012:10; Laeven *et al.*, 2014:28). The argument was made that the assessment of the MES of the ALSI relative to the S&P 500 could provide an indication of the systemic response of the SA market to the US market. The specification of the model in this way and the investigation of a potential systemic response represented a new contribution to the field. According to this model, no systemic response took place, therefore it is concluded that no significant transfer of systemic risk took place over the period.

The main sources of systemic risk in emerging markets are the pro-cyclicality of the financial sector and the volatility of capital flows. Both of these factors build up during upswings and can reverse quickly during downswings. A regression analysis was used to identify the main determinants of systemic risk and this study contributed new variables for SA. These are the volatility spillover from the US, and capital inflows to SA. Both variables were based on systemic risk literature which illustrates how emerging market economies are affected differently and have different sources of systemic risk. The capital inflows measure was found to be significant for SA.

Regulatory measures in both countries prior to the sub-prime crisis were analysed and the overall conclusion is that they were not adequately constructed to protect against a large-scale, low probability event of this nature. Subsequently, it should also be important for regulators to be aware of the amount of systemic risks within an economy, as well as the unique causes of this risk for their specific economies and financial sectors. Current systemic risk quantification methods appear to follow a blanket approach which assumes that systemic risk manifests the same in every financial sector and are not tailored to suit the inherent individual characteristics of a specific economy and financial sector.

The problem statement in this thesis made the case that correct regulations based on inaccurate measurements would be just as ineffectual as incorrect regulations based on accurate measurements. This thesis set out to improve systemic risk measurement by improving on the shortfalls of the current methodology for measuring SRISK. This was done by using a different approach for modelling the tail distribution component of MES (as explained above). Given the prominence of the US in the world economy, this study also provided a novel investigation of a systemic risk transfer, which highlighted the systemic connection between the SA and US sectors. Additionally, this study also offers an approach which is tailor-made to the individual economy and financial sector, as it identifies the individual determinants of systemic risk within each individual bank. As a result, regulators would not only be aware of the level of systemic risk in the financial sector and the amounts that individual banks contribute to the overall financial sector, but also which individual characteristics within each individual bank result in the bank contributing a specific amount of systemic risk. On a more granular level, the new variables in the

regression provide improved detail into unique characteristics, which are key to investigating and mitigating the effects of systemic risk that were not initially captured in the SRISK analysis. As a result of this increased level of detail, the new approaches proposed in this thesis could potentially be effective in providing superior risk management to the respective financial sectors and would be a more informative tool for regulators to base their decisions on.

6.2 CONCLUSIONS AND RECOMMENDATIONS

The level of systemic risk in the US decreased following the sub-prime crisis, but the total contribution of the five largest banks to the total financial sector systemic risk either increased or remained relatively the same. This raises questions regarding the success of regulatory measures, such as Basel III and the Dodd-Frank Act in addressing systemic risk. While they all have measures that are meant to target systemic risk specifically, the success of these measures thus far is arguable. Another question worth raising may be whether smaller banks are compensating for the large banks by holding capital surpluses, leading to a situation where the smaller banks offset the deficits of the larger banks, thereby creating the illusion of decreased systemic risk. This study negated this effect by only analysing the capital shortfalls and based on the evidence produced by this study, systemic risk in the US has not worsened since the sub-prime crisis, but it has also not improved. Additionally, many of the macroeconomic factors within the US that laid a foundation for systemic risk, such as loose monetary policy, were still evident in 2015. Whether this will improve as regulatory measures are updated is unclear.

The case for SA provides an interesting comparison. The largest contributor to systemic risk throughout most of the sample period was the smallest bank in the sample of five banks. However, when the stock market crash took place in 2002, systemic risk contributions from the other banks increased. A similar, more dramatic situation occurred during the sub-prime crisis. During both these periods, the total financial sector systemic risk also increased markedly. The implication is that systemic risk levels within SA seem to be largely dependent on external factors, regardless of the economic fundamentals of the country itself. This suggests that regulators should constantly require banks to be prepared for a systemic crisis. Whether regulatory measures are adequately considering these factors for financial stability is arguable.

The evidence for a direct systemic risk transfer from the US market to the SA market is weak, therefore pointing to factors such as capital inflows and their inherent volatility. Regression measures show that capital flows are a significant determinant of systemic risk for SA. Other individual banking characteristics that are significant determinants are the amount of banking activities which are market-based (more market-based, less systemically risky) and the degree of leverage the bank has (more leverage, more

systemic risk). Contrastingly, the systemic risk that US banks produce is likely to be a result of the size of the bank and the stability of its funding source, as well as the amount of leverage it has.

The implications of these results for regulations differ for the two economies. For the US, it may appear that the levels of systemic risk had not worsened in absolute terms, but the contributions of large banks had increased over time. A failure of one of these banks would therefore likely cause a financial crisis. Based on the results of this study, regulations that address bank size, leverage and the stability of its funding source may need to be re-examined as there were found to be the largest determinants of systemic risk. The US has already implemented regulations (discussed in Section 3.3.1) which address these factors, but it may take some time before these changes have an impact on systemic risk. However, it was expected that the rate of increase in systemic risk contributions of the biggest banks would have slowed, but this is not the case.

For SA, capital inflows, leverage, and the share of market-based activities were the most significant determinants of systemic risk. These results illustrate that the economic fundamentals of the country itself have little effect on systemic risk and that the stability of financial sectors in other countries is more important. The implication therefore is that in addition to complying with individual banking regulations, such as Basel, and corporate governance regulations promoting ethical behaviour, such as King III, the banks should ensure that they always have sufficient capital reserves in order to mitigate the effects of a period of financial turmoil in a foreign country.

The current regulations do not take this into account when addressing systemic risk and therefore a large outflow of capital is likely to result in a domestic financial crisis. In order to counteract this, a pre-emptive forecast of events which may cause capital outflows should be considered at all times. If outflows are predicted, banks could ensure that they hold additional capital for a certain period of time, or until regulators deem the economic environment to be stable. The calibration of such a regulation could draw inspiration from the countercyclical capital buffer, with the trigger events simply changing from upswings and downswings to certain user-specified events. Subsequently, the levels of capital required in these scenarios can be determined through worst-case scenario analyses (such as those in this study) to ensure that banks are sufficiently capitalised during a financial crisis and therefore protected from systemic risk.

The final conclusion made from this study, taking into account the different results for SA and the US, is that the measurement of systemic risk should not only take place on one level, but rather on a number of different levels. Given that systemic risk is an inherent part of a financial sector, its elimination is unlikely. Therefore the focus should be on understanding and monitoring its exact source. Measuring the amount of systemic risk in the financial sector should form only one aspect. The next aspect would involve

determining if this risk has the potential to be transferred from another market, or a number of other markets. The final aspect would be the identification of the specific characteristics within the institutions which result in them contributing a specific amount of systemic risk. As a result the measurement approach conducted in this study essentially lays the groundwork and motivation for a bespoke model approach to measuring systemic risk for individual countries.

6.3 SUGGESTIONS FOR FUTURE WORK

An adequate definition for systemic risk, which is both broad enough, yet limiting enough, needs to be identified. Given the varying ways in which systemic risk manifests in different economies, individualised definitions could also be proposed which take into factors related to the way in which systemic risk manifests in that particular economy. Furthermore, a way of subsequently quantifying systemic risk, based on these individual definitions, could be constructed.

Considering the increased systemic risk levels in SA following crisis periods in foreign countries, a classification system for the capital flows may be in order. This could mimic the way that securitised debt is split into tranches. For example, capital flows from Portugal which may be undergoing financial difficulties could be classified as riskier capital and would therefore be lower tranche, whereas capital from the UK would be considered a higher tranche. A haircut-type system could then be employed where top tranche capital flows are taken at a face value of 100 %, whereas the lower tranche capital flows are only taken at a face value of 60 %.

Additionally, internal factors that affect capital flows, such as domestic interest rates and credit ratings, could be investigated. The logic behind this is that if a decrease in interest rates is expected, banks would be aware that capital flows may decrease and lead to an increased capital shortfall (i.e. systemic risk). A credit rating downgrade could have the same effect. If banks are aware of these internal factors and the effects they may have, they could increase their capital reserves prior to the events taking place, and thereby ensure financial stability.

Finally, the interconnected and concentrated nature of SA should also be explored, as explained in Section 1.2. Given that the financial sector is dominated by a few institutions, and that all these institutions have some degree of transactional history with each other, it would follow that the failure of one large bank could end up having a chain reaction effect through to the rest of the financial sector. This is critically important and should be investigated in the near future.

BIBLIOGRAPHY

Acharya, V.V., Biggs, J., Le, H., Richardson, M., Ryan, S., Cooley, T.F. & Walter, I. 2010. Systemic risk and the regulation of insurance companies. (*In* Acharya, V.V., Cooley, T.F., Richardson, M.P. & Walter, I., eds. *Regulating Wall Street: The Dodd-Frank Act and the new architecture of global finance*. New Jersey: Wiley & Sons, Inc. p. 241-302).

Acharya, V.V., Cooley, T. & Richardson, M. 2010. Manufacturing tail risk: A perspective on the financial crisis of 2007-2009. *Foundations and trends in finance*, 4(4):247-325.

Acharya, V.V., Schnabl, P. & Suarez, G. 2013. Securitization without risk transfer. *Journal of financial economics*, 107(3):515-536.

Acharya, V.V. 2013. Adapting micro prudential regulation for emerging markets. (*In* Canuto, O. & Ghosh, S.R., eds. *Dealing with the challenges of macro financial linkages in emerging markets*. Washington, D.C.: World Bank. p. 57-88).

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. 2012. The Dodd-Frank Act and Basel III: Intentions, unintended consequences, and lessons for emerging markets. ADBI working paper series, no. 392.

Acharya, V.V. & Pedersen, L.H. 2005. Asset pricing with liquidity risk. *Journal of financial economics*, 77(2):375-410.

Acharya, V.V. & Richardson, M. 2009. Causes of the financial crisis. *Critical review*, 21(2-3):195-210.

Acharya, V.V. & Yorulmazer, T. 2003. Information contagion and inter-bank correlation in a theory of systemic risk. *Working paper*. London Business School.

Acharya, V.V. & Yorulmazer, T. 2008. Information contagion and bank herding. *Journal of money, credit and banking*, 40(1):215-231.

Acharya, V.V., Engle, R. & Richardson, M.P. 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.P. 2010. Measuring systemic risk. *Working paper*. New York University.

Addison, T. & Heshmati, A. 2003. The new global determinants of FDI flows to developing countries: The importance of ICT and democratization. World Institute for Development Economics (WIDER) Discussion Papers, No. 2003/45.

Adrian, T. & Brunnermeier, M.K. 2011. CoVaR. *Working paper no. 17454*. National Bureau of Economic Research.

Ahrend, R., Cournède, B. & Price, R. 2008. Monetary policy, market excesses and financial turmoil. *Working papers no. 597*. OECD Economics Department.

Aielli, G. 2009. Dynamic conditional correlations: On properties and estimation. Technical report, Department of Statistics, University of Florence.

Akdogan, K. & Yildirim, B.D. 2014. Non-core Liabilities as an indicator of systemic risk and a Liquidity stress test application on Turkish banking system. *Working Paper no. 1412*. Turkish Central Bank.

Akram, Q.F. & Christophersen, C. 2010. Interbank overnight interest rates-gains from systemic importance. *Working papers no. 11*. Norges Bank.

Alessandri, P., Gai, P., Kapadia, S., Mora, N. & Puhr, C. 2009. A framework for quantifying systemic stability. *International journal of central banking*, 5(3):47-81.

Allen, F. & Carletti, E. 2006. Credit risk transfer and contagion. *Journal of monetary economics*, 53(1):89-111.

Allen, F. & Gale, D. 2000. Financial contagion. *Journal of political economy*, 108(1):1-33.

Allen, F. & Gale, D. 2007. Systemic risk and regulation. (In Carey, M. & Stulz, R., eds. The risks of financial institutions. A National Bureau of Economic Research Conference Report. Chicago and London: University of Chicago Press. p. 341-368).

Allen, F., Babus, A. & Carletti, E. 2010. Financial connections and systemic risk. *Working paper no. 16177*. National Bureau of Economic Research.

Angelini, P., Neri, S. & Panetta, F. 2011. Monetary and macroprudential policies. *Working paper no.* 801. Bank of Italy Temi di Discussione.

Arnold, B., Borio, C., Ellis, L. & Moshirian, F. 2012. Systemic risk, macroprudential policy frameworks, monitoring financial systems and the evolution of capital adequacy. *Journal of banking & finance*, 36(12):3125-3132.

Asteriou, D. & Hall, S.G. 2011. Applied econometrics. New York: Palgrave Macmillan.

Babus, A.M. 2007. The formation of financial networks. *Discussion Paper Series*, TI 06-093/2. Tinbergen Institute.

Baek, I.M. 2006. Portfolio investment flows to Asia and Latin America: Pull, push or market sentiment? *Journal of Asian economics*, 17(2):363-373.

Baltagi, B.H. 2001. Econometric analysis of panel data. New York: John Wiley & Sons.

Bank for International Settlements (BIS). 2008. 78th Annual Report.
<http://www.bis.org/publ/arpdf/ar2008e.pdf> Date of Access: 22 Apr. 2015.

Bank for International Settlements (BIS). 2009. 79th Annual Report.
<http://www.bis.org/publ/arpdf/ar2009e.pdf> Date of Access: 10 Nov. 2015.

Bank for International Settlements (BIS). 2015. G10 publications.
<http://www.bis.org/list/g10publications/index.htm> Date of Access: 4 Sep. 2015.

Baron, N.D. 1996. The role of rating agencies in the securitization process. (*In* Kendall, L.T. & Fishman, M.J., eds. Cambridge and London: MIT Press. p. 81-90).

Barth, J.R., Brummer, C., Li, T. & Nolle, D.E. 2013. Systemically important banks (SIBs) in the post-crisis era: 'The' global response, and responses around the globe for 135 countries. Available at SSRN 2294641. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2294641 Date of Access: 10 Jun. 2015.

Barth, J.R., Prabha, A.P. & Wihlborg, C. 2014. The Dodd-Frank Act: Key features, implementation progress, and financial system impact. *Current Views* (February 2015). Milken institute.

Basel Committee on Banking Supervision (BCBS). 2004. International convergence of capital measurement and capital standards. A revised framework. <http://www.bis.org/publ/bcbs107.pdf> Date of Access: 18 Jun. 2015.

Basel Committee on Banking Supervision (BCBS). 2009. Guidelines for computing capital for incremental risk in the trading book. <http://www.bis.org/publ/bcbs159.pdf> Date of Access: 19 Jun. 2015.

Basel Committee on Banking Supervision (BCBS). 2010. Guidance for national authorities operating the countercyclical capital buffer. <http://www.bis.org/publ/bcbs187.pdf> Date of Access: 19 Jun. 2015.

Basel Committee on Banking Supervision (BCBS). 2011. Basel III: A global regulatory framework for more resilient banks and banking systems. <http://www.bis.org/publ/bcbs189.pdf> Date of Access: 19 Jun. 2015.

Basel Committee on Banking Supervision (BCBS). 2013. Global systemically important banks: updated assessment methodology and the higher loss absorbency requirement. <https://www.bis.org/publ/bcbs255.htm> Date of Access: 15 Jan. 2015.

Basel Committee on Banking Supervision (BCBS). 2014. A brief history of the Basel Committee. <http://www.bis.org/bcbs/history.pdf> Date of Access: 18 Jun. 2015.

Basel Committee on Banking Supervision (BCBS). 2015a. Instructions for the end-2014 G-SIB assessment exercise. http://www.bis.org/bcbs/gsib/instr_end14_gsib.pdf Date of Access: 9 Jun. 2015.

Basel Committee on Banking Supervision (BCBS). 2015b. Regulatory Consistency Assessment Programme (RCAP). Assessment of Basel II risk-based capital regulations – South Africa. <http://www.bis.org/bcbs/publ/d322.pdf> Date of Access: 22 Jul. 2015.

Batrancea, I., & Bechis, L. 2013. Systemic risk in banking sector. *The USV Annals of Economics and Public Administration*, 13(17):177-182.

Bauke, H. 2007. Parameter estimation for power-law distributions by maximum likelihood methods. *The European Physical Journal B-Condensed Matter and Complex Systems*, 58(2):167-173.

Baxter, R. 2009. The global economic crisis and its impact on South Africa and the country's mining industry. *Challenges for monetary policy-makers in emerging markets*, 105-116. South African Reserve Bank Conference Series.

