Systemic risk in banking and insurance with practical application to South African financial institutions

Robert Daniel Rusconi

Supervised by Professor Conrad Beyers and Dr Nadine Walters

A Thesis submitted to the Faculty of Natural & Agricultural Sciences at the University of Pretoria in accordance with the requirements of the degree of Doctor of Philosophy in Mathematics (Actuarial Science)

September 2024

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Abstract

In the highly interconnected financial sector, systemic risk represents a persistent concern for policymakers and the regulators of financial-sector entities. This research aims to enhance in practical ways the understanding of the nature of systemic risk in South Africa's banking and insurance markets. Five interlinked studies are presented, each a chapter of this thesis. Utilising both quantitative and qualitative methods, these studies aim to provide a range of insights to assist regulators to identify the sources of systemic risk and to mitigate the impacts of this risk more effectively.

Several findings may prove helpful, starting with those that apply to banks. Considering first the entities themselves, South Africa's largest banks appear to contribute disproportionately to levels of systemic risk. For some of them, the tail correlation of extreme events at individual banks and the market as a whole appears also to be greatest. Turning next to attributes of the banking system as a whole, analysis of the indicator of the level of systemic risk suggests a tipping point in its sensitivity to changes in the assumed extent to which a shock to one bank impacts the values of assets at other banks. In other words, while specific entities may contribute disproportionately to systemic risk, under certain conditions a small change to a single assumption could have substantial adverse impacts on system stability.

The research also considers the potential for systemic risk arising in insurers. A comprehensive review of the literature concludes that systemic risk arising in South African insurers is a realistic probability. A framework is proposed for classifying and hence identifying the risks that may be systemic in nature, using published information from South African insurers to show how the framework may be utilised in practice.

Each chapter provides a review of the relevant literature, describes the research approach and its findings, expresses the implications of these findings in practical ways and proposes further possibilities for enquiry. The emphasis throughout this work is on the application of the findings to a more effective regulatory system. Enhanced effectiveness benefits not only the customers of these banks and insurers but all who live in this country and are impacted by systemic insecurity.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Dedication

This study is dedicated to the Lord, giver of Life, Light and Love, and to those who, many years ago, encouraged me to reach a little further, school teachers Jenny Mallett and Barry Hart, lecturers Rob Dorrington and Eric Martens, honours supervisor Dave Bradfield and my first managers in the workplace, Margaret Hulme and Roy Stevenson. Thank you.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Declaration

I declare that this thesis, which I, Robert Daniel Rusconi, submit for the degree of PhD to the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other institution. I have received no financial support in the pursuit of this study. I am not aware of any conflicts of interest.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Acknowledgements

Teaching is difficult at any stage. So much depends on the willingness of the recipient of the information to respond positively to these inputs. It is my firm conviction that teaching at the highest level brings special challenges, especially when the student is older and rather more likely to be set in his ways. I owe a great deal to Prof Conrad Beyers and Dr Nadine Walters for the patience that they have demonstrated in bringing me to this point, for the guidance that they have provided and the knowledge that they have imparted. I have grown immeasurably through this experience. A great deal of that growth is attributable to them. Thank you also to Dr Walters for allowing me to scrutinise her modelling of banking networks in order to build further on her work, as reflected in the outputs of Chapters 2 and 3.

Contributions to some of the other chapters call for specific acknowledgement. For Chapter 4, insights gained from a conversation with cited author Prof Jones Odei Mensah were useful and are warmly acknowledged.

Chapter 5 builds on the research underlying my MSc thesis completed in 2019 at the University of Pretoria. I am grateful for the oversight of Prof Conrad Beyers and Prof Corlia van Heerden in that regard. Prof Rob Thomson, in his role as sponsor of the draft paper submitted to the 2020 Convention of the Actuarial Society of South Africa, provided deeply thought-provoking comments and suggestions. Mr Paul Zondagh added practical insights into the development of South Africa's prudential regulatory framework and thoughts on an early draft. Mr Ronald Richman provided input to the conceptual foundation underpinning the work. All comments received in response to the Convention submission are also gratefully acknowledged.

Chapter 6 has been accepted for publication by the South African Actuarial Journal. Comments received from anonymous reviewers of the draft submitted to the Journal are warmly acknowledged.

Finally, where would I be without my wife and children? Thank you for managing overnight computer runs and Saturday morning drafting and for encouraging me to keep going. Thank you also for your own examples of diligence and perseverance.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Contents

List of Figures

List of Tables

Chapter 1

Introduction

> "Chaos is found in greatest abundance wherever order is being sought. It always defeats order, because it is better organized." (Terry Pratchett)[1]

The blessing, or curse perhaps, of the Chinese philosopher has been granted us: we live in interesting times. Several attributes of this era are difficult to interpret. Is it a time of war or peace, of personal power or central control, of freedom or captivity? Is it a time of order or chaos?

Most would agree at least that this is an era of connectedness and that, while connections are helpful, they are also channels for transmitting systemic risk. They bring groups closer together, but they contribute also to polarisation. As effective as they might be at sharing information, they can sow panic and mistrust as well.

Enhanced interconnectedness, between people, between institutions and between nations, elevates levels of systemic risk, as lines of communication become channels of contagion. South Africans are increasingly aware of the nature of systemic risk in another facet of life. They understand the possibility of collapse to the national electricity grid. The power utility[2] and the responsible minister[3] have assured those living in this country that grid collapse is highly unlikely. Experts have indicated their support for this view.[4]

Nevertheless, politicians in the ruling party[5] and opposition[6] acknowledge grid failure as

[1]Confirming the veracity of a popularly accepted quote is frequently difficult, but this one is repeated by several reputable web sites.

[2]MyBroadBand (2023), 'Low chance of Eskom grid collapse', Myles Illidge, 14 May, accessed at https://mybroadband.co.za/news/energy/491751-low-chance-of-eskom-grid-collapse.html on 3 June 2023; IOL (2023), 'Eskom reassures SA the grid will not collapse', Philippa Larkin, 16 May, accessed at the IOL site on 3 June 2023 at https://www.iol.co.za/business-report/economy/eskom-reassures-sa-the-grid-will-not-collapse-bc6a05f6-deab-4c5b-9def-df3b77cdf16a

[3]eNCA(2023a), 'Ramokgopa says grid collapse "improbable"', 2 June, accessed an the eNCA site on 3 June 2023 at https://www.enca.com/news/sa-not-risk-grid-collapse-minister-electricity

[4]BusinessTech(2023a), 'Grid collapse in South Africa unlikely: experts', 14 May, accessed at BusinessTech at https://businesstech.co.za/news/energy/687777/grid-collapse-in-south-africa-unlikely-experts/ on 3 June 2023

[5]EWN(2023), 'South Africans will be "first to know" when power grid collapses, says Ramaphosa", accessed at https://ewn.co.za/0001/01/01/south-africans-will-be-first-to-know-when-power-grid-collapses-says-ramaphosa on 3 June 2023.

[6]TimesLIVE(2023), 'Malema's alarming speech on grid collapse and "gullible" South Africans: "We are

a possibility. That possibility is being seriously discussed, both in South Africa[7] and internationally.[8] Insurers are taking steps to protect themselves against its impacts, for example, by excluding damages resulting from a total blackout.[9] Business leaders are calling for scenario planning.[10] Banks are already preparing responses to the possibility.[11] The Reserve Bank has also undertaken contingency plans, expressing the view that some banking functionality could be maintained in a power blackout.[12]

While the potential for systemic risk in power generation and transmission has been much noted recently, South Africans are also all too well aware of systemic risk in banking. African Bank, VBS Mutual Bank and Ubank were placed under curatorship in 2014, 2018 and 2022 respectively. African Bank was rehabilitated, supported by a guarantee issued by government (SARB 2021a) and Ubank was purchased by African Bank. VBS was liquidated, however, impacting several non-bank entities in the process.[13]

The nature of channels of communication and contagion are perhaps nowhere more clearly illustrated as both blessing and curse than in the system of the world's financial markets:

> "a complex, adaptive system [...] robust and fragile [...] progressively more complex and less diverse" (Andrew Haldane)[14]

Despite the differences between the respective markets for financial services and power generation, the approaches used to mitigate systemic risk in these markets are similar to one another. Methods to protect against the risk of a failure of South Africa's power generation and transmission systems include utilising a margin for error and preparing contingency plans. Rolling blackouts are the first defence against the possibility of grid failure. They provide a margin for error. While the people of the country suffer the immediate impacts of regular power cuts, these interruptions, despite the associated cost to society, are an important part of a strategy to avoid a much greater disaster with consequences not only for the power sector but for the well-being of the economy and

going into darkness"', accessed at $https://www.youtube.com/watch?v = ZmG_v JyIrGY$ on 3 June 2023.

[7] eNCA(2023b), 'Threat of national electricity grid collapse', accessed through eNCA on 3 June 2023 at https://www.youtube.com/watch?v=HiwfBbmt5Vg; eNCA(2023c), 'Discussion — Eskom grid failure', accessed at https://www.youtube.com/watch?v=gdn85lnBHNQ on 3 June 2023

[8] BBC News(2023), 'Why the lights are going out in South Africa', accessed through the BBC at the web site https://www.youtube.com/watch?v=zh4yqhD98HU on 3 June 2023

[9] DailyInvestor(2023), 'Total blackout warning to South Africans', 7 May, accessed on 3 June 2023 at https://dailyinvestor.com/energy/16332/total-blackout-warning-to-south-africans/

[10] DailyMaverick(2023), 'We need to protect ourselves against the catastrophe of total electrical grid failure', Bonang Mohale, 7 May, accessed at https://www.dailymaverick.co.za/opinionista/2023-05-07-we-need-to-protect-ourselves-against-the-catastrophe-of-total-electrical-grid-failure/ on 3 June 2023

[11] Mail & Guardian (2023), 'Fearing three-week blackout, banks ramp up contingency plans', Mandisa Nyathi, 31 May, accessed at https://mg.co.za/business/2023-05-31-fearing-three-week-blackout-banks-ramp-up-contingency-plans/ on 3 June 2023

[12] News24(2023), 'SA grid collapse: Part of bank system could still function, says Reserve Bank', with Bloomberg News, 30 May, accessed at https://www.news24.com/fin24/economy/sa-grid-collapse-part-of-bank-system-could-still-function-says-reserve-bank-20230530 on 3 June 2023; BusinessTech(2023b), 'The Reserve Bank prepares for grid collapse', 31 May, accessed at https://businesstech.co.za/news/finance/692729/the-reserve-bank-prepares-for-grid-collapse/ on 3 June 2023

[13] Source: Author discussion with former regulator.

[14] 'Rethinking the Financial Network', speech delivered at the Financial Student Association, Amsterdam, April 2009, quotes from pages 3, 4 and 6.

the country as a whole. Planning for adverse scenarios is the second defence. Insurers[15] and banks,[16] business leaders,[17] even the South African Reserve Bank,[18] are responding to the risk by shaping their products and assessing their resilience to the possibility of a protracted power disaster.

Similar methods are used in the financial sector. First, banks and insurers are required to hold capital above minimum stipulated levels, along with sufficient liquidity, to mitigate the probability of insolvency. Failure of a single entity could be very damaging to the shareholders of that bank or insurer, and to its customers. But the greater concern to a wide range of stakeholders is the possibility that the collapse of an entity could trip the whole system, to borrow a metaphor from the power sector. Regulators of financial-sector entities for this reason insist on margins of conservatism, requiring minimum levels of capital or liquidity that might be regarded as excessive by the shareholders of these entities but are appropriate considering the risk of disaster borne by society more broadly. Second, financial-sector entities prepare for adversity. They run regular assessments of their ability to withstand adverse scenarios, even testing their potential to respond to insolvency. They prepare back-up systems, business continuity processes and disaster recovery plans. Under regulation, they are required to assess their operational robustness and organisational resilience to adversity (Prudential Authority 2023a,b).

It is nevertheless critical that policymakers and regulators remain vigilant concerning the attributes of financial markets or the activities and responses of financial-sector entities for any signs of elevated risk. The research described in this thesis aims to support this vigilance in practical ways.

This is a study of two markets, banking and insurance, that are similar, different and inextricably interwoven. Banks are, almost by their very nature, interlinked. As the source of liquidity, the lifeblood to economies, these entities are woven together in their continuous effort to balance assets and liabilities. Their channels of communication, however, are not only the means to absorb shock events by sharing their impacts. They are also avenues for transmitting disaster when these shocks cannot be absorbed, magnifying the effects of contagion and threatening the whole system.

Insurers, in contrast, appear to be different. They are providers of protection, not of liquidity, walls rather than channels, conservatively capitalised and sharing risk upwards rather than with peers. Yet they form part of the same financial system, they depend on

[15] DailyInvestor(2023), 'Total blackout warning to South Africans', 7 May, accessed on 3 June 2023 at https://dailyinvestor.com/energy/16332/total-blackout-warning-to-south-africans/.

[16] Mail & Guardian (2023), 'Fearing three-week blackout, banks ramp up contingency plans', Mandisa Nyathi, 31 May, accessed at https://mg.co.za/business/2023-05-31-fearing-three-week-blackout-banks-ramp-up-contingency-plans/ on 3 June 2023.

[17] DailyMaverick(2023), 'We need to protect ourselves against the catastrophe of total electrical grid failure', Bonang Mohale, 7 May, accessed at https://www.dailymaverick.co.za/opinionista/2023-05-07-we-need-to-protect-ourselves-against-the-catastrophe-of-total-electrical-grid-failure/ on 3 June 2023.

[18] News24(2023),'SA grid collapse: Part of bank system could still function, says Reserve Bank', with Bloomberg News, 30 May, accessed at https://www.news24.com/fin24/economy/sa-grid-collapse-part-of-bank-system-could-still-function-says-reserve-bank-20230530 on 3 June 2023; BusinessTech(2023b), 'The Reserve Bank prepares for grid collapse', 31 May, accessed at https://businesstech.co.za/news/finance/692729/the-reserve-bank-prepares-for-grid-collapse/ on 3 June 2023.

and contribute to banking services and they seem at times to have played a substantial role in adding to contagion in the global network.[19] If they contribute materially to system instability, how might the ways in which they do so and the options available to mitigate these effects be identified?

This study aims to contribute practical benefit through theoretical rigour. What it learns from much studied banks it applies to less well understood insurers, applying lessons from an obviously networked market to its sibling that may be less interconnected. Above all, it aims to be useful. It helps policymakers to improve the effectiveness of their mandate to encourage order in chaos. It assists regulators of banks and insurers by providing practical tools to understand better the dynamics of systemic risk, to identify symptoms of increases to ambient risk levels and to detect signs of problems at participating institutions.

This chapter is laid out as follows. It starts by expressing formally the goals of this research, explaining in broad terms how these goals are met and describing the contribution of these studies to the literature on systemic risk. Section 1.2 goes on to describe in more detail the five chapters that meet these goals. Each of these was prepared as as paper for publication, so they provide literature reviews pertinent to their respective purposes. However, since these reviews assume some prior knowledge of several underlying topics, an outline of the concepts pertinent to this foundation is provided in Section 1.3, using less formal language than in the papers and adding supporting illustrations in everyday terms. The discussion closes in Section 1.4 with an explanation, also in lay language, of the relevance and benefits of this research to the actuarial profession.

1.1 Objectives

The overarching objective of the research described in this thesis is to enhance the understanding of policymakers and regulators concerning the nature of systemic risk in South Africa's banking and insurance markets. Each study aims to assist decision-makers in practical ways, thereby contributing to more rapid identification of early warning signs and more effective mitigation of potential systemic risks.

This objective is achieved by:

- applying quantitative modelling techniques to questions of systemic risk arising in banking networks, suggesting the possibility of disproportionate contributions to systemic risk by large banks (Chapter 2) and of tipping points in ambient levels of systemic risk (Chapter 3);
- assessing alternative approaches to measuring the contribution to systemic risk by individual entities in both banking and insurance (Chapter 4);
- asking broad questions regarding the possibility of systemic risk arising in insurers through a detailed enquiry of the literature (Chapter 5), and

[19] AIG stands out as by far the largest insurance group to receive a bailout from the Treasury Troubled Asset Relief Program following the 2008-09 financial crisis, but it was not the only insurer to benefit from such support (SE Harrington 2009).

- putting forward a coherent framework for classifying and hence identifying the sources of insurance-related systemic risk and applying this to South Africa's insurers through a survey of publicly-available information (Chapter 6).

This work contributes to the literature on the subject of systemic risk in several ways. In banking, building on the existing body of knowledge in network modelling and the work of others in the South African banking industry (Walters et al. 2018), this research identifies aspects of the network of banks in a large developing country that contribute to elevated levels of systemic risk. Refer to Section 1.3.1 for a foundational description of the contribution of banks to systemic risk and Section 1.3.2 for a summary of the network models underpinning this work.

The next contribution to the literature is an exploration of the benefits and disadvantages of a relatively straightforward but intuitively helpful alternative approach to a widely used method for measuring the contribution to systemic risk by individual entities. This work also refers to the corresponding results of conventional approaches to South African data (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019; Manguzvane and Mwamba 2019). Analysis is carried out using banking data but the method has application to insurers save for the lack of publicly available information. By way of background, Section 1.3.6 summarises the respective banking and insurance markets in South Africa.

Systemic risk in insurance has not benefited from the intense study as its counterpart in banking, partly because it is generally agreed that insurers are less likely to contribute to systemic risk than banks (Eling and Pankoke 2016, among many, see Section 1.3.4). This research provides a thorough foundation for the possibility of systemic risk arising in insurers (Chapter 5). It then builds on the work of others (EIOPA 2017; IAIS 2019) to propose a coherent, holistic framework for classifying and hence identifying systemic risks contributed to by insurers, illustrating this framework with reference to publicly available data in South Africa (Chapter 6).

1.2 Approach

The discussion that follows describes the five studies comprising this thesis in more detail. The research aims to be practically helpful, to academics and to industry participants, but particularly to regulators. The findings from the quantitative methods applied to banks provide useful insights to assist regulators to identify the signs of elevated systemic risk more effectively. On insurance, an analysis of available quantitative methods is provided and the nature of potential systemic risk arising from insurers thoroughly discussed, but the key output from the research is an assessment of the most likely sources of such risk in the South African insurance market.

Chapter 2 applies a network model to South Africa's banks to explore the possibility that the largest banks contribute to levels of systemic risk to an extent that exceeds their proportional asset-based contribution to the industry. The methodology assesses systemic risk using contemporaneous book values of each bank as reported to the South African Reserve Bank on a monthly basis over a 66-month period. In order to determine the impact of the largest banks on levels of ambient systemic risk, it repeats the modelling over the same period, removing the largest banks from the data set and assessing the nature of market dynamics in their absence. The research strongly suggests that South Africa's largest five banks indeed contribute disproportionately to levels of systemic risk. The Matlab code used to undertake this analysis is provided in Appendix A4.

Chapter 3 uses the same data and largely the same methods as the study described in Chapter 2, applying the network model to South Africa's banks to identify the sensitivity of ambient levels of systemic risk to the set of assumptions used to calculate the likelihood of industry contagion. It aims to detect the possibility that a relatively small change to one assumption may provoke a substantial increase to the ambient levels of systemic risk. Such an increase signals a significant escalation in the instability of the system and hence the corresponding likelihood of systemic collapse conditional on the failure of one bank.

Five different assumptions are considered. Levels of systemic risk are found to be particularly sensitive to small changes to two parameters, in each case within a narrow range of the possible values for these parameters. In these two cases, evidence is found of a tipping point. Below the tipping point, the system displays stability, above it, significant instability. The values at which these tipping points occur is not stable over time, suggesting that policymakers should take care to understand the values taken by these parameters at any time in relation to these tipping points.

Chapter 4 describes how several researchers have suggested a range of quantitative approaches for determining the relationship between the risk contributed or felt by a single entity, typically a bank, and the corresponding level of risk of the system as a whole. Methods vary regarding the data utilised and the direction of the impact postulated. The most common sources of data used are book values, in most cases available only monthly or quarterly, or market values, commonly available every working day. Some researchers use a combination of the two, adjusting market values, for example, by overlaying information from the corresponding book values. Direction of impact varies as well. Some methods test for the impacts of a change in the level of risk at an institution on the corresponding risk for the market as a whole. Others consider the impact in the opposite direction.

The study describes an alternative, simplified approach to a widely used method called $\Delta CoVaR$. The method typically blends book values and market values and transforms the data using state variables, usually economic factors. The alternative uses only monthly book value information that does away with the need to transform the data and improves the extent to which intuitively helpful relationships between the risk of an entity and the corresponding risk of the market may be described. The results prove to be unstable over time, but the intuitive appeal of the calculation may be useful, and could form part of a standard regulatory toolkit. Nevertheless, further modifications may be called for to produce results that are more robust in their identification of systemically risky entities.

These three chapters describe different approaches to quantitative assessment of systemic risk levels in South Africa's banking industry that improve practitioners' understanding of the nature of systemic risk and of the appropriateness of the methods available for assessing it. Chapter 4 serves as the bridge between the papers on systemic risk in banking, which proceed it, and those considering systemic risk in insurance, which follow it, because the method could, subject to available data, be applied also to insurers.

Chapter 5 turns to the question of whether South African insurers might contribute to systemic risk. It does so through an assessment of the literature on systemic risk and the potential channels through which insurers might contribute to such risk. It also explores the question of the social and economic contribution of insurers to societies. The chapter concludes that, on balance of evidence, insurance indeed contributes positively to social and economic development but that there exists also a material possibility that South African insurers contribute to systemic risk levels in this country.

On the basis that insurers may contribute to systemic risk, **Chapter 6** asks what forms this contribution may take in this country. This chapter proposes a classification framework for categorising potential sources or channels of risk. The framework bears resemblance to existing regulatory approaches to identifying insurer-specific risks, which aids practical implementation. An assessment of the sources of risk most likely to occur in South Africa is carried out with reference first to the types of risk identified by several of South Africa's insurers in their published annual reports and second to the corresponding systemic risks noted by the regulator of insurers, the South African Reserve Bank. Annual reports as a source of information are unlikely to be completely objective, but regulators would have access to significantly more detailed information on insurers through the papers and supporting information submitted to them.

In sum, the approach aims to assist South African regulators by putting forward a method for classifying, identifying and evaluating potential sources of risk. It does so using a classification framework that is both collectively exhaustive and mutually exclusive, that is, complete in its breadth but defining possible risk types in sufficient detail and clarity to facilitate informative mapping of the risk environment.

1.3 Summary of foundational concepts

Each chapter in this thesis includes a review of the literature relevant to its focus of research. The discussion that follows outlines the context for this research and provides a summary of the foundational concepts and supporting literature. The language used in the description that follows is less formal than the corresponding language in the technical chapters and it is supported by analogies in everyday terms. Cross-references to the more detailed literature reviews in the chapters are provided along with simplified sets of sources. The data sets utilised and generated during the study and the corresponding Matlab code are available from the author on request.

1.3.1 Bank contribution to systemic risk

The importance of banks to the effective functioning of a modern economy is little disputed. They act as financial intermediaries in many ways, among them (ECB 2012; Ehlers and Villar 2015; Merton 1995; Tabak, Dalla Riva e Silva, and T. Silva 2016; Tagoe 2016):

- financing expenditure, in turn developing wider capital markets,
- facilitating transactions and trade through time and space,
- providing the means to defer consumption or to borrow, and
- assessing, mitigating, accepting and trading risk.

Banks often operate in concert with other types of entities, but they are typically located at the heart of financial markets as the key enabler and financier of economic activity (Tabak, Dalla Riva e Silva, and T. Silva 2016). While banks are connected to a substantial range of economic players of other types, they are connected to one another as well, lending to and borrowing from one another as a means to manage their own risk. These channels of connectedness facilitate the transmission and dilution of risk providing liquidity and absorbing stresses that occur on an ongoing basis. One bank finding itself in momentary difficulty has the means to borrow quickly from a peer. If the amounts involved are significant, then the lender has the option to borrow from others.

The connectedness between entities operates as both a blessing and a curse, however (Wang et al. 2022). The networks of channels for transmitting and absorbing risk are complex and fragile, complex because the number and types of interconnections is immeasurably large and fragile because capacity for absorption is not unlimited. Those channels that so easily redistribute stresses can become the means for the spreading of contagion. If a bank borrowing from another finds itself in a position in which it cannot pay back the loan at the agreed time, it may fail. This in turn could cause its lender to become insolvent as well. The dominoes fall. And because banks are so widely interconnected and so important to the effective functioning of the economy, the impacts of these falling dominoes is frequently felt well beyond the banks themselves, sometimes causing considerable damage to whole economies.

The risk of widespread failure is typically referred to as systemic risk. Like many other risks, systemic risk is difficult to define with precision, though easy to recognise when it materialises, 'something that becomes self evident under casual observation' (Hansen 2013, p.1). It is broadly agreed that systemic risk events are characterised by widespread adverse impacts on the financial sector and some form of spillover to the wider economy. The consequences of systemic risk events, typically referred to as externalities, often spread well beyond the markets themselves, sometimes with widespread, devastating impacts (Brunnermeier et al. 2009; Carvajal et al. 2009; IMF 2013, 2014b, 2018).

Those who have sought to define systemic risk more precisely (see Acharya, Pedersen, Philippon, and M. Richardson 2017; Claessens 2015; J. Cummins and Weiss 2014; Eling and Pankoke 2016; Kessler 2014, for example) typically do so by identifying several of its attributes. Among these are high levels of connectivity between financial entities, widespread detrimental impacts across the financial sector, spillover to other economic sectors and considerable damage to levels of confidence in financial markets (Chapter 5)

Systemic risk is of special concern to financial-sector regulators. This concern is attributable to the potentially devastating impacts of systemic risk. It exists also because regulated entities may regard systemic risk differently to idiosyncratic risk, which impacts them directly. They may not have the same natural incentives to mitigate their contribution to systemic risk as they do for idiosyncratic risk (S. Schwarcz 2008).

Is increasing connectedness necessarily a contributor to systemic instability? Despite their prevalence throughout history (Reinhart and Rogoff 2008, 2011), it is easy to assume on the basis of recent events that systemic crises have become more common with increasing complexity and connectedness. This may be an error. Several authors (see ADB 2017; Minoiu et al. 2013; Schmukler 2004) present evidence for such a link, but others (Bisias et al. 2012; Fell and Schinasi 2005; Oosterloo and De Haan 2003; Smaga 2014) have raised concerns regarding the validity of these conclusions.

This research finds its context in a complex setting.

1.3.2 Network models

A few paragraphs are needed on banking networks and the way they are typically conceptualised for purposes of modelling. The techniques used in Chapters 2 and 3 are developed on the foundation of the corresponding approaches of several authors (among them, Allen and Gale 2000; Boss et al. 2004; Freixas, Parigi, and Rochet 2000; Iori et al. 2008; Poledna et al. 2015; Walters et al. 2018). The banking industry is conceived as a network of interconnected entities corresponding to the number of banks, N say, in a marketplace. Each bank is represented by a node or apex in the network. The extent and direction of the connections between banks is represented by the links, or edges, between the nodes. It is typically assumed that no edges loop back from a node back to the same node. Even in the simplest network models, it is not necessary to assume that all banks are connected to one another or even that the number of such connections is known.

This makes it possible to model uncertainty concerning the nature of the network through the application of parameters that serve to describe the system as a whole without knowledge of the details of the connections between nodes in the system. The parameter $\overline{p}$ may be used to define the mean probability across the network of a connection between any pair of nodes, i and j, each forming part of the set of N nodes. One of the earliest network models, called the Erdös–Rényi network (Erdös and Rényi 1959), rests entirely on this parameter $\overline{p}$, making no further inferences regarding the nature of the edges between nodes. While this is typically not regarded as a realistic representation of a banking market, it may usefully form a base case for modelling against which variations may be tested (Boss et al. 2004; Fricke and Lux 2015; In't Veld and Van Lelyveld 2014; Roukny et al. 2013; Teteryatnikova 2014; Walters et al. 2018). These variations constrain the values attributed to the probabilities of connections between nodes to reflect assumptions regarding the nature of interconnections between banks. Under this approach $p_{i,j}$, the probability of a connection between node i and node j, depends on some defined attributes of the respective banks i and j, the size of their assets, for example, constraining the mean probability across all possible pairs to the assumed industry level $\overline{p}$.

The next question to consider is how the failure of a bank is assumed to impact its peer, conditional on a connection between these banks existing. Several different mechanisms are postulated (see Chapters 2 and 3). In each instance, the effect on the impacted bank depends on an assumed parameter and the actual state of that bank at the time of the postulated incident.

Let us assume, for example, that a proportion of the losses incurred by the shocked bank in excess of its available liquid assets at the time of the shock is to be borne by all other banks, spread among them in proportion to their total assets at the time. This is referred to in Chapters 2 and 3 as a credit shock.[20] The probability that the initial shock to bank i results in the failure of bank j, where $i \neq j$, depends on model parameters and the respective states of both banks at the time. Model parameters include S_i, the assumed size of the shock on bank i as a proportion of the total assets of the bank, and u, the proportion of the losses that are shared by other banks.[21] Bank-specific parameters include the size, at the time t of the incident, of the total assets, a_i^t and a_j^t, and of the corresponding liquid assets, c_i^t and c_j^t, of both the shocked bank i and its impacted peer j. If the shock to bank i causes the failure of its peer, bank j, then the corresponding impact on each other bank, say bank k, where $k \neq i \neq j$, is assessed until the system attains a state of equilibrium. The proportion of all banks that fail following the shock, called the systemic default indicator, is measured and recorded. This process is repeated, for each month of available data, by shocking in turn each bank and observing the impacts of that shock on all other banks.

This discussion is closed with a lay description of the process extending the analogy of the dominoes. Each domino, N in number, represents a bank and to each is assigned the measured attributes of that bank at the time of each experiment, corresponding to separate months. At the beginning of each experiment, all dominoes are set up standing on their ends. One is chosen and tipped over. This is the initial shock. The impact of that shock on each of the other dominoes is assessed. If any of them fall as a result of the shock, then the corresponding impact of that fall on the remaining standing dominoes is considered. This is repeated until equilibrium is reached. Between 1 and N dominoes have fallen; the proportion of the total, N, is recorded. The dominoes are set up again. Now, a different domino is tipped over and the consequences of this shock are observed and recorded. The dominoes are set up again and a third domino is tipped, again recording the impacts of that shock. This process is repeated until each of the dominoes has acted as the recipient of the initial shock. Then the whole process is repeated for the following month and so on through the period of investigation. For each repetition of the experiment, the systemic default indicator is determined as the proportion of the dominoes that have fallen, once

[20] In this particular case, the probability of the shock causing the failure of another bank is independent of the corresponding probability of a link between the banks, because all banks are assumed to share the financial impact of the shock to the initial bank. In other models, the impact on other banks depends on the probability of the existence of a link.

[21] In the studies described in Chapters 2 and 3, S_i is the same for every bank, allowing generalisation of the parameter to S.

an equilibrium position is reached.

In some arrangements of the experiment, the probabilities of links between entities is not relevant because risks are shared among all banks according to some formula. In those instances, a single experiment, starting with a tipped domino and ending with a count of the fallen, is sufficient. Where the probabilities of links between banks are relevant to the outcome, however, they are simulated. This means that they are assigned, for each instance of the experiment, to all pairs of banks, through a random process constrained by the assumed nature of the network. In these cases, the experiment is repeated, for time t and shocked domino i but with random probabilities of links between entities, several times, and the mean systemic default indicator across these repetitions is recorded. The processes described in Chapters 2 and 3 use 10 000 simulations for each tipped domino i and each time period t.

1.3.3 Alternatives to network models

Studies of systemic risk are not limited to network models. A fuller survey of these alternatives, summarised in the discussion that follows, is set out in Chapter 6. Researchers have sought to quantify the contribution of individual entities to system-wide risk by assessing the impact that a failure at one entity could have on the market as a whole. The conditional value-at-risk (CoVaR) measure, for example, isolates the marginal impact on the market of an entity in distress relative to its median state (Acharya, Pedersen, Philippon, and M. Richardson 2017; Z. Adams, Füss, and Gropp 2014; Adrian and MK Brunnermeier 2016; Chatterjee and Sing 2021; Gauthier, Lehar, and Souissi 2012; Leukes and Odei-Mensah 2019; Sedunov 2016; Zhang et al. 2015).

A number of related approaches have been explored. These are based on, for example: (1) the capital shortfall of a firm in the event of a market decline, the SRISK, closely related to CoVaR (Acharya, Engle, and M. Richardson 2012; Brownlees and Engle 2017; Chatterjee and Sing 2021); (2) the expected loss to a bank in the event of significant losses to the system as a whole, the marginal expected shortfall, (Acharya, Pedersen, Philippon, and Richardon 2010; Chatterjee and Sing 2021; Idier, Lamé, and Mésonnier 2014); (3) the joint default risk of entities based on information provided by credit default swaps (Giglio 2016); (4) the realized systemic risk beta (Hautsch, Schaumburg, and Schienle 2015); and (5) the market price of insurance against system-wide financial failure (X. Huang, Zhou, and Zhu 2012a,b). Different approaches can produce different results, as disclosed in a recent study of South Africa's largest banks (Chatterjee and Sing 2021) considered in more detail in Chapter 4.

1.3.4 Insurers in the context of the system

So much for banks and their significance; what about insurers? In economic history and popular culture, insurers do not seem to carry the same weight as banks. The Medici, Rothschild and Morgan reputations were built on banking, not insurance. Insurers are important, perhaps even critical to the successful functioning of an economy, but they are not as intricately part of just about every transaction as their banking counterparts.

Simplified as such generalisations may be, they carry with them more than a germ of truth. While the failure of an insurer might not go completely unnoticed, insurers are not considered systemically critical to the financial markets of the world in the same way as their banking counterparts (Chapters 5 and 6).

If conventional wisdom suggests that banks are more important than insurers in the assessment of the stability of the system, this appears to be supported by the sheer weight of academic literature pointing to the same conclusion (Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; Billio et al. 2012; Bobtcheff, Chaney, and Gollier 2019; Eling and Pankoke 2016; Kaserer and C. Klein 2019; Van Lelyveld, Liedorp, and Kampman 2019). There are good reasons for this. A few are considered, by way of illustration, in the list that follows (Baluch, Mutenga, and Parsons 2011; Besar et al. 2011; Billio et al. 2012; Bobtcheff, Chaney, and Gollier 2019; J. Cummins and Weiss 2014; Grace, Rauch, and Wende 2013; Kessler 2014; Trichet 2005):

- Banks are, almost by definition, connected to their peers. Insurers are not. They typically outsource their most significant risk to reinsurers, which operate as specialists on a different market plane, typically with exceptional capitalisation. Risk-sharing thus occurs vertically rather than horizontally.
- Banks continually balance their assets and liabilities, their deposits and their loans. Insurers as a rule do not. Premiums are received in advance. Claims are paid after an assessment of their validity. This timing difference gives to insurers high levels of natural liquidity.
- The liabilities of an insurer are typically triggered by random events like the death of a policyholder or the property losses following an earthquake. The same is not true of banks, which can find themselves called to make good on their liabilities by a market run triggered by nothing more than a loss of market confidence.
- Banks tend to be more speculative, notably through their investment banking units. Insurance models, in contrast, are built around the proposition of assuming the risk that policyholders cannot absorb themselves. This is typically undertaken with careful regard for the attributes of that risk and the likelihood of a claim.

Banks take risk not only on behalf of their clients, but directly as well, famously parcelling tranches of mortgage debt until the house of cards fell in 2008, leading to the confidence crisis and the global slowdown that followed it (SE Harrington 2009). Errors in banks' financial models became evident, confidence fled in a moment, liquidity vanished and the channels through which risk is dispersed froze.

This all suggests that regulators concerned about systemic risk need look no further than banks. That is not the case. There are several reasons for policymakers and regulators to oversee insurers with care (Baluch, Mutenga, and Parsons 2011; Barsotti, Milhaud, and Salhi 2016; Bierth, Irresberger, and GNF Weiß 2019; Bobtcheff, Chaney, and Gollier 2019; J. Cummins and Weiss 2014; Hauton and Héam 2015; Rudolph 2017; Russell et al. 2013). Insurers also engage in risky, speculative behaviour, as AIG did in the run-up to the crash in 2008. The liabilities of insurers are frequently linked to the health of the economy. During the COVID pandemic, life insurers suffered elevated levels of claims on the deaths of policyholders and non-life insurers found themselves facing unprecedented levels of payouts for business interruption insurance. These events impacted most insurers at the same time. The failure of a reinsurer could also have a serious impact on several insurers, one of the disadvantages of the hierarchy.

Bank risks clearly impact the whole system and regulators have to consider the possibility of a bank crash with widespread effects. For insurers, the link is not so obvious, perhaps leaving regulators perplexed about how much of their limited resources should be devoted to identifying and mitigating such risks deserve. This study aims to help South Africa's regulators in this regard with practical assistance. The next part of the discussion briefly considers the need for regulation of financial-sector entities.

1.3.5 The rationale for financial-sector regulation

The regulation of financial markets has a long history (Atack 2009; Gilligan 1992; Markham 2000, for example, see Chapter 5), developing organically alongside the corresponding development of financial markets themsevles in the nineteenth century (Swarup 2012). Defining the purpose of such regulation in terms of concrete objectives represents a relatively recent innovation, however (OECD 2010; S. Schwarcz 2019). Such a definition has developed largely from the concept of risk-based regulation under which the most significant risks to the industry and its participants were considered worthy of the greatest attention by regulators (Baldwin and J. Black 2016; FSA 2012).

Building a regulatory framework on the basis of publicly-stated objectives has several advantages. First, such an approach promotes accountability (Brandsma and Schillemans 2012; Gyong 2011; A. Sarkar 2009). Second, together with a statement of measurable outcomes, objectives provide a framework for assessing and reporting progress (Baldwin and J. Black 2016; Knot 2014). Third, the objectives contribute to the rationale for regulatory intervention, typically by identifying market failures and demonstrating how the intended regulatory intervention aims to prevent such failures or to manage their impacts (Cochrane 2014; OECD 2010).

The importance of regulatory intervention to mitigate the impacts of systemic risk has been identified by several regulators, in South Africa, for example, by the National Treasury (NTSA 2011a,b). Financial-sector entities have an incentive to control risks that impact them directly. They may not have the same motivation concerning risks to which they may contribute but which have only an indirect impact on their financial well-being yet potentially far-reaching impacts on the rest of the industry, or on society at large (S. Schwarcz 2008). This leaves to the regulator the critical role of mitigating the impacts of systemic risk through a range of tools and interventions. The research laid out in this thesis aims to support this process in practical ways.

1.3.6 South Africa's banking and insurance industry

Readers are justified in asking after the merit of studying aspects of South Africa's financial sector. Carrying out the study for a South African institution like the University of Pretoria is a good reason for those interested in the benefits for local policymakers, regulators and market participants. However, is a study of the South African market of any benefit to international readers without any direct interest in the country? It is. The market, and its systemic tendencies, are similar to those in other countries.

Several chapters, notably numbers 2, 5 and 6, describe the South African banking and insurance industries for the benefit of international readers, rendering a detailed description at this point superfluous. In defence of the value of a study of South Africa's banking and insurance industries, it is appropriate to summarises the key attributes of these markets as follows (IMF 2008, 2014a, 2015a,b, 2022d,e; Mlambo and Ncube 2011; Moyo 2018; Simatele 2015; Simbanegavia, Greenberg, and Gwatidzo 2015):

- large, sophisticated and deep,
- subject to broadly sound and improving standards of regulation, with a sound focus on systemic risk, but also
- concentrated and highly interconnected, particularly to other parts of the financial sector, notably through group structures.

The South African financial sector, in other words, in many ways similar to its counterparts in other developed and developing countries, nevertheless has systemic attributes that make it worthy of further attention. International observers, noting several symptoms of elevated levels of systemic risk (IMF 2022a,e), have called for strengthened and more effective macro-prudential regulatory policy (IMF 2022a,d).

This market has attributes worthy of study. Its financial sector is larger, relative to annual gross domestic product, than most developing markets (IMF 2022d), with sophisticated banking and insurance sectors, and it is generally well regulated. It shows several signs of systemic risk, however, that require ongoing attention by policymakers and would surely benefit from scrutiny by researchers.

All chapters devote space to a description of the data analysed. The South African Reserve Bank makes detailed monthly balance sheet data available for all banks. These standard outputs are referred to as BA900 forms.[22] A graphical representation of the information available in the BA900 forms is available at Appendix A.2.

1.4 Relevance to the Actuarial Profession

The discussion that follows outlines the significance of this research to members of the actuarial profession, in South Africa and further afield. The case is built on three statements regarding the interests or objectives of actuaries in South Africa and around the world.

First, a significant proportion of actuaries work in fields that are directly impacted by this research. Life and non-life insurers employ a significant proportion of the members of the

[22] This data was downloaded on 3 June, 5 August and 16 September 2020 and 13 January 2021 from the South African Reserve Bank web site, at https://www.resbank.co.za/en/home/what-we-do/statistics/releases/banking-sector-information/banks-ba900-economic-returns.

profession. A growing number of actuaries work for banks. Many more actuaries or actuarial students are employed by regulatory authorities that are responsible for overseeing insurers or by firms that provide professional services to insurers or banks. This research lies at the intersection of banking and insurance, on the one hand, and regulation, on the other. The research and its findings are thus important to actuarial professionals working in or alongside both of these sectors.

Second, actuaries have both a general and a specialised interest in risk management. All actuaries are trained in principles of risk management. They are taught to identify and quantify risks using a range of statistical and financial techniques. Many of them go on from this broad training to offer specialised risk management services of various kinds. They help to manage risk by developing products that contain or remove risk from economic entities such as households, businesses or groups of employees. They mitigate risk through the provision of strategic advice or programmes to corporations, pension funds or other financial-sector players of various kinds. They hedge risk by designing investment strategies to the benefit of their employers or clients. Some actuaries have a specific interest in systemic risks of various kinds, risks related to climate change, for example, or externalities attributable to financial-sector disruption. This research is explicitly concerned with the potential for such disruption to arise in insurance arrangements.

Third, actuaries are concerned about the societal impacts of their professional contributions. Some of them work explicitly to identify and measure the wider consequences of initiatives such as government programmes, social security arrangements, health-care schemes, pension funds and insurance companies, particularly those focused on low-income customers. Most actuarial organisations add to this an explicit commitment to improving the coherence and effectiveness of social protection systems, at the very least through understanding the impacts of actuarial work on the societies within which this work is carried out. The potential for financial entities to cause or significantly contribute to externalities that in turn could lead to widespread economic and social hardship should thus be of interest to all actuaries.

The research described in this thesis is directly relevant to the actuarial profession, in South Africa and internationally, because (1) it enlarges upon the current understanding, largely through quantitative approaches, of the potential for systemic risks arising in banks and, to a lesser extent, in insurers, and (2) it provides a qualitative methodology for identifying and mitigating potentially systemic risks in insurance. Actuaries working in banking, insurance and financial-sector regulation are directly impacted by this work. Finally, all actuaries concerned about the impacts of the profession on society should be interested in the findings and implications of this research.

Chapter 2

Investigating the Systemic Dominance of South Africa's Large Banks through a Network Simulation

A network of South African banks is simulated to explore the nature of the systemic risk that may be attributable to these banks. Three distinct channels of contagion following a bank failure are modelled: direct financial support by other banks, elevated provisions or fire-sale losses by these other banks, and losses to these banks attributable to deteriorating market sentiment related to perceptions of proximity to the initial failure. The validity of the overall approach appears to be confirmed against contemporaneous events and objective indicators of risk.

This study puts special emphasis on the contribution to systemic risk by the large banks. It does so by investigating whether self-similarity exists before and after the hypothetical removal of these banks from the market. Under assumptions of self-similarity, it is expected that, following the removal of the largest banks, the next in size would show similar patterns of domination. This does not appear to be the case, suggesting that the characteristic indication of systemic risk for the South African banking market may be attributable to the largest banks alone. This has implications for the attention that should be given to managing the potential for systemic risk from all banks in the system, but particularly the largest.

2.1 Introduction

Modern regulatory objectives are increasingly framed in terms of mitigating potential market failures (OECD 2010; S. Schwarcz 2019). Systemic risk is of special interest to regulators, for two reasons. First, it has the potential to cause widespread damage, not only to the entities that contribute to the risk but to markets and economies beyond this source. Second, regulated entities do not have a natural economic incentive to mitigate systemic risk which, typically, does not affect them as directly as idiosyncratic risk (S. Schwarcz 2008).

Regulators have come in for criticism from a number of sources for their approaches to mitigating systemic risk (Araten and Turner 2013; Casarano et al. 2017; Eling, Schmeiser, and Schmit 2007; Gatzert and Wesker 2012; Kim 2011; May and Arinaminpathy 2010; Moenninghoff, Ongena, and Wieandt 2015; Ötker-Robe et al. 2011; D. Schwarcz and S. Schwarcz 2014; Smaga 2014; Swarup 2012; Weber 2010, 2012). Few, however, would question the need for these regulators to understand better the nature of systemic risk and the factors that might contribute to elevated levels of systemic risk. This is particularly important for a banking regulator. The network of financial relationships between banks that allows entities to share their risks also provides the channels of contagion for widespread failure of the system. This research aims to contribute to this understanding by showing how insights into the nature of systemic risks in South Africa's banking market may be obtained by modelling these banks as a network.

The study applies three different channels of propagation to a stylised network of South Africa's banks using simplified balance sheet data over a 66-month period from April 2015 to September 2020 inclusive. First, when a bank fails as a result of a shock, other banks may be required to assist with financial support to avoid losses to the wider economy. Second, losses may be caused to other banks as a result of elevated provisions and market effects. Third, banks may suffer losses across their assets attributable to deteriorating market sentiment that is related to the perceived proximity of these banks to the shocked entity. The depressed sentiment typically triggers challenges in rolling forward short-term liabilities, leading to asset-value losses.

This assessment focuses particularly on the impacts of failure of the largest banks.

2.1.1 Research objectives

Walters et al. (2018) apply a network model to the simplified balance sheet data of South African banks to develop an indicator of systemic risk. They show that this indicator could be linked to concurrent subjective determinants of this risk level. This study builds on that work. It lengthens the period of investigation from two years to five and a half, including six months within the outbreak of the COVID-19 pandemic in South Africa, April to September 2020 inclusive, and explores the link between movements in the systemic risk indicator and contemporaneous events. It also assesses the respective contributions of individual banks to systemic risk.

Further, by hypothetically removing the largest banks from the market, it establishes how these banks impact the systemic risk indicator under the network model. The effects of this removal are assessed through the lens of self-similarity, by investigating whether indicators of systemic risk are broadly the same when the largest banks are removed as they are prior to this removal.

2.1.2 Key findings

The modelling confirms the appropriateness of the methodology, demonstrating a correlation between the calculated level of systemic risk and concurrent indicators of ambient risk such as the pandemic and its economic impacts.

Concerning individual banks, a number of findings are reported. Differences in the impacts of the failure of one bank on the respective probabilities of failure of each of the others show bank-specific points of weakness in the system. This finding has practical benefit, as these could be addressed through a number of mitigating actions by banking regulators. In particular, though it is widely expected that larger banks typically contribute more to systemic risk than their smaller counterparts (see Section 2.2), very little evidence of self-similarity is detected. Rather, incremental removal of the largest banks results in a marked decrease in levels of systemic risk, demonstrating unexpectedly high levels of resilience of the remaining banks but suggesting that the largest banks dominate the contribution to levels of systemic risk.

The next section reviews the literature and summarises the nature of the South African banking market. Thereafter, in Section 2.3, a description of the research methodology is provided. Section 2.4 presents and discusses the findings. Section 2.5 considers options for further research and concludes the study.

2.2 Review of the literature

Systemic risk may be described as the tendency for the actions of market participants to impair the financial stability of the entire marketplace, often with spillover effects into other markets and the economy as a whole. Despite the seriousness of systemic risk and its impacts, agreeing on a definition of systemic risk has not proved straightforward (Acharya, Pedersen, Philippon, and M. Richardson 2017; J. Cummins and Weiss 2014; ECB 2010; Eling and Pankoke 2016; SE Harrington 2009; Kessler 2014).

The levels and types of inter-connection appear to be key to the propensity to such risk. Connections help to absorb risk, but they also facilitate the propagation of risk through a system, potentially overwhelming it. This helps to explain why banking is typically regarded as a larger contributor to systemic risk than its counterparts like insurance, where peer connections play a much smaller role in industry operation (see Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; Billio et al. 2012; Bobtcheff, Chaney, and Gollier 2019; H. Chen, J. Cummins, et al. 2013; Eling and Pankoke 2016; Kaserer and C. Klein 2019; Van Lelyveld, Liedorp, and Kampman 2019).

The discussion that follows outlines the use of network models and their alternatives as a tool for detecting it. The concept of self-similarity is then considered and the literature review is completed with a brief description of South Africa's banking market.

2.2.1 Network models as a tool for understanding contagion

Over the last 20 years, considerable attention has been devoted to the subject of systemic risk, in particular the networks underpinning this risk. Early studies explored the impacts on the dynamics of contagion attributable to the structure of the system and its interconnectedness (Allen and Gale 2000; Freixas, Parigi, and Rochet 2000; Leitner 2005). This research identified the importance of capital buffers to mitigate the impacts of shock events, but also recognised that minimum capital requirements might not, on their own, be sufficient to protect against the risk of contagion in open markets (Brusco and Castiglionesi 2007).

Differences of substance emerged between these writers regarding the impacts on contagion of so-called 'complete markets', in which all entities were connected to all others (Allen and Gale 2000; Brusco and Castiglionesi 2007). This contributed to a range of empirical studies regarding the network dynamics in specific markets. These include examples for Germany (Upper and Worms 2004), Italy (Iori et al. 2008), Portugal (Cocco, Gomes, and Martins 2009), Denmark (Rørdam and Bech 2009), Austria (Boss et al. 2004), Japan (Inaoka et al. 2004), the United States (Saramäki et al. 2007), Mexico (Martinez-Jaramillo et al. 2015; Poledna et al. 2015), Angola (Borges, Ulica, and Gubareva 2020) and South Africa (Walters et al. 2018).

Considerable attention has been given to the effects of the network structure on the transmission of contagion between entities. This includes assessment of the impacts of network topology (Boss et al. 2004; Fricke and Lux 2015; In't Veld and Van Lelyveld 2014; Iori et al. 2008; Lenzu and Tedeschi 2012; Martinez-Jaramillo et al. 2015; Poledna et al. 2015; Roukny et al. 2013; T. Silva, Stancato de Souza, and Tabak 2016; Teteryatnikova 2014) and empirical investigations of the transmission mechanisms through networks (Georg and Brink 2011; Vallascas and Keasey 2012). A number of studies are concerned, through their assessment of network topology, with the concentration of system risk in large banks (Andries and Galasan 2020; Furceri and Mourougane 2009; Hüser 2016; Neveu 2018), the propagation of risk between entities of different sizes (Cocco, Gomes, and Martins 2009) and the nature of lending arrangements between such entities (Cocco, Gomes, and Martins 2009). This is supported by consideration of the regulatory implications of such concentration (Gauthier, Lehar, and Souissi 2012; Weber 2012) and the steps that some regulators have taken to mitigate the risk in large banks (Claessens 2015; X. Huang, Zhou, and Zhu 2012b).

Finally, several alternative contagion channels have been analysed through the lens of network modelling. These include market liquidity risk (Anand, Gai, and Marsili 2012; Gai, Haldane, and Kapadia 2010; Gai and Kapadia 2010; Krause and Giansante 2012; S. Lee 2013; May and Arinaminpathy 2010; Roukny et al. 2013; Upper 2011), international exposures (Garratt, Mahadeva, and Svirydzenka 2011) and overlapping portfolios (Caccioli, Shrestha, et al. 2014; Tasca, Mavrodiev, and Schweitzer 2014).

The research described in this article contributes to the body of research as a country-specific study based on a banking network model that considers three channels of contagion and focuses on the systemic risks associated with the largest banks in the market.

2.2.2 Self-similarity and the Pareto effect

In his famous rhetorical question concerning the length of Britain's coastline, Benoit Mandelbrot used the term 'self-similarity' to describe curves whose parts appear to be smaller versions of the whole (Mandelbrot 1967). The field of fractals was born. His observations in other domains, such as economics (Mandelbrot 1963), physics (Mandelbrot 1965) and the natural world (Mandelbrot 1983), indicated that such attributes are not limited to geographical features. Others built on Mandelbrot's pioneering work. Examples include the mathematical frameworks of John Hutchinson and Kenneth Falconer (Falconer 2014; Mandelbrot 1981). Progress has been made on identifying different forms of self-similarity (Aswathy and Mathew 2016) and on developing applications of self-similarity in financial markets (Campbell, Lo, and MacKinlay 1996). Wolpert and Macready (1998) propose a framework for utilising self-dissimilarity to evaluate complexity.

The power law, also known as the Pareto distribution, represents a narrow instance of self-similarity. The power law describes the characteristically exponential statistical distribution of wealth or asset-ownership empirically identified by Italian Vilfredo Pareto (Lopreato 1973; Schumpeter 1949). It has been frequently observed and applied since then in the fields of geology (Crovelli and Barton 1995) and other natural phenomena (Newman 2005), in communications network traffic (Leland et al. 1994; K. Park and Willinger 2000), and in the social sciences, such as the statistical distributions of income (Kämpke 2015; Randaldi 2023) and city sizes (Y. Chen 2014; Y. Chen and Jiang 2014).

Many of these studies explicitly link self-similarity to the power law because the power law leads to features of self-similarity. The Pareto distribution is scale invariant, which means that it may be applied to the income distributions of sub-sets of a population that itself displays the same features (Newberry and Savage 2019).

This study does not attempt to demonstrate or refute self-similarity or establish the existence of a Pareto effect in the patterns of systemic risk: with a small set of entities, this is not likely to be possible. However, it uses the principles of self-similarity to assess the impacts of large banks on measures of systemic risk by asking whether, in the hypothetical absence of these banks, similar patterns of systemic risk would exist.

2.2.3 The South African banking market

While the global economy may appear to be operating as a single entity, the distinct financial systems of countries vary in their attributes based largely on their historical development (Demirgüç-Kunt and RE Levine 1999; Levine 2002; Vitols 2001). In bank-based models, the primary role in mobilising and funding economic activity is played by banks. Examples of such models are Germany and Japan. In market-based models, such as the United Kingdom and United States, the capital markets play this role in the economy.

The debate regarding which of these models is better for a country, its development and its financial systems is long-standing and largely unresolved. Levine (2002) suggests that there is no empirical evidence supporting either view. Demirgüç-Kunt and RE Levine (1999) do not appear to express a view on one or the other, but point out the main factors contributing to the development of one more or the other. Bats and Houben (2017), using SRISK as their measure (see Section 1.3.3), find that systemic risk is more likely in bank-based models than in their market-based counterparts.

Whether South Africa's financial system is more bank-based, like Germany and Japan, or market-based, like the United Kingdom and United States, is subject to some debate. With its large stock exchange, South Africa might be defined as a market-based economy.[1] Under some assessments, however, the relatively low levels of activity in this market suggest a characterisation somewhat intermediate between the two extremes (Demirgüç-Kunt and RE Levine 1999).

South Africa's financial system is "large, well developed and sophisticated" (IMF 2022d, p 10) with total assets amounting to approximately three times gross domestic product, large by global standards (IMF 2022d; SARB 2021a). The recently modernised regulatory model is largely effective and the macroprudential framework has been significantly strengthened in the last few years (IMF 2022d,e). The banking sector is nevertheless highly concentrated (IMF 2022d), as confirmed by the data utilised for this study (see Section 2.3.5). Banks are also closely linked to non-bank entities in the South African and international financial markets, particularly the markets of South Africa's neighbours (IMF 2022d). International observers recommend continued strengthening of macroprudential powers (IMF 2022e) and enhanced independence and accountability of the banking regulator, the Prudential Authority (IMF 2022d).

Bank failures are not common but have occurred in the past few years. Such instances have been limited to smaller entities and resolution has been orderly. The curatorship of African Bank in 2014 was supported by a government-issued guarantee (SARB 2021a) and was accompanied by a sharp fall in return-on-equity metrics for small banks as a whole (SARB 2020a). VBS Mutual Bank, with some 30 000 customers, was placed in curatorship in 2018 and subsequently liquidated (FSB 2020; Prudential Authority 2019). Small retail entity Ubank was placed under curatorship in May 2022 (SARB 2022b) and subsequently merged with African Bank.[2]

2.3 Research methodology

The methodology utilised to undertake the study largely follows that of Walters et al. (2018). The text that follows provides a summary of the approach and more detailed descriptions of the parameters utilised and methodological variations employed. Supporting calculations are carried out in Matlab. The code used to carry out these calculations is provided in Appendix A4.

[1]Stock market capitalisation in 2013 amounted to over 2.8 times annual gross domestic product, more than twice the value of banking assets (IMF 2014a).

[2]Source: https://www.ubank.co.za/ubank-under-curatorship/, accessed 23 September 2023.

2.3.1 Summary of approach

South Africa's banking industry is modelled as a network of related entities. Each bank represents a node in this network. The channels through which contagion may traverse between the banks are the edges of the network.

The question asked through the modelling is how, in the event that a given bank experiences a shock sufficiently large for it to be rendered insolvent, this shock impacts its peers. These impacts may be felt in one of three ways, as described in Section 2.3.2. If any other banks are rendered insolvent by these impacts then, for each of them, similar knock-on effects on all other banks are modelled. This continues until the market reaches equilibrium under which no further bank failures occur.

This exercise is repeated by shocking in turn each of the banks, and observing the impacts. Then the entire process is repeated for each month of the period under consideration. The events leading to the initial shock are not considered relevant to the study and do not form part of the model.

The proportion of all banks that fail in a given month, averaged across 10 000 simulations of the model and across each of the shocks on all banks, is defined as the systemic default indicator. It provides a measure of the exposure of the banks in the network to the failure of one of their peers. The study is designed to assess whether the indicator varies over time and between networks, and whether these variations might be linked to contemporaneous events and a range of economic indicators.

The attributes of individual banks are also relevant to the study. These attributes may make it more likely, for that bank, either (1) for the shock to their assets to trigger the failure of other banks, contributing to systemic risk, or (2) to suffer failure in response to shocks to their peers, impacted by systemic risk.

2.3.2 Channels of contagion

The discussion that follows describes the channels through which contagion between banks may be transmitted. The subscript n is used to define values specific to a bank, but spare the reader the complexity of adding another subscript t to denote the time of the transaction, which is specific to each month of the period covered by the analysis. The asset and liquidity values and ratios attributable to each of the banks vary for each month of the study. The parameters utilised in the modelling, as described below, are constant, except for the proximity between banks, which may vary by bank pairs.