BCBS **see** Basel Committee on Banking Supervision.

Bean, C., Paustian, M., Penalver, A. & Taylor, T. 2010. Monetary policy after the fall. *Macroeconomic Challenges: The Decade Ahead*, 26-28.

Bebchuk, L.A. & Spamann, H. 2009. Regulating bankers' pay. Harvard Law School. John M. Olin Center for Law, Economics and Business Discussion Paper Series. Paper 634.

Belke, A.H. & Gros, D. 2010. Global liquidity, world savings glut and global policy coordination.

Bell, M., & Keller, B. 2009. Insurance and stability: The reform of insurance regulation. *Zurich Financial Services Group working paper*.

Beltratti, A. & Stulz, R.M. 2012. The credit crisis around the globe: Why did some banks perform better? *Journal of financial economics*, 105(1):1-17.

Benford, J., Berry, S., Nikolov, K., Young, C. & Robson, M. 2009. Quantitative easing. *Bank of England quarterly bulletin*, 49(2):90-100.

Bernanke, B.S. 2005. Monetary policy in a world of mobile capital. *Cato Journal*, 25(1):1-12.

Bernanke, B.S. 2009. Financial reform to address systemic risk. Technical report. *Speech at the council on foreign relations*.

Bernanke, B.S. 2010. Monetary policy and the housing bubble. *Speech at the annual meeting of the American Economic Association, Atlanta, Georgia*, Vol. 3.

Bessis, J. 2010. Risk management in banking. Chichester: John Wiley & Sons Ltd.

Biglaiser, G. & DeRouen, K.R. 2006. Economic reforms and inflows of foreign direct investment in Latin America. *Latin American research review*, 41(1):51-75.

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 **see** Bank for International Settlements.

Bisias, D., Flood, M.D., Lo, A.W. & Valavanis, S. 2012. A survey of systemic risk analytics. US Department of Treasury, Office of Financial Research, (0001).

Black, F. 1976. Studies in stock price volatility changes. Proceedings of the 1976 Meeting of the Business and Economic Statistics Section, American Statistical Association, pp. 177-181.

Blanchard, O.J., Dell'Ariccia, M.G. & Mauro, M.P. 2013. Rethinking macro policy II: Getting granular. International Monetary Fund.

Blanchard, O.J., Faruqee, H., Das, M., Forbes, K.J. & Tesar, L.L. 2010. The initial impact of the crisis on emerging market countries. *Brookings papers on economic activity*, 263-323.

Bloxham, E. 2015. A new Glass-Steagall for banks: One giant step for Congress, one small step for us all. http://fortune.com/2015/07/20/glass-steagall-banks/?xid=yahoo_fortune Date of Access: 21 Jul. 2015.

Bloomberg. 2015. (Data source, supplied by software).

Blum, J. & Hellwig, M. 1995. The macroeconomic implications of capital adequacy requirements for banks. *European economic review*, 39(3):739-749.

Blundell-Wignall, A. & Atkinson, P. 2009. Origins of the financial crisis and requirements for reform. *Journal of Asian economics*, 20(5):536-548.

Blundell-Wignall, A. & Atkinson, P. 2010. Thinking beyond Basel III. *OECD journal: Financial market trends*, 2010(1):9-33.

Blundell-Wignall, A., Atkinson, P. & Roulet, C. 2014. Bank business models and the Basel system. *OECD journal: Financial market trends*, 2013(2):43-68.

Bollerslev, T. 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *The review of economics and statistics*, 72(3):498-505.

Borio, C. & Drehmann, M. 2009. Towards an operational framework for financial stability: "fuzzy" measurement and its consequences. *BIS working papers no. 284*.

<http://www.bis.org/publ/work284.pdf> Date of Access: 15 Aug. 2015.

- Borio, C. 2003. Towards a macroprudential framework for financial supervision and regulation? *BIS Working Papers No. 128*. <http://www.bis.org/publ/work128.pdf> Date of Access: 15 Jul. 2015.
- Borio, C. 2010. Implementing a macroprudential framework: Blending boldness and realism. Bank for International Settlements (BIS). <http://www.bis.org/repofficepubl/hkimr201007.12c.pdf> Date of Access: 15 Jul. 2015.
- Borio, C. & Shim, I. 2008. What can (macro-)prudential policy do to support monetary policy? *BIS working papers no. 242*. <http://www.bis.org/publ/work242.pdf> Date of Access: 15 Jul. 2015.
- Borio, C., Drehmann, M. & Tsatsaronis, K. 2014. Stress-testing macro stress testing: does it live up to expectations? *Journal of financial stability*, 12(1):3-15.
- Branson, D.M. 2014. A return to old-time religion? The Glass-Steagall act, the Volcker rule, limits on proprietary trading, and sustainability. *University of St. Thomas law journal*, (forthcoming).
- Breitung, J. 2000. The local power of some unit root tests for panel data. (In Baltagi, B., eds. *Advances in econometrics*, Vol. 15: Nonstationary panels, panel cointegration, and dynamic panels. Amsterdam: JAI Press, p. 161–178).
- Britannica. 2015. Savings and loan association. <http://academic.eb.com.nwulib.nwu.ac.za/EBchecked/topic/525776/savings-and-loan-association> Date of Access: 21 Sep. 2015
- Broner, F., Didier, T., Erce, A. & Schmukler, S.L. 2013. Gross capital flows: Dynamics and crises. *Journal of monetary economics*, 60(1):113-133.
- Brownlees, C.T. & Engle, R.F. 2012. Volatility, correlation and tails for systemic risk measurement. *Available at SSRN 1611229*. Date of Access: 15 Jan. 2015.
- Brownlees, C.T. & Engle, R.F. 2015. SRISK: A conditional capital shortfall index for systemic risk measurement. Department of Finance, New York University.
- Brunnermeier, M.K. 2008. Deciphering the liquidity and credit crunch 2007-08. *Working paper no. 14612*. National Bureau of Economic Research.
- Brunnermeier, M.K. & Pedersen, L.H. 2009. Market liquidity and funding liquidity. *Review of financial studies*, 22(6):2201-2238.

- Brunnermeier, M.K., Crockett, A., Goodhart, C.A., Persaud, A. & Shin, H.S. 2009. *The fundamental principles of financial regulation* (Vol. 11). London: Centre for Economic Policy Research.
- Bruno, V. & Shin, H.S. 2015. Capital flows and the risk-taking channel of monetary policy. *Journal of monetary economics*, 71(1):119-132.
- Buiter, W. & Rahbari E. 2015. Global Economics View: High time to get low: getting rid of the lower bound on nominal interest rates. *Citi Research: Economics* (Developed Markets, Global), 1 – 21 (April).
- Bulow, J.I., Geanakoplos, J.D. & Klemperer, P.D. 1985. Multimarket oligopoly: Strategic substitutes and complements. *The journal of political economy*, 488-511.
- Burrows, O., Learmonth, D., McKeown, J. & Williams, R. 2012. RAMSI: a top-down stress-testing model developed at the Bank of England. *Bank of England quarterly bulletin*, Q3.
- Caballero, R.J. 2010. The "other" imbalance and the financial crisis. *Working paper no. 15636*. National Bureau of Economic Research.
- Canuto, O. & Ghosh, S. 2013. Dealing with the challenges of macro financial linkages in emerging markets. World Bank Publications.
- Caprio, G. & Levine, R. 2002. Corporate governance in finance: Concepts and international observations. (In Litan, R.E., Pomerleano, M. & Sundararajan, V., eds. *Financial sector governance: The roles of the public and private sectors*. Washington, D.C.: The Brookings Institute, p. 17-50).
- Carswell, A.T. 2012. *The encyclopedia of housing*. Vol. 1. Sage.
- Caruana, J. 2010. Systemic risk: how to deal with it. Bank for International Settlements (BIS). <http://www.bis.org/publ/othp08.htm> Date of Access: 29 May. 2015.
- Cecchetti, S.G. 2009. Crisis and responses: The Federal Reserve in the early stages of the financial crisis (digest summary). *Journal of economic perspectives*, 23(1):51-75.
- Cerutti, E., Claessens, S. & Laeven, L. 2015. The use and effectiveness of macroprudential policies: New evidence (No. 15-61). International Monetary Fund.

Cerutti, E., Claessens, S. & McGuire, P. 2012. Systemic risks in global banking: What can available data tell us and what more data are needed? *BIS working paper no. 376*.

<http://www.bis.org/publ/work376.pdf> Date of Access: 15 Aug. 2015.

Cerutti, E., Claessens, S. & Ratnovski, L. 2014. Global liquidity and drivers of cross-border bank flows. International Monetary Fund.

Cetorelli, N. & Goldberg, L.S. 2011. Global banks and international shock transmission: Evidence from the crisis. *IMF economic review*, 59(1):41-76.

Chance, D.M. & Brooks, R.E. 2008. An introduction to derivatives and risk management. Mason, OH: Thomson/South-Western.

Chen, S.X. 2008. Nonparametric estimation of expected shortfall. *Journal of financial econometrics*, 6(1):87-107.

Christoffersen, P. F. 2011. Elements of financial risk management. San Diego: Academic Press.

Cifuentes, R., Ferrucci, G. & Shin, H.S. 2005. Liquidity risk and contagion. *Journal of the European Economic Association*, 3(2-3):556-566.

Claessens, S. 2012. How to prevent and better handle the failures of global systemically important financial institutions. (In Baldwin, R. & Vines, D., eds. *Rethinking Global Economic Governance in Light of the Crisis New Perspectives on Economic Policy Foundations*. London: Centre for Economic Policy Research. p. 75-83).

Claessens, S. 2014. An overview of macroprudential policy tools. International Monetary Fund. No. *Working paper no. 14-214*.

Claessens, S. & Ghosh, S.R. 2012. Macro-Prudential Policies: Lessons for and from emerging markets. Prepared for the East-West Center and the Korea Development Institute conference entitled: "Financial regulations on international capital flows and exchange rates". Hawaii. 19-20 July.

Claessens, S. & Ghosh, S.R. 2013. Capital flow volatility and systemic risk in emerging markets: The policy toolkit. (In Canuto, O. & Ghosh, S.R., eds. *Dealing with the challenges of macro financial linkages in emerging markets*. Washington, D.C.: World Bank. p. 91-118).

Claessens, S., Ghosh, S.R. & Mihet, R. 2013. Macro prudential policies to mitigate financial vulnerabilities in emerging markets. (In Canuto, O. & Ghosh, S.R., eds. *Dealing with the challenges of macro financial linkages in emerging markets*. Washington, D.C.: World Bank. p. 155-178).

Claessens, S., Herring, D.J. & Schoenmaker, D. 2010. A safer world financial system: Improving the resolution of systemic institutions. *Geneva reports on the world economy* 12. International Center for Monetary and Banking Studies.

Claessens, S., Kose, M.A. & Terrones, M.E. 2012. How do business and financial cycles interact? *Journal of international economics*, 87(1):178-190.

Claessens, S., Laeven, L., Igan, D. & Dell'Ariccia, M.G. 2010. Lessons and Policy Implications from the Global Financial Crisis. International Monetary Fund. *Working paper no. 10/44*.

Claessens, S., Pazarbasioglu, C., Laeven, L., Dobler, M., Valencia, F., Nedelescu, O. & Seal, K. 2011. Crisis management and resolution: Early lessons from the financial crisis. IMF Staff Discussion Note. <http://www.imf.org/external/pubs/ft/sdn/2011/sdn1105.pdf> Date of Access: 5 Jun. 2015.

Clement, P. 2010. The term "macroprudential": origins and evolution. *BIS quarterly review*, March. http://www.bis.org/publ/qtrpdf/r_qt1003h.pdf Date of Access: 22 Jun. 2015.

Collins, D. & Biekpe, N. 2003. Contagion: a fear for African equity markets? *Journal of economics and business*, 55(3):285-297.

Collins, C. 2013. Riding the roller coaster: Managing capital flows to emerging markets. Presentation at the International Finance Forum. Washington, D.C., October. <https://www.iif.com/publication/meeting-document/riding-roller-coaster-managing-capital-flows-emerging-markets>. Date of Access: 21 May. 2015.

Committee on the Global Financial System (CGFS). 2010. Macroprudential instruments and frameworks: a stocktaking of issues and experiences. *CGFS papers no. 38*. <http://www.bis.org/publ/cgfs38.pdf> Date of Access: 23 Jun. 2015.

Crain, M. 2014. Financial markets and online advertising: Reevaluating the dotcom investment bubble. *Information, communication & society*, 17(3):371-384.

Crotty, J. 2009. Structural causes of the global financial crisis: a critical assessment of the 'new financial architecture'. *Cambridge journal of economics*, 33(4):563-580.

Curdia, V. & Woodford, M. 2009. Credit frictions and optimal monetary policy. *BIS working papers no. 278*. <http://www.bis.org/publ/work278.pdf> Date of Access: 20 Jul. 2015.

Dahlhaus, T. & Vasishtha, G. 2014. The impact of US monetary policy normalization on capital flows to emerging-market economies. Bank of Canada. Working paper no. 53.

Danthine, J.P. 2013. Causes and consequences of low interest rates. Speech presented at the Swisscanto market outlook 2014. Lausanne, Switzerland.

Davis Polk. 2015. Dodd-Frank five-year anniversary progress report. http://www.davispolk.com/sites/default/files/2015-07-16_Dodd-Frank_Progress_Report_Five-Year_Anniversary.pdf Date of Access: 28 Jul. 2015.

De Bandt, O. & Hartmann, P. 2000. Systemic risk: A survey. *Working paper no. 35*. European Central Bank.

De Bandt, O., Hartmann, P. & Peydró, J. 2009. Systemic risk in banking: an update. (In Berger, A.N., Molyneux, P. & Wilson, J.O.S., eds. *The Oxford Handbook of Banking*. Oxford: Oxford University Press. p. 633-672).

De Beer, B. 2015. South Africa's experience with capital flows since the financial crisis. From measurement to analysis. Paper presented at the IFC satellite meeting during the 60th ISI conference. Rio de Janeiro, Brazil. 24 July 2015.

De Nicolo, M.G. & Kwast, M.L. 2002. Systemic risk and financial consolidation: Are they related? *Journal of banking & finance*, 26(5):861-880.

De Nicolo, M.G., Favara, G. & Ratnovski, L. 2012. Externalities and macro-prudential policy. International Monetary Fund.

De Vries, C.G. 2005. The simple economics of bank fragility. *Journal of banking & finance*, 29(4):803-825.

Diamond, D.W. & Rajan, R. 2009. The credit crisis: Conjectures about causes and remedies. National Bureau of Economic Research. *Working paper no. 14739*.

- Dickey, D.A. & Fuller, W.A. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a):427-431.
- Didier, T., Hevia, C. & Schmukler, S. L. 2012. How resilient and countercyclical were emerging economies during the global financial crisis? *Journal of International Money and Finance*, 31(8), 2052-2077.
- Diebold, F.X. & Yilmaz, K. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal*, 119(534):158-171.
- Ding, Z. & Engle, R. 2001. Large scale conditional covariance matrix modeling, estimation and testing.
- Dodd, R. & P. Mills. 2008. Outbreak: U.S. subprime contagion. *Finance and development*, 45(2):14-18.
- Dodd-Frank Wall Street Reform and Consumer Protection Act **see** United States of America.
- Dornbusch, R., Park, Y.C. & Claessens, S. 2000. Contagion: How it spreads and how it can be stopped. *World Bank research observer*, 15(2):177-197.
- Drehmann, M., Borio, C.E. & Tsatsaronis, K. 2011. Anchoring countercyclical capital buffers: the role of credit aggregates. *International journal of central banking*, 7(4):189-240.
- Drumond, I. 2009. Bank capital requirements, business cycle fluctuations and the Basel Accords: a synthesis. *Journal of economic surveys*, 23(5):798-830.
- Drysdale, L. & Keest, K.E. 1999. Two-Tiered consumer financial services marketplace: The fringe banking system and its challenge to current thinking about the role of usury laws in today's society, *The SCL Rev.*, 51, 589.
- Eisenberg, L. & Noe, T.H. 2001. Systemic risk in financial systems. *Management science*, 47(2):236-249.
- Elliott, D.J. & Litan, R.E. 2011. Identifying and regulating systemically important financial institutions: The risks of under and over identification and regulation. *Brookings working paper* no. s6.
- Ellul, A. & Yerramilli, V. 2013. Stronger risk controls, lower risk: Evidence from US bank holding companies. *The journal of finance*, 68(5):1757-1803.

- Ellul, A., Jotikasthira, C., Lundblad, C. & Wang, Y. 2013. Mark-to-market accounting and systemic risk in the financial sector. *Fordham University Schools of Business research papers*, 17.
- Elmer, P.J. 1999. Conduits: Their structure and risk. *FDIC banking review*, 12(3):27-40.
- Engel, K.C. & McCoy, P.A. 2002. A tale of three markets: The law and economics of predatory lending. *Texas Law Review*, 80, 1255-1337.
- Engel, K.C. & McCoy, P.A. 2007. Turning a blind eye: Wall Street finance of predatory lending. *Fordham Law Review*, 75, 2039.
- Engel, K.C. & McCoy, P.A. 2008. From credit denial to predatory lending: The challenge of sustaining minority homeownership. (In Carr, J.H. & Kutty, N.K., eds. Segregation: The rising costs for America. New York: Routledge. p. 81-123).
- Engle, R. 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of business & economic statistics*, 20(3):339-350.
- Engle, R. 2009. Anticipating correlations: a new paradigm for risk management. Princeton University Press.
- Engle, R. & Granger, C.W. 1987. Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, 55(2):251-276.
- Engle, R. & Mezrich, J. 1996. GARCH for Groups: A round-up of recent developments in GARCH techniques for estimating correlation. *Risk*, 9(1):36-40.
- Engle, R., Jondeau, E., & Rockinger, M. 2015. Systemic risk in Europe. *Review of Finance*, 19(1):145-190.
- Englert, S. & Stracca, L. 2015. G-SIFI contagion. Paper presented at the INFINITI Conference on international finance. Ljubljana, Slovenia. 8-9 June 2015.
- Erkens, D.H., Hung, M. & Matos, P. 2012. Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. *Journal of corporate finance*, 18(2):389-411.

Fahlenbrach, R. & Stulz, R.M. 2011. Bank CEO incentives and the credit crisis. *Journal of financial economics*, 99(1):11-26.

FASB **see** Financial Accounting Standards Board.

Federal Reserve (Fed), Federal Deposit Insurance Corporation (FDIC), Office of the Comptroller of the Currency (OCC). 2013. Agencies adopt supplementary leverage ratio notice of proposed rulemaking. <http://www.federalreserve.gov/newsevents/press/bcreg/20130709a.htm> Date of Access: 14 Jul. 2015.

Federal Reserve Board. 2015. H.15 Selected interest rates. Historical data. Conventional Mortgages. Annual Rates. <http://www.federalreserve.gov/releases/h15/data.htm> Date of Access: 26 Feb. 2015.

Financial Accounting Standards Board (FASB). 2010. Statement of financial accounting standards no. 157. http://www.fasb.org/pdf/aop_FAS157.pdf Date of Access: 2 Apr. 2015.

Financial Stability Board (FStB). 2010a. Intensity and effectiveness of SIFI supervision. Recommendations for enhanced supervision. http://www.financialstabilityboard.org/wp-content/uploads/r_101101.pdf Date of Access: 7 Jul. 2015.

Financial Stability Board (FStB). 2010b. Overview of progress in the implementation of the G20 recommendations for strengthening financial stability. Report of the Financial Stability Board to G20 Finance Ministers and Governors. http://www.financialstabilityboard.org/wp-content/uploads/r_100627c.pdf Date of Access: 13 May. 2015.

Financial Stability Board (FStB). 2014. Key attributes of effective resolution regimes for financial institutions. http://www.financialstabilityboard.org/2014/10/r_141015/ Date of Access: 15 Jan. 2015.

Financial Stability Oversight Council (FSOC). 2011. Annual report. <http://www.treasury.gov/initiatives/fsoc/Documents/FSOCAR2011.pdf> Date of Access: 30 Apr. 2015.

Fisher, R.A. 1932. Statistical methods for research workers. Edinburgh: Oliver & Boyd.

Forbes, K.J. & Rigobon, R. 2002. No contagion, only interdependence: measuring stock market comovements. *The journal of finance*, 57(5):2223-2261.

Frank, N. & Hesse, H. 2009. Financial spillovers to emerging markets during the global financial crisis. International Monetary Fund.

Freixas, X., Parigi, B.M. & Rochet, J.C. 2000. Systemic risk, interbank relations, and liquidity provision by the central bank. *Journal of money, credit and banking*, 32(3):611-638.

FSOC **see** Financial Stability Oversight Council.

FStB **see** Financial Stability Board.

Funk, R.J. & Hirschman, D. 2014. Derivatives and deregulation financial innovation and the demise of Glass–Steagall. *Administrative science quarterly*, 59(4):669-704.

Furfine, C.H. 2003. Interbank exposures: Quantifying the risk of contagion. *Journal of money, credit and banking*, 35(1):111-128.

G20 (Group of Twenty). 2010. The Seoul summit document.

<http://www.oecd.org/g20/meetings/seoul/Seoul-Summit-Document.pdf> Date of Access: 15 Jan. 2015.

Gai, P. & Kapadia, S. 2010. Contagion in financial networks. *Proceedings: Mathematical, physical and engineering sciences*, 466(2120):2401-2423

Gambro, M.S. & Leichtner, S. 1997. Selected legal issues affecting securitization. *NC Banking Inst.*, 1, 131.

Gates, S.W., Perry, V.G. & Zorn, P.M. 2002. Automated underwriting in mortgage lending: good news for the underserved? *Housing policy debate*, 13(2):369-391.

Georg, C.P. 2011. Basel III and systemic risk regulation: what way forward? *Working papers on global financial markets no. 17*. Universities Jena and Halle.

Georg, C.P. 2013. The effect of the interbank network structure on contagion and common shocks. *Journal of banking & finance*, 37(7):2216-2228.

Georg, C.P. & Poschmann, J. 2010. Systemic risk in a network model of interbank markets with central bank activity. *Jena economic research papers no. 2010*, 033.

Ghosh, S.R. 2010. Dealing with the challenges of capital inflows in the context of macrofinancial links. *Economic Premise Note Number 19*. World Bank.

- Ghosh, A.R., Qureshi, M.S. & Sugawara, N. 2014. Regulating capital flows at both ends: Does it work? *IMF Working papers no. 14/188*.
- Giglio, S., Kelly, B. T. & Pruitt, S. 2015. Systemic risk and the macroeconomy: An empirical evaluation. National Bureau of Economic Research. *Working paper no. 20963*.
- Girardi, G. & Ergun, A. 2013. Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of banking and finance*, 37(1):3169-3180.
- Glosten, L.R., Jagannathan, R. & Runkle, D.E. 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, 48(5):1779-1801.
- Goldie, C.M., & Smith, R.L. 1987. Slow variation with remainder: Theory and applications. *The quarterly journal of mathematics*, 38(1):45-71.
- Goodhart, C. 2010. Is a less pro-cyclical financial system an achievable goal? *National institute economic review*, 211(1):17-26.
- Gordy, M.B. 2003. A risk-factor model foundation for ratings-based bank capital rules. *Journal of financial intermediation*, 12(3):199-232.
- Gorton, G.B. 2009. Information, liquidity, and the (ongoing) panic of 2007. National Bureau of Economic Research. *Working paper no. 14649*.
- Gorton, G. & Metrick, A. 2012. Securitized banking and the run on repo. *Journal of financial economics*, 104(3):425-451.
- Gossel, S.J. & Biekpe, N. 2013. The cyclical relationships between South Africa's net capital inflows and fiscal and monetary policies. *Emerging markets finance and trade*, 49(2):64-83.
- Gramlich, E.M. 2007. Subprime mortgages: America's latest boom and bust. Washington, D.C.: The Urban Institute Press.
- Gray, D.F., & Jobst, A.A. 2011. Modelling systemic financial sector and sovereign risk. *Sveriges Riksbank Economic Review*, 2(1):68-97.
- Green, R.K. & Wachter, S.M. 2007. The housing finance revolution. Paper presented at the Federal Reserve Bank of Kansas City Symposium, Jackson Hole, Wyoming. 31 August -1 September.

- Greenbaum, S.I. & Thakor, A.V. 1987. Bank funding modes: Securitization versus deposits. *Journal of banking & finance*, 11(3):379-401.
- Greenspan, A. 2009. The Fed didn't cause the housing bubble. *Wall Street Journal*, 11, A15.
- Guidara, A., Lai, V.S., Soumaré, I. & Tchana, F.T. 2013. Banks' capital buffer, risk and performance in the Canadian banking system: Impact of business cycles and regulatory changes. *Journal of banking and finance*, 37(9):3373-3387.
- Gujarati, D.N. 2003. Basic econometrics. Boston: McGraw Hill.
- Gupta, K., Krishnamurti, C. & Tourani-Rad, A. 2013. Is corporate governance relevant during the financial crisis? *Journal of international financial markets, institutions and money*, 23(1):85-110.
- Gürkaynak, R.S. & Wright, J.H. 2012. Macroeconomics and the term structure. *Journal of economic literature*, 50(2):331-367.
- Hadri, K. 2000. Testing for stationarity in heterogeneous panel data. *The Econometrics Journal*, 3(2):148-161.
- Hahm, J.H., Mishkin, F.S., Shin, H.S. & Shin, K. 2012. Macroprudential policies in open emerging economies. National Bureau of Economic Research. *Working paper no. 17780*.
- Haldane, A.G. 2009. Rethinking the financial network. Speech delivered at the Financial Student Association. Amsterdam.
- Hansen, L.P. 2012. Challenges in identifying and measuring systemic risk. National Bureau of Economic Research. *Working paper no. 18505*.
- Harrington, S.E. 2009. The financial crisis, systemic risk, and the future of insurance regulation. *Journal of risk and insurance*, 76(4):785-819.
- Hasanhodzic, J. & Lo, A.W. 2011. Black's leverage effect is not due to leverage. Available at SSRN 1762363. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1762363 Date of Access: 14 Sep. 2015.
- Hausman, J.A. 1978. Specification tests in econometrics. *Econometrica: Journal of the Econometric Society*, 46(6):1251-1271.

- Hellwig, M.F. 2007. Switzerland and Euroland: European Monetary Union, monetary stability and financial stability. *MPI collective goods preprint*, (9).
- Hellwig, M.F. 2009. Systemic risk in the financial sector: An analysis of the subprime-mortgage financial crisis. *De Economist*, 157(2):129-207.
- Hellwig, M.F. & Staub, M. 1996. Panel discussion-statements and comments capital requirements for market risks based on inhouse models-aspects of quality assessment. *Schweizerische Zeitschrift für Volkswirtschaft und Statistik*, 132, 755-775.
- Hendricks, D. 2009. Defining systemic risk. *Pew financial reform project, briefing paper*, (1):6.
- Herrmann, S. & Mihaljek, D. 2013. The determinants of cross-border bank flows to emerging markets. *Economics of transition*, 21(3):479-508.
- Hibbard, J. 2005. Morgan Stanley: No stars - and lots of top tech IPOs. *Businessweek*. 56, 17 Jan.
- Higgins, M., Klitgaard, T. & Lerman, R. 2006. Recycling petrodollars. *Current Issues in economics and finance*, 12(9).
- Hill, B.M. 1975. A simple general approach to inference about the tail of a distribution. *The annals of statistics*, 3(5), 1163-1174.
- Hofmann, B. & Bogdanova, B. 2012. Taylor rules and monetary policy: A global 'great deviation'? *BIS quarterly review September*.
- Hsiao, C. 2014. *Analysis of panel data* (Vol. 54). Cambridge University Press.
- Huang, X., Zhou, H. & Zhu, H. 2009. A framework for assessing the systemic risk of major financial institutions. *BIS Working Papers No. 281*. <http://www.bis.org/publ/work281.pdf> Date of Access: 23 Jul. 2015.
- Huizinga, H. & Laeven, L. 2012. Bank valuation and accounting discretion during a financial crisis. *Journal of financial economics*, 106(3):614-634.
- Hull, J. 2012. *Options, futures, and other derivatives*. Boston: Pearson.
- Hull, J. 2015. *Risk management and financial institutions*. Hoboken: Wiley.

IASB **see** International Accounting Standards Board.

IIF **see** Institute of International Finance.

Im, K.S., Pesaran, M.H. & Shin, Y. 2003. Testing for unit roots in heterogeneous panels. *Journal of econometrics*, 115(1):53-74.

IMF **see** International Monetary Fund.

IMF, BIS & FStB **see** International Monetary Fund (IMF), Bank for International Settlements (BIS), & Financial Stability Board (FStB).

Immergluck, D. 2009. Core of the crisis: Deregulation, the global savings glut, and financial innovation in the subprime debacle. *City & Community*, 8(3):341-345.

INET BFA Dataset. 2015. (Data source, supplied by software).

Ingves, S. 2010. Monetary policy and financial stability - some future challenges. Speech at the Swedish Economics Association. Stockholm.

Ingves, S. 2011. Challenges for the design and conduct of macroprudential policy. *BIS papers no. 60*. <http://www.bis.org/publ/bppdf/bispap60c.pdf> Date of Access: 16 Jul. 2015.

Ingves, S. 2014. Monetary policy and financial stability in a globalised world. Speech at the Swedish Economics Association. Stockholm.
http://www.riksbank.se/Documents/Tal/Ingves/2014/tal_ingves_140528_eng.pdf Date of Access: 17 Jul. 2015.

Institute of Directors Southern Africa (IODSA). 2012. King report on corporate governance for South Africa (King III). <http://www.iodsa.co.za>. Date of Access: 20 Jan. 2015.

Institute of Directors Southern Africa (IODSA). 2015. King IV: Question and Answers. <http://www.iodsa.co.za/?page=KingIV>. Date of Access: 22 Jan. 2015.

Institute of International Finance (IIF). 2010. Comments on BCBS consultative documents “Strengthening the resilience of the banking sector” and “International framework for liquidity risk measurement, standards and monitoring”. <http://www.bis.org/publ/bcbs165/ioif.pdf> Date of Access: 24 Jun. 2015.

International Accounting Standards Board (IASB). 2010. International financial reporting standards (IFRS). *The conceptual framework for financial reporting*.
http://eifrs.ifrs.org/eifrs/bnstandards/en/2014/conceptual_framework_unaccompanied.pdf Date of Access: 2 Apr. 2015.

International Accounting Standards Board (IASB). 2011. International financial reporting standards (IFRS) 13. *Fair Value Measurement*. <http://eifrs.ifrs.org/eifrs/bnstandards/en/2014/ifrs13.pdf> Date of Access: 2 Apr. 2015.

International Monetary Fund (IMF), Bank for International Settlements (BIS), and Financial Stability Board (FStB). 2009. Guidance to assess the systemic importance of financial institutions, markets, and instruments: Initial consideration. Report to the G-20.
<https://www.imf.org/external/np/g20/pdf/100109a.pdf> Date of Access: 30 Mar. 2015.

International Monetary Fund (IMF). 2005. Building institutions. World Economic Outlook, September 2005. <https://www.imf.org/external/pubs/ft/weo/2005/02/>. Date of Access: 26 May. 2015.

International Monetary Fund (IMF). 2007. Market developments and issues. Global Financial Stability Report, April 2007. <http://www.imf.org/external/pubs/ft/gfsr/2007/01/pdf/text.pdf> Date of Access: 26 May. 2015.

International Monetary Fund (IMF). 2008a. Containing systemic risks and restoring financial soundness. Global Financial Stability Report, April 2008.
<http://www.imf.org/External/Pubs/FT/GFSR/2008/01/index.htm> Date of Access: 17 Feb. 2015.

International Monetary Fund (IMF). 2008b. Financial stress and deleveraging: macro-financial implications and policy. Global Financial Stability Report, October 2008.
<http://www.imf.org/External/Pubs/FT/GFSR/2008/02/index.htm> Date of Access: 17 Feb. 2015.

International Monetary Fund (IMF). 2009. World Economic Outlook Database, October 2009.
<https://www.imf.org/external/pubs/ft/weo/2009/02/weodata/index.aspx> Date of Access: 7 Apr. 2015.

International Monetary Fund (IMF). 2010. United States: Financial system stability assessment. *Country Report No. 10/247*. <http://www.imf.org/external/pubs/ft/scr/2010/cr10247.pdf> Date of Access: 27 Mar. 2015.

International Monetary Fund (IMF). 2013. The interaction of monetary and macroprudential policies. <https://www.imf.org/external/np/pp/eng/2013/012913.pdf> Date of Access: 17 Jul. 2015.

International Monetary Fund (IMF). 2014. South Africa: Financial system stability assessment. *Country Report No. 14/340*. <https://www.imf.org/external/pubs/ft/scr/2014/cr14340.pdf> Date of Access: 15 Jan. 2015.