From a set of N banks an entity is selected, bank n, with assets of a_n and liquid capital of c_n, defined as equal to the available Common Equity Tier I (CET1) at the time.[3] The scenario starts when the bank is assumed to lose a proportion S of its assets as a result of an initial shock, where S is assumed to be the same for all banks. Other banks may

[3]This study considers CET1 as that part of the balance sheet providing capital support, because it can quickly be converted into cash in an emergency. In this respect this study follows the methodology of Walters et al. (2018), as well as Gai and Kapadia (2010), Wells (2004) and Mistrulli (2011).

be impacted if Sa_n, the shock experienced by the bank, is larger than the available CET1 capital, c_n. The shock is propagated to these banks in three different ways.

First, the other banks are required by the regulator to assist with capitalisation of the shocked entity to mitigate against the possibility of losses spreading to other economic entities or individuals. This may be referred to as a **credit shock**. In this instance, a proportion u, of the loss suffered by the shocked bank in excess of its liquid assets, $Sa_n - c_n$, is borne by the other banks in proportion to the size of their assets at the time.

Second, the other banks suffer balance sheet impacts attributable to elevated provisions or the forced sale of assets, a **liquidity shock**, where the reduction in asset values may impact assets of different terms to varying extents. The reduction in asset value a_i of bank i ($i \neq n$), attributable to the parameter under the liquidity shock, say η, is given by the expression, $a_i \exp(-\eta)$. This is applied separately to short-term assets, $a^{(s)}$, medium-term assets, $a^{(m)}$, and long-term assets, $a^{(l)}$, where $\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$ are used to represent the respective parameters applied to short-term, medium-term and long-term assets.

Third, the value of the assets of other banks fall under market-sentiment effects that depend on the proximity of these banks to the shocked bank and the scale of the assumed impact on these banks. This is referred to as a **proximity shock**. The extent of the adverse sentiment, α, is applied to reduce asset values in the same way as under the liquidity shock.

It is further modified, however, under the proximity model of contagion, by the shortest possible distance between the two nodes in the network, $d(i, n)$. This is an integer that is impacted by the network structure utilised and the overall probability of connections between pairs of banks (see Section 2.3.4). A small value of $d(i, n)$ is indicative of a perceived tendency for bank i to experience similar problems to those experienced by bank n, the shocked bank.

The resulting reduction in the asset value a_i of bank i, that is attributable to the parameter under the proximity shock α between two banks with shortest possible distance between them of $d(i, n)$, is given by the expression $a_i \exp(-\alpha/d(i, n))$. This channel is of particular interest to this research because it calls for recognition that the financial exposure of banks to one another may not be evenly distributed through the market.

In summary, a shock is applied to bank n and its impact on all other banks through one or more channels is observed. If any of these banks, say bank i ($i \neq n$) fails, then the impact on all remaining banks is also observed. The process is repeated until the system comes to rest. At that point, between one and N banks has failed, a proportion of the total of between $\frac{1}{N}$ and one inclusive. The systemic risk indicator is defined as the average proportion failed, for that month, over all simulations.

2.3.3 Testing the impacts of removing banks

The impact of removing banks is tested by re-running the entire simulation with specified banks removed. This process is started by removing the two banks with the largest assets. Size is determined by averaging over the entire period, though rankings by asset size for the largest banks are stable through the period of investigation. The entire simulation is run without any changes to the assumptions or the corresponding data that applies to the other banks. Next, three more banks are removed, those ranked third to fifth in the original ordering, and rerun the simulation, again without any changes to the data of the remaining banks that form part of the analysis.

The pattern of the systemic risk indicator over time and the contribution of individual banks to the failure of others are examined, comparing the respective results for two and five banks removed with those where all banks are included. Retention, after removing some of the banks, of the characteristic pattern of the systemic risk indicator that exists before removal would suggest the existence of self-similarity. A marked increase or decrease in the level of the systemic risk indicator, in contrast, would suggest that the banks removed from the market have either a very large or very small overall impact on systemic risk.

2.3.4 Network structures

In the discussion that follows, the six market structures utilised in this modelling, following the approach of Walters et al. (2018), are summarised. In all cases, the probabilities, p_{ij}, of connections between nodes i and j, $i \neq j$, are adjusted to produce a specified average for the network as a whole given by $\overline{p}$. The benefit of utilising an average probability of connection across the market is that it facilitates comparison across differences in structure.

1. **Erdös-Rényi**. Under this model, which is a random network, the probability of linkages between nodes in the network is constant across the market, following the seminal formulation by Erdös and Rényi (1959).

2. **Attraction to size**. Also referred to as 'Flight to quality', under this structure, the probability that a large bank triggers difficulty at a smaller bank is high, but the corresponding probability in the event of the initial failure of a small bank is low.

3. **Assortativeness**. Under this structure, banks of similar size have a higher probability of connection. Large banks are more likely to be connected to other large banks and small banks to small banks.

4. **Disassortativeness**. In this case, banks are assumed more likely to be connected to other banks that are of different size. Small banks are more likely to be connected to large banks and the other way around.

5. **Tiered Type I**. In the first of two core-peripheral network structures, it is assumed that the large banks are connected to one another with high probability, that small banks have a low probability of being connected to each other and that the corresponding probability of large and small banks being connected to one another lies between these extremes.

6. **Tiered Type II**. The second core-peripheral structure refines from the first the likelihood of contagion running from large to small banks. Under this model, the

probability of a small bank being connected to another small bank is low and the probability of a small bank being connected to a large bank is higher, but also relatively low. In contrast, large banks are connected to one another with high probability and the probability of a large bank connecting to a small bank is relatively high as well.

Charting the outputs for all network structures simultaneously facilitates an understanding of the impacts of the assumed network model on the indicator of systemic risk.

2.3.5 Data sources and preparation

The discussion that follows describes the data forming part of the study, summarises its attributes, and explains how CET1 data is interpolated and extrapolated where not available for every month across the study.

The South African Reserve Bank makes available the monthly balance sheets, called BA900s, of all regulated banks in standard format.[4] Checks of the data show it to be of reliable quality and consistency throughout the period of investigation. For the purposes of the study, the assets of the banks are split into short-, medium- and long-term categories. The approach used is consistent with the corresponding methodology of Walters et al. (2018).

Some 34 banks form part of the BA900 data at the beginning of the study period, and 36 at the end, though only 30 of these are part of the set throughout the period. Furthermore, banks could only be included in the study if CET1 data of a reliable quality was also available. Seven of the banks were discarded, leaving a total of 23 banks to form part of the study. The assets of these banks constituted between 98.0 percent and 98.7 percent of the total assets of all regulated banks across the period of investigation, regarded as sufficient for purposes of the study.

Table 1 in the Appendix shows the average assets of each bank over the period of investigation and the distribution of these assets across the short-, medium- and long-term categories utilised in this study. Four banks stand out as being particularly large, followed by one medium-to-large bank. The largest four banks comprise 83.4 percent of total assets, averaged over the period of investigation, and the largest five 91.5 percent. The largest banks typically have the lowest proportional allocation to short-term assets.

CET1 is not available in the BA900 balance sheets. Figures were obtained from publicly-available documents, most commonly the Pillar 3 reports of the banks, supported in some instances by annual reports or other documents. Care was taken to distinguish between CET1 and other Tier I measures of capital and between the capital figures of banks and the groups of which some of these banks formed a part, but errors of interpretation are possible.[5]

[4]Balance sheet data was downloaded from the web site of the South African Reserve Bank, at the address https://www.resbank.co.za/en/home/what-we-do/statistics/releases/banking-sector-information/banks-ba900-economic-returns, on 3 June, 5 August and 16 September 2020 and 13 January 2021.

[5]CET1 data was only accepted if it was published in rand terms. Measures expressed as a percentage

Banks typically publish CET1 figures quarterly but, in some instances, these figures are available only annually. Within these limitations, complete or nearly complete records were compiled for the 23 banks included. Banks excluded from the data were typically omitted on the basis of concerns regarding the credibility or completeness of data. Many of these excluded banks provided some data but with large parts of the study period empty.

CET1 data was collected as rand amounts but, since total assets were available on a monthly basis, and CET1 at best quarterly, interpolation for missing values was based on the equivalent percentage of assets. The interpolation of these proportions was carried out using a straight-line method where data for both of the extreme points for any given period was available. Where data needed to be extrapolated a weighted average of the nearest three ratios was utilised, where the weights used were respectively $\frac{1}{2}$, $\frac{1}{3}$ and $\frac{1}{6}$ for the nearest available ratio and the next two. The resulting series of monthly values for the CET1 ratio was converted back to rand amounts for the purposes of the computation in the model.[6]

Table 1 in the Appendix provides the mean CET1 ratio for each bank in the study, along with the corresponding sample standard deviation of the series of ratios for each bank. The larger banks in the set typically have lower CET1 ratios and lower variability of their ratios. The most noteworthy exceptions to this generalisation are the small foreign-owned banks, many of which also have relatively low CET1 ratios.

2.3.6 Assumption set

For the purposes of this study, a base case combining a set of parameters is defined that follows one of the scenarios considered by Walters et al. (2018), to enable comparison with those findings, though over a longer period of investigation. This was supported by an alternative combination of parameters to examine the impacts of these changes on the systemic risk indicator.

The combination of parameters forming the base case, *Assumption Set 1*, is as follows (the variables are defined in Sections 2.3.2 and 2.3.4 and the relevant contagion channel is indicated with each parameter):

1. **Initial shock** (S, pertinent to all channels of contagion), the proportion of the assets of the bank affected by the impacted shock that are assumed to have been lost in the event, 0.4;
2. **Loss shared** (u, credit shock), the proportion of the losses of the shocked bank assumed to be borne by the other banks in the network, 0.3;
3. **Market impacts on short-term assets** ($\eta^{(s)}$, liquidity shock), the scale of the reduction to the value of short-term assets of affected banks, 0.015;

of assets were not considered as they were regarded as insufficiently accurate and prone to errors of interpretation.

[6]Small differences exist in the methodology for filling missing CET1 ratios compared to the corresponding methodology used by Walters et al. (2018), but this does not have a material impact on the results, as indicated at the end of Section 2.4.1.

4. **Market impacts on medium-term assets** ($\eta^{(m)}$, liquidity shock), the reduction to the value of medium-term assets of affected banks, 0.015;

5. **Market impacts on long-term assets** ($\eta^{(l)}$, liquidity shock), the reduction to the value of long-term assets of affected banks, 0.03;

6. **Probability of inter-connectedness** ($\overline{p}$, proximity shock), the average probability that any pair of banks in the network is connected, 0.5; and

7. **Impacts attributable to proximity, the sentiment factor** (α, proximity shock), the reduction to the value of the assets of banks assumed to be affected by virtue of their proximity to the shocked bank, 0.015.

One particular combination of parameters is accorded more attention because it brings to light both differences between network structures and differences between individual banks. It is referred to henceforth as *Assumption Set 2*. Refer to the summary of assumptions in Table 2.1.

The parameters in question, which form part of the tests of the proximity shock, combine the same level of initial shock as in *Assumption Set 1* with a low probability of inter-connectedness and a high impact on the assets of affected banks attributable to proximity.[7] This set of parameters magnifies the links when they occur, by reducing the overall probability of links, and raising the effects of such links, by virtue of the high impact on affected banks.

	Assumption Set 1	Assumption Set 2
Initial shock, S	0.400	0.400
Loss shared, u	0.300	n/a
Market impacts, short, $\eta^{(s)}$	0.015	n/a
Market impacts, medium, $\eta^{(m)}$	0.015	n/a
Market impacts, long, $\eta^{(l)}$	0.030	n/a
Probability of inter-conectedness, $\overline{p}$	0.500	0.200
Sentiment factor, α	0.015	0.060

Table 2.1: Summary of parameters under the standard assumption sets
The parameters pertinent to credit shock and liquidity shock are not required for Assumption Set 2, which is limited to the proximity shock.

2.4 Modelling results and their implications

The most important results of the modelling are considered in this section, along with the implications of each of these results. The discussion starts by considering the overall consistency of findings with those of the first such study (Walters et al. 2018) and reflecting on the appropriateness of the methodology overall. Thereafter, it turns to the results under *Assumption Set 2* before considering the impacts of the largest banks on systemic risk across the market.

[7] The loss-shared parameter and the liquidity-shock parameters are not needed as the combination is designed to test the impacts of the proximity shock only. They are set to zero for purposes of the simulation.

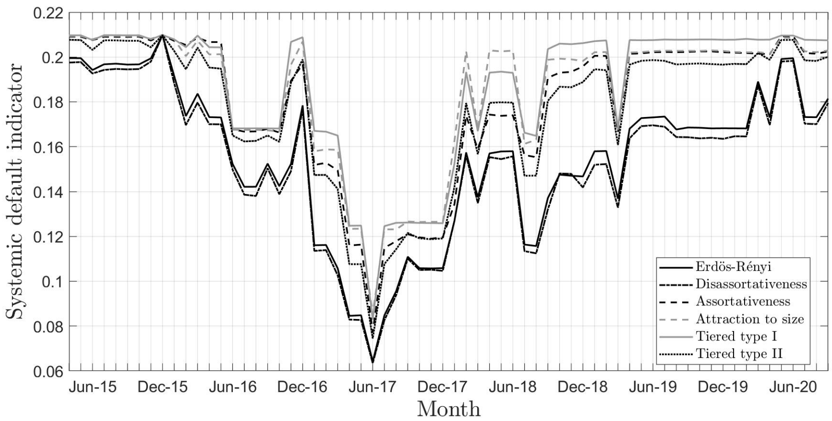


Figure 2.1: Average probability of default, *Assumption Set 1*: all channels
The chart shows the systemic default indicator, across the period of the investigation, for each market network model, on *Assumption Set 1*.

2.4.1 Appropriateness of methodology

Figure 2.1 shows the systemic default indicator, for all included banks, separately for each of the modelled market networks, over the entire assessed period, under *Assumption Set 1*. The results are consistent with those presented in Walters et al. (2018), with probabilities by market network displaying the same characteristic ranking.

The shape of the curves over the first two years of this output, which coincides with the corresponding period in Walters et al. (2018), is also similar, with the peaks in December 2015 and November 2016. The levels of systemic risk over the additional three and a half years are intuitively sound. Elevated levels for most of 2018 and 2019 are consistent with raised fears of a credit downgrade. The effects of the economic malaise associated with the COVID-19 pandemic are also evident, particularly in March 2020, when the hard lock-down was imposed, and in May and June that year, when the corresponding economic impacts were becoming evident.

Tests of correlation with several economic indicators also show intuitive results. The systemic risk indicators for all six networks are positively correlated with year-on-year changes in the money supply measure, M0, in most cases at a level of statistical significance below 0.1 percent. Inverse correlations with the prime overdraft rate and business cycle indicator are also detected with varying levels of significance across the network models. These correlations suggest that regulatory action in respect of systemic risk is possible on the basis of a range of economic indicators without necessarily carrying out the calculations described in this study.

Table 2.2 provides a breakdown of default probabilities for all combinations of shocked banks and impacted banks. Since the shocked bank is always impacted, the diagonal consists of a series of ones. Banks are ranked and labelled according to the average size of their assets across the period of investigation. See Table 1 in the Appendix for identification of the banks by these labels.

A notable feature of the table is that the other banks fail in response to a shock to an initial bank only when the shock is applied to one of the largest four banks by average assets. The corresponding month-by-month probabilities, across the 10 000 simulations, for any given shocked bank, are identical for all impacted banks (except on the diagonal). For this set of assumptions, only the four largest banks trigger defaults. Each instance of a shock of one of these large banks causes the failure of either all or none of the other banks.[8]

This feature of the model is considered below with other parameter combinations, noting at this point that, for other mixes of parameters, the probabilities of default across impacted banks are not the same for a given shocked bank. Consideration is also given, in Section 2.4.2 to the question of whether the apparent domination of the largest banks is a feature of the market that is repeated in similar patterns through the smaller banks, demonstrating characteristic self-similarity, or whether differences emerge with the removal of the largest banks.

This discussion closes with an illustration of a combination of parameters of special interest to this research, *Assumption Set 2*, because it illustrates the impacts of differences between market networks. Figure 2.2 depicts the systemic default indicator, over time and for each market network, under *Assumption Set 2*, that is at low probabilities of connection between banks but high shock impact or sentiment factor. The shape of the curves is characteristic of the overall levels of systemic risk illustrated in the other charts, but the differences attributable to market network models are greater than in other instances. The bank-by-bank detail is provided in Table 2 in the Appendix for the Erdös-Rényi network.

The results are largely intuitive. First, it makes sense that, if the probabilities of connections between pairs of banks are low but the effects of a connection high, then the assumed network model is likely to have a significant impact on levels of systemic risk.

Second, the Tiered Type I and Tiered Type II risk indicators are higher than for the other networks. This is because, under these networks, the larger banks, which contribute more to systemic risk levels, are more likely to be connected to one another, but small banks are also affected by their large counterparts.

Third, the corresponding levels of the systemic default indicator are lower in the case of the Assortativeness model and its Attraction-to-size alternative and both of these are lower than the random-connections approach that is intrinsic to the Erdös-Rényi network. This is because only the failures of the large banks tend to bring about the downfall of others and these are limited in number.

Finally, under this combination of variables, significant differences emerge in the bank-specific probabilities of default, except under the Erdös-Rényi network model, where these differences exist but are much smaller. Table 3 in the Appendix shows these probabilities under the Assortativeness market structure, illustrating a much lower dependence on the largest four banks than in other scenarios as well as more distinct differences between banks.

[8] This is not evident from Table 2.2, but is demonstrated in the month-by-month iterations of the results in this table.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18	Bank 19	Bank 20	Bank 21	Bank 22	Bank 23
Bank 1	1	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86	.86
Bank 2	.79	1	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79	.79
Bank 3	.64	.64	1	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64	.64
Bank 4	.40	.40	.40	1	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40	.40
Bank 5	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 6	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 7	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 8	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 9	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 10	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 11	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 12	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 13	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 14	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 15	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00
Bank 16	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00
Bank 17	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00
Bank 18	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00
Bank 19	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00
Bank 20	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00
Bank 21	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00
Bank 22	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00
Bank 23	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1

Table 2.2: Bank-specific average probabilities of default, random probability of connections

Note. This table shows, for each combination of shocked banks (down the left) and impacted banks (across the top) the probability of bank default across the study period on the Erdös-Rényi network structure and *Assumption Set 1*. Unity values through the diagonal are consistent with the shocked bank always being impacted.

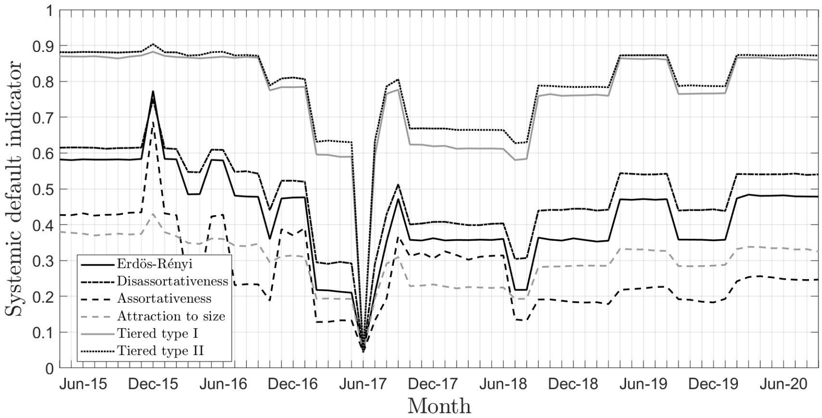


Figure 2.2: Average probability of default, *Assumption Set 2*: proximity channel only
The chart shows the systemic default indicator, for all market networks, considering only the proximity shock contagion mechanism, with a probability of links between banks at 0.2 and a shock impact factor of 0.06, *Assumption Set 2*.

In summary, three conclusions may be drawn based on the evidence presented thus far. First, the broad appropriateness of the methodology underpinning the model, which is the same as in Walters et al. (2018) is affirmed over a longer period of investigation, notwithstanding small differences in the data set utilised. Second, under *Assumption Set 1* but not *Assumption Set 2*, the systemic risk indicator appears to be determined solely by the largest four banks. Third, the results are sensitive to changes in the network models and assumed parameters.

2.4.2 Impacts of individual bank attributes and removal of large banks

The significance of the systemic impacts attributable to the largest banks, at least where all three channels of contagion are assumed to operate, raises questions of whether the South African market is consistently prone to such domination.

As described in Section 2.3.3, banks are ranked by asset size. The largest banks are incrementally removed from the market, repeating the modelling on *Assumption Set 1* and *Assumption Set 2* in each instance. In the first instance, the largest two banks are removed, and then the next three in addition. This synthetic set of scenarios asks whether the pattern of systemic default indicators is broadly the same when the largest banks are removed but are replaced by the new dominant banks, or whether significant differences are evident. The former result would suggest self-similarity of the market, while the latter would present evidence against self-similarity.

Figure 2.3 and Figure 2.4 show the impacts of removing respectively two and five banks from the data and running the model on *Assumption Set 1* which combines all three of the channels of contagion. These results illustrate marked decreases in the overall level of the systemic default indicator but show elements of variation over time consistent with the corresponding patterns observed over a number of different parameter combinations for the full set of banks.

The bank-by-bank detail is revealing. This is available in Table 4 and Table 5 in the

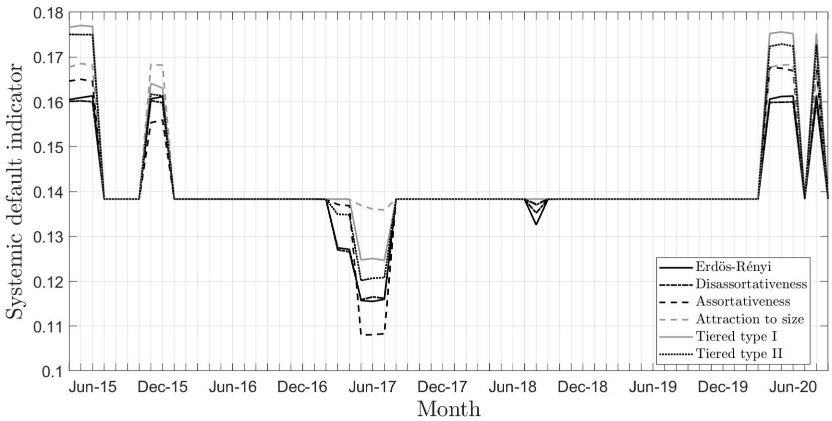


Figure 2.3: Average probability of default, *Assumption Set 1*, two banks removed
The chart shows the systemic default indicator, combining all channels of contagion on *Assumption Set 1*, but with the largest two banks removed from the data.

Appendix. The modelling shows that, with the removal of two banks, a small transfer of risk to the next largest bank occurs, but that risk remains concentrated in the largest banks. In this instance, the remaining two large banks contribute nearly all of the defaults to the systemic default indicator, with a small additional contribution by the bank now ranked third in the set. This changes when five banks are removed. The sixth-ranked bank (the largest when five are removed) never causes defaults of other banks and the eighth-ranked bank (third, when five have been removed) suffers a higher probability of default than its larger counterparts.

With five banks removed (see Table 6), the systemic default indicator under *Assumption Set 1* is not only substantially lower than under the full market, but it shows no evidence of the previously characteristic pattern of domination by the larger banks (see Table 2.2). The bank that is the largest in this hypothetical market is the sixth-ranked bank, which has a particularly low allocation to long-term assets and average CET1 levels among the highest in the market (see Table 1 in the Appendix). Its failure as initial bank under *Assumption Set 1* does not trigger insolvency in any of the other banks. The key insight to be drawn from this analysis concerns not primarily the sturdiness of the sixth-ranked bank, noteworthy as this may be, but the appearance of a much more resilient market in general.

In summary, while mild signs of self-similarity may be perceived when the largest two banks are removed, these signs completely disappear from the signature of the systemic default indicator and the bank-to-bank analysis when five banks are removed from the market. The absence of self-similarity strongly suggests that the largest banks contribute significantly to systemic risk, dominating the risk profile of the market.

A number of provisos need to be expressed. Some of these are concerned with generic limitations of the modelling. For example, simplified balance sheet structures are utilised, no information is known or considered regarding interbank exposures and parameters are applied to the data in inflexible ways that do not take into account of contemporaneous factors.

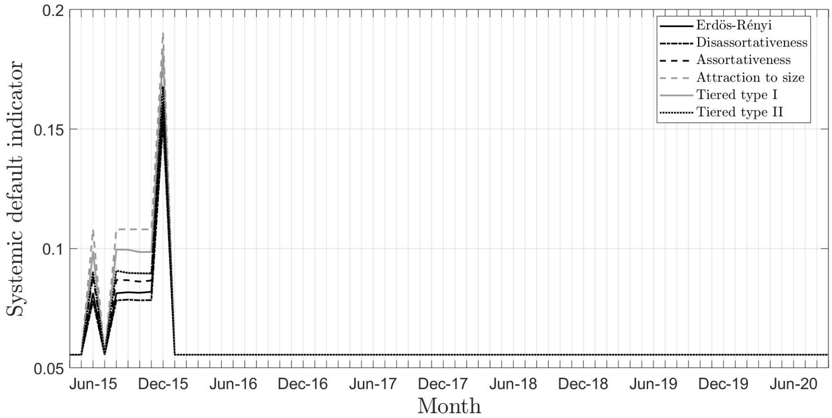


Figure 2.4: Average probability of default, *Assumption Set 1*, five banks removed
The chart shows the systemic default indicator, combining all channels of contagion on *Assumption Set 1*, but with the largest five banks removed from the data.

Perhaps the most significant limitation, however, is the assumption that the same proportional reduction of a bank's asset value is assumed at the time of the initial shock regardless of the size of the bank. When the bank is large, a higher value of assets need to be covered by other banks. That this is worsened by the generally lower CET1 levels of the large banks does not dilute the possibility for the equal-proportion approach to the initial shock to be unrealistic. Further research may be helpful in this regard, as noted in Section 2.5.

Furthermore, the model assumes that all three channels of contagion operate under a certain set of assumptions. The change in the mix of the respective contributions to the systemic risk by the banks is not as straightforward under different sets of assumptions. Figure 2.5 shows the corresponding signature of the systemic default indicator under *Assumption Set 2*, which considers proximity as the only channel of contagion and assumes low probability of inter-connectedness and high impacts where banks are connected. For long parts of the period under investigation, the systemic default indicator is low, but it exhibits periods of high systemic risk. The corresponding tables of bank-to-bank risks (see Table 6 and 7 in the Appendix) show different mixes of the contribution to systemic risk by different banks.

This study is characterised by considerable complexity of combinations. It is not possible to draw decisive conclusions regarding the respective contributions to systemic risk of the individual banks and it would be unwise to do so. This part of the report nevertheless shows detectable differences in the respective contributions to systemic risk of the banks. These differences are attributable to a number of different factors. One of these is size. It appears that the largest four or five banks contribute substantially to systemic risk and that the profile of risk would be materially different if they were not part of the market.

These findings suggest, in sum, that ongoing research may prove beneficial and that a nuanced bank-specific regulatory approach to the potential for systemic risk is likely to be appropriate. The South African Reserve Bank has taken steps in this regard by identifying

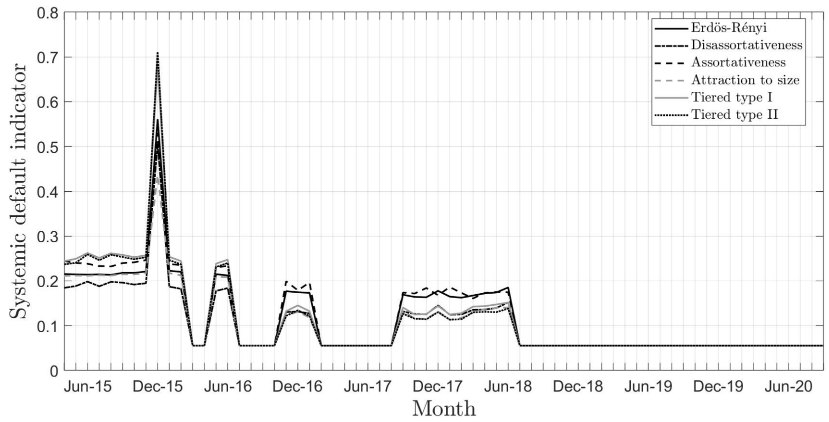


Figure 2.5: Average probability of default, *Assumption Set 2*, five banks removed
The chart shows the systemic default indicator, for *Assumption Set 2*, considering only the proximity shock channel of contagion, but with the largest five banks removed from the data.

the six largest banks as systemically risky (SARB 2019), but details of the regulatory submissions required of these banks or the potential regulatory actions against them are not available.

2.5 Conclusion

This study describes a network model of the South African banking system that simulates the effect of a bank failure on the remainder of the banking market, using the financial attributes of each bank at the time of the simulation. The output of the model provides a measure of the level of systemic risk at each month for the duration of the study. The systemic risk indicator shows patterns over time that are intuitively logical and appropriately correlated with economic metrics. The most significant finding of this research, however, is the extent of the change to the systemic risk indicator when the five largest banks are hypothetically removed from the market. This indicates that features of self-similarity with respect to the bank-specific contributions to systemic risk do not exist. It suggests in turn that the largest banks dominate the contribution to systemic risk, confirming the special attention placed by the regulator on these banks.

Several proposals for further research follow. First, it is regarded as unrealistic simply to remove banks from a market without considering the impacts of such a removal on the rest of the banks. Those remaining banks would surely change in response to the disappearance of their peers, perhaps absorbing a large proportion of the additional available customers. If the assets and liabilities of the largest banks were transferred to their surviving competitors, then these newly dominant banks might well exert a level of systemic influence similar to their erstwhile counterparts. Consideration could be given to the impacts of the hypothetical responses of various kinds.