International Monetary Fund (IMF). 2015a. World Economic Outlook database. <http://www.imf.org/external/pubs/ft/weo/2014/02/weodata/index.aspx> Date of Access: 26 Mar. 2015.

International Monetary Fund (IMF). 2015b. South Africa: Financial system stability assessment. *Country Report No. 15/170*. <http://www.imf.org/external/pubs/ft/scr/2015/cr15170.pdf> Date of Access: 14 Sep. 2015.

IODSA **see** Institute of Directors Southern Africa.

Iori, G., Jafarey, S. & Padilla, F.G. 2006. Systemic risk on the interbank market. *Journal of economic behavior & organization*, 61(4):525-542.

Jackson, P. 1999. Capital requirements and bank behaviour: The impact of the Basle Accord. *Basle Committee on Banking Supervision Working papers no. 1*.

Johansen, S. 1991. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica: Journal of the Econometric Society*, 59(6):1551-1580.

Johansen, S. 1995. Likelihood-based inference in cointegrated vector autoregressive models. Oxford: Oxford University Press.

Kacperczyk, M. & Schnabl, P. 2009. When safe proved risky: Commercial paper during the financial crisis of 2007-2009. National Bureau of Economic Research. *Working Paper no. 15538*.

Kahn, C. & Santos, J. 2008. Liquidity, payment and endogenous financial fragility. *Working paper*. Federal Reserve Bank of New York.

Kaminsky, G.L., Reinhart, C. & Vegh, C.A. 2003. The unholy trinity of financial contagion. National Bureau of Economic Research. *Working paper no. 10061*.

- Kanas, A. 1998. Volatility spillovers across equity markets: European evidence. *Applied financial economics*, 8(3):245-256.
- Kane, E.J. 2007. Basel II: a contracting perspective. *Journal of financial services research*, 32(1-2):39-53.
- Kao, C. 1999. Spurious regression and residual-based tests for cointegration in panel data. *Journal of econometrics*, 90(1):1-44.
- Kapadia, S., Drehmann, M., Elliott, J. & Sterne, G. 2012. Liquidity risk, cash flow constraints, and systemic feedbacks. (In Haubrich, J.G. & Lo, A.W., eds. *Quantifying systemic risk*. Chicago, IL: University of Chicago Press. p. 29-61).
- Kaufman, G.G. 1994. Bank contagion: A review of the theory and evidence. *Journal of financial services research*, 8(2):123-150.
- Kaufman, G.G. & Scott, K.E. 2003. What is systemic risk, and do bank regulators retard or contribute to it? *Independent review*, 7(3):371-391.
- Kelly, L.R. 2015. Citi economist says it might be time to abolish cash.
<http://www.bloomberg.com/news/articles/2015-04-10/citi-economist-says-it-might-be-time-to-abolish-cash> Date of Access: 1 Jun. 2015.
- Kim, J.S. & Ryu, D. 2015. Effect of the subprime mortgage crisis on a leading emerging market. *Investment analysts journal*, 44(1):20-42.
- King, M.A. & Wadhvani, S. 1990. Transmission of volatility between stock markets. *Review of financial studies*, 3(1):5-33.
- Kirkpatrick, G. 2009. The corporate governance lessons from the financial crisis. *OECD Journal: Financial market trends*, 2009(1):61-87.
- Kliesen, K.L. 2003. The 2001 recession: How was it different and what developments may have caused it? *Federal Reserve Bank of St. Louis Review*, 85(September/October 2003).
- Koepke, R. 2014. Institute of International Finance capital flows user guide. Institute of International Finance. <https://www.iif.com/publication/capital-flows/capital-flows-user-guide> Date of Access: 21 May. 2015.

- Koepke, R. 2015. What drives capital flows to emerging markets? A survey of the empirical literature. Institute of International Finance. *Working paper*. <https://www.iif.com/publication/capital-flows/what-drives-capital-flows-emerging-markets-2> Date of Access: 20 May. 2015.
- Krainer, R.E. 2012. Regulating Wall Street: The Dodd–Frank Act and the New Architecture of Global Finance, a review. *Journal of Financial Stability*, 8(2):121-133.
- 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. 2010. Principal components as a measure of systemic risk. Revere Street working paper series: Financial economics 272-27.
- Laeven, L. 2013. Corporate governance: what's special about banks? *Annual review of financial economics*, 5(1):63-92.
- Laeven, L. & Levine, R. 2009. Bank governance, regulation and risk taking. *Journal of financial economics*, 93(2):259-275.
- Laeven, L. & Valencia, F. 2010. Resolution of banking crises: The good, the bad, and the ugly. International Monetary Fund.
- Laeven, L. & Valencia, F. 2013. Systemic banking crises database. *IMF economic review*, 61(2):225-270.
- Laeven, L., Ratnovski, L. & Tong, H. 2014. Bank size and systemic risk. International Monetary Fund.
- Lagunoff, R. & Schreft, S.L. 2001. A model of financial fragility. *Journal of economic theory*, 99(1):220-264.
- Landau, J.P. 2009. Procyclicality: what it means and what could be done. Remarks at the Bank of Spain's conference on procyclicality and the role of financial regulation. Madrid, Spain. <http://www.bis.org/review/r090805d.pdf> Date of Access: 29 May. 2015.
- Lehar, A. 2005. Measuring systemic risk: A risk management approach. *Journal of banking & finance*, 29(10):2577-2603.
- Levin, A., Lin, C.F. & Chu, C.S.J. 2002. Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of econometrics*, 108(1):1-24.

- Liebenberg, F.J.N. 2012. The volatility spillover effect of a dual-listed stock for international markets. Potchefstroom: NWU. (Dissertation – MCom).
- Liedtke, P.M. 2010. The lack of an appropriate definition of systemic risk. *Insurance and Finance*, 6.
- Longstaff, F.A. 2008. Flight-from-leverage in distressed financial markets. *Unpublished working paper*.
- Longstaff, F.A. 2010. The subprime credit crisis and contagion in financial markets. *Journal of financial economics*, 97(3):436-450.
- Maddala, G.S. & Wu, S. 1999. A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and statistics*, 61(S1):631-652.
- Mansfield, C.L. 1999. Road to subprime HEL was paved with good congressional intentions: Usury deregulation and the subprime home equity market, *The. SCL Rev.*, 51, 473.
- Mayer, R. 2012. Loan sharks, interest-rate caps, and deregulation. *Wash. & Lee L. Rev.*, 69(2):807-848.
- Mayordomo, S., Rodriguez-Moreno, M. & Peña, J.I. 2014. Derivatives holdings and systemic risk in the US banking sector. *Journal of banking & finance*, 45(1):84-104.
- McCoy, P.A. & Renuart, E. 2008. The legal infrastructure of subprime and nontraditional home mortgages. (In Retsinas, N.P. & Belsky, E.S., eds. James A. Johnson Metro Series. Washington, D.C.: Brookings Institution Press; Joint Center for Housing Studies, Harvard University: Cambridge. p. 110-137).
- McNeil, A. J., & Frey, R. 2000. Estimation of tail-related risk measures for heteroscedastic financial time series: An extreme value approach. *Journal of empirical finance*, 7(3):271-300.
- Milesi-Ferretti, G.M. & Tille, C. 2011. The great retrenchment: international capital flows during the global financial crisis. *Economic policy*, 26(66):289-346.
- Miller, M., Weller, P. & Zhang, L. 2002. Moral hazard and the US stock market: Analysing the Greenspan put. *The economic journal*, 112(478):171-186.
- Mishkin, F.S. 2007a. Systemic risk and the international lender of last resort. *BIS review*, 109, 1-7.
- Mishkin, F.S. 2007b. The economics of money, banking, and financial markets. Pearson education.

Mishkin, F.S. 2010. Over the cliff: From the subprime to the global financial crisis. National Bureau of Economic Research. *Working paper no.* 16609.

Mistrulli, P.E. 2011. Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. *Journal of banking & finance*, 35(5):1114-1127.

Miyakoshi, T. 2003. Spillovers of stock return volatility to Asian equity markets from Japan and the US. *Journal of international financial markets, institutions and money*, 13(4):383-399.

Mohan, R. 2009. Global financial crisis – Causes, impact, policy responses and lessons. Speech at the 7th Annual India Business Forum conference. London Business School. London. United Kingdom.

Mohanty, D. 2009. The global financial crisis: Genesis, impact and lessons. Speech delivered in Hyderabad, India. 30 December.

Moon, G.H., & Yu, W.C. 2010. Volatility spillovers between the US and China stock markets: structural break test with symmetric and asymmetric GARCH approaches. *Global Economic Review*, 39(2), 129-149.

Nadarajah, S., Zhang, B. & Chan, S. 2014. Estimation methods for expected shortfall. *Quantitative finance*, 14(2):271-291.

National Treasury **see** South Africa. National Treasury.

Nelson, D.B. 1991. Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 59(2):347-370.

New York University Stern Volatility Laboratory (V-Lab). 2015a. GJR-GARCH model. <http://vlab.stern.nyu.edu/doc/3?topic=mdls>. Date of Access: 14 Aug. 2015.

New York University Stern Volatility Laboratory (V-Lab). 2015b. GJR-DCC model. <http://vlab.stern.nyu.edu/doc/14?topic=mdls> Date of Access: 17 Nov. 2015.

New York University Stern Volatility Laboratory (V-Lab). 2015c. Systemic Risk Rankings. <http://vlab.stern.nyu.edu/doc/16?topic=mdls> Date of Access: 17 Nov. 2015.

Nier, E., Yang, J., Yorulmazer, T. & Alentorn, A. 2007. Network models and financial stability. *Journal of economic dynamics and control*, 31(6):2033-2060.

Norton, J.O. 2013. A more prominent role for the leverage ratio in the capital framework. Speech delivered to the Florida Bankers Association. Orlando, Florida. 6 February.

Nuyts, J. 2010. Inference about the tail of a distribution: Improvement on the Hill estimator. *International Journal of mathematics and mathematical sciences*, 2010.

Obstfeld, M. 2012. Financial flows, financial crises, and global imbalances. *Journal of international money and finance*, 31(3):469-480.

Obstfeld, M. & Rogoff, K. 2009. Global imbalances and the financial crisis: Products of common causes. Paper prepared for the Federal Reserve Bank of San Francisco Asia Economic Policy Conference. Santa Barbara, California. 18-20 October.

Orphanides, A. & Wieland, V. 2008. Economic projections and rules of thumb for monetary policy. *Federal Reserve Bank of St. Louis Review*, 90(4):307-24.

Parlour, C.A. & Winton, A. 2013. Laying off credit risk: Loan sales versus credit default swaps. *Journal of financial economics*, 107(1):25-45.

Pedroni, P. 2004. Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric theory*, 20(3):597-625.

Peterson, C.L. 2003. Truth, understanding, and high-cost consumer credit: The historical context of the truth in lending act. *Fla. L. Rev.*, 55, 807.

Phillips, P.C. & Perron, P. 1988. Testing for a unit root in time series regression. *Biometrika*, 75(2):335-346.

Pickands, J.I. 1975. Statistical inference using extreme value order statistics. *Annals of Statistics*, 3(1):119–131.

Pickworth, E. 2014. Risk management systems highlighted by African Bank failure. <http://www.bdlive.co.za/business/financial/2014/09/10/risk-management-systems-highlighted-by-african-bank-failure>. Date of Access: 20 Jan. 2015.

Polito, V. & Wickens, M. 2014. Modelling the US sovereign credit rating. *Journal of banking & finance*, 46(9):202-218.

Portes, R. 2009. Global imbalances. (In Dewatripont, M., Freixas, X. & Portes, R., eds. Macroeconomic stability and financial regulation: *Key issues for the G20*. Centre for Economic Policy Research. p. 19-26).

Prasad, M. 2006. The politics of free markets: The rise of neoliberal economic policies in Britain, France, Germany, and the United States. University of Chicago Press.

QMS **see** Quantitative Micro Software.

Quantitative Micro Software (QMS). 2013. EViews user guide 2.

Rabemananjara, R. & Zakoian, J. M. 1993. Threshold ARCH models and asymmetries in volatility. *Journal of applied econometrics*, 8(1):31-49.

Reiss, R.D., & Cormann, U. 2008. An example of real-life data where the Hill estimator is correct. (In Arnold, B., Balakrishnan, N., Sarabia, J.M. & Minguéz, E., eds. *Advances in mathematical and statistical modelling*. Birkhäuser Boston. p. 209-216).

Richardson, M., Smith, R. & Walter, I. 2010. Large banks and the Volcker rule. (In Acharya, V.V., Cooley, T.F., Richardson, M.P. & Walter, I., eds. *Regulating Wall Street: The Dodd-Frank Act and the new architecture of global finance*. New Jersey: Wiley & Sons, Inc. p. 181-212).

Rigbi, O. 2013. The effects of usury laws: Evidence from the online loan market. *Review of economics and statistics*, 95(4):1238-1248.

Rivas, A., Verma, R., Rodriguez, A. & Verma, P. 2008. International transmission mechanism of stock market volatilities. *Latin American Business Review*, 9(1):33-68.

Rodriguez-Moreno, M. & Pena, J.I. 2013. Systemic risk measures: the simpler the better? *Journal of banking & finance*, 37(1):1817–1831.

Roengpitya, R., Tarashev, N.A. & Tsatsaronis, K. 2014. Bank business models. *BIS quarterly review December*.

Rosengren, E.S. 2010. Asset bubbles and systemic risk. Speech delivered at the Global Interdependence Center's Conference on "Financial interdependence in the world's post-crisis capital markets". Philadelphia. 3 March.

Russell, E. 2007. *New deal banking reforms and Keynesian welfare state capitalism*. New York: Routledge.

Ryan, S.G. 2008. Accounting in and for the subprime crisis. *The accounting review*, 83(6), 1605-1638.

S&P/Case-Shiller U.S. National Home Price Index. 2015. Federal Reserve Bank of St. Louis. <https://fred.stlouisfed.org/series/CSUSHPINSA> Date of Access: 27 Mar. 2015

Saigal, K. 2016. Barclays Africa: The tough sell: A stalling economy and a tough regulatory environment mean that Barclays PLC could find it difficult to offload its Africa business. *African Business*, 430.

Scarrott, C., & MacDonald, A. 2012. A review of extreme value threshold estimation and uncertainty quantification. *REVSTAT–Statistical Journal*, 10(1):33-60.

Schwarcz, S.L. 1994. Alchemy of asset securitization, *The. Stan. JL Bus. & Fin.*, 1, 133.

Schwerter, S. 2011. Basel III's ability to mitigate systemic risk. *Journal of financial regulation and compliance*, 19(4):337-354.

Shin, H.S. 2009a. Reflections on Northern Rock: the bank run that heralded the global financial crisis. *The journal of economic perspectives*, 23(1):101-120.

Shin, H.S. 2009b. Securitisation and financial stability. *The economic journal*, 119(536):309-332.

Shin, H.S. 2013. Adapting macro prudential approaches to emerging and developing economies. (In Canuto, O. & Ghosh, S.R., eds. *Dealing with the challenges of macro financial linkages in emerging markets*. Washington, D.C.: World Bank. p. 17-55).

Sjostrom, W.K. 2009. The AIG bailout. *Washington and Lee Law Review*, 66, 943.

Skoglund, J. & Chen, W. 2015. *Financial risk management: Applications in market, credit, asset and liability management and firmwide risk*. Hoboken: Wiley.

Sorkin, A.R. 2009. *Too big to fail: the inside story of how Wall Street and Washington fought to save the financial system... and themselves*. New York: Viking.

Sorkin, A.R. 2010. At Lehman, watchdogs saw it all. <http://dealbook.nytimes.com/2010/03/16/at-lehman-watchdogs-saw-it-all/> Date of Access: 19 Jun. 2015.

South Africa. National Treasury. 2011. A safer financial sector to serve South Africa better. National treasury policy document. Pretoria.

South Africa. National Treasury. 2014. Financial sector regulation bill. National treasury policy document. Pretoria.

South African Reserve Bank (SARB). 2013. Financial stability review. September, 2013.

South African Reserve Bank (SARB). 2014. Financial stability review. September, 2014.

Stegman, M.A. 2007. Payday lending. *The journal of economic perspectives*, 21(1):169-190.

Stoyanov, S.V., Rachev, S.T., Racheva-Iotova, B. & Fabozzi, F.J. 2011. Fat-tailed models for risk estimation. Working paper series in economics, no. 30. Karlsruhe Institute of Technology, Germany.

Tarashev, N., Borio, C. & Tsatsaronis, K. 2010. Attributing systemic risk to individual institutions. *BIS working papers no. 308*.

Tarullo, D. 2010. Lessons from the crisis stress tests. Speech Presented at the Federal Reserve Board international research forum on monetary policy. Washington, DC. 26 March.

Taylor, J.B. 1993. Discretion versus policy rules in practice. In *Carnegie-Rochester conference series on public policy* 39:195-214. North-Holland.

Taylor, J.B. 2009. The financial crisis and the policy responses: An empirical analysis of what went wrong. National Bureau of Economic Research. *Working paper no. 1463*.

Taylor, J.B. 2010a. Defining systemic risk operationally. (In Shultz, G., Scott, K., Taylor, J., eds. Ending government bailouts as we know them. Stanford: Hoover Institution Press. p. 33-58).

Taylor, J.B. 2010b. The fed and the crisis: a reply to Ben Bernanke. *Wall Street Journal* (In press)

The Financial Crisis inquiry report: Final report of the national commission on the causes of the financial and economic crisis in the United States **see** United States.

Torres, C. & Son, H. 2009. Bernanke says insurer AIG acted like a hedge fund.

<http://www.bloomberg.com/apps/news?pid=newsarchive&sid=aqw5b2yJyB1o&refer=home> Date of Access: 29 Apr. 2015.

Tressel, T. & Zhou, J. 2013. Macroprudential oversight and the role of the European Systemic Risk Board. (*In* Enoch, M.C., Everaert, M.L., Tressel, M.T. & Zhou, M.J.P., eds. From fragmentation to financial integration in Europe. International Monetary Fund. p. 371-392).

United States of America. 2010. Dodd-Frank Wall Street Reform and Consumer Protection Act.

United States of America. 2011. The Financial Crisis inquiry report: Final report of the national commission on the causes of the financial and economic crisis in the United States. Official Government Edition, US Government Printing Office, Washington, D.C.

United States Census Bureau. 2015. New residential construction definitions.

<http://www.census.gov/construction/nrc/definitions/index.html> Date of Access: 24 Nov. 2015.

Université de Lausanne Center for Risk Management. 2015. Systemic Risk.

<http://www.crml.ch/index.php?id=4> Date of Access: 28 Sep. 2015.

US House of Representatives, 1967. Consumer Credit Protection Act, *Hearings Before the Subcommittee on Consumer Affairs of the House Committee on Banking and Commerce on H.R. 11601*, 90th Congress.

V-Lab **see** New York University Stern Volatility Laboratory.

Valukas, A.R. 2010. Volume 7 of 9. (*In* Valukas, A.R., ed. *In re* Lehman Brothers Holdings Inc. – Report of Anton. R Valukas – Bankruptcy Examiner. United States Bankruptcy Court Southern District of New York. p. 1-120).

Van Vuuren, G. 2012. Basel III countercyclical capital rules: Implications for South Africa. *South African journal of economic and management sciences*, 15(3):309-324.

Viñals, J., Pazarbasioglu, C., Surti, J., Narain, A., Erbenova, M.M. & Chow, M.J.T. 2013. Creating a safer financial system: will the Volcker, Vickers, and Liikanen Structural measures help? International Monetary Fund.

Wang, S. 2013. Application of actuarial science to systemic risks. Society of Actuaries, Casualty Actuarial Society, Canadian Institute of Actuaries. Canada.

<https://www.societyofactuaries.mobi/files/research/projects/research-2013-app-act-science-report.pdf>

Date of Access: 23 Nov. 2015.

- Weistroffer, C., Speyer, B., Kaiser, S. & Mayer, T. 2011. Identifying systemically important financial institutions (SIFIs). *International topics - Current issues*. Deutsche Bank Research.
http://www.expeditiondeutschland.de/prod/dbr_internet_en-prod/prod0000000000276722.pdf Date of Access: 13 Jun. 2015.
- Weithers, T. 2007. Credit derivatives, macro risks, and systemic risks. *Economic review-Federal Reserve Bank of Atlanta*, 92(4):43.
- Wims, W. 2014. The dark side of the Basel Committee's Pillar 3 framework. Paper presented at the XBRL week of the National Bank of Belgium, Brussels, Belgium, 25 November. <http://www.ebf-fbe.eu/wp-content/uploads/2014/11/w1521mew.pdf> Date of Access: 19 Jun. 2015.
- Wong, T.C., Fong, T., Li, K.F. & Choi, H. 2011. Loan-to-Value ratio as a macroprudential tool: Hong Kong's experience and cross-country evidence. *Working paper no. 01/2011*. Hong Kong Monetary Authority.
- Woodford, M. 2012. Inflation targeting and financial stability. National Bureau of Economic Research. *Working paper no. 17967*.
- Wooldridge, J. 2015. *Introductory econometrics: A modern approach*. Mason: South-Western.
- World Bank. 2013. Bank regulation and supervision survey dataset.
<http://go.worldbank.org/wfief81ap0> Date of Access: 10 Jun. 2015.
- World Bank. 2015. World development indicators. <http://data.worldbank.org/data-catalog/world-development-indicators>. Date of Access: 26 Mar. 2015.
- Yuksel, M. 2014. Identifying global systemically important financial institutions. *RBA Bulletin*, 63-72.
- Zhang, I.X. 2007. Economic consequences of the Sarbanes–Oxley Act of 2002. *Journal of accounting and economics*, 44(1):74-115.

APPENDICES

APPENDIX A

US SRISK RESULTS

Bank (LRMES) in 2013	SRISK
Bank of America Corporation	33.04 %
Citigroup Inc.	25.45 %
Morgan Stanley	19.34 %
JPMorgan Chase & Co.	14.98 %
Goldman Sachs Group, Inc.	6.00 %
Popular, Inc.	0.56 %
First BanCorp	0.25 %
Zions Bancorporation	0.24 %
Astoria Financial Corporation	0.15 %
American Express Company	0.00 %
BB&T Corporation	0.00 %
BOK Financial Corp.	0.00 %
Capital One Financial Corp	0.00 %
Cathay General Bancorp	0.00 %
Central Pacific Financial Corp	0.00 %
City National Corporation	0.00 %
Comerica Incorporated	0.00 %
Community Bank System, Inc.	0.00 %
CVB Financial Corp.	0.00 %
Dime Community Bancshares	0.00 %
East West Bancorp, Inc.	0.00 %
Fifth Third Bancorp	0.00 %
First Commonwealth Financial	0.00 %
First Horizon National Corp	0.00 %
First Midwest Bancorp, Inc.	0.00 %
First Niagara Financial Group	0.00 %
Fulton Financial Corporation	0.00 %
HSBC USA, Inc.	0.00 %
Huntington Bancshares Inc.	0.00 %
Independent Bank Corp	0.00 %
KeyCorp	0.00 %
M&T Bank Corporation	0.00 %
New York Community Bancorp	0.00 %
Northern Trust Corporation	0.00 %
PNC Financial Services	0.00 %
Regions Financial Corporation	0.00 %
State Street Corporation	0.00 %
Stifel Financial Corp	0.00 %
SunTrust Banks, Inc.	0.00 %
Synovus Financial Corp.	0.00 %
TCF Financial Corporation	0.00 %
Trustmark Corporation	0.00 %
U.S. Bancorp	0.00 %
UMB Financial Corp.	0.00 %
Webster Financial Corporation	0.00 %
Wells Fargo & Company	0.00 %
Wintrust Financial Corporation	0.00 %

Bank (LRMES) in 2008	SRISK
Citigroup Inc.	23.89 %
JPMorgan Chase & Co.	19.92 %
Bank of America Corporation	18.43 %
Goldman Sachs Group, Inc.	8.36 %
Morgan Stanley	7.89 %
Wells Fargo & Company	7.18 %
PNC Financial Services Group	2.18 %
SunTrust Banks, Inc.	1.55 %
Regions Financial Corporation	1.52 %
Fifth Third Bancorp	1.26 %
Capital One Financial Corp	1.22 %
KeyCorp	1.08 %
State Street Corporation	1.00 %
Comerica Incorporated	0.66 %
BB&T Corporation	0.64 %
Huntington Bancshares Inc	0.51 %
Zions Bancorporation	0.50 %
Popular, Inc.	0.41 %
First Horizon National Corp	0.27 %
Synovus Financial Corp.	0.23 %
M&T Bank Corporation	0.22 %
First BanCorp	0.20 %
Webster Financial Corporation	0.17 %
Astoria Financial Corporation	0.16 %
Wintrust Financial Corporation	0.10 %
East West Bancorp, Inc.	0.08 %
TCF Financial Corporation	0.08 %
Cathay General Bancorp	0.06 %
Central Pacific Financial Corp	0.05 %
Fulton Financial Corporation	0.05 %
First Midwest Bancorp, Inc.	0.02 %
Trustmark Corporation	0.02 %
Independent Bank Corp	0.01 %
Dime Community Bancshares	0.01 %
BOK Financial Corp.	0.01 %
CVB Financial Corp.	0.01 %
New York Community Bancorp	0.01 %
First Commonwealth Financial	0.00 %
American Express Company	0.00 %
City National Corporation	0.00 %
Community Bank System, Inc.	0.00 %
First Niagara Financial Group	0.00 %
HSBC USA, Inc.	0.00 %
Northern Trust Corporation	0.00 %
Stifel Financial Corp	0.00 %
U.S. Bancorp	0.00 %
UMB Financial Corp.	0.00 %

APPENDIX B

REGRESSION TESTING

EGARCH MODEL

Null Hypothesis: LALSI has a unit root				
Exogenous: Constant, Linear Trend				
Lag Length: 1 (Automatic - based on SIC, maxlag=13)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-2.095486	0.5441
Test critical values:				
	1% level		-4.014288	
	5% level		-3.437122	
	10% level		-3.142739	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(LALSI)				
Method: Least Squares				
Date: 10/07/15 Time: 11:45				
Sample (adjusted): 2001M03 2014M12				
Included observations: 166 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LALSI(-1)	-0.038100	0.018182	-2.095486	0.0377
D(LALSI(-1))	0.293883	0.074959	3.920578	0.0001
C	0.349899	0.163716	2.137236	0.0341
@TREND("2001M01")	0.000428	0.000213	2.006048	0.0465
R-squared	0.100164	Mean dependent var		0.010173
Adjusted R-squared	0.083500	S.D. dependent var		0.041613
S.E. of regression	0.039838	Akaike info criterion		-3.584186
Sum squared resid	0.257106	Schwarz criterion		-3.509199
Log likelihood	301.4875	Hannan-Quinn criter.		-3.553748
F-statistic	6.010924	Durbin-Watson stat		1.960682
Prob(F-statistic)	0.000658			

Null Hypothesis: D(LALSI) has a unit root				
Exogenous: Constant, Linear Trend				
Lag Length: 0 (Automatic - based on SIC, maxlag=13)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-9.646897	0.0000
Test critical values:				
	1% level		-4.014288	
	5% level		-3.437122	
	10% level		-3.142739	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(LALSI,2)				
Method: Least Squares				

Date: 10/07/15 Time: 11:46
Sample (adjusted): 2001M03 2014M12
Included observations: 166 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LALSI(-1))	-0.725197	0.075174	-9.646897	0.0000
C	0.007091	0.006384	1.110659	0.2684
@TREND("2001M01")	1.84E-06	6.52E-05	0.028250	0.9775
R-squared	0.363441	Mean dependent var		-0.000478
Adjusted R-squared	0.355630	S.D. dependent var		0.050142
S.E. of regression	0.040250	Akaike info criterion		-3.569490
Sum squared resid	0.264075	Schwarz criterion		-3.513249
Log likelihood	299.2677	Hannan-Quinn criter.		-3.546662
F-statistic	46.53213	Durbin-Watson stat		1.945224
Prob(F-statistic)	0.000000			

Null Hypothesis: LSP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.002265	0.5955
Test critical values:		
1% level	-4.014288	
5% level	-3.437122	
10% level	-3.142739	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LSP)
Method: Least Squares
Date: 10/07/15 Time: 11:47
Sample (adjusted): 2001M03 2014M12
Included observations: 166 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LSP(-1)	-0.037285	0.018621	-2.002265	0.0469
D(LSP(-1))	0.257285	0.075910	3.389345	0.0009
C	0.251888	0.128718	1.956897	0.0521
@TREND("2001M01")	0.000186	7.96E-05	2.341989	0.0204
R-squared	0.098656	Mean dependent var		0.002738
Adjusted R-squared	0.081964	S.D. dependent var		0.040574
S.E. of regression	0.038876	Akaike info criterion		-3.633099
Sum squared resid	0.244833	Schwarz criterion		-3.558111
Log likelihood	305.5472	Hannan-Quinn criter.		-3.602661
F-statistic	5.910536	Durbin-Watson stat		1.962957
Prob(F-statistic)	0.000749			

Null Hypothesis: D(LSP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
--	-------------	--------

Augmented Dickey-Fuller test statistic	-10.01351	0.0000		
Test critical values:	1% level	-4.014288		
	5% level	-3.437122		
	10% level	-3.142739		
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(LSP,2)				
Method: Least Squares				
Date: 10/07/15 Time: 11:47				
Sample (adjusted): 2001M03 2014M12				
Included observations: 166 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LSP(-1))	-0.761333	0.076031	-10.01351	0.0000
C	-0.005546	0.006204	-0.893932	0.3727
@TREND("2001M01")	9.08E-05	6.43E-05	1.412747	0.1596
R-squared	0.380881	Mean dependent var		0.000176
Adjusted R-squared	0.373284	S.D. dependent var		0.049558
S.E. of regression	0.039233	Akaike info criterion		-3.620701
Sum squared resid	0.250891	Schwarz criterion		-3.564460
Log likelihood	303.5182	Hannan-Quinn criter.		-3.597872
F-statistic	50.13860	Durbin-Watson stat		1.954718
Prob(F-statistic)	0.000000			

Heteroskedasticity Test: ARCH				
F-statistic	2.899112	Prob. F(1,164)		0.0905
Obs*R-squared	2.883494	Prob. Chi-Square(1)		0.0895
Test Equation:				
Dependent Variable: WGT_RESID^2				
Method: Least Squares				
Date: 03/06/17 Time: 06:38				
Sample (adjusted): 2001M03 2014M12				
Included observations: 166 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.884400	0.142108	6.223452	0.0000
WGT_RESID^2(-1)	0.132339	0.077724	1.702678	0.0905
R-squared	0.017370	Mean dependent var		1.018608
Adjusted R-squared	0.011379	S.D. dependent var		1.532212
S.E. of regression	1.523470	Akaike info criterion		3.691833
Sum squared resid	380.6373	Schwarz criterion		3.729327
Log likelihood	-304.4221	Hannan-Quinn criter.		3.707052
F-statistic	2.899112	Durbin-Watson stat		1.960240
Prob(F-statistic)	0.090523			

Null Hypothesis: RESID02 has a unit root				
Exogenous: Constant, Linear Trend				
Lag Length: 0 (Automatic - based on SIC, maxlag=13)				

		t-Statistic	Prob.*	
Augmented Dickey-Fuller test statistic		-9.961738	0.0000	
Test critical values:	1% level	-4.014288		
	5% level	-3.437122		
	10% level	-3.142739		
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RESID02)				
Method: Least Squares				
Date: 03/06/17 Time: 06:36				
Sample (adjusted): 2001M03 2014M12				
Included observations: 166 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID02(-1)	-0.746506	0.074937	-9.961738	0.0000
C	0.006206	0.004275	1.451478	0.1486
@TREND("2001M01")	-6.51E-05	4.39E-05	-1.481552	0.1404
R-squared	0.378478	Mean dependent var		-0.000610
Adjusted R-squared	0.370852	S.D. dependent var		0.033740
S.E. of regression	0.026763	Akaike info criterion		-4.385723
Sum squared resid	0.116746	Schwarz criterion		-4.329482
Log likelihood	367.0150	Hannan-Quinn criter.		-4.362894
F-statistic	49.62968	Durbin-Watson stat		1.983947
Prob(F-statistic)	0.000000			