Second, further research could consider alternative tests of the impacts of individual banks on levels of systemic risk (see Section 2.4.2). One way to test whether the impacts are based simply on size rather than on the characteristic attributes of each bank is to remove the size effect by rendering the total assets of the banks all the same. This begs the question of whether other attributes of the banks, for example the CET1 ratios, should reasonably be altered in response to the changes in asset size, but it could at least shed light on the factors that contribute most strongly to the apparent domination by the large banks.

Third, research could scrutinise more closely at bank level why the medium-sized banks do not appear to contribute significantly to systemic risk. If they are more conservatively managed, then it is not clear that this would continue were they to attain positions of market dominance. Perhaps their mix of assets, supporting higher minimum liquidity requirements, reduces their contribution to systemic risk. This is not necessarily attributable to conservatism: it could reflect the mix of liabilities on books. This may, in turn, be partly attributable to the relative size of these banks in the market and might change were they to grow, most likely diversifying their mix of customers in the process. A more detailed study of the attributes of these banks that reduce their contribution to systemic risk would be helpful, particularly against the corresponding attributes of the larger banks.

Fourth, sensitivity of results to changes in the network model, the assumed channels of contagion and the modelling parameters could fruitfully show the robustness of these results to different circumstances. The differences between the respective results under *Assumption Set 1* and *Assumption Set 2* suggest that understanding the conditions under which self-similarity may exist could be beneficial.

Finally, a cost-benefit analysis of the options available to the regulatory authorities to reduce the systemic risks of the largest banks would help to identify the trade-offs involved in evaluating these options.

Regulating a banking industry is no easy task. It calls for constant vigilance of the economic environment and of the activities of these banks and the propensity for either of these to contribute to a systemic risk event. It is hoped that this research contributes to an improved understanding of this propensity and to more effective regulation.

Chapter 3

A Network Simulation of the South African Banking Market: Evidence for Tipping Points in Systemic Risk Levels

This chapter reports on the findings of a study of the potential for systemic risk based on a model of South African banks as a network of connected entities. The study seeks evidence of tipping points in the system, that is small changes to any of the variables that trigger transformation of the whole system, significantly increasing levels of instability and potentially leading to its collapse.

The model, utilising a simulation approach and actual monthly balance sheet data over a 66-month period, considers the impacts on the peers of a bank of a shock to the position of that bank sufficient to trigger its default. It assumes, as base case, the Erdös-Rényi network, with randomly determined links between entities within the framework of a stated overall probability of such links. Three different channels of contagion are considered. Tests of sensitivity to changes in each of the variables that serve as inputs to the model are undertaken. Tests of of the key result to an alternative representation of the banking network, the so-called attraction-to-size model, are also carried out.

The study provides evidence that South Africa's banking system indeed exhibits tipping points in response to changes in the values of two of the variables. Such evidence exists for both of the alternative networks investigated, suggesting that it may represent a characteristic of the market under an array of networks.

This has significant implications for the regulatory process because changes to the conditions governing the relationships between banks appear to have a substantial impact on the stability of the system overall. It suggests that improving the understanding of the nature and state of the network could prove helpful to assess interventions to improve the stability of the banking sector.

3.1 Introduction

Financial-sector regulators typically express their responsibility in terms of objectives framed around mitigating market failures (OECD 2010; S. Schwarcz 2019). One such failure is systemic risk. Difficult to define (Acharya, Pedersen, Philippon, and M. Richardson 2017; J. Cummins and Weiss 2014; ECB 2010; Eling and Pankoke 2016; SE Harrington 2009; Kessler 2014), systemic risk may be described as the tendency for the actions of one or more participants in a marketplace to impair the financial stability of the marketplace as a whole.

Reducing systemic risk and its impacts is a critical goal of financial regulation because of the potentially devastating potential of a system-wide failure (Brunnermeier et al. 2009), aptly demonstrated by the 2008-09 crisis and its impacts. Another reason that regulators place a high priority on assessing and managing systemic risk is that regulated entities do not have a natural economic incentive to mitigate a risk whose impacts typically affect others, at least in aggregate, more than they affect the entity itself (Grochulski and Morrison 2014; S. Schwarcz 2008). Regulators have been criticised from a number of sources for their approaches to mitigating systemic risk (Araten and Turner 2013; Casarano et al. 2017; Eling, Schmeiser, and Schmit 2007; Gatzert and Wesker 2012; Kim 2011; May and Arinaminpathy 2010; Moenninghoff, Ongena, and Wieandt 2015; Ötker-Robe et al. 2011; D. Schwarcz and S. Schwarcz 2014; Smaga 2014; Swarup 2012; Weber 2010, 2012). This research aims to assist regulators with an improved understanding of the nature of systemic risk. It does so by providing insights into such risks in South Africa's banking market by modelling these banks as a network.

This study, building on the work of Walters et al. (2018), applies three channels of propagation to a stylised network of South Africa's banks. Each simulation starts with the failure of a bank and then considers these three channels in turn. First, other banks may be called on to assist with direct financial support to avoid further contagion. Second, the other banks may suffer losses attributable to elevated provisions and market effects. Third, losses may be incurred by other banks as a result of deteriorating market sentiment resulting in increasing funding costs and ill-timed sale of assets. The other banks may suffer bankruptcy as a result of one or more of these effects, in turn triggering further adverse impacts and potentially further defaults as part of looming systemic failure.

The study is empirical, utilising balance sheet data for the banks over the period April 2015 to September 2020 and testing the impacts of these three channels of contagion on the robustness of the system as a whole. In particular, careful attention is paid to the impacts of variations to the parameters underlying the operation of these channels, focusing on tipping points in these parameters. Evidence of significant tipping points is presented. This is important because it alerts policymakers and regulators to the possibility of system weaknesses and provides tools to monitor the possibility for these weaknesses to contribute to the potential for systemic failure.

The term 'tipping point' and several variations such as 'phase transition', 'regime shifts' or 'critical transition' are used in a number of sciences and can refer to different features of the systems under consideration. This chapter considers the ways in which these phrases are used and defines the use of the term in this study (Section 3.2.1). It then turns to a description of the literature on banking networks (Section 3.2.2) and the nature of the South African banking market (Section 3.2.3). Section 3.3 describes the methodology underpinning this model and sets out the parameters utilised. This is followed by Section 3.4, which presents and discusses the results. Section 3.5 concludes, setting out thoughts for further research.

3.2 Review of literature

The discussion that follows starts by summarising some of the research in tipping points and related fields. It then outlines studies of systemic risk in financial networks and the application of tipping points to these networks, clarifying the contribution of this study to the literature. It closes by describing the South African banking sector in broad terms.

3.2.1 Tipping points

The term 'tipping point' and several variations are used, somewhat loosely at times, to describe widespread systemic response to a small change in an input variable. The discussion that follows considers some of the uses of this term and its alternatives, and describes their applications to a range of sciences. This prepares the way for clarification of its meaning in the study described in this chapter.

The concept of the tipping point in the scientific and social literature may be traced back to nineteenth-century studies of chemistry (Hoadley 1884) and mathematics (Poincaré 1885). Bifurcation, a concept introduced by Poincaré (1885), occurs when a small change to a parameter results in a significant change in the structure or state of an entire system. Bifurcation theory is extensively used in mathematics, applied mathematics and physics (Courtney et al. 1995; JD Crawford 1991; Founargiotakis et al. 1997; Kuznetsov 1997; Peters and Jaffé 1994) and has a wide range of applications, for example, in engineering (Troger and Steindl 1991) and medical science (Karagueuziah, Stepanyan, and Mandel 2013; P. Verma et al. 2020).

A number of other expressions are used, however, to describe the point at which a small change in input assumptions causes a system-wide impact. The designation 'phase transition' is frequently used by researchers of the physical sciences (Bruce and Cowley 1981; Landau 1936; Solé 2011; Stinchcombe 1988). In their study of power systems, Ren and Watts (2015) prefer the label 'critical transition'. Different terms are also used in the social and ecological sciences. Holling (1973), for example, focuses on the resilience of the system rather than its tendency to experience transitions. This lays a foundation for work on systemic shifts by providing examples of possible systemic behaviours. Schelling (1971) introduces the terms 'tipping' and 'neighbourhood tipping' to his widely cited analysis of social segregation.

Scientists of climate systems refer to 'regime shifts' or 'abrupt shifts' (Beaugrand 2004;

Drijfhout et al. 2015; Rocha, Peterson, and R. Biggs 2015; Rocha, Peterson, Bodin, et al. 2018), 'self-reinforcing feedbacks' (W. Steffen et al. 2018), 'critical transitions' (Scheffer, Bascompte, et al. 2009; Scheffer, Carpenter, et al. 2012), 'climate transitions' (Schneider, Kaul, and Pressel 2019), and 'tipping points' or close variations of these terms (Ashwin et al. 2012; Bentley et al. 2014; Lenton 2013; Lenton, Held, et al. 2008; Lenton, Rockstrom, et al. 2019). While 'tipping point' has grown rapidly in usage in the last fifteen years, perhaps stimulated by the popularity of the book by the same name (Gladwell 2000), 'regime shift', 'critical transition' and others, such as 'alternative stable state' and 'punctuated equilibrium' have continued in use (Milkoreit et al. 2018).

More important than the chosen terminology is its meaning. Ashwin et al. (2012) take care to distinguish between three different classes of tipping point, which they refer to as bifurcation, noise-induced tipping and rate-dependent tipping, citing the similarly careful terminology of others (Thompson and Sieber 2011; Wieczorek, Ashwim, et al. 2011). These authors also describe and illustrate some of the variations available within these classes, echoing the efforts of a number of others across the sciences to model and describe the complex effects of bifurcations and tipping points of various kinds (Scheffer, Carpenter, et al. 2012; Spaiser et al. 2018; W. Steffen et al. 2018; P. Verma et al. 2020; Wieczorek, Krauskopf, et al. 2005). The pursuit of the research described in this article is somewhat simpler. In this case, a point is reached at which a small incremental change to a variable causes a substantial change to the system in the form of widespread and irreversible insolvency of banks.

In summary, in all sciences, accurate use of terminology matters. Milkoreit et al. (2018) raise concerns that the term tipping point in social-ecological systems like financial markets does not have the same meaning as the same phrase in climate science, let alone the precisely defined bifurcation in physics. They go on to suggest a definition of tipping point that brings together the themes identified in their assessment of a range of papers as follows (Milkoreit et al. 2018, p. 11):

> ... a tipping point is a threshold at which small quantitative changes in the system trigger a non-linear change process that is driven by system-internal feedback mechanisms and inevitably leads to a qualitatively different state of the system, which is often irreversible.

This is the meaning attributed to the term 'tipping point' in this study. The changes sought are internal to the system. A small increase to the tested variable leads to a large increase in the proportion of failed banks. The impacts of the change on the characteristics of the system are significant, completely out of proportion to the corresponding change in the tested variable. These impacts are also irreversible: the model assumes that a failed bank does not recover and concludes its iteration when all banks reach their respective equilibrium states, solvent or failed.

The approach used in this study may be criticised for its simplicity. It could be argued that testing for changes to one variable at a time is unrealistic and that a multivariate approach should be used, as in S. Chen and Desiderio (2022), for example. The preference for the more straightforward investigation is deliberate. The study steers clear of a mathematical definition involving multiple variables because of the complexity that such a method would introduce, and noted in Section 3.5 as a possibility for further research.

3.2.2 Banking networks

Systemic risk events in financial markets, it is broadly agreed, are characterised by widespread adverse impacts on the financial sector, market failure of some form, reduced market confidence leading to a loss of economic value, significant reductions to the value of financial entities and typically a spillover in the wider economy (Brunnermeier et al. 2009; Carvajal et al. 2009; IMF 2013, 2014b, 2018). For this reason, systemic risk is of special concern to financial-sector regulators.

While an unambiguous classification of the sources of systemic risk appears to be elusive, a wide range of contributing factors may be identified (Allen and Gu 2018; De Bandt and Hartmann 2000; SE Harrington 2009; Nier et al. 2007). Levels of inter-connection, however, are key to a propensity to systemic risk. This is because connections facilitate the propagation of risk through a system. This helps to explain why banking is generally regarded as a greater contributor to systemic risk than its counterparts in other financial markets, like insurance, where peer connections are less significant to the operation of the industry (see Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; Billio et al. 2012; Bobtcheff, Chaney, and Gollier 2019; H. Chen, J. Cummins, et al. 2013; Eling and Pankoke 2016; Kaserer and C. Klein 2019; Van Lelyveld, Liedorp, and Kampman 2019).

A number of the early studies of financial networks explored the impacts of the structure of the system and its inter-connectedness (Allen and Gale 2000; Freixas, Parigi, and Rochet 2000). Consideration was given to the policymaker problem that the linkages between banks that facilitate contagion are also the channels through which the potential for such contagion could most effectively be dissipated (Brusco and Castiglionesi 2007; Leitner 2005). It was recognised also that minimum capital requirements might, alone, not be sufficient to protect against the risk of contagion in the context of open markets (Brusco and Castiglionesi 2007).

Substantial attention was placed on the impacts of the network structure on the likelihood of contagion and different views were put forward regarding the propagation properties of so-called ‘complete markets’, in which all entities were connected to all others (Allen and Gale 2000; Brusco and Castiglionesi 2007). Studies of network structure were further extended to consideration of the impacts of network topology (Boss et al. 2004; Fricke and Lux 2015; In’t Veld and Van Lelyveld 2014; Iori et al. 2008; Lenzu and Tedeschi 2012; Martinez-Jaramillo et al. 2015; Poledna et al. 2015; Roukny et al. 2013; T. Silva, Stancato de Souza, and Tabak 2016; Teteryatnikova 2014) and to empirical approaches to understanding the dynamics of transmission (Georg and Brink 2011; X. Huang, Zhou, and Zhu 2012a; Vallascas and Keasey 2012).

A wide range of contagion channels has also been considered. These include overlapping portfolios (Caccioli, Shrestha, et al. 2014; Tasca, Mavrodiev, and Schweitzer 2014), market liquidity risk (Anand, Gai, and Marsili 2012; Gai, Haldane, and Kapadia 2010; Gai and Kapadia 2010; Krause and Giansante 2012; S. Lee 2013; May and Arinaminpathy 2010; Roukny et al. 2013; Upper 2011), and exposure to international markets (Garratt, Mahadeva, and Svirydzenka 2011).

Empirical approaches have been utilised to explore the network dynamics in specific markets (Borges, Ulica, and Gubareva 2020; Boss et al. 2004; Cocco, Gomes, and Martins 2009; Inaoka et al. 2004; Iori et al. 2008; Martinez-Jaramillo et al. 2015; Poledna et al. 2015; Rørdam and Bech 2009; Saramäki et al. 2007; Upper and Worms 2004; Walters et al. 2018), building on the corresponding methods aiming to identifying the attributes of networks, particularly in the context of limited data (Bargigli et al. 2020; S. Chen and Desiderio 2022; Cimini et al. 2015; Di Gangi, Lillo, and Pirino 2018; Musmeci et al. 2013). None of these papers appear to explore the existence of tipping points in their respective country studies but recent work (Guleva 2020; Kostanjcar et al. 2016) describe how such tipping points may occur in banking networks and Gai, Haldane, and Kapadia (2010) demonstrate the existence of tipping points in financial networks. Other researchers have considered evidence for the existence of tipping points in economic networks (Battiston et al. 2016; Gai, Haldane, and Kapadia 2010; Georg 2013; Hüser 2016; May and Arinaminpathy 2010).[1] Utilizing a network simulation, Georg (2013) demonstrates the existence of a tipping point in changes to his connectedness parameter, showing how the system quickly switches from stability to instability as this tipping point is passed.

This study contributes to the literature by undertaking a country-specific empirical study, based on a banking-network model, that shows evidence of tipping points in the underlying assumptions. The study shows, where the existence of a tipping point in any parameter is claimed, that, conditional on the prior failure of one bank, (1) changes to the stability of the system for values of that parameter up to the tipping point are small, (2) at the tipping point, system stability is irreversibly impacted by the failure of one bank, and (3) the same system instability applies for all values of the parameter beyond the tipping point. This process follows the advice of Neveu (2018) to identify such tipping points in the interests of regulatory intervention to manage systemic risk. Tests of sensitivity to changes in parameters and to an alternative network framework are described.

3.2.3 South African banking market

South Africa's financial sector is large and sophisticated (IMF 2008, 2022d), with total assets in 2020 amounting to approximately three times annual gross domestic product (GDP), larger than the corresponding multiple in most emerging markets (IMF 2022d). Assets in the banking sector exceed 130 percent of GDP.

The South African financial sector nevertheless defies a straightforward categorisation, in terms of its development or current state, as either market-based, like the United States and United Kingdom, or bank-based, like Germany, France and Japan (Detzer 2014; Sternfors et al. 2014; Vitols 2001). With its large stock exchange, South Africa's

[1] Lessons from the examination of financial networks have also been applied to climate policy (Stolbova, Monasterolo, and Battiston 2018).

financial system might be described as market-based.[2] Some, however, on the basis of low levels of activity in the stock market, have described the South African financial sector as a hybrid market-based and bank-based system (Demirgüç-Kunt and RE Levine 1999).

Regulation of the banking sector is generally sound (IMF 2022d). Its macro-prudential framework has improved over the last few years (IMF 2022e). Objectives of financial stability and minimum liquidity levels were met through the economic turmoil associated with the COVID-19 pandemic (IMF 2022a). Bank profits remained positive through the pandemic and the sector is soundly capitalised overall, though with significant variation across entities (IMF 2022a). Recent changes to the regulatory model, introducing a twin focus on prudential regulation and market conduct oversight, aim to improve the effectiveness of the framework (IMF 2022a).

International commentators nevertheless note several systemic weaknesses and recommend continued efforts to strengthen the regulatory framework. The IMF observes improvements to competitive dynamics, with several digital banks entering the market, but has repeatedly noted high levels of concentration in the banking industry and considerable connectedness with other parts of the financial sector (IMF 2014a, 2022d). These concerns parallel those expressed by others regarding high concentration and the corresponding evidence for weak competition in the South African banking market (Mlambo and Ncube 2011; Moyo 2018; Simatele 2015; Simbanegavia, Greenberg, and Gwatidzo 2015). The IMF calls for strengthened macro-prudential policy (IMF 2022a) and notes limitations in central bank access to appropriate data which constrains the calibration of macro-prudential tools (IMF 2022e). It also recommends improvements to regulatory independence and accountability and a clearer distinction between the micro-prudential mandate of the regulator, the Prudential Authority, and the corresponding responsibility of its parent body, the South African Reserve Bank, to monitor and mitigate systemic risk (IMF 2022d).

The South African banking market, and wider financial-services sector, notwithstanding several unique attributes, has characteristics that make it an appropriate source of insights for application elsewhere. Banks in South Africa are broadly well managed, solvent on the basis of sophisticated measures and carefully regulated. They are nevertheless prone to systemic risk, some of which may be attributed to the network of relationships between them, which makes them similar to their counterparts in many other countries, and some of which are attributable to weaknesses in their developing-country context.

The research described in this study aims to assist the South African regulatory authorities by identifying attributes of the systemic risk framework that are specific to the local environment. On the basis that the financial sector in this country bears some resemblance to the corresponding markets in other countries, particularly in larger developing economies, these lessons may be applied also to addressing risks in these countries.

The key features of the banking data utilised for this study are described in Section 3.3.2.

[2]Stock market capitalisation in 2013 amounted to over 2.8 times annual gross domestic product and more than twice the value of banking assets (IMF 2014a).

3.3 Research methodology

The methodology employed follows the corresponding methodology of Walters et al. (2018). A summary of approach follows, along with a description of the parameters utilised.

3.3.1 Modelling approach in summary

The banking industry of South Africa is represented as a network of related entities. In the language of the network, each bank is a node and the channels of transmission are the edges of the network. As far as possible, the entire banking market is included in the study. Banks excluded are those for which adequate data is not available (see Section 3.3.2).

A bank is chosen, bank n, that has assets of a_n and liquid capital of c_n, defined by the Common Equity Tier I (CET1) capital. CET1 is utilised for purposes of solvency testing, because it is quickly convertible into cash in an emergency. This is consistent with Gai and Kapadia (2010), Mistrulli (2011), Walters et al. (2018) and Wells (2004). Bank n is assumed to lose a proportion, S_n, of its assets from an initial shock, the cause of which is not considered. Since the same proportion is used for all banks, the suffix may be discarded, leaving the assumed proportion as S and the size of the affected assets as Sa_n in the case of bank n. Other banks may be impacted to the extent that this shock, Sa_n, exceeds the CET1, c_n, of that bank. The shock is propagated to the other banks in three different ways, henceforth referred to as: **credit shock**, **liquidity shock** and **proximity shock**. These are described more fully in the paragraphs that follow.

Under the **credit shock** mechanism of transmission, the other banks are required to assist with capitalisation of the shocked entity. A fraction, u, of the loss suffered by the shocked bank in excess of its liquid assets, $Sa_n - c_n$, is contributed by the other banks in proportion to the size of their assets, in turn impacting their solvency position. The total shock borne by the other banks is thus dependent on the size of the shocked entity, its solvency position, the quantum of the initial shock and the fraction of the loss transferred to these banks.

Where propagation occurs through a **liquidity shock**, the other banks suffer impacts resulting from elevated provisions or the forced sale of assets. These impacts are assumed to be in proportion not to the size of the shocked bank or the losses that it experiences but to the assets of the impacted bank. Different assumptions may be utilised regarding the respective impacts on the short-term, medium-term and long-term assets of the impacted banks. The reduction to the asset value of bank i, a_i, that is attributable to the parameter η under the liquidity shock is given by the expression, $a_i exp(-\eta)$. This is applied separately to the short-term assets, $a_i^{(s)}$, medium-term assets, $a_i^{(m)}$, and long-term assets, $a_i^{(l)}$, of bank i, where $\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$ represent the parameters respectively applied to short-term, medium-term and long-term assets.

Under the **proximity shock**, the asset values of other banks reduce under the assumption by market participants that their closeness to the shocked bank renders them vulnerable to difficulty. The extent of the reduction in asset values depends on two parameters, the proximity of these banks to the shocked bank and the scale of the assumed impact on these banks. The extent of the adverse sentiment, α, is applied to modify asset values downwards. This is similar to the liquidity shock. Under the proximity shock, however, the quantum of the shock is further modified by the shortest possible distance between two nodes in the network, $d_{i,n}$. This is an integer, taking the value of one or two, that is impacted by the network structure utilised and the overall probability of connections between pairs of banks, $\overline{p}$. The resulting reduction in the asset value, a_i, of bank i, between this bank and the shocked bank, bank n, with shortest possible distance between them of $d_{i,n}$, is given by the expression $a_i \exp\left(-\alpha/d_{i,n}\right)$. The lower the value of this distance, $d_{i,n}$, and greater the reduction in the asset value.

If the losses suffered by bank i from all channels of contagion included in the scenario exceed the available liquid capital of that bank, c_i, then that bank is assumed to have failed. The process of assessing the impact of this failure on all other banks proceeds in the same way as if that bank had failed as a result of the initial shock. The analysis continues until an equilibrium position is reached in which no further failures occur. The total number of failed banks, including the bank subject to the initial shock, is determined and computed as a proportion of all banks. This is the systemic default indicator. The process is repeated by shocking, for that month, each of the banks in turn. This is repeated for 10 000 simulations.[3] Then it is iterated across the period of investigation. The systemic default indicator is defined as the unweighted proportion of all banks rendered insolvent in a given month. This is averaged across all simulations. This indicator, which varies over time, provides a measure of the exposure of the banks in the network to failure of their peers.

In the interest of simplicity all modelling is initially undertaken utilising the Erdös-Rényi network (Erdös and Rényi 1959), with randomly determined links between entities within the framework of a stated overall probability of such links, $\overline{p}$. This method serves as the base case for the study. Where evidence exists of tipping points in the assumptions, notably under the liquidity shock where the effects of the tipping point are strongest, the modelling is repeated under an alternative assumption that the larger the bank, the more likely it is to be connected to other banks, following the approaches of Bargigli et al. (2020) and Di Gangi, Lillo, and Pirino (2018). This is undertaken to test the sensitivity of results to assumptions regarding the structure of the banking network. It also addresses concerns regarding the Erdös-Rényi network that the probability of a connection between banks is fixed: under the attraction to size model, this probability depends on the size of the shocked bank relative to its peers, which varies over time. Further network models could be considered, as set out in proposals for further research in Section 3.5, but these two alternatives demonstrate the robustness of results to widely differing network structures. Variations to the model assumptions, set out in Section 3.3.3 could also form part of additional research, also noted in Section 3.5.

The model and its assumptions are nevertheless stylised, simplified representations of

[3]Simulations are only required for all scenarios involving the proximity shock because results for credit shocks and liquidity shocks are independent of the probability of connections between pairs of banks, $\overline{p}$.

a more complex reality. It may be unrealistic to assume that banks are required to share in the capitalisation of shocked entities to the point of putting their own solvency at risk, that the central bank would not assist more directly or that bank shareholders, particularly international shareholders, would not respond more directly. These limitations are acknowledged in the face of the overall intention to determine the possibilities of substantial sensitivity to changes in the circumstances underpinning the market. Proposals are put forward in Section 3.5 to investigate the impact of allowing for greater realism of assumptions.

3.3.2 Data sources and preparation

Monthly balance sheets, BA900s, of all regulated banks are available from the South African Reserve Bank.[4] Tests on the data in this set demonstrated reliable quality and consistency. The approach used for splitting bank assets into short-, medium- and long-term groupings follows the methodology of Walters et al. (2018).

CET1 is not available in the BA900 data and was gathered manually from documents published by the banks, quarterly Pillar 3 reports, supported by annual reports and other sources. CET1 disclosed as a percentage of assets, common in financial reports, was not considered on grounds of imprecision or the risk of misinterpretation. Errors of interpretation are possible, as the CET1 data sought in financial reports could be confused with other Tier I measures or with the figures of the financial group of which the bank formed a part. This was mitigated by tests of the consistency of CET1 ratios over time.

In most instances, quarterly data was obtained. In some cases, the information was available less frequently, typically annually, or a quarterly report could not be found. While data was collected as a rand amount, interpolation between quarterly data points was based on the equivalent percentage of assets, using a straight-line method. Extrapolation outside of available data points was based on a weighted average of the nearest three ratios, utilising respective weights $\frac{1}{2}$, $\frac{1}{3}$ and $\frac{1}{6}$ for the closest available ratio and the next two.

BA900 data for 30 banks is available throughout the study period. Seven of the 30 were removed on the basis that the available CET1 data was inadequate for reliable inference, typically because data could not be found for large parts of the study. Banks removed from the data are smaller than average, the assets of the 23 banks accounting for at worst 98.0 percent and at best 98.7 percent of total industry assets across the study period, which is regarded as adequate for the purposes of this study.

Several aspects of these banks are not taken into account in the analysis. The mix of assets and liabilities, for example, may influence the outcome of a shock to another bank. Shareholding could also determine its response: in response to a shock, foreign shareholders might top up the assets of the entity immediately, though they could also withdraw from the market. Suggestions for improving this simplified and somewhat stylised analytical

[4]Data is available from the South African Reserve Bank at https://www.resbank.co.za/en/home/what-we-do/statistics/releases/banking-sector-information/banks-ba900-economic-returns. The web site was accessed on 3 June 2020, 5 August 2020, 16 September 2020 and 13 January 2021.

process are noted in Section 3.5.

A summary of statistics for the included banks is provided in Table 1 in the Appendix. The larger banks and foreign-owned small banks typically have lower CET1 ratios and lower variability of their ratios.

3.3.3 Model assumptions

The discussion turns next to the parameters required for the modelling and the choice of base-case values for these parameters. These values, together referred to henceforth as *Assumption Set 1*, are chosen to test for consistency of results with those of Walters et al. (2018), which are based on only two years of data in contrast to the 5.5 years utilised in this study.

The combination of parameters forming *Assumption Set 1* is set out in the list below. The relevant contagion channel is indicated in brackets with each parameter.

1. **Initial shock impact** (S, pertinent to all channels of contagion), the proportion of the assets of the bank affected by the shock assumed to have been lost in the event, 0.4;

2. **Loss shared** (u, credit shock), the proportion of the losses of the shocked bank assumed to be borne by the other banks in the network, 0.3;

3. **Market impacts on short-term, medium-term and long-term assets** ($\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$, liquidity shock), the scale of the reduction to the value of short-term, medium-term and long-term assets of affected banks, respectively 0.015, 0.015 and 0.03;

4. **Probability of inter-connectedness** ($\overline{p}$, proximity shock), the mean probability, across all bank pairs, that a pair of banks in the network is connected, 0.5;

5. **Impacts attributable to proximity, the sentiment factor** (α, proximity shock), the reduction to the value of the assets of banks assumed to be affected by virtue of their proximity to the shocked bank, 0.015.

Some of the parameters appear to display a tipping point in which the market experiences widespread contagion for values in excess of this point. The next section discusses these results.

3.4 Modelling results and their implications

In the discussion that follows, the response of the systemic risk indicator to changes in the values of alternative parameters is considered, identifying evidence of tipping points in the process. All results presented up to Section 3.4.5 are based on an Erdös-Rényi network model. The impacts of an alternative network formulation are discussed in that Section.

Figure 3.1 shows the systemic default indicator for the base case combination of parameters forming *Assumption Set 1*, combining the effects of all sources of contagion. The pattern of risk over time is consistent with Walters et al. (2018) and contemporaneous events. Peaks or sustained high levels of systemic risk coincide with the political and economic uncertainty triggered in December 2015 by the sudden removal of the Minister of Finance, the growing threat of a downgrade in South Africa's sovereign ratings in 2019 and the advent of the COVID-19 pandemic and associated measures from March 2020.

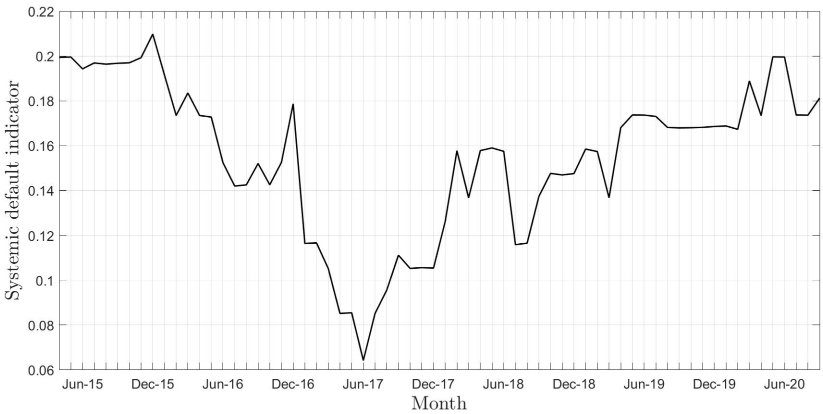


Figure 3.1: Systemic default indicator, all three shock mechanisms included
The chart shows the systemic default indicator for *Assumption Set 1*, the combination of contagion channels and default assumptions described in Section 3.3.3.

All three mechanisms or channels of contagion are operating in concert for the purposes of this scenario. The discussion that follows considers the sensitivity of the systemic default indicator to changes in each of the input variables. It first considers such sensitivity in the context of a single contagion mechanism in isolation, assessing each of the channels in turn. Then it tests whether the sensitivity differs in a combination of channels. In all cases, evidence is sought of sudden movements in the indicator in response to small changes in each of the input parameters. Where such tipping points appear to exist, the extent to which they vary over the time span of the investigation is considered and the analysis is repeated using the attraction to size network model to tests the robustness of results to changes in the structure of the network.

3.4.1 Credit shocks

Credit shocks are propagated through the model when part of the loss suffered by the bank that is initially shocked is absorbed by that bank's peers in order to prevent wider catastrophe (see the description in Section 3.3.1). Two parameters determine the extent of the shock, the proportion of the assets of the initial bank that are assumed to be lost, S, and the proportion of the loss (in excess of that bank's solvency capital, CET1) that is absorbed by the other banks, u. As demonstrated in the discussion that follows the systemic risk indicator is not particularly sensitive to changes in these variables, assuming that only the credit shock applies.

Figure 3.2 illustrates the impacts on the systemic default indicator of variations to the size of the loss suffered by the shocked bank as a proportion of its total asset value, S, for

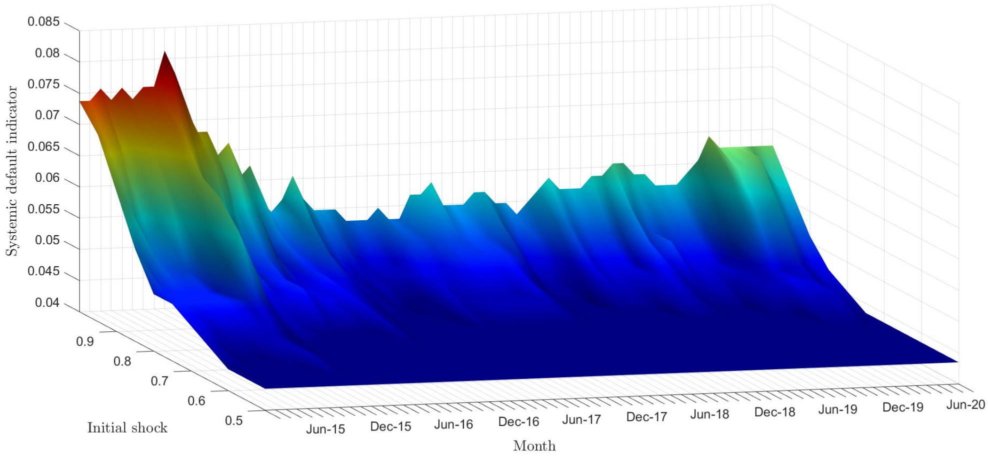


Figure 3.2: Systemic default indicator, credit shock only, varying initial shock
The chart shows the systemic default indicator, considering only the credit shock contagion mechanism, with loss shared, u, of 0.3 and varying levels of initial shock, S.

a fixed value of the loss shared, u.[5] The results for each month of the investigation are shown from left to right across the x-axis and the value of the systemic default indicator on the vertical z-axis. The value of the initial shock, along the y-axis, is varied from 0.5 (at the front of the chart), at which no banks fail except for the entity subjected to the initial shock,[6] up to 1 (at the back).

For any given month, the systemic default indicator increases with rising levels of the initial shock. This is intuitively sound. The greater the proportion of the assets of the shocked bank that are assumed to be absorbed by other banks, the greater the chance that the other banks fail as a result of this. The sensitivity of results to changes in the initial shock, S, is low. The highest level of the systemic default indicator, approximately 0.08, which is attained in December 2015, corresponds to a value of the initial shock of 1. The main reason for this low sensitivity is that the loss absorbed by the other banks depends on the size of the shocked bank. Shocking a small bank has little or no impact on the rest of the market. Some evidence exists of differences over time of the sensitivity of the indicator to this variable, mildly echoing the pattern illustrated in Figure 3.1 and showing changes to market conditions over time.

Figure 3.3 shows the impact of varying the proportion of the losses of the shocked bank, u, that is absorbed by the other banks. The shock parameter, S, varies from 0.5 to 1. The impacts of changes to this parameter are larger than the corresponding impacts of changes to the size of the initial shock, with a higher maximum systemic default indicator of approximately 0.12. The chart does not indicate any evidence of sudden changes to system risk levels in response to changes to the proportion of the loss shared. Month-to-month variation in the relationship between the tested variable and the level of systemic risk is again evident.

[5]Liquidity and proximity shock parameters are all set to zero for the purposes of this analysis.
[6]Since the shocked bank is counted in the defaults and 23 banks form part of the modelling, the lowest possible value for the systemic default indicator is 0.043, equal to $\frac{1}{23}$.

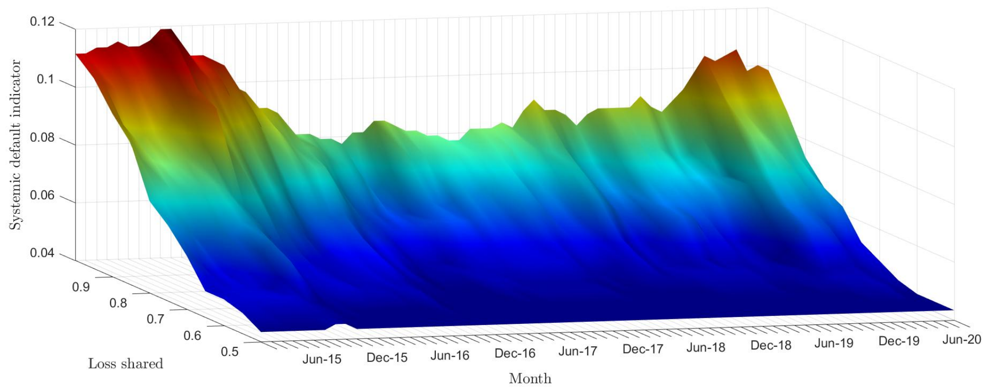


Figure 3.3: Systemic default indicator, credit shock only, varying loss shared
The chart shows the systemic default indicator, considering only the credit shock contagion mechanism, with initial shock, S, of 0.4 and varying levels of loss shared, u.

Combinations of the two factors, the extent of the shock and the proportion of the shock absorbed by other banks have also been tested. The systemic default indicator shows substantially lower sensitivity to changes in this combination of variables than to the factors considered under the liquidity shock and proximity shock. Descriptions of these effects follow.

3.4.2 Liquidity shocks

The second channel of contagion, the liquidity shock, is concerned with the potential effect of raised provisions and mark-to-market effects on the solvency of the other banks in the network. The values of short-, medium- and long-term assets are respectively modified by the reduction factors $\eta^{(s)}$, $\eta^{(m)}$, and $\eta^{(l)}$ (see Section 3.3.1). Under *Assumption Set 1*, these take the respective values of 0.015, 0.015 and 0.03. The discussion that follows considers the sensitivity of results to variations in these parameters, illustrated in Figure 3.4.[7] Simultaneous changes are considered to all three of the liquidity-shock parameters in proportion to their original values, rather than considering them one at a time. Sensitivity to such individual changes was found to be low.

At low values of the reduction factor, the systemic default indicator exhibits no responsiveness to changes in the parameters. At a certain point, however, which varies over time, a small further increase in this factor triggers a very large increase in the systemic default indicator, in most instances from 0.043 ($\frac{1}{23}$) to nearly 1 (typically $\frac{22}{23}$). Across the period of investigation, the tipping point occurs for values of the reduction factor, for short-term assets, of between 0.032 and 0.042. In some periods, early in the study or during the COVID-19 pandemic of 2020, the tipping point is as low as 0.033 and in other months, notably June 2016, it is at around 0.04. These changes in what may referred to as the ambient level of systemic risk correspond broadly with the peaks and troughs of the systemic default indicator shown in Figure 3.1. This suggests that, while the effects of

[7]The loss shared parameter, u, is set to zero to remove the credit shock. Similarly, the value zero is assigned to the proximity parameter, α. The initial shock parameter, S, is required for all simulations and takes the value of 0.4.

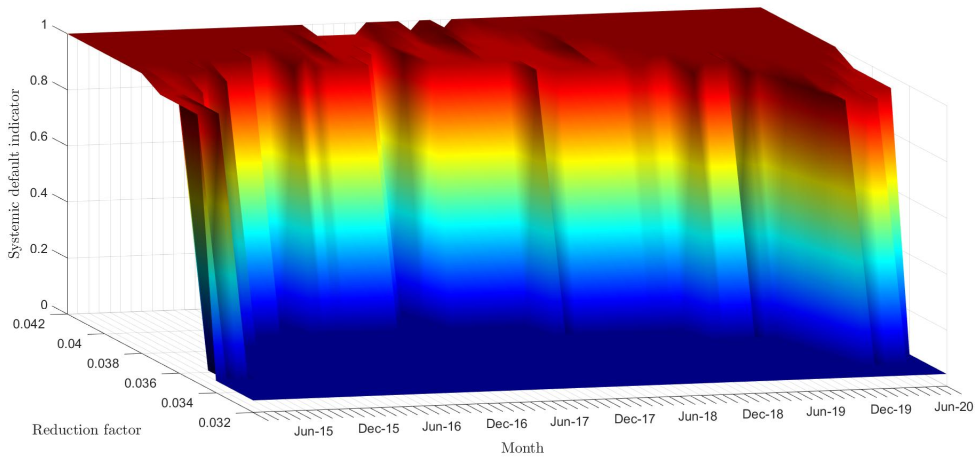


Figure 3.4: Systemic default indicator, liquidity shock only
The chart shows the systemic default indicator, considering only the liquidity shock contagion mechanism, at varying levels of the respective liquidity shock parameters, $\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$. The indicated reduction factor applies to the first two of these, $\eta^{(s)}$ and $\eta^{(m)}$, while the value of the third, $\eta^{(l)}$, is equal to double each of the others at all times. The size of the initial shock as a proportion of the assets of the shocked bank, S, is 0.4.

reaching the tipping point are, in all cases, severe for the industry, the tipping point itself varies in line with fluctuations in this ambient level. At times of high risk, the tipping point is reached at lower levels of the parameter than at more settled times.

The existence of the tipping point suggests that banks hold similar levels of solvency capital, in excess of the minimum, by much the same amount so that, when the shock is greater than this excess, they are all similarly impacted. This is not the case. The banks hold quite different levels of CET1 as a proportion of total assets (see Table 1 in the Appendix). If one bank, however, is brought down by the failure of the shocked bank, then the process is repeated, the reduction factors are applied again, and a chain reaction may follow because the values of the assets of the other banks are subjected to reduction for a second time.

It is not clear that, in second and subsequent cases, applying the same reduction factors to surviving banks represents the best approach to the problem. On the one hand, it could be argued, subsequent reductions to the value of the assets of the remaining banks should be lower as this represents a second shock and the market may have taken into account in advance the possibility of a second failure. On the other, if the market is counting on regulatory intervention to prevent a chain reaction, the effect of the second shock may be larger than the corresponding effect of the first. The possibility of further investigation in this regard is noted in the conclusion to this chapter, Section 3.5.

3.4.3 Proximity shocks

The proximity shock represents the impact of a deterioration in market sentiment based on the perceived exposure of each bank to a failed entity. The extent to which a bank is impacted by that initial shock is dependent on the probability of a link between the pair of

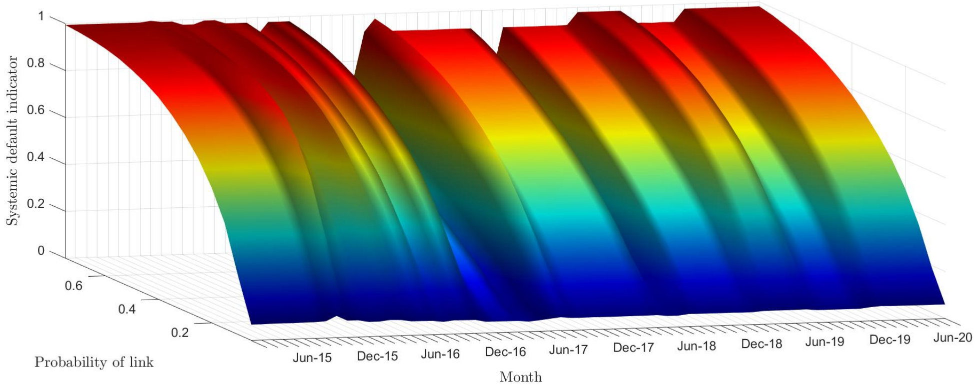


Figure 3.5: Systemic default indicator, proximity shock only, varying probabilities of connection

The chart shows the systemic default indicator, considering only the proximity shock contagion mechanism, at varying average probability of links between banks, $\overline{p}$, and sentiment factor, α, at 0.06. The size of the initial shock as a proportion of the assets of the shocked bank, S, is 0.4.

banks in question and the extent of the reduction to the value of the assets of the affected bank, the so-called sentiment factor, α. Under the Erdös-Rényi approach, the probability of a link between the pair of banks is randomly determined for each pair of banks in each simulation, based on the average probability of pair-wise links across the market, $\overline{p}$.

Figure 3.5 and Figure 3.6 show the respective effects of variations in the two assumptions driving proximity shocks. Figure 3.5 considers the impact of the probability of linkages, $\overline{p}$, while Figure 3.6 illustrates the effect of the sentiment factor, α, the extent of the impact on the connected bank of the failure at the initial bank.[8]

In any given month, the average probability of linkages between banks has a monotonically increasing impact on the systemic default indicator (see Figure 3.5). Differences in the sensitivity to changes in this parameter are evident over time, particularly low in June 2017 for example and higher than surrounding months in December 2015 and during the COVID-19 pandemic. This is consistent with other findings regarding the presence of generally elevated or dampened ambient levels of systemic risk. For a given month, the curve of the systemic default indicator against the probability of linkages is convex, except at the lowest levels of $\overline{p}$. This is most likely because, at high levels of $\overline{p}$, bank failures occur immediately following the first shock, after which these banks cannot impact others. At lower levels, however, scope remains for failures resulting from banks other than the entity subject to the original shock, creating disproportionate impacts on the overall probability of failure. Tipping points in response to changes in this parameter do not appear to exist.

The sensitivity of systemic risk to changes in the sentiment factor is not smooth over the range of values for the variable (see Figure 3.6). Strong evidence for tipping points is presented in the range of 0.04 to 0.06. In some cases, two distinct tipping points appear

[8]The loss shared parameter, u, is set to zero to remove the credit shock. The reduction factors under the liquidity shock mechanism, $\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$ are also set to 0. The initial shock, S, takes the value of 0.4.

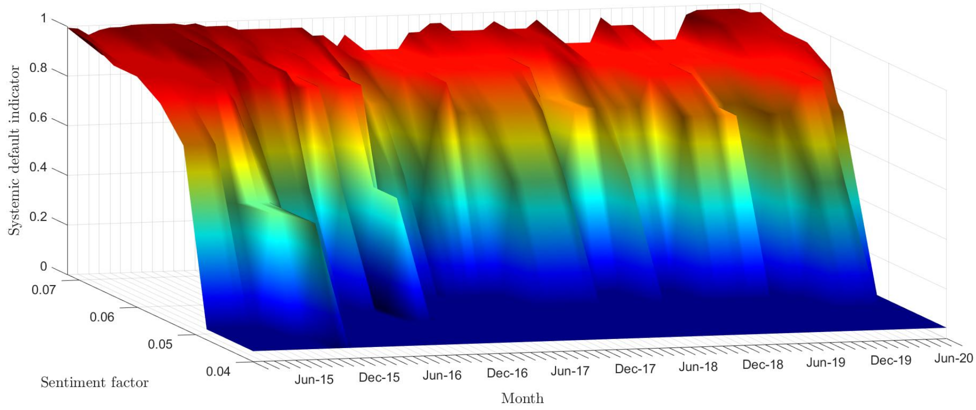


Figure 3.6: Systemic default indicator, proximity shock only, varying levels of shock
The chart shows the systemic default indicator, considering only the proximity shock contagion mechanism, at varying levels of the shock, α, with a constant probability of links between banks, $\overline{p}$, of 0.5. The size of the initial shock as a proportion of the assets of the shocked bank, S, is 0.4.

to exist. The value at which the tipping point occurs is lower during certain periods, December 2015 and most of 2020, for example, and higher during other periods, notably June 2017. This is consistent with the evidence throughout this study that changing levels of ambient levels of risk are evident in the modelling outputs.

The quanta of the impacts on the systemic default indicator at the respective tipping points in each month are smaller than the corresponding quanta applying to credit shocks. This may be explained as follows. The mechanism by which the sentiment factor, α, reduces the value of assets under the proximity shock is similar to the corresponding effect of the reduction factor under the liquidity shocks, $\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$, setting aside the fact that the liquidity shock results from the combined impact of three different factors on the assets at the respective duration ranges. The sentiment factor, however, is further reduced by the factor $d_{i,n}$, the shortest possible distance between two nodes in the network. This is an integer, typically taking the value one or two (refer to the discussion of methodology in Section 3.3.1). This damps the scale of the impact for the sentiment factor under the proximity mechanism compared to the corresponding impact of the reduction factor under the liquidity mechanism.

Two further points are noted in closing. First, as for liquidity shocks, the impact on other banks in the event of the failure of a second bank is assumed to be the same as for the corresponding impact of the failure of the bank initially shocked. This may not be realistic, as discussed in more detail in Section 3.4.2. Second, the shape of the surface is characteristically subject to more variation (it is less smooth) than the corresponding surfaces considered thus far. This may be attributable to the complexity of factors affecting the overall propensity to bank failure, some of them dependent on bank-specific attributes that vary month by month.

3.4.4 Multiple shocks

Tests for tipping points for each of the shock mechanisms represent valid exploration of sensitivity, but the market is likely to be affected by multiple mechanisms simultaneously. It is helpful to explore the existence of these tipping points in the presence of simultaneous mechanisms. All charts referred to in the discussion that follows are provided in the Appendix.

Figure 1 shows how the systemic default indicator varies in response to changes in the liquidity shock reduction factor while allowing also for the proximity shock.[9] This chart may best be compared with Figure 3.4 and Figure 3.6. The results are intuitively sound. The tipping points under the impacts of the liquidity mechanism are evident in this output, but occur at lower values of the reduction factor, $\eta^{(s)}$, and the effect is slightly dampened by the simultaneous impacts of the proximity mechanism.

The next study considers impacts of changes to the sentiment factor, under the proximity mechanism of contagion, in the presence of the liquidity mechanism (Figure 2). The tipping points associated with changes to the sentiment factor that exist when the proximity shock is the only mechanism operating on the market remain in evidence and occur at lower levels of sentiment factor, with characteristic month-to-month variations. These impacts are somewhat dampened by the contributing impact of the liquidity shock, which also raises the level of the systemic default indicator at low levels of the sentiment factor.

Consideration is finally given to a combination of all three factors with variation to the liquidity parameters. Refer to Figure 3, which is best compared with the corresponding combination of liquidity and proximity factors in Figure 1.[10] The combination of factors is evident, first, in the higher level of the systemic default indicator at very low levels of the reduction factor and, second, in reduced clarity of the month-to-month patterns as the impacts of the respective factors tend to muffle these differences, though the peak in December 2015 and trough in June 2017 are still evident. Even so, tipping points based on changes to the value of the liquidity mechanism reduction factor remain strongly evident.

3.4.5 Sensitivity to network model

The results discussed up to this point assume that the banking network follows the Erdös-Rényi model, under which links between entities are determined randomly within the framework of an overall probability of such links and a proximity modification (refer to the description in Section 3.3.1). Consideration has also been given to the effects of an alternative network model, in this case the so-called attraction to size model, under which

[9] The parameters utilised for the proximity shock are constant throughout this modelling, as set out in the notes supporting the chart. They are set at relatively low levels so as not to overwhelm the market with defaults, in the process retaining the potential to observe the impacts of changes to the reduction factors under the liquidity mechanism.

[10] This is the three-dimensional chart that corresponds to the simple two-dimensional base case set out in Figure 3.1. The characteristic pattern of the simpler version corresponds to a left-to-right cross-section of the surface at a reduction factor of 0.015, slightly back from the leading edge of the surface, which shows the systemic default indicator at a reduction factor of 0.012.

shocks to large banks are expected to have a greater impact on the market, attributable to greater inter-connectedness, than shocks to smaller banks.

Figure 4 in the Appendix shows the sensitivity of the systemic default indicator to changes in the liquidity shock parameters, under the network construct of attraction to size and the assumption that only the liquidity shock applies to the market. This image should be compared to the corresponding indication of the sensitivity of the systemic default indicator to liquidity shocks under the Erdös-Rényi model in Figure 3.4 in Section 3.4.2. The effects on the results are very small. The differences between the respective charts are scarcely discernible and can only be detected by considering the corresponding contour lines that indicate the systemic default indicator for each value of the liquidity shock parameter. This suggests that concerns regarding the sensitivity of the market to small changes in the liquidity shock parameter, particularly within a certain range of values for that parameter, are valid under alternative network assumptions.

Similar conclusions may be drawn regarding sensitivity to changes in the sentiment factor, the reduction to the value of the assets of banks by virtue of their proximity to the shocked bank, under the proximity shock model. This has also been reconsidered under the assumption that the attraction to size network model prevails in the market. The results are presented in Figure 5 in the Appendix, which may be compared to Figure 3.6 in Section 3.4.3. Differences between the respective charts are detectable but are very small and do not materially detract from the concern that the market may show a material risk of a tipping point in systemic risk levels with respect to changes in the sentiment factor.

These outputs suggest that, even under an alternative market network, evidence of extreme sensitivity of systemic risk to small changes in two of the assumptions underlying these models remains strong. As noted in the concluding discussion that follows, tests of these results to other network models may strengthen these findings.

3.5 Conclusion

The study that this chapter describes utilises a network model, three different contagion mechanisms and actual monthly balance sheet data for South Africa's banks to determine the sensitivity of systemic risk indicators to changes in a number of input variables. Evidence is put forward of significant tipping points in the level of systemic risk in response to two of the input variables. Very low sensitivity of this finding to a rather different banking network indicates a degree of robustness to variations in the assumed structure of the network and suggests that possibility that the feature may exist in the market regardless of the nature of the network in practice.

This finding should be of particular concern to policymakers because it suggests the existence of serious systemic vulnerability. However, the insights gleaned also provide the opportunity for informed observation of the factors that might lead to elevated levels of risk. It suggests that South African banking regulators should aim to understand empirically the state of the parameters governing these models. This is noted in the proposals for further research that follow.

A number of limitations to this study are pointed out, each of them leading to proposals for further research. First, bank-specific attributes could be considered. These may take into account the mix of assets and liabilities, the nature of the parent company, or other factors. While it is difficult in some cases to make sound assumptions regarding the response of management or shareholders to adverse circumstances, tests of the sensitivity of results to such changes could be helpful.

Second, the central bank itself may intervene in different ways to those suggested in this stylised modelling. Such variations in approach could be used to protect against systemic market weakness. The sensitivity of the results to different approaches could be investigated.

Third, as noted in the discussion of results (refer to Sections 3.4.2 and 3.4.3), it may be unrealistic to apply the same proportional reduction to the value of the assets of surviving banks on second and subsequent defaults of their peers as is applied following the initial shock. A number of variables are utilised in the model and the addition of others would complicate matters further, but one option is to introduce a decay factor under which the quantum of subsequent shocks is assumed to reduce over time. Under this formulation, the decay factor utilised in this study is one. Perhaps the most significant problem with this approach is empirically justifying any variation to this as real-world cascades are rare.

Fourth, the methodology underpinning these findings could be refined. The methods employed in this study are somewhat rudimentary in that they explore evidence for tipping points by varying one parameter at a time, though combinations of the channels for contagion are also considered. This approach is employed on the basis of the intractability of the problem in the context of multiple variables. An advantage of the approach is that it produces results that are intuitively insightful, but this may come at the cost of compromised rigour. Furthermore, the methodology does not facilitate tests of the statistical significance of impacts, in the process providing a quantitative definition of a tipping point. Multi-variate methods, such as those utilised in S. Chen and Desiderio (2022), may prove helpful in this regard to build on this introductory analysis.

Fifth, it would be useful to understand the likelihood that each of the contagion channels exists. A greater number of mechanisms raises the overall level of risk and lowers the level at which any given factor may trigger a tip into widespread default, but it also defuses risk more quickly through the system and limits a sharp dependence on a single factor.

Sixth, further testing of the sensitivity of results to changes in the modeling parameters (see Section 3.3.3), particularly where multiple effects are assumed to exist, could contribute an understanding of the robustness of results to changes in assumptions.

Seventh, for each of those channels that appear to exist, empirical or experimental examination of the likely values for each of the assumptions characterising that channel would be helpful. This could lead to practical tools for monitoring market proximity to a tipping point at any time.

Eighth, the attention in this study is limited to two network types, the Erdös-Rényi market network model, which is based on a pattern of random connections between banks and an alternative model in which the probability of connections is proportional to the size of the banks. Understanding the potential for tipping points in different types of networks is potentially useful in illuminating the nature of the problem to policymakers.

Finally, further research into the nature of the network characterising the South African banking market would be helpful. The tipping points themselves depend on the nature of the network.

The tipping points identified in this chapter are a reminder of the fragility that characterises the South African banking system. It is hoped that the insights provided by this study are helpful to those responsible for mitigating the contribution by these banks to systemic risk.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Chapter 4

Assessing Systemic Risk in South African Banks through Delta CoVaR

This paper describes an approach to the calculation of $\Delta CoVaR$ for the purpose of estimating systemic risk that uses returns based on monthly balance sheet book values rather than on the more commonly used quoted stock market prices blended with book values. The method is simpler and more transparent than the alternatives typically utilised in the literature. As it does not make use of daily market data, it need not utilise state variables to filter superfluous fluctuations in such data. The primary advantage of the approach is that it contributes intuitive understanding of the nature of the relationship between the returns of a bank and those of the market as whole.

The method is applied to analyse the contribution of South African banks to systemic risk over the period February 2001 to February 2021 inclusive. The larger banks in the sample generally have higher values of $\Delta CoVaR$, which is consistent with patterns observed in the literature. Results do not display stability over time, however, detracting from the usefulness of the approach. This may be at least partly attributable to the use of monthly data, which is sparse in comparison to the corresponding data used in other studies. On grounds of its intuitive value, the method is still considered a helpful tool for regulators to investigate sources of market fluctuation.

4.1 Introduction

Considerable attention has recently been given to the problem of systemic risk attributable to the inter-connectedness of financial entities, especially banks, particularly since the financial turmoil of 2008 and 2009. Such concern has been elevated by the global pandemic and its effects from 2020. Several measures have been developed to estimate the extent to which a financial institution contributes to systemic risk. These include calculation of SRISK, the estimated capital shortfall at an entity in the event of an industry crisis

(Acharya, Engle, and M. Richardson 2012; Brownlees and Engle 2017), studies of Granger causality (Billio et al. 2012) and models of the joint probabilities of default across several entities (Segoviano and Goodhart 2009).

One of these approaches is known as $\Delta CoVaR$. This is the marginal impact on the value at risk of the system as a whole conditional on the distressed state of a particular institution, relative to the corresponding state of the system conditional on the institution in its median position. (Refer to the description in Section 4.2.2.)

This chapter describes an alternative approach to determining $\Delta CoVaR$ that is simpler than the method commonly used. Two key simplifications are introduced. First, while approaches to $\Delta CoVaR$ described in the literature typically blend monthly or quarterly book-value data with daily market data, the data in this study is limited to monthly book values. Second, the use of monthly data does away with the need, also typical to approaches described in the literature, to filter daily data using state variables to remove market noise.

The remainder of this introduction describes the research objectives and outlines the key findings. Section 4.2 summarises the literature on $\Delta CoVaR$ and Section 4.3 sets out the methodology applied in this study. Section 4.4 discusses the results and Section 4.5 concludes, providing thoughts on possibilities for further research.

4.1.1 Research objectives

This study investigates the viability of calculating $\Delta CoVaR$ based on different underlying data to that used under the common approach. It aims, on practical grounds, to be simpler to implement and intuitively more helpful to regulators in the insights that it provides regarding indicators of systemic risk and the relationships between adverse events at individual entities and the market as a whole. Though it is applied in this study to banking data it could be extended to other markets, insurance for instance, subject to the availability of data.