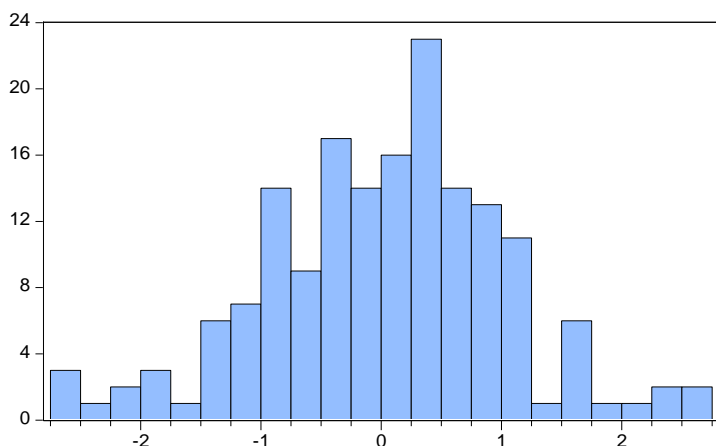
Null Hypothesis: RESID02 has a unit root				
Exogenous: Constant				
Lag Length: 0 (Automatic - based on SIC, maxlag=13)				
		t-Statistic	Prob.*	
Augmented Dickey-Fuller test statistic		-9.816426	0.0000	
Test critical values:	1% level	-3.469933		
	5% level	-2.878829		
	10% level	-2.576067		
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RESID02)				
Method: Least Squares				
Date: 03/06/17 Time: 06:37				
Sample (adjusted): 2001M03 2014M12				
Included observations: 166 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID02(-1)	-0.728322	0.074194	-9.816426	0.0000
C	0.000673	0.002089	0.322003	0.7479
R-squared	0.370108	Mean dependent var		-0.000610
Adjusted R-squared	0.366267	S.D. dependent var		0.033740

S.E. of regression	0.026860	Akaike info criterion	-4.384395
Sum squared resid	0.118318	Schwarz criterion	-4.346901
Log likelihood	365.9047	Hannan-Quinn criter.	-4.369176
F-statistic	96.36221	Durbin-Watson stat	1.994130
Prob(F-statistic)	0.000000		

Null Hypothesis: RESID02 has a unit root				
Exogenous: None				
Lag Length: 0 (Automatic - based on SIC, maxlag=13)				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-9.842279	0.0000
Test critical values:	1% level		-2.578967	
	5% level		-1.942757	
	10% level		-1.615431	
*MacKinnon (1996) one-sided p-values.				
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RESID02)				
Method: Least Squares				
Date: 03/06/17 Time: 06:38				
Sample (adjusted): 2001M03 2014M12				
Included observations: 166 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESID02(-1)	-0.726827	0.073847	-9.842279	0.0000
R-squared	0.369710	Mean dependent var		-0.000610
Adjusted R-squared	0.369710	S.D. dependent var		0.033740
S.E. of regression	0.026787	Akaike info criterion		-4.395811
Sum squared resid	0.118393	Schwarz criterion		-4.377064
Log likelihood	365.8523	Hannan-Quinn criter.		-4.388201
Durbin-Watson stat	1.995917			

Dependent Variable: DALSI				
Method: ML - ARCH				
Date: 10/02/15 Time: 09:13				
Sample (adjusted): 2001M02 2014M12				
Included observations: 167 after adjustments				
Convergence achieved after 60 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.752573	0.044342	16.97195	0.0000
C	0.006962	0.001991	3.496233	0.0005
Variance Equation				
C(3)	-0.060317	0.001295	-46.58114	0.0000
C(4)	-0.066350	0.000325	-204.3062	0.0000
C(5)	0.031283	0.017673	1.770176	0.0767
C(6)	0.986053	0.000471	2094.880	0.0000

R-squared	0.538834	Mean dependent var	0.010449
Adjusted R-squared	0.536039	S.D. dependent var	0.041640
S.E. of regression	0.028363	Akaike info criterion	-4.351744
Sum squared resid	0.132734	Schwarz criterion	-4.239720
Log likelihood	369.3706	Hannan-Quinn criter.	-4.306276
Durbin-Watson stat	1.415616		



Series: Standardized Residuals	
Sample 2001M02 2014M12	
Observations 167	
Mean	0.030289
Median	0.092303
Maximum	2.565088
Minimum	-2.697464
Std. Dev.	1.017046
Skewness	-0.158198
Kurtosis	3.226754
Jarque-Bera	1.054349
Probability	0.590270

Dependent Variable: DALSI				
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)				
Date: 05/14/17 Time: 20:47				
Sample (adjusted): 2001M02 2014M12				
Included observations: 167 after adjustments				
Convergence achieved after 68 iterations				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)				
*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(6)*RESID(-1)				
/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.746536	0.038204	19.54067	0.0000
C	0.007175	0.002029	3.536123	0.0004
Variance Equation				
C(3)	-0.031460	0.069789	-0.450788	0.6521
C(4)	0.196723	0.202316	0.972357	0.3309
C(5)	-0.317500	0.219134	-1.448889	0.1474
C(6)	0.017933	0.026225	0.683793	0.4941
C(7)	0.983669	0.007887	124.7250	0.0000
R-squared	0.539096	Mean dependent var	0.010449	
Adjusted R-squared	0.536303	S.D. dependent var	0.041640	
S.E. of regression	0.028355	Akaike info criterion	-4.343818	
Sum squared resid	0.132659	Schwarz criterion	-4.223123	
Log likelihood	373.0488	Hannan-Quinn criter.	-4.330772	
Durbin-Watson stat	1.416379			

Dependent Variable: DALSI				
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)				
Date: 05/14/17 Time: 20:50				
Sample (adjusted): 2001M02 2014M12				
Included observations: 167 after adjustments				

Convergence achieved after 57 iterations
 Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) \cdot \text{ABS}(\text{RESID}(-1) / \sqrt{\text{GARCH}(-1)}) + \text{C}(5) \cdot \text{ABS}(\text{RESID}(-2) / \sqrt{\text{GARCH}(-2)}) + \text{C}(6) \cdot \text{ABS}(\text{RESID}(-3) / \sqrt{\text{GARCH}(-3)}) + \text{C}(7) \cdot \text{RESID}(-1) / \sqrt{\text{GARCH}(-1)} + \text{C}(8) \cdot \text{LOG}(\text{GARCH}(-1))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.690448	0.041881	16.48600	0.0000
C	0.009383	0.002195	4.274628	0.0000
Variance Equation				
C(3)	-7.550152	3.273182	-2.306670	0.0211
C(4)	0.369097	0.237472	1.554272	0.1201
C(5)	0.250877	0.343406	0.730555	0.4651
C(6)	-0.172069	0.230528	-0.746413	0.4554
C(7)	-0.275567	0.128766	-2.140060	0.0323
C(8)	-0.000130	0.418026	-0.000311	0.9998
R-squared	0.535919	Mean dependent var		0.010449
Adjusted R-squared	0.533106	S.D. dependent var		0.041640
S.E. of regression	0.028452	Akaike info criterion		-4.276219
Sum squared resid	0.133573	Schwarz criterion		-4.126854
Log likelihood	365.0643	Hannan-Quinn criter.		-4.215595
Durbin-Watson stat	1.416867			

Dependent Variable: DALSI
 Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
 Date: 05/14/17 Time: 20:50
 Sample (adjusted): 2001M02 2014M12
 Included observations: 167 after adjustments
 Convergence achieved after 51 iterations
 Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) \cdot \text{ABS}(\text{RESID}(-1) / \sqrt{\text{GARCH}(-1)}) + \text{C}(5) \cdot \text{RESID}(-1) / \sqrt{\text{GARCH}(-1)} + \text{C}(6) \cdot \text{LOG}(\text{GARCH}(-1)) + \text{C}(7) \cdot \text{LOG}(\text{GARCH}(-2))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.765658	0.063741	12.01204	0.0000
C	0.006809	0.002104	3.236418	0.0012
Variance Equation				
C(3)	-0.372805	0.452473	-0.823927	0.4100
C(4)	0.181536	0.198120	0.916291	0.3595
C(5)	0.005686	0.054315	0.104688	0.9166
C(6)	0.576288	1.515639	0.380228	0.7038
C(7)	0.393420	1.480134	0.265800	0.7904
R-squared	0.538526	Mean dependent var		0.010449
Adjusted R-squared	0.535729	S.D. dependent var		0.041640
S.E. of regression	0.028372	Akaike info criterion		-4.314817
Sum squared resid	0.132823	Schwarz criterion		-4.184122
Log likelihood	367.2872	Hannan-Quinn criter.		-4.261771
Durbin-Watson stat	1.415524			

Dependent Variable: DALSI
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/17 Time: 20:50
Sample (adjusted): 2001M02 2014M12
Included observations: 167 after adjustments
Convergence achieved after 22 iterations
Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) \cdot \text{ABS}(\text{RESID}(-1)) / \text{SQRT}(\text{GARCH}(-1)) + \text{C}(5) \cdot \text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1)) + \text{C}(6) \cdot \text{LOG}(\text{GARCH}(-1)) + \text{C}(7) \cdot \text{LOG}(\text{GARCH}(-2)) + \text{C}(8) \cdot \text{LOG}(\text{GARCH}(-3))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.772423	0.055440	13.93260	0.0000
C	0.007231	0.001899	3.808018	0.0001

Variance Equation

C(3)	-0.678193	0.450986	-1.503799	0.1326
C(4)	0.339531	0.138809	2.446034	0.0144
C(5)	0.010318	0.062820	0.164249	0.8695
C(6)	0.257321	0.072438	3.552315	0.0004
C(7)	-0.176417	0.062053	-2.842997	0.0045
C(8)	0.865537	0.076140	11.36767	0.0000

R-squared	0.539090	Mean dependent var	0.010449
Adjusted R-squared	0.536297	S.D. dependent var	0.041640
S.E. of regression	0.028355	Akaike info criterion	-4.345597
Sum squared resid	0.132660	Schwarz criterion	-4.196232
Log likelihood	370.8573	Hannan-Quinn criter.	-4.284973
Durbin-Watson stat	1.418109		

Dependent Variable: DALSI
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/17 Time: 20:51
Sample (adjusted): 2001M02 2014M12
Included observations: 167 after adjustments
Convergence achieved after 46 iterations
Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) \cdot \text{ABS}(\text{RESID}(-1)) / \text{SQRT}(\text{GARCH}(-1)) + \text{C}(5) \cdot \text{ABS}(\text{RESID}(-2)) / \text{SQRT}(\text{GARCH}(-2)) + \text{C}(6) \cdot \text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1)) + \text{C}(7) \cdot \text{LOG}(\text{GARCH}(-1)) + \text{C}(8) \cdot \text{LOG}(\text{GARCH}(-2))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.699550	0.056022	12.48709	0.0000
C	0.009751	0.002234	4.365269	0.0000

Variance Equation

C(3)	-3.664826	2.340302	-1.565963	0.1174
C(4)	0.369043	0.209468	1.761809	0.0781
C(5)	0.385851	0.220911	1.746632	0.0807
C(6)	-0.264286	0.123928	-2.132580	0.0330
C(7)	-0.169329	0.153651	-1.102038	0.2704
C(8)	0.744827	0.169760	4.387545	0.0000

R-squared	0.536550	Mean dependent var	0.010449
Adjusted R-squared	0.533741	S.D. dependent var	0.041640

S.E. of regression	0.028433	Akaike info criterion	-4.317764
Sum squared resid	0.133392	Schwarz criterion	-4.168399
Log likelihood	368.5333	Hannan-Quinn criter.	-4.257140
Durbin-Watson stat	1.415840		

Dependent Variable: DALSI
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/17 Time: 20:51
Sample (adjusted): 2001M02 2014M12
Included observations: 167 after adjustments
Convergence achieved after 46 iterations
Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) * \text{ABS}(\text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1))) + \text{C}(5) * \text{ABS}(\text{RESID}(-2) / \text{SQRT}(\text{GARCH}(-2))) + \text{C}(6) * \text{ABS}(\text{RESID}(-3) / \text{SQRT}(\text{GARCH}(-3))) + \text{C}(7) * \text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1)) + \text{C}(8) * \text{LOG}(\text{GARCH}(-1)) + \text{C}(9) * \text{LOG}(\text{GARCH}(-2))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.701996	0.057701	12.16605	0.0000
C	0.009670	0.002228	4.339776	0.0000

Variance Equation

C(3)	-3.538604	2.622494	-1.349328	0.1772
C(4)	0.383474	0.229299	1.672378	0.0944
C(5)	0.372356	0.249479	1.492535	0.1356
C(6)	-0.029602	0.227695	-0.130008	0.8966
C(7)	-0.256533	0.129102	-1.987056	0.0469
C(8)	-0.163254	0.168818	-0.967041	0.3335
C(9)	0.753096	0.181855	4.141193	0.0000

R-squared	0.536896	Mean dependent var	0.010449
Adjusted R-squared	0.534090	S.D. dependent var	0.041640
S.E. of regression	0.028422	Akaike info criterion	-4.305967
Sum squared resid	0.133292	Schwarz criterion	-4.137931
Log likelihood	368.5482	Hannan-Quinn criter.	-4.237765
Durbin-Watson stat	1.416191		

Dependent Variable: DALSI
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/17 Time: 20:52
Sample (adjusted): 2001M02 2014M12
Included observations: 167 after adjustments
Convergence achieved after 22 iterations
Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) * \text{ABS}(\text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1))) + \text{C}(5) * \text{ABS}(\text{RESID}(-2) / \text{SQRT}(\text{GARCH}(-2))) + \text{C}(6) * \text{RESID}(-1) / \text{SQRT}(\text{GARCH}(-1)) + \text{C}(7) * \text{LOG}(\text{GARCH}(-1)) + \text{C}(8) * \text{LOG}(\text{GARCH}(-2)) + \text{C}(9) * \text{LOG}(\text{GARCH}(-3))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.715137	0.033309	21.46948	0.0000
C	0.005727	0.001574	3.638788	0.0003

Variance Equation

C(3)	-2.440732	1.763273	-1.384205	0.1663
C(4)	0.379844	0.128056	2.966226	0.0030

C(5)	0.441883	0.134901	3.275604	0.0011
C(6)	-0.094089	0.022040	-4.269057	0.0000
C(7)	-0.241931	0.081554	-2.966499	0.0030
C(8)	0.147439	0.088957	1.657417	0.0974
C(9)	0.856156	0.092448	9.260917	0.0000
R-squared	0.533876	Mean dependent var		0.010449
Adjusted R-squared	0.531051	S.D. dependent var		0.041640
S.E. of regression	0.028515	Akaike info criterion		-4.373187
Sum squared resid	0.134161	Schwarz criterion		-4.205152
Log likelihood	374.1611	Hannan-Quinn criter.		-4.304985
Durbin-Watson stat	1.403852			

Dependent Variable: DALSI
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/17 Time: 20:55
Sample (adjusted): 2001M02 2014M12
Included observations: 167 after adjustments
Convergence achieved after 19 iterations
Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) * \text{ABS}(\text{RESID}(-1) / @\text{SQRT}(\text{GARCH}(-1))) + \text{C}(5) * \text{RESID}(-1) / @\text{SQRT}(\text{GARCH}(-1)) + \text{C}(6) * \text{RESID}(-2) / @\text{SQRT}(\text{GARCH}(-2)) + \text{C}(7) * \text{LOG}(\text{GARCH}(-1))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.692718	0.036057	19.21161	0.0000
C	0.008514	0.001737	4.901516	0.0000
Variance Equation				
C(3)	-0.008665	0.000334	-25.94542	0.0000
C(4)	-0.089605	2.49E-05	-3605.102	0.0000
C(5)	-0.330028	0.041762	-7.902593	0.0000
C(6)	0.358168	0.053453	6.700677	0.0000
C(7)	0.990590	0.000350	2828.029	0.0000
R-squared	0.536477	Mean dependent var		0.010449
Adjusted R-squared	0.533668	S.D. dependent var		0.041640
S.E. of regression	0.028435	Akaike info criterion		-4.343387
Sum squared resid	0.133413	Schwarz criterion		-4.252692
Log likelihood	374.6828	Hannan-Quinn criter.		-4.350341
Durbin-Watson stat	1.417788			

Dependent Variable: DALSI
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 05/14/17 Time: 20:57
Sample (adjusted): 2001M02 2014M12
Included observations: 167 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
 $\text{LOG}(\text{GARCH}) = \text{C}(3) + \text{C}(4) * \text{ABS}(\text{RESID}(-1) / @\text{SQRT}(\text{GARCH}(-1))) + \text{C}(5) * \text{RESID}(-1) / @\text{SQRT}(\text{GARCH}(-1)) + \text{C}(6) * \text{RESID}(-2) / @\text{SQRT}(\text{GARCH}(-2)) + \text{C}(7) * \text{RESID}(-3) / @\text{SQRT}(\text{GARCH}(-3)) + \text{C}(8) * \text{LOG}(\text{GARCH}(-1))$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DLSP	0.695784	0.039175	17.76071	0.0000