The majority of researchers (Adrian and MK Brunnermeier 2008, 2016; Chatterjee and Sing 2021; Fong et al. 2009, for example) have followed the same broad approach to calculating $\Delta CoVaR$ (refer to the literature review in Section 4.2). Returns are determined from market-adjusted book values, which are then processed through a set of state variables in order to remove noise, improving consistency over time. The relationship between the series of modified returns of an institution and the corresponding returns for the market as a whole, excluding that institution, is then determined using quantile regression, producing the respective conditional values at risk needed to calculate $\Delta CoVaR$.

The study described in this paper uses different data to produce the market returns series. Monthly book values, available at the South African Reserve Bank, are used to determine the corresponding return on equity for each month, for the bank and for the market. This data is not adjusted using state variables, partly because market noise need not be removed from data spaced at monthly intervals and partly because the respective return series of the banks are so different that a set of variables appropriate to all banks could not be identified. The relationship between bank returns and market returns is assessed, using quantile regression, in the same way as under other studies.

The primary value of this approach, apart from its computational simplicity, is that it lends itself to a more intuitive approach to understanding the relationship between bank and market returns. For this purpose, the methodology is illustrated graphically. Furthermore, as it does not (1) adjust book values using market data, or (2) use state variables to filter returns data, the results are not affected by the methods or variables used to undertake these modifications. The primary benefit of the method to regulators is that, on grounds of its practical simplicity, it is easier to measure and understand patterns in the data, some of which could point to signs of systemic instability.

The main disadvantages of the method stem from the use of monthly data. Reliable results require sufficient data, which calls for information spanning a long term, but they do not display stability over time. As a result, it is unclear how much credibility to assign to any apparent evidence of bank-specific contributions to systemic risk.

4.1.2 Key findings

Results are set out for 20 South African banks for the full 20-year period covered by the study and for successive non-overlapping 10-year and 5-year periods. The values of $\Delta CoVaR$ for the respective banks are mostly positive, but not in all cases. This suggests that, in most cases, adverse events at entities occur more frequently in periods of market distress but that, for some banks, monthly profit patterns are inversely correlated with the corresponding market patterns. These banks might detract from systemic risk rather than contributing to it.

Among the larger banks, the values of $\Delta CoVaR$ over the full period are largest for two banks, Standard Bank and Investec, followed by First Rand. Standard Bank is the largest bank by assets, First Rand the second and Investec the fifth largest. Results are not consistent across sub-periods, however. This suggests that the method is not suitable for detecting covariate adverse results between entities and the market with reliability, that monthly data is too sparse for such detection or that actual patterns of covariance change over time.

Despite the inconsistency of outcomes, the straightforward, practical methodology provides insights to regulators looking to identify banks that may contribute to systemic risk by virtue of the covariate relationship between adverse bank and market outcomes. Several suggestions are set out for further research.

4.2 Review of literature

The discussion that follows summarises the literature covering the calculation of $\Delta CoVaR$ as a measure of banks' respective contributions to systemic risk. Section 4.2.1 outlines developments in the calculation of $\Delta CoVaR$. This is followed by summaries of the most common methods used to determine the $\Delta CoVaR$ metric (Section 4.2.2), quantile regression as an assessment of the relationships between variables (Section 4.2.3) and the corresponding approaches used to identify and measure bank returns (Section 4.2.4). The discussion is completed in Section 4.2.5, which sketches the results from studies of the $\Delta CoVaR$ of South African banks.

4.2.1 The use of $\Delta CoVaR$ as a measure of systemic risk

Proposals to consider $\Delta CoVaR$ as a basis for estimating the contribution of a financial-sector entity to systemic risk appear to have their genesis in the thinking of Tobias Adrian and Markus Brunnermeier (2008). They refined this position twice (Adrian and MK Brunnermeier 2011, 2016), though the original discussion paper was also republished in 2014. Adrian and Brunnermeier established the foundation of the $\Delta CoVaR$ approach, which may be defined as the difference between the value at risk of the system conditional on the financial distress of an entity and the corresponding system value at risk given the entity in its median state.

Value at risk is an extreme value measure that estimates the level of the capital loss, the inverse of profit, that is exceeded at a specified probability, say 5% or 1%, on the assumed statistical distribution of outcomes over the course of a fixed period, typically a year. The system value at risk is the corresponding extreme value aggregated across all entities in the system, for the purposes of the $\Delta CoVaR$ calculation excluding the entity under consideration. This value is then calculated conditional on the state of the entity itself, in the first instance conditioning on the entity in a state of distress and in the second on that entity under median circumstances. Adrian and Brunnermeier utilize quantile regression to estimate model parameters but stress that alternative approaches may also be considered.

Other studies followed in the months immediately after the financial crisis (Chan-Lau et al. 2009; Fong et al. 2009). The $\Delta CoVaR$ approach has been applied to the markets of several developing countries, among them, Turkey (Civan, Simsek, and Akay 2020), Indonesia (Muharam and Erwin 2017) and South Africa (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019; Manguzvane and Mwamba 2019). Researchers typically use market data for their analysis, though some (Chan-Lau et al. 2009, for example) utilise credit default swaps instead of the quoted stock market prices pioneered by Adrian and MK Brunnermeier. The technique was not used only to quantify the contribution of individual entities to systemic risk. Fong et al. (2009) applies it to an assessment of the interdependence of Hong Kong banks. Chan-Lau et al. (2009) considers $\Delta CoVaR$ as one of four alternative measures to assess systemic linkages, noting the disadvantage that the method can be adversely impacted by market efficiency factors.

A number of variations and alternatives have been considered (Z. Adams, Füss, and Gropp 2014; Hautsch, Schaumburg, and Schienle 2015). Several studies have been carried out using different methods (Acharya, Engle, and M. Richardson 2012; Acharya, Pedersen, Philippon, and Richardon 2010; Acharya, Pedersen, Philippon, and M. Richardson 2017; Brownlees and Engle 2017; Foggitt et al. 2017; Gauthier, Lehar, and Souissi 2012; Giglio 2016; X. Huang, Zhou, and Zhu 2012b; Sedunov 2016). Zhang et al. (2015) consider a range of alternatives, raising concerns regarding the predictive power of each of the modelling approaches considered, even the $\Delta CoVaR$ method.

Other techniques are also used to assess the relationships between the respective statistical distribution of returns of the respective entities forming a market. In contrast to $\Delta CoVaR$ and its variations, which seek to assess the co-movements between distress at an entity and the corresponding distress on the wider market, SRISK aims to detect impacts of market distress on participating entities. It is calculated as the shortfall in the available capital at an entity conditional on the event of a market crisis (Acharya, Engle, and M. Richardson 2012; Acharya, Pedersen, Philippon, and Richardon 2010; Brownlees and Engle 2017). Other approaches are indifferent to the direction of impact or are focused on identifying relationships between entities. These include assessments of joint probabilities of default (Segoviano and Goodhart 2009), economic connectedness (Billio et al. 2012; H. Chen, J. Cummins, et al. 2013) and network effects (S. Lee 2013; Martinez-Jaramillo et al. 2015; Poledna et al. 2015).

Though this study focuses on a simpler alternative to the widely-used method of $\Delta CoVaR$, regulators should consider using a range of methods to detect levels of risk intrinsic to the financial system over time.

4.2.2 Summary of methods utilised

Researchers applying the $\Delta CoVaR$ method (see Section 4.2.1) use broadly the same approaches as Adrian and MK Brunnermeier (2008; 2011; 2016) for assessing the contribution of individual entities to systemic risk. In all cases, the definitions of $CoVaR$ and $\Delta CoVaR$ stem from the expression of the value at risk of an entity i, or the whole system, defined at a specified q probability level as follows:

$$Pr(X^i \leq VaR_q^i) = q \tag{4.1}$$

where X^i represents the distribution of losses of entity i and, by convention, VaR_q^i takes a positive sign for large values of q.

This leads to the definition for $CoVaR$. It is given by the value at risk of the financial system conditional on an adverse event $C(X^i)$ impacting the losses X^i of entity i. The expression $system_i$ is defined as the collection of all entities excluding institution i and X^{system_i} is defined as the aggregate distribution of losses of this collection of entities. Then $CoVaR$ is implicitly defined by the quantile q of the conditional probability distribution (following the approach of Adrian and MK Brunnermeier 2016):

$$Pr(X^{system_i} \leq CoVaR_q^{system_i} | C(X^i)) = q. \tag{4.2}$$

The event C is typically chosen so that it has the same probability of occurring no matter which institution i is selected. For this purpose, the value VaR_q^i is helpful because q, the probability that X^i exceeds this value, is the same for all institutions, as given by Equation 4.1.

Now $\Delta CoVaR_q^{system_i}$ at percentile q, for all participants in the system excluding entity i, is defined as the difference between (1) the system $CoVaR$ conditional on the distress of the entity,[1] and (2) the corresponding value of the system $CoVaR$ when the entity return is at median level.

This can be inverted. Rather than using losses for institutions, returns data may be utilised. This is the approach used in this study. (Refer to the supporting diagram at Figure 4.1.) Under this approach, however, it is understood that VaR_q^i, in this case defined at small values of q rather than large, can take negative values and no longer conveys the intuitive meaning typically ascribed to the term value at risk of the (positive) level of capital required to absorb a rare loss, but simply the quantile of the distribution of returns.

Applied to returns data, $\Delta CoVaR_q^{system_i}$ may then be defined as follows:

$$\Delta CoVaR_q^{system_i} = CoVaR_q^{system_i|X^i=VaR_{0.5}^i} - CoVaR_q^{system_i|X^i=VaR_q^i} \tag{4.3}$$

Both expressions to the right of the equality indicate calculation of $CoVaR_q^{system_i}$ at the quantile q for the system excluding institution i. The conditions differ. The first expression is conditional on median returns for institution i and the second on adverse experience for that institution, represented by a return at quantile q.

On the basis that adverse events at large institutions may impact the market more than the corresponding events at small institutions, Adrian and MK Brunnermeier (2016) scale this result by the market equity of the institution, to calculate what they refer to as $\Delta^{\$}CoVaR_q^i$.

The parameters underlying the model are typically estimated using quantile regression, a method that does not depend on assumptions regarding the statistical distributions of the explanatory variables in the regression. (Refer to the brief description of quantile regression in Section 4.2.3.) The equation that follows shows the predicted value of the returns of the financial system X_q^{system}, given X^i, using a quantile regression on the corresponding losses of entity i at the q^{th} quantile:

$$\hat{X}_q^{system|X^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{4.4}$$

where $\hat{X}_q^{system|X^i}$ represents the predicted value for the system return at the (small) q^{th} quantile conditional on the value X^i for the return of entity i.[2] This is the same as the value at risk of the system conditional on X^i, so it follows that:

$$CoVaR_q^i = VaR_q^{system|X^i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{4.5}$$

[1] Formally, this is the q^{th} percentile, for large values of q, of the distribution of losses for institution i of VaR_q^i.

[2] Alternatively, high values of q could be used with the distribution of losses, the inverse of the returns.

From this equation, $\Delta CoVaR_q^i$ may be calculated as:

$$\Delta CoVaR_q^i = CoVaR_q^{system|VaR_{0.5}^i} - CoVaR_q^i = \hat{\beta}_q^i(VaR_{0.5}^i - VaR_q^i) \tag{4.6}$$

where $VaR_{0.5}^i$ and VaR_q^i may be determined respectively as the median value and (small) q^{th} percentile of the distribution of returns X^i of entity i.

Save for the difference that many researchers define $\Delta CoVaR_q^i$ in terms of losses rather than returns, this is the method utilised in the majority of papers described in the literature review. This study also utilises the method described in Equations 4.5 and 4.6. To estimate parameters it uses quantile regression, described in Section 4.2.3. It differs, however, in its treatment of the underlying returns data, set out in the discussion in Section 4.2.4.

4.2.3 Quantile regression

Like standard regression such as ordinary least square regression, quantile regression describes the relationship between a dependent variable and one or more input variables. Unlike least squares regression, quantile regression is not limited to estimating the mean value of the dependent variable, given the corresponding values of the input variables. Through its assessment of conditional quantiles, often referred to as percentiles, quantile regression may be used to infer qualities throughout the conditional distribution of the dependent variable (He et al. 2023; Rodriguez and Yao 2017; Yu, Lu, and Stander 2003).

The method does not require prior knowledge or assumptions regarding the underlying statistical distributions and it is generally robust to the presence of outliers (He et al. 2023). Quantile regression has several common applications, among them, survival analysis and financial research, which it is particularly useful for modelling the tails of distributions, notably value at risk (Yu, Lu, and Stander 2003). Probably its key drawbacks are that it typically requires more data than ordinary least squares regression to produce reliable results and that fitted quantiles can overlap, particularly at extreme values of the input variables (Koenker 2005).

Several parametric and non-parametric approaches are available for fitting conditional quantile regression curves (Yu, Lu, and Stander 2003). The simplest of these assumes a linear regression model of the relationship between the dependent variable y_i and p independent variables $x_{i1}, x_{i2}, ..., x_{ip}$, given a data set $\{x_{i1}, x_{i2}, ..., x_{ip}, y_i\}_{i=1}^n$.

This relationship may be specified for quantile level τ as follows (Rodriguez and Yao 2017):

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau)x_{i1} + ... + \beta_p(\tau)x_{ip}, \quad i = 1, 2, ..., n \tag{4.7}$$

The coefficients in β are estimated by minimizing as follows:

$$\min_{\beta_0(\tau),\ldots,\beta_p(\tau)} \sum_{i=1}^{n} \rho_\tau \left(y_i - \beta_0(\tau) - \sum_{j=1}^{p} x_{ij}\beta_j(\tau) \right) \tag{4.8}$$

The function $\rho_\tau(r)$ in Equation 4.8, called the check loss (Rodriguez and Yao 2017) or check function (Yu, Lu, and Stander 2003), is defined as follows:

$$\rho_\tau(r) = \tau max(r, 0) + (1 - \tau)max(-r, 0) \tag{4.9}$$

In summary, in contrast to the ordinary least squares method, the quantile regression approach minimises the weighted sum of differences between data points and regressed values, by applying a weight of q to differences above the regression line and $1 - q$ to differences below the line, for small values of q. Optimisation is typically empirical as quantile regression does not lend itself to a formula-based approach. This can be computationally intensive. Approximate methods have been proposed (He et al. 2023), but such methods have not been required for this study.

This method may be extended to higher-order polynomials or alternative equation forms (see, for example, the linear B-spline in Koenker 2005). Non-parametric approaches are also available (Yu, Lu, and Stander 2003). Goodness-of-fit statistics may be computed for comparing two quantile regression estimates, one unconstrained and the other constrained, to calculate the marginal impact of the constraint, but determining appropriate test statistics is generally not straightforward (Koenker and Machado 1999).

4.2.4 Generating the series of market returns

The studies described in the literature review all use quoted market information, either stock prices or credit default swaps (Chan-Lau et al. 2009; X. Huang, Zhou, and Zhu 2012a). However, in all cases, market returns are modified to allow for accounting information. In order to do this, researchers compute what is typically referred to as market-valued assets for each of the entities included and then model the derived returns as a linear function of a set of state variables, using quantile regression to estimate the parameters. All identified studies based on South African data (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019; Manguzvane and Mwamba 2019) follow this approach.

The return series of market valued assets X_t^i in such instances, for entity i at time t, is given (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019) by:

$$X_t^i = \frac{A_t^i - A_{t-1}^i}{A_{t-1}^i} = \frac{ME_t^i \cdot LEV_t^i - ME_{t-1}^i \cdot LEV_{t-1}^i}{ME_{t-1}^i \cdot LEV_{t-1}^i} \tag{4.10}$$

where A_t^i is the market valued total financial assets for entity i at time t, ME_t^i is the equity market value for the same entity, and LEV_t^i is the corresponding ratio of book assets BA_t^i to book equity BE_t^i. The book value of assets, BA_t^i, is given by

$$BA_t^i = TA_t^i - (TL_t^i - TIA_t^i) \tag{4.11}$$

where TA_t^i, TL_t^i and TIA_t^i are respectively the total assets, total liabilities and total intangible assets of entity i at time t.

Book values depend on the availability of accounting data, as explicitly stated by Leukes and Odei-Mensah (2019). This suggests that, even if market data at daily or weekly intervals are utilised where possible, adjustments for book value are limited to the frequency with which this accounting information is available, typically monthly at best. Adrian and MK Brunnermeier (2016) indicate the use of daily market data collapsed to weekly frequency for market-related information, but combined with quarterly balance sheet data to adjust for book values. This suggests considerable smoothing of the market data and/or a wide range of implicit or explicit assumptions for the purposes of determining the returns on the market valued financial assets as described in Equation 4.10.

The returns determined from Equation 4.10 are filtered using a set of state variables to allow for changes in the values of $CoVaR_{q,t}^i$ and $VaR_{q,t}^i$ over time t. Quantile regression is used to estimate the parameters under the following relationship (Adrian and MK Brunnermeier 2016), where $\mathbf{M}_t$ is a vector of state variables that serve to remove market-related noise from the sequence of returns:

$$X_t^i = \alpha_q^i + \gamma_q^i \mathbf{M}_{t-1} + \epsilon_{q,t}^i \tag{4.12}$$

and

$$X_t^{system|i} = \alpha_q^{system|i} + \gamma_q^{system|i} \mathbf{M}_{t-1} + \beta_q^{system|i} X_t^i + \epsilon_{q,t}^{system|i} \tag{4.13}$$

The method permits the calculation of time-varying measures of $\Delta CoVaR$, but at the cost of some modelling risk. Results depend on the choice of state variables and the relationships between these variables and the series of bank returns. They also depend on the frequency of the available accounting information and the method used to integrate high-frequency market information with this accounting data.

Table 4.1 summarises the methods utilised for other South African assessments of $\Delta CoVaR$. This study differs from these in that it uses exclusively accounting data to calculate book returns directly rather than deriving such returns from a combination of market- and accounting data and regressing this over a set of state variables. The approach is preferred because it is simpler to implement, intuitively clearer to users and utilises a great deal less supporting data and assumptions.

4.2.5 Summary of results from South African banks

The results of studies assessing South African entities (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019; Manguzvane and Mwamba 2019) are set out in Table 4.1. These show reasonable consistency across the studies, at least in the relative values across banks. This consistency is evident notwithstanding significant differences in the data range, the percentile at which the $\Delta CoVaR$ is determined, the manner in which market returns are calculated and the choice of state variables utilised to model these returns.

Lead author	Leukes	Manguzvane	Chatterjee
Publication date	2019	2019	2021
Data span	May 2005 - Dec 2017	Jun 2007 - Apr 2016	Mar 2002 - Oct 2020
Market returns	Modified	Direct	Modified
State variables	United States	South Africa	Combination
$\Delta CoVaR$ percentile	0.05	0.01	Not stated
$\Delta CoVaR$ results			
Standard	0.0158	0.0259	0.0418
First Rand	0.0183	0.0278	0.0507
ABSA	0.0166	0.0259	0.0479
Nedbank	0.0149	0.0218	0.0299
Investec	0.0101	n/a	0.0091
Capitec	0.0047	0.0121	n/a

Table 4.1: Summary of $\Delta CoVaR$ studies of South African banks
The table describes differences in the methods of three South African $\Delta CoVaR$ studies, showing results for the largest banks, listed in decreasing size of assets in 2021. Sources: Leukes and Odei-Mensah (2019), Manguzvane and Mwamba (2019) and Chatterjee and Sing (2021).

4.3 Research methodology

The discussion that follows describes the sources of the data used and the approach to determining appropriate values for $\Delta CoVaR$ for the banks included in the study. As the methodology is based on alternative data to the conventional approach, this difference and its implications form a large part of the discussion that follows.

4.3.1 Data sources

Monthly balance sheet data was downloaded from the SARB for the period January 2001 to February 2021 inclusive.[3]

Earlier information is also available, converted from the different formats used in the 1990s. Tests suggested flaws in the internal consistency of this information. As a result, data up to the end of 2000 was regarded as unreliable and unsuitable for use. Notwithstanding the reliability of bank data from January 2001 onwards, several banks appeared to have data missing from this period. Even where this did not include the key values of assets, liabilities and equity, the credibility of the data sources was regarded as compromised in these cases and these banks were discarded from the set. Finally, banks were considered only if data were available for those banks throughout the period of investigation, resulting in the exclusion of entities such as Mercentile and Societe General, both of which closed operations towards the end of the period.

[3] https://www.resbank.co.za/en/home/what-we-do/statistics/releases/banking-sector-information/banks-ba900-economic-returns, accessed on several different dates: 3 June, 5 August and 16 September 2020, and 13 January, 9 April and 31 July 2021.

The full BA900 set consists of 46 banks in total, of which 37 are present in the January 2001 and 34 in February 2021. The 20 banks that met the criteria set for data credibility were included in the analysed data set. These banks represent between 77.2% and 96.3% of industry assets. This proportion is low at the beginning of the period of investigation but it grows steadily through the period.[4] No other data was required for the purposes of the modelling described in this chapter.

4.3.2 Summary of approach

The method underpinning the research described in this study is fundamentally the same as utilised by Adrian and MK Brunnermeier (2008, 2011, 2016) and many others, as listed in Section 4.2 and described in Equations 4.2 and 4.3. It utilises different data, however, drawing on monthly balance sheet information for South Africa's banks published by the South African Reserve Bank, rather than utilising quoted market information and adjusting this for book valuations.[5]

Return calculation

The monthly return for each bank is defined as the change in equity over the course of the month divided by the total assets at the beginning of the month, adjusted for the corresponding change to shareholder capital. The change in equity in month t without adjustment is given by the following equation, discarding the reference to each bank:

$$X_t = (E_{t+1} - E_t)/A_t = [(A_{t+1} - L_{t+1}) - (A_t - L_t)]/A_t \tag{4.14}$$

In this formula, X_t is the unadjusted monthly return on assets in month t, A_t and L_t represent respectively the values of the total balance sheet assets and liabilities of the company at time t, and E_t is the corresponding value of equity of the company at time t, the difference between assets and liabilities.

The adjustment for shareholder capital removes from the return calculation any dividends paid to shareholders or capital injection received from them, leaving only the change in profit attributable to the operations of the bank in that month. Failing to adjust for changes in share capital would conflate the increase in equity attributable to business operations and the corresponding increase attributable to transactions with shareholders. For the purposes of this study, only the first of these factors is sought.

The modified formula is thus given as follows:

$$X'_t = [(E_{t+1} - E_t) - (S_{t+1} - S_t)]/A_t \tag{4.15}$$

[4]In January 2003, this proportion exceeded 90% and, in July 2009, 94%. In each case, the proportion attributable to the 20 included banks did not fall below these levels after these dates.

[5]All calculations are carried out in Matlab by MathWorks. The quantile regression calculations, developed by Aslak Grinstead, is available at mathworks.com. All code is available from the author on request.

where X'_t is the monthly return on assets in month t adjusted for changes to shareholder capital, and S_t is the value of shareholder capital in the bank at time t.

Consideration was given to the question of whether the returns available from this balance sheet data should be fitted to a set of state variables to allow for changes over time, in line with the method used by other South African researchers (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019; Manguzvane and Mwamba 2019), as set out in Equations 4.12 and 4.13. The rationale for this approach is that it permits a determination of $\Delta CoVaR$ that varies over time by removing time-varying noise from the bank returns. On the other hand, the choice of state variables introduces an element of variability to the results that would not exist were this approach not used.[6]

The decision was made not to attempt to allow for time variation in parameters via state variables. The rationale for this follows. This study uses balance sheet returns not market data. Modelling these returns using external variables that are the same for all banks is challenging: running linear regressions of bank returns X'^i_t against a range of economic factors results in wide differences between banks in the set of factors that fit the return series with statistically significance. On the basis of this evidence, it is not considered possible to choose a set of state variables that, appropriate for each bank, might be suitable for adjusting for variation over time as described in Equations 4.12 and 4.13. This suggests that the available data should be modelled directly, retaining the distinct characteristics of each of the banks in the process.

Illustration of calculation methodology

Figure 4.1 shows how $\Delta CoVaR$ is calculated with direct reference to the underlying monthly data. The chart is a scatter plot of the monthly returns of bank i, in this case Standard Bank, as defined under Equation 4.15, against the corresponding series for the market as a whole, adjusted by the removal of the contribution of Standard Bank.[7] Each of the grey spots represents a combination for one month in the series.

The green, yellow and red circles represent the respective fits of the quantile regressions at the 50th, 25th and 5th percentiles of the return series for bank i against the corresponding series for the system excluding bank i, as set out in Equation 4.4. The fit is based on a linear formulation, the same as Equation 4.4, as follows:

$$\hat{X}_q^{system|X^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{4.16}$$

Higher-order equations, such as quadratics, were investigated. Refer to Figure 9 in the Appendix, which shows the second-order fit for Standard Bank. Results are unstable, with extreme values contributing significantly to the fit of the curves. Moreover, the rationale for non-linear approaches is not clear and no evidence was found in the literature of any

[6] The appropriateness of state variables from international markets by (Leukes and Odei-Mensah 2019) is not clear. Neither is the effect of this choice on the results of the modelling.

[7] The same formula is used for the market, but it is applied to the sum of the corresponding data across all banks except the bank in question, in this case, Standard Bank.

alternatives to linear approaches. These alternatives are not considered further.

Each of the points in green (median), yellow (25th percentile) and red (5th percentile) represents, on the vertical axis, $CoVaR^i_{q,t}$, the conditional system value at risk. This is specified for a particular percentile q, conditional on the outcome of the return variable X^i_t, for bank i, Standard Bank, specific to month t. The value of the return variable X^i_t is represented by the position of the point with respect to the horizontal axis.

The discussion is limited henceforth to values taken by the quantile regressions at the 5th percentile, the red circles, and on specific values in this set. The vertical component of the black square is the conditional system value at risk, $CoVaR^i_{0.05}$. This value is conditional on the return for bank i, Standard Bank, taking the 5th percentile of the distribution of such returns. That percentile is given by the value at risk $VaR^i_{0.05}$ for bank i. The vertical component of the red square is the corresponding conditional system value at risk conditional on a median monthly return, $VaR^i_{0.5}$ for bank i. The vertical difference between these two values is $\Delta CoVaR^i_{0.05}$, the sought-after value for bank i at the 5th percentile over the full period of investigation.[8]

This provides an intuitive, practical conception of the value of $\Delta CoVaR^i_{0.05}$ for a particular bank, in this case Standard Bank. The higher the (positive) slope coefficient of the quantile

[8] In the results presented in this chapter, $\Delta CoVaR$ results are annualised in line with the conventional treatment of value at risk as a forward measure with a one-year horizon. An alternative approach would have been to annualise all monthly returns prior to calculation of $\Delta CoVaR$, which would have given the same result.

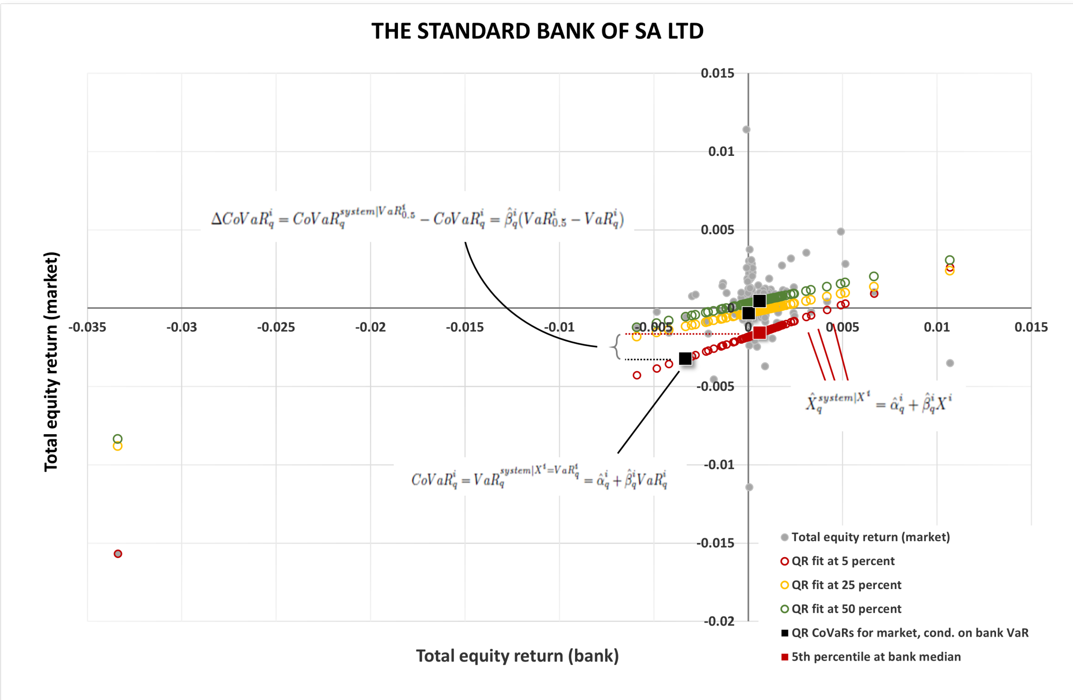


Figure 4.1: $\Delta CoVaR$ calculation, illustration of methodology
The chart demonstrates the approach to the calculation of $\Delta CoVaR$, using data for Standard Bank covering the full period of investigation and demonstrating the application of Equations 4.4, 4.5 and 4.6 to this particular bank.

regression, given by $\hat{\beta}^i_{0.05}$ and the greater the difference between the median bank return, $VaR^i_{0.5}$, and its 5th percentile, $VaR^i_{0.05}$, the greater the value of $\Delta CoVaR^i_{0.05}$. This means that banks whose returns are strongly (positively) related to system returns and banks with larger variation in their returns are more likely to produce high values of $\Delta CoVaR^i_q$. This is consistent with the intuition that they are more likely to be systemically risky on the basis of the co-movement of their returns with the corresponding aggregate returns of the banks in the remainder of the system.