C	0.007703	0.001812	4.250948	0.0000
Variance Equation				
C(3)	0.001812	7.97E-10	2272946.	0.0000
C(4)	-0.077992	0.001076	-72.51465	0.0000
C(5)	-0.247337	0.111243	-2.223395	0.0262
C(6)	0.023395	0.165936	0.140988	0.8879
C(7)	0.249851	0.096753	2.582342	0.0098
C(8)	0.993333	5.10E-05	19471.69	0.0000
R-squared	0.536320	Mean dependent var		0.010449
Adjusted R-squared	0.533510	S.D. dependent var		0.041640
S.E. of regression	0.028440	Akaike info criterion		-4.332126
Sum squared resid	0.133458	Schwarz criterion		-4.242761
Log likelihood	377.2475	Hannan-Quinn criter.		-4.361502
Durbin-Watson stat	1.416300			

SRISK - SA

Panel unit root test: Summary				
Series: SRISK				
Date: 11/11/15 Time: 13:25				
Sample: 2001 2013				
Exogenous variables: Individual effects, individual linear trends				
User-specified lags: 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Balanced observations for each test				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-6.06254	0.0000	5	55
Breitung t-stat	0.14827	0.5589	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.03043	0.0212	5	55
ADF - Fisher Chi-square	21.6071	0.0172	5	55
PP - Fisher Chi-square	15.5655	0.1128	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Null Hypothesis: Stationarity		
Series: SRISK		
Date: 11/11/15 Time: 13:26		
Sample: 2001 2013		
Exogenous variables: Individual effects, individual linear trends		
Newey-West automatic bandwidth selection and Bartlett kernel		
Total (balanced) observations: 65		
Cross-sections included: 5		
Method	Statistic	Prob.**
Hadri Z-stat	5.90554	0.0000
Heteroscedastic Consistent Z-stat	10.8642	0.0000
* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.		
** Probabilities are computed assuming asymptotic normality		

Intermediate results on SRISK				
Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1439	1.83E+20	0.0	13
2	0.1339	3.20E+19	3.0	13
3	0.5000	1.90E+19	12.0	13
4	0.4207	8.28E+18	10.0	13
5	0.1499	2.56E+19	0.0	13

Panel unit root test: Summary				
Series: LSIZE				
Date: 11/11/15 Time: 13:27				
Sample: 2001 2013				
Exogenous variables: Individual effects, individual linear trends				
User-specified lags: 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Balanced observations for each test				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.16550	0.0000	5	55
Breitung t-stat	-0.04611	0.4816	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.08624	0.0185	5	55
ADF - Fisher Chi-square	22.1662	0.0143	5	55
PP - Fisher Chi-square	4.38496	0.9283	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Null Hypothesis: Stationarity				
Series: LSIZE				
Date: 11/11/15 Time: 13:27				
Sample: 2001 2013				
Exogenous variables: Individual effects, individual linear trends				
Newey-West automatic bandwidth selection and Bartlett kernel				
Total (balanced) observations: 65				
Cross-sections included: 5				
Method	Statistic	Prob.**		
Hadri Z-stat	4.07393	0.0000		
Heteroscedastic Consistent Z-stat	3.64495	0.0001		
* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.				
** Probabilities are computed assuming asymptotic normality				
Intermediate results on LSIZE				
Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1621	0.025312	1.0	13
2	0.0908	0.005286	1.0	13
3	0.1409	0.049770	2.0	13
4	0.1354	0.040347	2.0	13
5	0.1447	0.094103	0.0	13

Panel unit root test: Summary
Series: CAP
Date: 11/11/15 Time: 13:28
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.36130	0.0000	5	55
Breitung t-stat	-2.95571	0.0016	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.93992	0.0262	5	55
ADF - Fisher Chi-square	20.6335	0.0238	5	55
PP - Fisher Chi-square	36.7224	0.0001	5	60

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity
Series: CAP
Date: 11/11/15 Time: 13:28
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	4.50533	0.0000
Heteroscedastic Consistent Z-stat	11.1197	0.0000

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
** Probabilities are computed assuming asymptotic normality

Intermediate results on CAP

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.5000	0.055371	12.0	13
2	0.5000	0.261771	12.0	13
3	0.0874	0.999272	2.0	13
4	0.1461	0.278390	4.0	13
5	0.1388	3.825148	1.0	13

Panel unit root test: Summary
Series: ACT1
Date: 11/11/15 Time: 13:29
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-13.6798	0.0035	5	55
Breitung t-stat	-1.04500	0.1446	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.69488	0.0000	5	55
ADF - Fisher Chi-square	31.3949	0.0000	5	55
PP - Fisher Chi-square	5.35918	0.8659	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Null Hypothesis: Stationarity
Series: ACT1
Date: 11/11/15 Time: 13:29
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	3.26773	0.0005
Heteroscedastic Consistent Z-stat	5.64157	0.0000

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
** Probabilities are computed assuming asymptotic normality

Intermediate results on ACT1

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.3544	0.000168	9.0	13
2	0.1372	0.001709	0.0	13
3	0.1117	0.002061	0.0	13
4	0.1346	0.000851	0.0	13
5	0.1226	0.005244	1.0	13

Panel unit root test: Summary
Series: ACT2
Date: 11/11/15 Time: 13:40
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.12220	0.0169	5	55
Breitung t-stat	1.05807	0.8550	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.07124	0.5284	5	55
ADF - Fisher Chi-square	10.3204	0.4128	5	55

PP - Fisher Chi-square	10.8637	0.3682	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Null Hypothesis: Stationarity
Series: ACT2
Date: 11/11/15 Time: 13:40
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	4.09042	0.0000
Heteroscedastic Consistent Z-stat	7.03995	0.0000

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
** Probabilities are computed assuming asymptotic normality

Intermediate results on ACT2

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.0833	0.001439	1.0	13
2	0.1534	0.002411	1.0	13
3	0.1061	0.000438	0.0	13
4	0.5000	6.34E-05	12.0	13
5	0.1484	0.010434	2.0	13

Panel unit root test: Summary
Series: GARCH01
Date: 11/11/15 Time: 13:33
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-13.7147	0.0000	5	55
Breitung t-stat	-0.66221	0.2539	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-7.46404	0.0000	5	55
ADF - Fisher Chi-square	57.5347	0.0000	5	55
PP - Fisher Chi-square	31.6945	0.0005	5	60

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity
Series: GARCH01
Date: 11/11/15 Time: 13:33
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends

Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	2.70030	0.0035
Heteroscedastic Consistent Z-stat	2.70030	0.0035

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
** Probabilities are computed assuming asymptotic normality

Intermediate results on GARCH01

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1171	4.72E-08	1.0	13
2	0.1171	4.72E-08	1.0	13
3	0.1171	4.72E-08	1.0	13
4	0.1171	4.72E-08	1.0	13
5	0.1171	4.72E-08	1.0	13

Panel unit root test: Summary
Series: FUND
Date: 11/11/15 Time: 13:34
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.37277	0.0000	5	55
Breitung t-stat	-2.99451	0.0014	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.62223	0.0001	5	55
ADF - Fisher Chi-square	31.7942	0.0004	5	55
PP - Fisher Chi-square	23.9774	0.0077	5	60

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity
Series: FUND
Date: 11/11/15 Time: 13:34
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	2.07744	0.0189
Heteroscedastic Consistent Z-stat	8.39822	0.0000

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.

** Probabilities are computed assuming asymptotic normality

Intermediate results on FUND

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.5000	0.001167	12.0	13
2	0.1397	0.002833	0.0	13
3	0.3122	0.000220	8.0	13
4	0.0764	0.010823	1.0	13
5	0.0898	0.018358	2.0	13

Panel unit root test: Summary

Series: LPORT

Date: 11/11/15 Time: 13:35

Sample: 2001 2013

Exogenous variables: Individual effects, individual linear trends

User-specified lags: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.69996	0.0035	5	55
Breitung t-stat	-5.51912	0.0000	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.60104	0.0046	5	55
ADF - Fisher Chi-square	24.4353	0.0065	5	55
PP - Fisher Chi-square	11.6830	0.3068	5	60

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity

Series: LPORT

Date: 11/11/15 Time: 13:35

Sample: 2001 2013

Exogenous variables: Individual effects, individual linear trends

Newey-West automatic bandwidth selection and Bartlett kernel

Total (balanced) observations: 65

Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	2.18524	0.0144
Heteroscedastic Consistent Z-stat	2.18524	0.0144

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.

** Probabilities are computed assuming asymptotic normality

Intermediate results on LPORT

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1075	0.011522	3.0	13
2	0.1075	0.011522	3.0	13
3	0.1075	0.011522	3.0	13
4	0.1075	0.011522	3.0	13

5	0.1075	0.011522	3.0	13
---	--------	----------	-----	----

Panel unit root test: Summary
Series: LVG
Date: 11/12/15 Time: 09:10
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.18124	0.0000	5	55
Breitung t-stat	-1.98502	0.0236	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.56612	0.0002	5	55
ADF - Fisher Chi-square	30.8178	0.0006	5	55
PP - Fisher Chi-square	17.2408	0.0692	5	60

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity
Series: LVG
Date: 11/12/15 Time: 09:11
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	2.46744	0.0068
Heteroscedastic Consistent Z-stat	8.27067	0.0000

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
** Probabilities are computed assuming asymptotic normality

Intermediate results on LVG

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1116	0.943047	0.0	13
2	0.5000	0.733430	12.0	13
3	0.2653	0.363037	6.0	13
4	0.1187	1.967146	3.0	13
5	0.1106	157.6570	2.0	13

Dependent Variable: SRISK
Method: Panel Least Squares
Date: 11/12/15 Time: 09:12
Sample: 2001 2013
Periods included: 13
Cross-sections included: 5
Total panel (balanced) observations: 65

Variable	Coefficient	Std. Error	t-Statistic	Prob.
SIZE	0.012395	0.011521	1.075893	0.2868
CAP	-6564374.	1.08E+09	-0.006097	0.9952
ACT1	-9.81E+10	2.81E+10	-3.489057	0.0010
GARCH01	5.70E+11	6.44E+12	0.088569	0.9298
FUND	-5.84E+09	1.58E+10	-0.369429	0.7133
LPORT	-9.01E+09	5.91E+09	-1.526213	0.1329
LVG	2.81E+08	2.18E+08	1.287325	0.2036
C	7.13E+10	3.32E+10	2.146135	0.0365
Effects Specification				
Cross-section fixed (dummy variables)				
R-squared	0.757073	Mean dependent var	-7.57E+09	
Adjusted R-squared	0.706654	S.D. dependent var	1.96E+10	
S.E. of regression	1.06E+10	Akaike info criterion	49.16921	
Sum squared resid	5.94E+21	Schwarz criterion	49.57063	
Log likelihood	-1585.999	Hannan-Quinn criter.	49.32760	
F-statistic	15.01570	Durbin-Watson stat	1.527103	
Prob(F-statistic)	0.000000			

Redundant Fixed Effects Tests			
Equation: Untitled			
Test cross-section fixed effects			
Effects Test	Statistic	d.f.	Prob.
Cross-section F	18.039768	(4,53)	0.0000
Cross-section Chi-square	55.854084	4	0.0000

Dependent Variable: SRISK				
Method: Panel EGLS (Cross-section random effects)				
Date: 11/12/15 Time: 09:13				
Sample: 2001 2013				
Periods included: 13				
Cross-sections included: 5				
Total panel (balanced) observations: 65				
Swamy and Arora estimator of component variances				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
ACT1	-9.18E+10	2.56E+10	-3.581559	0.0007
LPORT	-4.68E+09	2.13E+09	-2.192144	0.0322
LVG	4.04E+08	1.91E+08	2.110781	0.0389
C	4.58E+10	1.54E+10	2.970763	0.0042
Effects Specification				
			S.D.	Rho
Cross-section random			1.30E+10	0.6132
Idiosyncratic random			1.03E+10	0.3868
Weighted Statistics				
R-squared	0.349617	Mean dependent var	-1.63E+09	
Adjusted R-squared	0.317631	S.D. dependent var	1.26E+10	

S.E. of regression	1.04E+10	Sum squared resid	6.63E+21
F-statistic	10.93028	Durbin-Watson stat	1.481145
Prob(F-statistic)	0.000008		
Unweighted Statistics			
R-squared	0.294882	Mean dependent var	-7.57E+09
Sum squared resid	1.72E+22	Durbin-Watson stat	0.688412

Correlated Random Effects - Hausman Test			
Equation: EQ01			
Test cross-section random effects			
		Chi-Sq. Statistic	
Test Summary		Chi-Sq. d.f.	Prob.
Cross-section random	0.104344	3	0.9913

SRISK- USA

Panel unit root test: Summary				
Series: SRISK				
Date: 11/11/15 Time: 13:42				
Sample: 2001 2013				
Exogenous variables: Individual effects, individual linear trends				
User-specified lags: 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Balanced observations for each test				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-0.68360	0.2471	5	55
Breitung t-stat	0.26859	0.6059	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.21567	0.4146	5	55
ADF - Fisher Chi-square	12.2035	0.2717	5	55
PP - Fisher Chi-square	5.82625	0.8296	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Panel unit root test: Summary				
Series: D(SRISK)				
Date: 11/11/15 Time: 13:43				
Sample: 2001 2013				
Exogenous variables: Individual effects, individual linear trends				
User-specified lags: 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Balanced observations for each test				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.05013	0.0000	5	50

Breitung t-stat	-1.44624	0.0741	5	45
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.67108	0.0474	5	50
ADF - Fisher Chi-square	18.7643	0.0434	5	50
PP - Fisher Chi-square	17.1894	0.0703	5	55
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Null Hypothesis: Stationarity					
Series: D(SRISK)					
Date: 11/11/15 Time: 13:43					
Sample: 2001 2013					
Exogenous variables: Individual effects, individual linear trends					
Newey-West automatic bandwidth selection and Bartlett kernel					
Total (balanced) observations: 60					
Cross-sections included: 5					
Method		Statistic		Prob.**	
Hadri Z-stat		3.35861		0.0004	
Heteroscedastic Consistent Z-stat		6.07216		0.0000	
* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.					
** Probabilities are computed assuming asymptotic normality					
Intermediate results on D(SRISK)					
	Cross section	LM	Variance HAC	Bandwidth	Obs
	1	0.1253	2.62E+21	1.0	12
	2	0.1039	2.88E+21	2.0	12
	3	0.2625	6.29E+19	6.0	12
	4	0.2404	6.72E+20	6.0	12
	5	0.1685	3.26E+19	4.0	12

Panel unit root test: Summary					
Series: LSIZE					
Date: 11/11/15 Time: 13:44					
Sample: 2001 2013					
Exogenous variables: Individual effects, individual linear trends					
User-specified lags: 1					
Newey-West automatic bandwidth selection and Bartlett kernel					
Balanced observations for each test					
Method		Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)					
Levin, Lin & Chu t*		-1.10233	0.1352	5	55
Breitung t-stat		0.90466	0.8172	5	50
Null: Unit root (assumes individual unit root process)					
Im, Pesaran and Shin W-stat		1.88985	0.9706	5	55
ADF - Fisher Chi-square		2.61587	0.9891	5	55
PP - Fisher Chi-square		1.34008	0.9994	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.					