In this case, the value for $\Delta CoVaR^i_{0.05}$ is positive, reflective of the upward-sloping line and consistent with a positive value for the parameter $\hat{\beta}^i_{0.05}$ in Equation 4.16. This suggests that, over the term of investigation for the bank in question, the monthly return on equity for the bank is positively related to the corresponding monthly return on equity for the industry as a whole excluding that bank. This is broadly indicative of tail dependency but it should not be used to infer causality. To emphasise, it is not correct to conclude from this empirical relationship that adverse circumstances at the bank in question cause poor results for the rest of the system.

The process of calculating values for $\Delta CoVaR^i_q$ is repeated for all banks i included in the data set (see Section 4.3.1) and tested over sub-periods of the data. The results are discussed in Section 4.4. Alternative values for the percentile q were considered. Smaller values of q helpfully consider the relationship between bank and industry for more extreme results, but they are less stable by virtue of their outlying position on the statistical distribution of results. This limitation is particularly pertinent in this case, with data limited to 20 years of monthly information. The calculation of $\Delta CoVaR^i_q$ for values of q less than 0.05 was not considered appropriate on the basis of paucity of information. Larger values of q may be considered more reliable statistically but provide less insight into extreme events. In summary, the results described in Section 4.4 are limited to a value of 0.05.

Finally, to scale for the size of the respective banks, each instance of $\Delta CoVaR^i_q$ is multiplied by the asset size of the bank at the end of the period of investigation, following the methodology of Adrian and MK Brunnermeier (2016). This gives a value referred to as $\Delta^R CoVaR^i_q$. It may be considered the marginal rand impact on the market value at risk of a shift, for bank i, from its median value to the q^{th} percentile of its return distribution. All outputs show, for all banks in the sample, values of both $\Delta CoVaR^i_q$ and $\Delta^R CoVaR^i_q$.

Concluding comments

The pictorial approach can be repeated for every bank and for each distinct period under investigation. The straightforward methodology helps to promote a practical understanding of the relationship between the extreme events for a bank and for the industry as a whole. Furthermore, as returns are not processed through the lens of market variables, as undertaken by many other researchers, the size and direction of this relationship is more easily understood. The approach is also easily adapted to other measures of bank viability, such as solvency, as illustrated by the example at the end of Section 4.4.

The primary disadvantages are that, with only monthly balance sheet data available, results are not stable over time and changes in values of $\Delta CoVaR$ for different periods are not reliable indicators of a changing contribution to systemic risk by a bank.

4.4 Modelling results and their implications

The results of the analysis for the 20 banks over the full period of investigation are presented in Table 4.2. Standard Bank shows high levels of $\Delta CoVaR$ over the period of investigation. Scaled by asset size, furthermore, Standard Bank strongly dominates the contribution to systemic risk, according to this methodology. Among the large banks, Investec also shows high levels of $\Delta CoVaR$, followed by First Rand. On the whole, the larger banks rank higher on this list and, not surprisingly, on the corresponding list of $\Delta^R CoVaR$ values.

The Bank of China stands out among small banks for its high $\Delta CoVaR$ value. This serves as a reminder that the tail dependency indicated by these results is not the same as causation, as noted by Adrian and MK Brunnermeier (2016). Scaled by size, Bank of China appears lower in the rankings, after the large five banks.

The data and calculation method for Standard Bank is illustrated in Figure 4.1 in Section 4.3.2. The high slope coefficient $\hat{\beta}^i_{0.05}$ is evident in the slope described by the red points. The corresponding pattern of data for Investec is shown in Figure 4.2. The positive slope of the quantile regression at the 5th percentile is evident, reflected in the relatively high value of $\Delta CoVaR^i_{0.05}$ in Table 4.2. The corresponding flatter shapes of the fitted curves at the 25th percentile and the median suggest that the relationship between the returns of the bank and those of the market is less marked under more normal market conditions.

Turning back to the question of co-movement in the tails of the distributions, the corresponding charts for First Rand, ABSA and Nedbank banks are provided in Figure 6, 7 and 8 in the Appendix. The First Rand regression has the largest positive coefficient and the others smaller positive coefficients. In each of these three cases, considering the period as a whole, a relatively weak tail relationship is detected between the monthly returns of the bank and the corresponding returns for the remainder of the market.

Some of the values of $\Delta CoVaR$ for the smaller banks are negative. This suggests that, at least at the extremes, adverse returns for these banks tend to coincide with better returns for the market as a whole.

Table 4.3 shows the results of these calculations for periods corresponding to the studies of other researchers of South African banks (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019; Manguzvane and Mwamba 2019) and should be compared with the corresponding results in Table 4.1. Note one important difference between the studies that all results under this study are calculated at the 5th percentile, matching only Leukes and Odei-Mensah (2019).[9] The focus of the comparison should be on the ranking of the banks

[9] Manguzvane and Mwamba (2019) calculate $\Delta CoVaR$ at the level of the 1st percentile and Chatterjee and Sing (2021) do not disclose the percentile at which calculations are undertaken

	$CoVaR^i_{0.50}$ monthly	$CoVaR^i_{0.05}$ monthly	$\Delta CoVaR^i_{0.05}$ annualised	$\Delta^R CoVaR^i_{0.05}$ R'000
Standard	-0.00158	-0.00322	0.0198	30 786 394
B of China	-0.00171	-0.00271	0.0121	595 506
Investec	-0.00223	-0.00315	0.0110	5 604 700
First Rand	-0.00226	-0.00289	0.0075	10 417 191
Sasfin	-0.00181	-0.00206	0.0030	25 118
Nedbank	-0.00195	-0.00214	0.0024	2 615 531
Grindrod	-0.00173	-0.00189	0.0020	23 972
HBZ	-0.00174	-0.00190	0.0019	12 683
Bidvest	-0.00173	-0.00187	0.0017	21 259
ABSA	-0.00192	-0.00205	0.0017	2 189 305
Deutsche	-0.00159	-0.00173	0.0016	27 353
Citibank	-0.00180	-0.00192	0.0015	128 800
B of Taiwan	-0.00178	-0.00185	0.0009	2 237
Capitec	-0.00166	-0.00173	0.0009	134 880
Albaraka	-0.00176	-0.00177	0.0002	1 600
B of India	-0.00177	-0.00178	0.0001	848
B of Athens	-0.00172	-0.00162	-0.0012	-3 389
UBank	-0.00171	-0.00157	-0.0017	-9 705
China Constr.	-0.00180	-0.00166	-0.0017	-65 526
Habib	-0.00175	-0.00156	-0.0022	-2 308

Table 4.2: Results for the full study period, February 2001 - February 2021
Notes: $CoVaR^i_{0.50}$ is the system value at risk conditional on the median monthly return for bank i and $CoVaR^i_{0.05}$ is the corresponding system value at risk for the 5th percentile of bank i returns. The difference between these, annualised, is $\Delta CoVaR^i_{0.05}$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR^i_{0.05}$.

rather than the absolute values computed. On this basis, the consistency with the respective studies by Leukes and Odei-Mensah (2019) and Manguzvane and Mwamba (2019) is reasonably close, except that the results in this study for First Rand and ABSA are rather higher than in the comparative studies. In contrast, the results of this study do not match those of Chatterjee and Sing (2021) well.

Comparative study Data span	Leukes May 2005 - Dec 2017	Manguzvane Jun 2007 - Apr 2016	Chatterjee Mar 2002 - Oct 2020
Standard	0.0186	0.0198	0.0199
First Rand	0.0564	0.0568	0.0076
ABSA	0.0312	0.0487	0.0017
Nedbank	0.0169	0.0182	0.0022
Investec	0.0105	0.0108	0.0107
Capitec	0.0015	0.0041	0.0018

Table 4.3: Summary of $\Delta CoVaR$ results for periods covered by other studies
The table shows the values for $\Delta CoVaR$ calculated on the basis described in this study for the periods covered by the respective studies by Leukes and Odei-Mensah (2019), Manguzvane and Mwamba (2019) and Chatterjee and Sing (2021).

The differences in results against other investigations of South African banks may be attributed partly to the use of differing periods of investigation and percentiles. As each entity is compared to the market, the completeness of market data would also impact the results and could introduce differences between researchers. The methodology and the use of monthly unadjusted data (see Section 4.2.4) must play a part in these differences as well. One possibility is that the method that these researchers use to modify the raw stock exchange data, effectively to remove market-related noise from that data, could have a significant impact on the results that emerge. The consistency of those results to one another (see Table 4.1) may be more a feature of the method of filtering the raw data than an intrinsic contribution by the banks to systemic risk. It could alternatively be a spurious consequence of market trading patterns that reflect the view of market participants regarding the banks most likely to contribute to aggregate risk. Similar methods for blending book- and market-based information (also described in Section 4.2.4) may, in addition, introduce spurious consistency to results.

Tables 4.4 and 4.5 set out the corresponding results separately for the respective decades making up the period of investigation. Immediately apparent is the low consistency of the $\Delta CoVaR_q^i$ and $\Delta^R CoVaR_q^i$ values for each bank across the respective periods of investigation. Of larger entities, only Standard Bank and Nedbank feature high on the list in both instances. The $\Delta CoVaR_{0.05}^i$ value for Investec, in contrast, is the highest of all banks in the first period, but negative in the second. Closer examination of the data may reveal higher correlation of results for the larger banks with the industry as a whole over the period of the financial crisis, causing them to feature more prominently on the results for the decade to 2011 than in the next decade. Tentative evidence for this is presented in Table 9 in the Appendix, covering the period of the 2008-09 financial crisis, where the five largest banks appear in the top seven positions. First Rand and ABSA return particularly

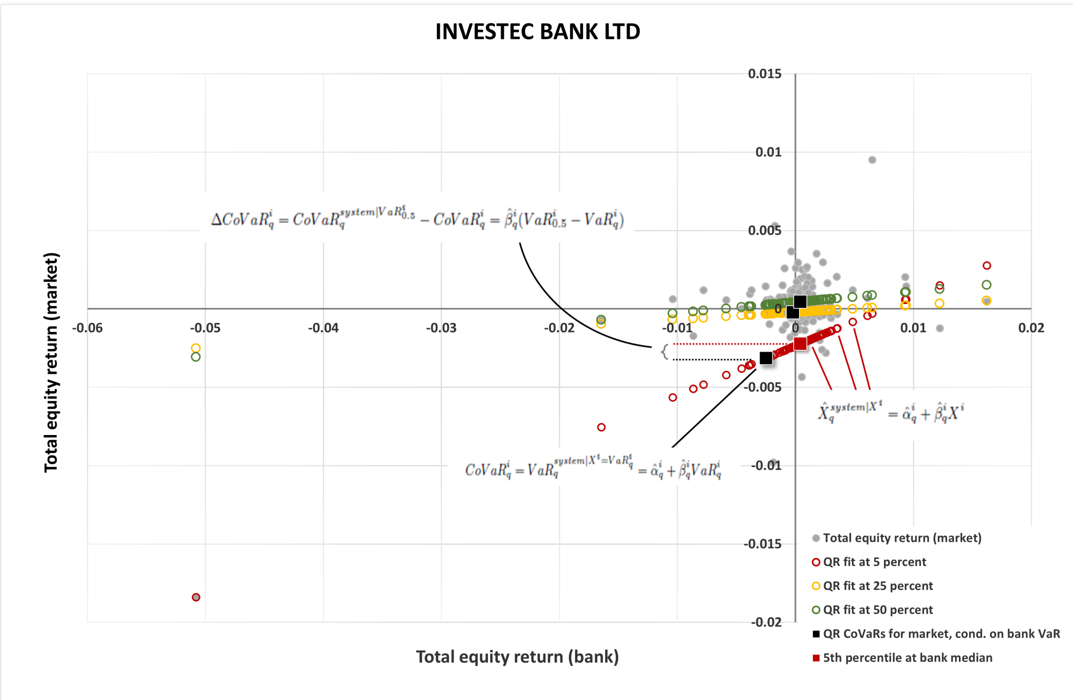


Figure 4.2: $\Delta CoVaR$ calculation, Investec
The chart shows the data underpinning the calculation of $\Delta CoVaR$, using data for Investec covering the full period of investigation.

high scores for $\Delta CoVaR_q^i$ and $\Delta^R CoVaR_q^i$ over this period.

The second observation is that negative values for $\Delta CoVaR$ are more common in the most recent ten years, even for three of the larger banks. Two of these banks also return negative values for $\Delta CoVaR$ in the last five years of the study (see Table 11). If these are a true reflection of negative relationships between the performance of a large bank and its peers, then policymakers may take some comfort in the appearance of a diverse set of results, but they may also reflect data outliers that disproportionately impact the limited set of information. Further investigation is recommended, as set out in Section 4.5.

The final observation is that results over adjacent periods do not appear to display properties of additivity. Nedbank, for example, features high on the chart for the decade to 2011 and right at the top for the following decade but, over the 20 year period, does not have a particularly high rating. This should not be surprising. The analysis considers extreme values and does not depend on assumptions of the statistical distribution. It makes interpretation a little more difficult, however. Using monthly information exacerbate this, contributing to a problem of thin data.

	$CoVaR_{0.50}^i$ monthly	$CoVaR_{0.05}^i$ monthly	$\Delta CoVaR_{0.05}^i$ annualised	$\Delta^R CoVaR_{0.05}^i$ R'000
Investec	-0.00250	-0.00428	0.0215	4 614 810
First Rand	-0.00406	-0.00577	0.0208	12 371 253
B of China	-0.00186	-0.00355	0.0205	95 303
Sasfin	-0.00225	-0.00351	0.0152	31 436
Nedbank	-0.00250	-0.00328	0.0093	5 030 775
B of Taiwan	-0.00210	-0.00284	0.0089	8 455
Standard	-0.00240	-0.00310	0.0084	6 487 886
Grindrod	-0.00177	-0.00210	0.0039	9 859
ABSA	-0.00237	-0.00260	0.0028	1 846 319
Capitec	-0.00177	-0.00190	0.0016	22 308
Bidvest	-0.00176	-0.00188	0.0014	3 712
B of Athens	-0.00180	-0.00191	0.0013	1 693
Citibank	-0.00186	-0.00195	0.0011	51 175
HBZ	-0.00174	-0.00178	0.0004	1 009
Albaraka	-0.00178	-0.00179	0.0002	486
UBank	-0.00176	-0.00160	-0.0019	-6 637
China Constr.	-0.00197	-0.00175	-0.0027	-19 647
Habib	-0.00186	-0.00159	-0.0032	-2 472
Deutsche	-0.00183	-0.00135	-0.0058	-222 950
B of India	-0.00200	-0.00149	-0.0062	-13 513

Table 4.4: Results for February 2001 - January 2011

Notes: $CoVaR_{0.50}^i$ is the system value at risk conditional on the median monthly return for bank i and $CoVaR_{0.05}^i$ is the corresponding system value at risk for the 5th percentile of bank i returns. The difference between these, annualised, is $\Delta CoVaR_{0.05}^i$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR_{0.05}^i$.

The corresponding outputs for four separate five-year periods are set out in the supporting information in the Appendix. The values for each bank fluctuate considerably from period to period, suggesting either that contributions to systemic risk by banks do not exist with

	$CoVaR^i_{0.50}$ monthly	$CoVaR^i_{0.05}$ monthly	$\Delta CoVaR^i_{0.05}$ annualised	$\Delta^R CoVaR^i_{0.05}$ R'000
Nedbank	-0.00102	-0.00282	0.0219	24 167 993
UBank	-0.00157	-0.00233	0.0091	52 117
Albaraka	-0.00141	-0.00200	0.0071	60 134
Capitec	-0.00113	-0.00172	0.0071	1 104 704
Standard	-0.00094	-0.00148	0.0065	10 146 205
HBZ	-0.00145	-0.00191	0.0056	37 549
Deutsche	-0.00143	-0.00180	0.0044	75 108
B of Taiwan	-0.00141	-0.00164	0.0027	6 734
Grindrod	-0.00153	-0.00174	0.0025	31 138
Sasfin	-0.00148	-0.00167	0.0022	18 344
B of India	-0.00151	-0.00163	0.0014	17 428
B of Athens	-0.00151	-0.00152	0.0001	280
Bidvest	-0.00150	-0.00149	-0.0001	-1 400
China Constr.	-0.00153	-0.00147	-0.0007	-28 229
Investec	-0.00160	-0.00150	-0.0012	-605 647
B of China	-0.00148	-0.00130	-0.0022	-108 110
Habib	-0.00155	-0.00130	-0.0030	-3 135
ABSA	-0.00186	-0.00140	-0.0055	-7 169 996
Citibank	-0.00183	-0.00127	-0.0068	-583 576
First Rand	-0.00202	-0.00121	-0.0097	-13 395 665

Table 4.5: Results for February 2011 - February 2021

Notes: $CoVaR^i_{0.50}$ is the system value at risk conditional on the median monthly return for bank i and $CoVaR^i_{0.05}$ is the corresponding system value at risk for the 5th percentile of bank i returns. The difference between these, annualised, is $\Delta CoVaR^i_{0.05}$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR^i_{0.05}$.

consistency or that the method used does not detect such contributions with reliability. Analysing the factors that contribute to poor months for both banks and the market may contribute to an understanding of tail dependency that varies over time.

Finally, given the wealth of balance sheet information available through the BA900 forms available from the South African Reserve Bank, similar methods could be applied to other variables. Figure 4.3 illustrates a similar approach to a solvency metric, in this case the monthly change in the ratio of equity to assets. The strong positive slope of the fitted 5th quantile curve is noteworthy, suggesting a material tail correlation between adverse solvency movements at Standard Bank and for the market as a whole. The corresponding hypothetical $\Delta CoVaR$ results are available in Table 12 in the Appendix. The four largest banks appear in the top six of the rankings, suggesting that this may be an alternative approach for assessing systemic risk.

4.5 Concluding comments

This study aims to contribute to the growing literature exploring systemic risk by studying the monthly book values of South African banks. The method contrasts the approach widely used by other researchers investigating $\Delta CoVaR$. That approach typically involves analysing daily or weekly stock market returns, blending them with returns based on book values and filtering these through the lens of a set of state variables to remove market noise and facilitate the detection of time-varying contributions to systemic risk. In this regard, their methods appear to work. The results of this study, in contrast, fluctuate over time and do not appear to facilitate reliable conclusions regarding the contribution of South African banks to systemic risk.

The study nevertheless contributes to an understanding of the dynamics of market-wide risk and raises several questions that may benefit from further research, First, why are some of the results of this study different from the corresponding results of the other studies exploring the South African banking industry (Chatterjee and Sing 2021; Leukes and Odei-Mensah 2019; Manguzvane and Mwamba 2019), themselves consistent with one another? Second, why are these results unstable over time? The problem may be attributable to the use of monthly data, insufficient to detect stable patterns, but other studies may introduce spurious patterns into the data through their filtering methods and their process of adjustment of book values.

Several thoughts for further research follow. First, sub-periods of the data may be scrutinised more closely for correlations between bank and industry performance over particular periods, for example, during the financial crisis, when co-movement of returns may be more likely. This could involve careful analysis of bank-specific balance sheet data to identify the reasons for co-movements between banks and the market as a whole.

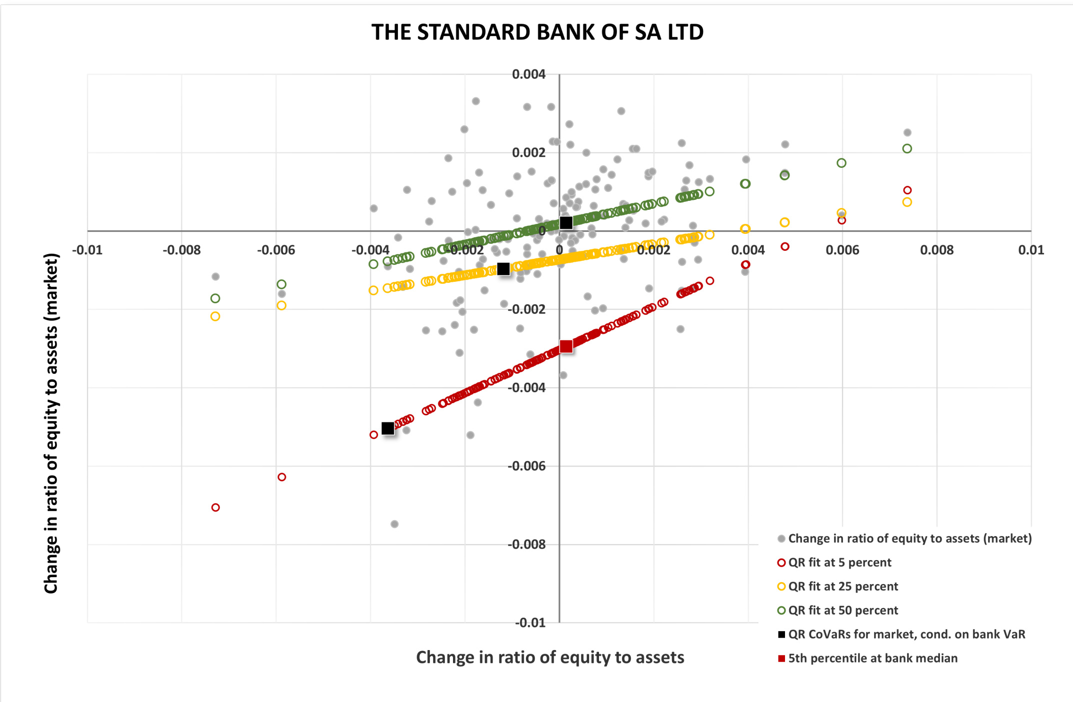


Figure 4.3: $\Delta CoVaR$ calculation applied to solvency
The chart demonstrates the fitted linear quantile relationships between monthly solvency metrics for Standard Bank and the corresponding metrics for the rest of the market covering the full period of investigation. The measure of solvency used is the monthly change to the ratio of equity to assets.

Second, alternative approaches to adjusting book values may be considered. Though book value information is unlikely to be reliably available except on a monthly basis, market values could be used to fill in these missing values if some reliable linking relationship may be found between book and market values. This may assist in the development of an alternative blended approach that combines the qualities of both sets of information.

Third, different approaches may be used to adjust the values utilised in existing studies. Alternative approaches to adjusting book values should be considered, as mentioned under the previous point. The sensitivity of results to different sets of state variables could also be explored.

Fourth, since thin data may contribute to the problems underpinning the analysis described in this chapter, efforts should be made to understand the effects of outliers on this data. The impacts of unusual months, like March 2020 at the beginning of the COVID pandemic in South Africa, could be so substantial that their removal from the data may significantly improve the consistency of results.[10] Of course, outliers are sought in a study of extreme values, so an alternative approach is not to remove them from the data but to study industry dynamics in these months more closely for clues of channels of contagion.

Fifth, all of the attention has been focused, in this study and in others, on one measure of return. Contagion may exist through other channels and may be easier to detect in those channels, on either the asset- or liability side of the balance sheet. This is illustrated by the cursory analysis of a measure of solvency in this study. Applying the methods in this and other studies to different parts of the banking balance sheet may reveal some useful insights. Investigating balance sheets in more detail may serve another purpose, for example, helping to explain the presence or absence of the relationship between bank and market returns. This could be linked to the study of outlier events, as noted under the previous point.

Finally, this study should be applied to other types of entities. Here, data may be the problem. In South Africa, insurers were required to provide detailed monthly data for the duration of the COVID pandemic, but this requirement was recently suspended. The success of the approach depends not only on the data available from individual institutions, but also on reliable aggregate information representing the whole market.

[10]Total banking-industry assets grew, in March 2020 alone, from R6.07 billion to R6.58 billion. Different banks, however, took very different actions during that month. Of the R96.8 billion growth in the assets of ABSA, for example, R62.5 billion was attributable to derivative instruments. In the case of Investec, in contrast, R26.1 billion of its R34.2 billion growth in assets occurred in its holdings of central bank money and gold.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Chapter 5

The Contribution of South Africa's Insurers to Systemic Risk: Thoughts for Policymakers

The rationale for regulating financial markets is strong. First, these markets have a critical role to play in the well-being of economies of all sizes. Second, the consequences of failure of these markets is frequently felt well outside of the markets themselves. This regulation should be based on the foundation of a clearly-written publicly-stated set of objectives. One of these objectives ought to be the mitigation of systemic risk, that is the risk that the actions of a financial-sector entity could trigger widespread damage to large parts of the financial markets and to the real economy. Establishing and utilising an appropriate mix of regulatory methods, however, is rendered extraordinarily challenging by the intrinsic complexity, delicacy even, of these markets. This paper explores these issues, applies them to insurance markets, in general and then in South Africa, and asks whether more could be done by South Africa's insurance regulators to mitigate the systemic risk attributable to the country's insurers. At heart is the concern that increasingly sophisticated efforts to measure and manage entity-specific risk may have the consequence of adding materially to systemic risk.

5.1 Introduction

Financial intermediaries like banks and insurers play a very significant role in servicing economic players in a country and around the world. The financial markets of which these intermediaries form a part are subject to considerable frailty. Failure of these markets can have a considerable impact, not just on intermediaries and their customers, but on national and global economies and all of those who participate in these economies. Regulation plays a critical role in mitigating this risk, but this responsibility is not easily carried out.

The global financial crisis of 2008–09 brought to the fore the challenges of systemic risk in financial markets, that is the risk that actions taken by players in these markets could have repercussions well beyond the reach of those players or even the markets in which they participate. It is not clear that the steps taken by policymakers and regulators to manage these risks have always been appropriate. This article focuses on the insurance space. Notwithstanding the high-profile failure of American International Group (AIG) and other insurers, during or after the financial crisis, the role of insurers in the development of systemic risk is insufficiently understood. While the model adopted globally for regulating insurers focuses attention on a special grouping of these insurers, colloquially labelled "too big to fail", it is not clear that such an approach to these entities is merited or if sufficient attention is given to the risks incurred by insurers falling outside of this group.

This paper asks a number of questions regarding the contribution to systemic risk by South African insurers and puts forward recommendations in this regard for consideration by regulators. More specifically, it asks whether policymakers, regulators and market participants risk being misled by the sophisticated approach to idiosyncratic risk that might actually be contributing to elevated levels of systemic risk.

The section that follows this introduction describes the complexity of financial markets, the significance of their role, the potential for market failure and the widespread consequences of that failure. In the process it builds the rationale for regulating these markets. Section 5.3 builds a case for insurance by considering the theoretical and empirical evidence that insurance contributes to economic and social value added. Section 5.4 turns to the topic of systemic risk: how it is defined, whether insurers contribute to systemic risk and how such risk might be mitigated. That section closes by describing the philosophical basis underpinning the regulation of insurance. Section 5.5 describes the South African market and the basis for insurance regulation in this country and Section 5.6 draws the discussion to a close by considering the effectiveness of this system. Section 5.7 proposes further research and Section 5.8 concludes.

Notwithstanding the fact that the paper takes a generally broad view of the subject that it explores, it is limited in an important respect. It is largely constrained, in its framework and argument, to the presuppositions of neo-classical economics. While it does not support the pursuit of economic growth at all costs, it also does not consider the potential consequences of this pursuit.

5.2 Rationale for regulating financial markets

The discussion that follows builds the case for regulating financial markets by pointing out, first, the significance of financial markets to those who depend on them, second, the intrinsic complexity of these markets and, third, a number of ways in which these markets might fail. This establishes the rationale for regulation but also explains recent trends under which regulatory models are developed on the foundation of a set of objectives, typically to mitigate the impacts of market failure.

5.2.1 The nature and substance of financial markets

It is difficult to express with any accuracy the importance of financial markets to the parties that they serve. The discussion that follows considers the functions of these markets and then describes their complexity and the ways in which they might fail.

Financial systems play a critical role in facilitating transactions between sectors and players in an economy of any size, allocating resources between these players across time and space. Among the functions played by financial markets are (CFRNZ n.d.; Fohlin 2014; Merton 1995; OECD 2010; World Bank 2012):

- facilitating payments for the exchange of goods and services,
- pricing, pooling, managing and transferring risk,
- pooling and mobilising resources for capital expenditure and infrastructural or social development,
- mobilising savings and financial liquidity, and
- facilitating trade in goods and services between countries and regions.

Whether the financial system plays a part in fostering economic development has been the subject of debate for some time. Commentators like Bagehot in the 1870s (World Bank 2012), Schumpeter in the 1930s and a number of economists in the 1960s (Reid 2010) argued that the financial system plays a significant role in development.[1] Lucas (1988), on the other hand, cited by the World Bank (2012) and by Stanley Fischer (2003)[2] took the alternative position, suggesting that it would be an exaggeration to describe financial markets as driving development. Perhaps the most important contributions in this regard have come from those who have suggested that it would be better for policymakers to focus on the needs of economic players in their countries rather than aiming for a financial system with a specified set of characteristics (Reid 2010).[3] Section 5.3 considers evidence for the corresponding economic and social contributions of insurance.