Panel unit root test: Summary
Series: D(LSIZE)
Date: 11/11/15 Time: 13:44
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-9.23917	0.0000	5	50
Breitung t-stat	-3.14850	0.0008	5	45
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-3.55474	0.0002	5	50
ADF - Fisher Chi-square	30.2650	0.0008	5	50
PP - Fisher Chi-square	49.5317	0.0000	5	55

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity
Series: D(LSIZE)
Date: 11/11/15 Time: 13:44
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 60
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	7.84029	0.0000
Heteroscedastic Consistent Z-stat	16.2902	0.0000

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
** Probabilities are computed assuming asymptotic normality

Intermediate results on D(LSIZE)

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.5000	0.001589	11.0	12
2	0.5000	0.000935	11.0	12
3	0.0877	0.013501	2.0	12
4	0.5000	0.001567	11.0	12
5	0.2677	0.009549	6.0	12

Panel unit root test: Summary
Series: ACT_1
Date: 11/11/15 Time: 13:45
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Cross-sections	Obs
5	12

Method	Statistic	Prob.**	sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.59980	0.0548	5	55
Breitung t-stat	-2.50949	0.0060	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.48611	0.6866	5	55
ADF - Fisher Chi-square	5.70857	0.8391	5	55
PP - Fisher Chi-square	7.34154	0.6929	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Panel unit root test: Summary				
Series: D(ACT_1)				
Date: 11/11/15 Time: 13:45				
Sample: 2001 2013				
Exogenous variables: Individual effects, individual linear trends				
User-specified lags: 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Balanced observations for each test				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-4.48051	0.0000	5	50
Breitung t-stat	-4.19683	0.0000	5	45
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-1.15507	0.1240	5	50
ADF - Fisher Chi-square	14.8113	0.1391	5	50
PP - Fisher Chi-square	47.5701	0.0000	5	55
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Null Hypothesis: Stationarity				
Series: ACT_1				
Date: 11/11/15 Time: 13:45				
Sample: 2001 2013				
Exogenous variables: Individual effects, individual linear trends				
Newey-West automatic bandwidth selection and Bartlett kernel				
Total (balanced) observations: 65				
Cross-sections included: 5				
Method		Statistic		Prob.**
Hadri Z-stat		3.10050		0.0010
Heteroscedastic Consistent Z-stat		2.82512		0.0024
* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.				
** Probabilities are computed assuming asymptotic normality				
Intermediate results on ACT_1				
Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1073	0.004104	2.0	13
2	0.1385	0.008864	0.0	13
3	0.1081	0.012713	1.0	13
4	0.1127	0.003918	1.0	13

5	0.1307	0.033595	1.0	13
---	--------	----------	-----	----

Panel unit root test: Summary
Series: FUND
Date: 11/11/15 Time: 13:48
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.72263	0.0032	5	55
Breitung t-stat	-0.17493	0.4306	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.48140	0.6849	5	55
ADF - Fisher Chi-square	6.91819	0.7331	5	55
PP - Fisher Chi-square	5.28930	0.8710	5	60

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(FUND)
Date: 11/11/15 Time: 13:48
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-3.15814	0.0008	5	50
Breitung t-stat	-5.58962	0.0000	5	45
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.78607	0.2159	5	50
ADF - Fisher Chi-square	12.4913	0.2535	5	50
PP - Fisher Chi-square	55.1568	0.0000	5	55

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity
Series: FUND
Date: 11/11/15 Time: 13:48
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	3.79136	0.0001
Heteroscedastic Consistent Z-stat	3.55104	0.0002

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
 ** Probabilities are computed assuming asymptotic normality

Intermediate results on FUND

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1417	0.007949	2.0	13
2	0.0997	0.002075	1.0	13
3	0.1606	0.002986	1.0	13
4	0.1257	0.001963	0.0	13
5	0.1374	0.007877	2.0	13

Panel unit root test: Summary
 Series: CAP
 Date: 11/11/15 Time: 13:49
 Sample: 2001 2013
 Exogenous variables: Individual effects, individual linear trends
 User-specified lags: 1
 Newey-West automatic bandwidth selection and Bartlett kernel
 Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.44117	0.0073	5	55
Breitung t-stat	-0.74915	0.2269	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.20788	0.4177	5	55
ADF - Fisher Chi-square	10.0062	0.4400	5	55
PP - Fisher Chi-square	23.5727	0.0088	5	60

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
 Series: D(CAP)
 Date: 11/11/15 Time: 13:50
 Sample: 2001 2013
 Exogenous variables: Individual effects, individual linear trends
 User-specified lags: 1
 Newey-West automatic bandwidth selection and Bartlett kernel
 Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.86820	0.8074	5	50
Breitung t-stat	-1.15830	0.1234	5	45
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.34928	0.6366	5	50
ADF - Fisher Chi-square	7.61081	0.6668	5	50
PP - Fisher Chi-square	36.4110	0.0001	5	55

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Panel unit root test: Summary
Series: D(CAP,2)
Date: 11/11/15 Time: 13:50
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.27957	0.1003	5	45
Breitung t-stat	-3.25688	0.0006	5	40
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-0.85754	0.1956	5	45
ADF - Fisher Chi-square	16.8115	0.0786	5	45
PP - Fisher Chi-square	84.9866	0.0000	5	50

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Null Hypothesis: Stationarity
Series: CAP
Date: 11/11/15 Time: 13:50
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
Newey-West automatic bandwidth selection and Bartlett kernel
Total (balanced) observations: 65
Cross-sections included: 5

Method	Statistic	Prob.**
Hadri Z-stat	3.79441	0.0001
Heteroscedastic Consistent Z-stat	7.38335	0.0000

* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.
** Probabilities are computed assuming asymptotic normality

Intermediate results on CAP

Cross section	LM	Variance HAC	Bandwidth	Obs
1	0.1336	1.884103	2.0	13
2	0.1344	1.844883	1.0	13
3	0.5000	0.132636	12.0	13
4	0.1179	0.689708	1.0	13
5	0.1373	90.55493	2.0	13

Panel unit root test: Summary
Series: LVG
Date: 11/11/15 Time: 13:51
Sample: 2001 2013
Exogenous variables: Individual effects, individual linear trends
User-specified lags: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-5.04343	0.0000	5	55
Breitung t-stat	-1.15444	0.1242	5	50
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-2.30090	0.0107	5	55
ADF - Fisher Chi-square	23.2402	0.0099	5	55
PP - Fisher Chi-square	22.1454	0.0144	5	60
** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.				

Null Hypothesis: Stationarity					
Series: LVG					
Date: 11/11/15 Time: 13:51					
Sample: 2001 2013					
Exogenous variables: Individual effects, individual linear trends					
Newey-West automatic bandwidth selection and Bartlett kernel					
Total (balanced) observations: 65					
Cross-sections included: 5					
<hr/>					
Method		Statistic		Prob.**	
Hadri Z-stat		3.61569		0.0001	
Heteroscedastic Consistent Z-stat		8.28381		0.0000	
<hr/>					
* Note: High autocorrelation leads to severe size distortion in Hadri test, leading to over-rejection of the null.					
** Probabilities are computed assuming asymptotic normality					
Intermediate results on LVG					
<hr/>					
	Cross section	LM	Variance HAC	Bandwidth	Obs
	1	0.5000	5.444695	12.0	13
	2	0.1135	114.2062	2.0	13
	3	0.2239	2.565576	6.0	13
	4	0.1315	5.404806	4.0	13
	5	0.1384	37.20441	2.0	13
<hr/>					

Kao Residual Cointegration Test			
Series: SRISK SIZE ACT_1 FUND			
Date: 11/12/15 Time: 12:28			
Sample: 2001 2013			
Included observations: 65			
Null Hypothesis: No cointegration			
Trend assumption: No deterministic trend			
User-specified lag length: 1			
Newey-West automatic bandwidth selection and Bartlett kernel			
<hr/>			
	ADF	t-Statistic	Prob.
		-1.980042	0.0238
<hr/>			
	Residual variance	1.18E+21	
	HAC variance	9.73E+20	
<hr/>			

Pedroni Residual Cointegration Test	
Series: SRISK SIZE ACT_1 FUND	

Date: 11/12/15 Time: 12:29
Sample: 2001 2013
Included observations: 65
Cross-sections included: 5
Null Hypothesis: No cointegration
Trend assumption: No deterministic trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	<u>Statistic</u>	<u>Prob.</u>	Weighted <u>Statistic</u>	<u>Prob.</u>
Panel v-Statistic	0.207914	0.4176	-0.326648	0.6280
Panel rho-Statistic	0.656670	0.7443	1.262893	0.8967
Panel PP-Statistic	-0.893658	0.1858	-0.274233	0.3920
Panel ADF-Statistic	-0.117241	0.4533	-0.878333	0.1899

Alternative hypothesis: individual AR coefs. (between-dimension)

	<u>Statistic</u>	<u>Prob.</u>
Group rho-Statistic	2.256484	0.9880
Group PP-Statistic	-0.317045	0.3756
Group ADF-Statistic	0.074086	0.5295

Pedroni Residual Cointegration Test

Series: SRISK SIZE ACT_1 FUND
Date: 11/12/15 Time: 12:29
Sample: 2001 2013
Included observations: 65
Cross-sections included: 5
Null Hypothesis: No cointegration
Trend assumption: Deterministic intercept and trend
User-specified lag length: 1
Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	<u>Statistic</u>	<u>Prob.</u>	Weighted <u>Statistic</u>	<u>Prob.</u>
Panel v-Statistic	-1.117275	0.8681	-1.439282	0.9250
Panel rho-Statistic	1.284667	0.9005	1.845081	0.9675
Panel PP-Statistic	-1.194650	0.1161	-0.614461	0.2695
Panel ADF-Statistic	0.874124	0.8090	0.239410	0.5946

Alternative hypothesis: individual AR coefs. (between-dimension)

	<u>Statistic</u>	<u>Prob.</u>
Group rho-Statistic	2.580447	0.9951
Group PP-Statistic	-1.964205	0.0248
Group ADF-Statistic	1.128622	0.8705

Pedroni Residual Cointegration Test

Series: SRISK SIZE ACT_1 FUND
Date: 11/12/15 Time: 12:29
Sample: 2001 2013
Included observations: 65
Cross-sections included: 5
Null Hypothesis: No cointegration
Trend assumption: No deterministic intercept or trend
User-specified lag length: 1

Newey-West automatic bandwidth selection and Bartlett kernel

Alternative hypothesis: common AR coefs. (within-dimension)

	Statistic	Prob.	Weighted Statistic	Prob.
Panel v-Statistic	0.531904	0.2974	-0.520896	0.6988
Panel rho-Statistic	0.389371	0.6515	0.664692	0.7469
Panel PP-Statistic	-0.618893	0.2680	-0.711791	0.2383
Panel ADF-Statistic	-0.789678	0.2149	-1.647176	0.0498

Alternative hypothesis: individual AR coefs. (between-dimension)

	Statistic	Prob.
Group rho-Statistic	1.742386	0.9593
Group PP-Statistic	-0.401197	0.3441
Group ADF-Statistic	-0.953698	0.1701

Johansen Fisher
Panel Cointegration Test

Series: SRISK SIZE ACT_1 FUND
Date: 11/12/15 Time: 12:29
Sample: 2001 2013
Included observations: 65
Trend assumption: No deterministic trend
Lags interval (in first differences): 1 1

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	6.931	0.7319	6.931	0.7319
At most 1	104.7	0.0000	69.83	0.0000
At most 2	57.52	0.0000	50.23	0.0000
At most 3	22.78	0.0116	22.78	0.0116

Johansen Fisher
Panel Cointegration Test

Series: SRISK SIZE ACT_1 FUND
Date: 11/12/15 Time: 12:30
Sample: 2001 2013
Included observations: 65
Trend assumption: No deterministic trend (restricted constant)
Lags interval (in first differences): 1 1

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	6.931	0.7319	6.931	0.7319
At most 1	530.9	0.0000	530.9	0.0000
At most 2	71.39	0.0000	49.77	0.0000
At most 3	36.93	0.0001	36.93	0.0001

* Probabilities are computed using asymptotic

Chi-square distribution.

Johansen Fisher
Panel Cointegration Test

Series: SRISK SIZE ACT_1 FUND

Date: 11/12/15 Time: 12:30

Sample: 2001 2013

Included observations: 65

Trend assumption: Linear deterministic trend

Lags interval (in first differences): 1 1

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	6.931	0.7319	6.931	0.7319
At most 1	75.07	0.0000	75.07	0.0000
At most 2	62.27	0.0000	46.65	0.0000
At most 3	36.11	0.0001	36.11	0.0001

* Probabilities
are computed
using asymptotic
Chi-square distribution.

Johansen Fisher
Panel Cointegration Test

Series: SRISK SIZE ACT_1 FUND

Date: 11/12/15 Time: 12:30

Sample: 2001 2013

Included observations: 65

Trend assumption: Linear deterministic trend (restricted)

Lags interval (in first differences): 1 1

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	6.931	0.7319	6.931	0.7319
At most 1	41.00	0.0000	41.00	0.0000
At most 2	1317.	0.0000	92.10	0.0000
At most 3	24.79	0.0058	24.79	0.0058

* Probabilities
are computed
using asymptotic
Chi-square distribution.

Johansen Fisher
Panel Cointegration Test

Series: SRISK SIZE ACT_1 FUND

Date: 11/12/15 Time: 12:30

Sample: 2001 2013

Included observations: 65

Trend assumption: Quadratic deterministic trend

Lags interval (in first differences): 1 1

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Hypothesized No. of CE(s)	Fisher Stat.* (from trace test)	Prob.	Fisher Stat.* (from max-eigen test)	Prob.
None	6.931	0.7319	6.931	0.7319
At most 1	23.97	0.0077	23.97	0.0077
At most 2	75.07	0.0000	75.07	0.0000
At most 3	49.15	0.0000	49.15	0.0000

* Probabilities
are computed
using asymptotic
Chi-square distri-
bution.

Dependent Variable: DSRISK
Method: Panel Least Squares
Date: 11/11/15 Time: 13:52
Sample (adjusted): 2002 2013
Periods included: 12
Cross-sections included: 5
Total panel (balanced) observations: 60

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DLSIZE	9.47E+10	3.74E+10	2.532253	0.0145
DCAP	-1.49E+09	2.39E+09	-0.624213	0.5353
ACT_1	-3.75E+10	5.69E+10	-0.658763	0.5131
FUND	6.95E+10	7.79E+10	0.892480	0.3764
LVG	2.96E+09	8.11E+08	3.655904	0.0006
C	-6.70E+10	6.83E+10	-0.980348	0.3316

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.356239	Mean dependent var	2.94E+09
Adjusted R-squared	0.240363	S.D. dependent var	3.82E+10
S.E. of regression	3.33E+10	Akaike info criterion	51.44411
Sum squared resid	5.53E+22	Schwarz criterion	51.79316
Log likelihood	-1533.323	Hannan-Quinn criter.	51.58064
F-statistic	3.074292	Durbin-Watson stat	1.887025
Prob(F-statistic)	0.005204		

Redundant Fixed Effects Tests

Equation: Untitled

Test cross-section fixed effects

Effects Test	Statistic	d.f.	Prob.
Cross-section F	2.046060	(4,57)	0.1000
Cross-section Chi-square	8.720818	4	0.0685

Dependent Variable: DSRISK
Method: Panel Least Squares
Date: 11/12/15 Time: 09:21
Sample (adjusted): 2002 2013

Periods included: 12
 Cross-sections included: 5
 Total panel (balanced) observations: 60

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DSIZE	0.128214	0.028168	4.551817	0.0000
DFUND	1.22E+11	6.90E+10	1.765314	0.0830
LVG	3.39E+09	6.03E+08	5.614710	0.0000
C	-5.43E+10	1.06E+10	-5.104394	0.0000
R-squared	0.389292	Mean dependent var		2.94E+09
Adjusted R-squared	0.356576	S.D. dependent var		3.82E+10
S.E. of regression	3.06E+10	Akaike info criterion		51.19140
Sum squared resid	5.25E+22	Schwarz criterion		51.33102
Log likelihood	-1531.742	Hannan-Quinn criter.		51.24601
F-statistic	11.89896	Durbin-Watson stat		2.080571
Prob(F-statistic)	0.000004			

LIST OF ACRONYMS

ABIL	African Bank Investments Limited
ABS	Asset-Backed Security
ADF	Augmented Dickey-Fuller
AIG	American International Group
BCBS	Basel Committee on Banking Supervision
BIS	Bank for International Settlements
CoVaR	Conditional Value-at-Risk
DCC	Dynamic Conditional Correlation
EGARCH	Exponential Generalised Autoregressive Conditional Heteroskedasticity
ES	Expected Shortfall
Fannie Mae	Federal National Mortgage Association
FDI	Foreign Direct Investment
Fed	Federal Reserve System
Freddie Mac	Federal Home Loan Mortgage Corporation
FSeB	Financial Services Board
FSOC	Financial Stability Oversight Council
FStB	Financial Stability Board
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GJR	Glosten-Jagannathan-Runkle
GPD	Generalised Pareto Distribution
IMF	International Monetary Fund
IODSA	Institute of Directors in Southern Africa
IPS	Im-Pesaran-Shin
JSE	Johannesburg Stock Exchange
LLC	Levin-Lin-Chu
LVG	Leverage Indicator
LRMES	Long-Run Marginal Expected Shortfall
MBS	Mortgage Backed Security
MES	Marginal Expected Shortfall
RAMSI	Risk Assessment Model of Systemic Institutions
SA	South Africa
SARB	South African Reserve Bank
SES	Systemic Expected Shortfall
SRISK	Systemic Risk Index
TED	Treasury Bill and Eurodollar Spread
TGARCH	Threshold Generalised Autoregressive Conditional Heteroskedasticity
UK	United Kingdom
US	United States
VaR	Value-at-Risk
V-Lab	New York University Stern Volatility Laboratory