Another question much debated is whether increasingly integrated financial markets have led to improved or poorer stability. Some (ADB 2017; Schmukler 2004) have suggested that increasing integration of financial markets contributed to a number of the financial crises of the last two decades. Others have questioned the extent of this link, raising questions of measures of financial risk (Smaga 2014), definitional challenges (Bisias et al. 2012; Oosterloo and De Haan 2003) and the assessment of financial stability (Fell and Schinasi (2005), and see Section 5.4). Winkler (1998) considers the financial sector a facilitator of development and source of crises. This is widely echoed by more recent

[1] This is not to suggest that these writers claimed that development would follow smoothly. Schumpeter, for example, advocated the need for so-called creative destruction to remove inefficient entities and support economic growth (Dekker 2018; Perelman 1995; Smart 2012). Markets, furthermore, can fail, with widespread adverse consequences. See Section 5.2.2 and writers like S. Sarkar (2012).

[2] Fischer, S (2003). 'The Importance of Financial Markets in Economic Growth', speech delivered in Brazil in his capacity as Citigroup executive, 21 August, mimeo. Fischer described himself as holding to the same view in the 1980s.

[3] This leaves open the point of whether the intermediaries that make up the financial system are themselves also economic players.

research suggesting the existence of tipping points in market stability, famously expressed by Andrew Haldane, director of financial stability at the Bank of Economy, as both "robust and fragile".[4]

In summary, while intense debate continues regarding the roles played by financial markets and the possibility of their contribution to systemic risk, there is little doubt regarding the significance of these markets.

Financial markets are not only highly significant, they are also complex. Financial systems vary considerably country by country, not only by the extent of development, which might be measured by attributes such as depth, access, efficiency and stability (World Bank 2012), but also by their fundamental attributes, often linked to their origins. Systems may, for example, be bank-based or market-based (Detzer 2014; Vitols 2001), which tends to influence the mix and strength of other market participants. Banking services may be specialised by institution or universal and they may be provided through direct relationship between investor and recipient or on an arms-length basis (Fohlin 2014).

Readers of this paper will be familiar with many of the financial intermediaries contributing to the operation of the system. An incomplete list of these entities includes (CFRNZ n.d.; ECB 2012; Merton 1995; Tagoe 2016):

- banks of various types,
- non-bank deposit-takers,
- other types of credit institution, for example, specialist mortgage- or microfinance providers,
- insurers and reinsurers,
- unit trust or collective investment vehicles,
- operators in foreign-exchange markets and capital markets,
- intermediaries and service-providers of various types in money-market, debt and equity markets,
- providers of saving facilities like banks, investment intermediaries, burial societies and mutual-assistance organisations, many of which provide other products and services as well,
- financial vehicle corporations and others carrying out securitisation activities,
- stock- and bond exchanges,
- security- and derivative dealers,
- venture capital providers and other forms of development entities,
- providers of payment services,

[4]Haldane, AG (2009). 'Rethinking the Financial Network', speech delivered at the Financial Student Association, Amsterdam, April, page 3.

- central counterparties and other settlement systems,
- entities offering custodial services of various types, and
- those participating in extensive derivative markets or in the development of other financial instruments.

Markets are also subject to rapid forces of change. The products offered by providers are converging. Global conglomerates have arisen providing a full suite of financial services to a range of customers (OECD 2010) in turn adding to market complexity (Erskine 2014).

This complexity of markets may be illustrated, along with their significance to the economies that they serve, with reference to the impacts of their failure. Instances of such failure are widespread (Reinhart and Rogoff 2008, 2011) but the corresponding financial and social impacts of such failures are typically difficult to measure after the event, much less predict in advance.[5]

This is problematic, for if the regulation of financial markets (see Section 5.2.3) is to add value, credible ways need to be established to demonstrate this value. Regulatory Impact Assessment (RIA) is the term typically used to determine the value of any regulatory initiative. RIA is mandated by governments in many jurisdictions, in principle at least, to assess the benefits and corresponding costs of regulation across a number of fields (Adelle, Macrae, et al. 2015; Adelle, Weiland, et al. 2016; OECD 2009; Radaelli 2005). RIA has been shown to provide significant benefits to the regulatory process (Gordon 2014; Posner and Weyl 2013b; Rose and Walker 2013; Sunstein 2015). A number of practical difficulties of implementation in financial regulation exist, however (Bartlett III 2014; BDI 2016; Cochrane 2014; Parker 2002; Posner and Weyl 2015; Reverz 2016; Zilgalvis 2014). These difficulties lead some to suggest that doggedly insisting on RIA in the financial-market space is counter-productive (Arthur and Booth 2010; Coates 2015; Cochrane 2014; Gordon 2014).

The next part of this discussion considers the fragility of financial markets. This leads to consideration of the role of regulation to mitigate the risks associated with this fragility.

5.2.2 Financial market failure and its consequences

The regulation of financial markets is frequently justified on the basis that such regulation protects against the prospect of market failure (Falkena et al. 2001; Llewellyn 1999; NTSA 2011b; OECD 2010). If that is the case, then the types of failure and its potential impacts ought to be soundly understood. Some commentators prefer terms such as 'imperfections' or 'distortions' to 'failure' when referring to the shortcomings in financial markets. Such imperfections, however, may be used to describe market attributes that, perhaps violating the underlying assumptions of neo-classical economics, are less likely to have deeply deleterious consequences. Such impacts may better be considered a poor market outcome

[5]See Coates (2015), Cochrane (2014) and Posner and Weyl (2013a), for example, for illustrations of the range of estimates of the cost of the 2008–09 financial crisis on the global economy.

rather than a failure (FCA 2013).[6]

If regulation is to be designed to address market failures, it would be useful to establish a sound system for describing and classifying these failures. Researchers, however, have taken various approaches to this problem and have come up with different categories of the causes of market failures (Brunnermeier et al. 2009; CFRNZ n.d.; De la Dehesa 2010; FCA 2013; OECD 2010; Parker 2002). The most commonly mentioned candidate causes of the failure of financial markets appear to be the following:

- Externalities are the costs (and benefits) experienced by those outside of the financial system that result from the actions of those operating within that system (Brunnermeier et al. 2009; Carvajal et al. 2009; Grochulski and Morrison 2014; IMF 2013, 2014b, 2018). These are sometimes also called social costs or spillovers.[7] The widespread impacts of the 2008–09 financial crisis, which impacted poverty levels around the world, represent perhaps the best-known recent examples of externalities.

- Information inequity, sometimes called information asymmetry or information imperfection, is represented by differences in the levels of information available to the two parties to a transaction (Barr and Diamond 2006; Healy and Palepu 2001). Information inequity is well known in insurance circles to operate, between insurer and customer, in both directions.[8]

- Market-power imbalances result from excessive concentration of power in the hands of a few market players and may result in rent-seeking actions that take advantage of this power, potentially costly to the economy (Khwaja and Mian 2011).

- Principal-agency conflict typically results from inequity of incentives of the parties to a transaction (Gintis 1981), inducing agents to put their own interests above those of their customers (CFRNZ n.d.; Laffont and Martimort 2002). It can also have widespread adverse impacts (see, for example, NTSA 2012, 2013a, for South African application). Principal-agency conflict is frequently associated with moral hazard and the market distortions and rent-seeking associated with pricing choices.

With the global financial crisis of 2008–09 fresh in the mind, the first of these typically gains the lion's share of the attention of researchers and regulators. It is the key focus of this paper, which considers the potential for a material contribution to systematic risk by South African insurers. The list above would nevertheless not be complete without consideration of the possibility of regulatory failure (Acharya, Cooley, et al. 2011; Cochrane 2014; FCA

[6]Syll (2010) discusses the gap between the standard assumptions of economic theory and the real world that such theory aims to describe. Behavioural biases and their impacts on decision-making, for example, have been the subject of economic research for some time (see Benartzi and Thaler 1995, 2007; Chuah and Devlin 2011; Johnson et al. 1993; Tversky and Kahneman 1991).

[7]Cost-shifting is the term typically given to known or deliberate negative externalities (see Martínez-Alier 2012; Spash 2019; Swaney and Evers 1989). Environmental externalities frequently fall into this category.

[8]The existence of information inequity in those instances in which the customer is aware of features of the risk that the insurer does not know about, provides additional rationale for insurance regulation, because it demands of the insurer a conservative approach to estimating its liabilities (Swarup 2012).

2013; Gillingham and Sweeney 2010; Parker 2002; Winston 2006), which ought to give policymakers careful pause for thought.

Increasing market complexity brings elevated levels of uncertainty regarding, in general, the future of markets and their effects and, in particular, the impacts of regulation (Whitehead 2012) and the potential for regulatory errors (Bisias et al. 2012). Regulation can do more harm than good (Australian Government 2014; Falkena et al. 2001). Regulators, themselves with the power to impact significantly the nature of the markets that they regulate (Weiß, Boxtandzic, and Neumann 2014) often find themselves having to undo the adverse impacts of pre-existing regulations (Cochrane 2014). Regulators often exert profound impacts on markets, even if unintentional, for example, by introducing moral hazard through the approach to systemically significant entities (Kim 2011; Ötker-Robe et al. 2011, see Section 5.4.3). The complexity faced by these regulators is intrinsically intractable (Weber 2011, 2012), calling ideally for an understanding of the concepts underpinning complexity theory itself (Battiston et al. 2016).

Financial markets, in summary, are complex networks of intermediaries that play a critical role within or between the economies in which they are located. Failure of these markets, which may take a number of different forms, can have substantial impacts that are felt not only within but also far outside of the markets themselves.

5.2.3 The role of regulation of financial markets

The rationale for financial regulation is frequently expressed in terms of efforts to mitigate against the potential for market failure (OECD 2010; S. Schwarcz 2019). This typically finds its expression in objectives-based regulatory models under which the success of regulation is judged by the extent to which pre-stated objectives are met.

The regulation of financial markets has a history stretching back for centuries (Atack 2009; Gilligan 1992; Komai and G. Richardson 2011; Markham 2000; Quinn and Roberds 2009; Shea 2009; Velde 2009). The regulation of insurance developed organically in the 19th century alongside the industry (Swarup 2012). Models of objectives-based regulation made a relatively recent appearance in the unfolding of regulatory approaches. These models may be traced back roughly to the development of the Financial Services Authority, as the single regulator in the United Kingdom, which took place in phases between 1997 and 2001 (J. Black 2004; FSA 2006, 2007; Llewellyn 1999). The approach was further refined by models of risk-based regulation in various countries that sought to apportion effort and resources to those parts of the regulatory environment that would most benefit from such allocation (Baldwin and J. Black 2016; J. Black 2004; J. Black and Baldwin 2010, 2012; FSA 2012). Objectives typically also play a key role in the establishment of regulatory infrastructure focused on market conduct (see, for example, APRA 2014; Australian Government 1997; Feasibility 2010; FSA 2006, 2012; NTSA 2011a) and on systemic risk (NTSA 2011a). In both instances such initiatives seek to defend against the impacts of one or more of the market failures identified in Section 5.2.2.

Three reasons may be put forward for the use of objectives in financial regulation. First, objectives promote accountability, a key determinant of good governance in a democracy

(Brandsma and Schillemans 2012; Gyong 2011; A. Sarkar 2009). For this purpose, the success of any actions of government should ideally be assessed against predetermined publicly-stated objectives (CFRNZ n.d.). Second, objectives, appropriately translated into measurable outcomes (J. Black 2012), provide the means to track and report progress (Baldwin and J. Black 2016; Knot 2014). Third, the objectives themselves help to provide the rationale for regulatory intervention in financial markets. They should do this by identifying market failures or desirable social outcomes and showing how the intended regulatory interventions are designed to mitigate the impacts of these failures or support the achievement of the outcomes (Cochrane 2014; NTSA 2011b; OECD 2010).

The rationale for regulating financial markets on the basis of their significance and complexity may be sound, but these attributes must surely call for careful attention to the challenges intrinsic to this regulation, given its potential to cause harm (see Section 5.2.2). Regulation is not cost-free (see Section 5.2.1).[9] Furthermore, the assumption that market failures can be identified and corrected has been strongly criticised (Zerbe Jr and McCurdy 2000). Researchers have also pointed out the danger of ignoring the potential for interaction between market failures (FCA 2013; Murray, A. Manrai, and L. Manrai 2017). Julia Black (2013) argues that the very concept of these markets within an economic framework is inappropriate because markets are essentially social entities (see also J. Black and Baldwin 2010). Policymakers have increasingly recognised that framing the objectives of regulation as merely the absence of market failures is not necessarily acceptable to society at large, because markets do not naturally meet wider societal objectives (NTSA 2011a).[10]

In short, while the regulation of financial markets is justifiable, exactly how to exercise this responsibility is far from clear; yet the consequences of errors can be enormous and wide-ranging.

5.3 The Economic and Social Contributions of Insurance

Having considered the role and intricacy of financial markets and the merit of their regulation, the discussion now focuses more narrowly on insurance. The fundamental question to ask is whether insurance plays a meaningful role in the economic and social development of the people that it serves. This is not intended as a challenge to the right of the existence of insurance. If insurance is to be effectively regulated, however, then its value needs to be understood and, as far as possible, quantified. This in turn might form the basis for the regulatory impact assessment that ought to undergird any regulatory intervention in insurance markets.

The United Nations affirmed in the 1960s, admittedly perhaps a different era of economic

[9] Refer to Colliard and Georg (2020) for an assessment of regulatory complexity and Chenyu, Haomiao, and Ning (2019) and Fidrmuc and Lind (2018) for discussion of the cost of raising minimum capital requirements.

[10] The supportive priority given by governments to the development of the microinsurance sector is a useful example of policymaker focus on encouraging markets to meet a social imperative (see, for example, Churchill 2008; Churchill and McCord 2012; Cohen and Sebstad 2008; Deblon and Loewe 2012; Jacquier et al. 2008; NTSA 2011a).

thought, the importance of insurance to economic development, stating, "a sound national insurance and reinsurance market is an essential characteristic of economic growth." (UNCTAD 1964, p.55). The discussion that follows starts by outlining the theoretical benefits of insurance. This is followed by a description of the technical models linking insurance to growth of the wider economy.

5.3.1 Theoretical case

The most significant theoretical economic and social benefits identified[11] are as follows (Bajar and Rajeev 2015; Borensztein, Cavallo, and Leanne 2017; H. Cai et al. 2015; J. Cai 2016; Carter and Barrett 2006; Chamberlain, Camargo, and Coetzee 2017; Chatterjee and Turnovsky 2012; Clarke, Poulter, and The 2017; Cole, Gine, and Vickery 2013; Deblon and Loewe 2012; Dercon and Christiaensen 2007; Dickinson 1998; Guochen and Chi Wei 2012; Jacquier et al. 2008; Janzen and Carter 2018; Karlan et al. 2014; Kugler and Ofoghi 2005; Outreville 2013; Radermacher, McGowan, and Dercon 2012; Skipper 1997; Thom et al. 2019; UNCTAD 2015; UNEPFI 2014):[12]

- insurance accepts risk of various types, transferring it away from economic entities unable or unwilling to bear that risk at acceptable cost, in the process promoting the financial resilience of businesses and households, reducing the anxiety associated with such risk (and the consequences should it be realised), allowing consideration of riskier ventures at similar cost, freeing resources for more productive uses and giving access to services such as credit, health-care and education;

- insurance also promotes the effective management of risk, not only through the pricing and acceptance of risk, but through mechanisms of pooling and risk reduction and through signalling competitive pricing of risk to economic entities;

- insurance mobilises and allocates saving, providing a security buffer to households that facilitates income- and consumption smoothing, and supporting economic growth in the process;

- insurance helps to grow markets for credit by protecting against default and contributing to appropriate pricing of risk;

- insurance contributes to the development of capital markets by adding significantly to the available pool of investable assets and encouraging the allocation of new capital, particularly because insurance liabilities are typically long-term in nature, and aids in the development of the physical and social infrastructure that supports economic growth and can improve the productivity, earning potential and welfare of the poor, reducing inequality in the process;

[11] Some of the authors cited also report on assessments of the microeconomic benefits of insurance. These are not considered further in the discussion of empirical evidence that follows in Section 5.3.2, which summarises findings on the corresponding macroeconomic benefits of insurance.

[12] A number of authors, also exploring the benefits of insurance, tend to focus on a smaller set, typically risk transfer and management, financial intermediation and the contribution to the development and deepening of capital markets through investment activities (Hussels, Ward, and Zurbruegg 2005; C. Lee, W. Huang, and Yin 2013; Liedtke 2007; G. Liu et al. 2014; Nektarios 2010; Njegomir and Stojić 2010).

- insurance plays a number of financial intermediation roles, facilitating mechanisms of trade, commerce and entrepreneurial initiative, and fostering the efficient allocation of capital;
- insurance substitutes or complements state-led efforts to provide social security to its citizens, through enabling (typically savings) and protective (typically insurance) vehicles, or through providing protection against natural disasters and the potential for rapid recovery; and
- insurers typically have economic incentives to reduce the losses faced by the businesses that they insure, bringing their expertise to the benefit of the insured.[13]

The diversity of insurance business types and hence liabilities encourages the investment of assets into a wide range of needs. It is acknowledged that not all of the activities of insurance are necessarily always in the interests of all of society. The typically narrow subdivision of policyholders into risk categories, for example, may mitigate against social objectives of sharing risk more widely (McLeod 2005). The concerns that the private operation of markets can mitigate against social objectives are not unique to insurers within the broader financial-market sphere.

5.3.2 Macroeconomic empirical evidence

Is there evidence that insurers indeed contribute to economic growth and development? This has proven a difficult question to answer, perhaps well illustrated by the assertion of Rudra Pradhan and his colleagues that: "There is no universally held view of the nature of causality between insurance market activities and economic growth" (Pradhan, Dash, et al. 2017, p.18).[14]

Evidence exists that, in many countries, and over many periods, insurance and economic growth are strongly correlated and that insurance indeed contributes to economic growth, but that this is by no means universally the case. The presentation starts with the helpful summary of (Pradhan, Dash, et al. 2017) setting out the four possible causal relationships between insurance markets and economic growth:[15]

- the supply-leading hypothesis takes the position that causality runs from the activities of insurance markets to economic growth,

[13]Sources from insurance providers or representative bodies, or those funded by the industry have been assessed with caution. Among the additional benefits cited by these sources are (Brainard 2008; D. Cummins et al. 2018; Grant 2012; Kessler, De Montchalin, and Thimann 2016; Weisbart 2018): (1) insurance allows households and small businesses the opportunity to assess opportunities that they might not otherwise be able to consider, in the process fostering economic growth, (2) the long-term capital provided by insurers stabilises economic volatility and provides finance for infrastructure development, and (3) insurance helps to contribute solutions to global challenges like population ageing, climate change and cyber risk.

[14]Pradhan, Dash, et al. (2017) also describe the level of attention given to the nexus between insurance and economic growth as "scant" (p.20). Perhaps this is expressed in contrast to the correspondingly significant volumes of work concerning the analogous impacts of banks and stock markets (see Arena 2008; Haiss and Sümegi 2008, for example).

[15]Pradhan, Dash, et al. (2017) also provides a list of papers that indicate research into each of these models. The literature surveys by Outreville (2013) and Din, Abu-Bakar, and Regupathi (2017) are also recommended..

- the demand-following alternative adopts the opposite direction of causality, in other words that economic growth stimulates the development of insurance markets,
- the feedback hypothesis rests on the viewpoint that economic growth and the development of insurance markets mutually stimulate one another, and
- the neutrality hypothesis takes the view that there is no causal relationship between economic growth and the development of insurance markets.

Early research tended to focus on the second hypothesis as it sought to understand the factors that stimulated the development of insurance markets (Outreville 1990, 1996; Ward and Zurbruegg 2000). The bulk of this work concluded that, indeed, economic growth contributes to the development of insurance markets.[16] For the purposes of this study, however, evidence is sought supporting the existence of the supply-leading hypothesis, but any signals that development is mutual, along the lines of the feedback hypothesis is helpful as well.

A number of empirical studies have been published considering the thesis that insurance contributes to economic growth.[17] On the whole, recent papers are more inclined to assess the markets of multiple countries together and to study the relationship in terms of Granger causality rather than merely correlation or cointegration.

In the pursuit of a definitive answer to the direction of impact, the research is not easily summarised. Evidence, for example, is found of a positive impact of insurance on economic growth in India, China, the emerging economies of Europe and, over a long period, in Sweden:

- life insurance in India appears to stimulate economic growth (Ghosh 2013; A. Verma and Bala 2013) and evidence for the reverse relationship has not been found (Ghosh 2013),
- a causal link between insurance and economic growth is found across the provinces of China, except for low-income provinces in the case of life insurance (Guochen and Chi Wei 2012),
- a study of emerging European markets for 2010–2014 shows a positive impact of insurance on economic growth (Stojaković and Jeremić 2016), and
- insurance in Sweden appears to have exerted a positive effect on economic growth over the period 1830–1998 (M. Adams et al. 2008).

In studies covering the developed countries of the OECD and EU, however, while some evidence of this relationship is found, it appears to be limited to certain countries, or temporary in nature:

- across 55 countries, for the period 2006–2014, both life and non-life insurers have a significant causal impact on economic growth, but for life insurers this is prevalent

[16]Tien and Yang (2014) find higher growth among smaller insurers during times of stronger economic growth in Taiwan, suggesting that the economic growth is positive for competitive dynamics across the market. This possibility is worthy of further research.

[17]Further related studies are available at Enz (2010), Garcia (2012) and Li et al. (2007).

in high-income countries and for non-life insurers in low-income countries (Arena 2008);

- in ten OECD countries for the period 1979–2006, one-way Granger causality is found from insurers to economic growth in five countries, causality the other way for three countries (but in one such instance only for life insurance, not non-life), in both directions for one country, and not at all in the case of four countries (T. Chang, C. Lee, and C. Chang 2014);[18]

- life insurance is found to have a positive impact on economic growth in 18 Western European countries but, for new European Union member states from eastern parts of the continent, the causal link insurance and economic growth is found in the case of liability insurance rather than life insurance (Haiss and Sümegi 2008);

- mixed results are found from a study of European countries, 2004–2015, where three countries show causality from insurance to economic growth, two present evidence of the flow the other way, one shows causality in both directions and a final country shows no causal relationship at all (Peleckienė et al. 2019);

- while long-run evidence exists in a 34-country EU study spanning the years 1988 to 2012 that insurance supports economic development, short-run variations appear, suggesting the possibility of feedback loops in the pattern of development (Dash et al. 2018; Pradhan, Arvin, and Norman 2015);

- evidence of causality from insurance to economic growth is found in analysis of 19 EU countries for 1980–2014, but the consistency of this relationship appears to be weak (Pradhan, Dash, et al. 2017);

- the relationship between insurance and economic growth in nine OECD countries between 1961 and 1996 shows Granger causality running in one direction in some countries and in the opposite direction in others (Ward and Zurbruegg 2000); and

- a strong causal relationship across 55 countries, for the period 1980–1996, appears to exist from both insurers and banks to economic growth, controlling for a number of alternative variables regarded as contributing to growth (Webb, Grace, and Skipper 2002).

Mixed evidence also appears to be uncovered concerning the differences between developed countries and their developing counterparts. Pradhan, Arvin, Bahmani, et al. (2016) report significant cointegration of insurance market activities, economic growth, financial depth and government consumption expenditure across 18 middle-income countries, including South Africa, between 1980 and 2012. They also found significant causal impacts of insurance on economic growth. Han et al. (2010) describe the relationship between insurance and economic growth as stronger in developing countries than in developed, while Haiss and Sümegi (2008) report finding this relationship only in the case of developed economies. Din, Abu-Bakar, and Regupathi (2017) found that the role of insurance in

[18] Some countries are included in more than one of these categories in respect of different periods or different classes of insurance.

promoting economic growth is more significant for non-life insurers than for life insurers. Outreville (2013) suggests that these differences may be attributable to the distinct strength of the relationships in the cases of life and non-life insurance and the relative weightings of the business lines in different markets, life insurance typically playing a small role in developing markets than non-life insurance.

Mixed results are also evident from studies of African countries:

- Insurance markets appears to contribute significantly to economic growth in a panel study of 30 sub-Saharan African countries for the period 1986 to 2011 (T. Akinlo and Apanisile 2014).
- Mixed results are shown from a study of a set of countries for the period 1970 to 2013. Significant causality is found between insurance and economic growth for Egypt. For Kenya, Mauritius and South Africa, this relationship appears to be present but only in the long run. In contrast, negative impacts of insurance on economic growth are uncovered in Algeria, Nigeria, Tunisia and Zimbabwe (Olayungbo and A. Akinlo 2016).
- The result for Nigeria appears to be confirmed in a separate study (Olayungbo 2015), but contradicted by another, considering the period 1986 to 2010, that suggests strong cointegration of insurance with economic growth and statistical significance of the contribution of insurance to economic growth (Yinusa and T. Akinlo 2013).
- A positive relationship between insurance and economic growth is shown for Kenya (Ndalu 2016), but it is not clear whether the study demonstrates causality as well as correlation.
- A significant relationship is found in South Africa, for the period 1990 to 2012, between long-term insurance and the economy where causality is found to run from the economy to the industry. In contrast, no causal relationship is found between short-term insurance and economic growth (Sibindi and Godi 2014).

Some studies consider different measures of financial market development, alongside insurance and different measures of economic growth. Ramoutar (2020), for example, assessing 33 developed and developing countries—South Africa included—over the period 2000 to 2016, considers life insurance and non-life insurance premiums and assets, mutual fund assets and pension fund assets. He finds positive relationships between insurance assets and GDP, between mutual fund assets and GDP and between non-life insurance premiums and GDP, but a neutral relationship between pension fund assets and GDP and a negative relationship between life insurance premium volumes and GDP. The study-of-studies by Zuzana Richterková and Petr Koráb (2013) concludes that insurance activity indeed has a positive impact on economic growth.

5.3.3 Concluding thoughts

In summary, a robust foundation exists for the theory that insurance markets support economic growth. This appears to occur primarily through the mechanisms of risk management, financial intermediation and capital market development.

The empirical evidence that the same relationship holds is more difficult to confirm. This should perhaps not be surprising. Numerous studies have been undertaken, but they have utilised different definitions of insurance market size and economic growth, considered different countries or combinations of countries, assessed different periods and applied different technical methods. Despite these differences, there appears to be support for the position that insurance markets and economic development are strongly cointegrated. Causality is more difficult to establish and appears to run in both directions for different countries and at different times.

Overall, taking theoretical and empirical research into account, a reasonably strong case may be made that insurance plays a meaningful role in stimulating economic growth. This in turn encourages the conclusion that sustaining healthy and growing insurance markets represents a sound and logical objective of insurance regulation.

5.4 Insurer contribution to systemic risk

Having considered the nature and frailty of financial markets, the rationale for regulating them and the contribution of insurance to economic development, the discussion turns to systemic risk, the core subject of the paper. It seeks to define and describe systemic risk and considers the nature and extent of the insurer contribution to systemic risk. It then outlines some of the methods typically used to mitigate systemic risk and summarises the concerns that have been raised regarding these methods, closing the discussion with a focus on insurers. This leads to the discussion of prudential regulation of South African insurers in the following section.

5.4.1 Systemic risk across financial markets

What is systemic financial risk? While the concept of systemic risk has been considered from a number of different angles (Claessens 2015; ECB 2010; Eling and Pankoke 2016; Galati and Moessner 2014; Hansen 2013), broad consensus on the nature of this concept, let alone on the metrics that might be used to describe it, seems elusive:

> One possibility is simply to concede that systemic risk is not something that is amenable to quantification. Instead it is something that becomes self evident under casual observation. (Hansen 2013, p.1)

As difficult as it might be to define with precision, most researchers have recognised the importance of some form of description of systemic risk, to delineate it from other forms of financial distress or market failure. They have done so (Acharya, Pedersen, Philippon, and M. Richardson 2017; Bisias et al. 2012; Cerra and Saxena 2017; J. Cummins and Weiss 2014; De Bandt and Hartmann 2000; Eling and Pankoke 2016; Geneva Association 2010b; Georg 2011; Group of Ten 2001; SE Harrington 2009; Kessler 2014; Nier et al. 2007; Safa, Hassan, and Maroney 2013; Weiß and Mühlnickel 2014), with reference to a number of attributes, for example:

- widespread adverse impacts on the financial sector, typically based on the preconditions of extensive market interdependencies and the associated risk of contagion,
- externalities or market failure of some form,
- significant loss of confidence, typically resulting in an associated loss in economic value, and
- severe and widespread impairment of financial-sector entities, often spilling over into the wider economy.

Georg (2011) suggests that the financial upheaval of 2008–09 and the contagion that followed it stimulated a significant change in the meaning attributed to systemic risk. Before the crisis, the term was typically used to describe the potential for contagion stimulated default cascades. The crisis, he proposes, showed that systemic risk may also be attributable to a common shock that leads to simultaneous default or informational spillovers increasing the cost of debt.

A number of researchers have utilised a range of approaches in an effort to quantify systemic risk or the respective contributions of financial institutions to systemic risk. Refer to Acharya, Pedersen, Philippon, and M. Richardson (2017), Bierth, Irresberger, and GNF Weiß (2019), H. Chen and Sun (2019), Dijkman (2010), Hufeld, Koijen, and Thimann (2017) and Kanno (2016), and the survey of alternatives in Bisias et al. (2012). Where researchers or commentators adopt a definition of systemic risk, they commonly do so with reference to the definition adopted by the Financial Stability Board, quoted by the Geneva Association as follows:

> The risk of disruption to the flow of financial services that is (i) caused by an impairment of all or parts of the financial system; and (ii) has the potential to have serious negative consequences for the real economy. Fundamental to this definition is the notion that systemic risk is associated with negative externalities and/or market failure and that a financial institution's failure or malfunction may impair the operation of the financial system and/or the real economy. (Geneva Association 2010b, p.23, citing the Financial Stability Board)

This definition is helpful to this research because it links systemic risk directly to the existence of externalities, one of the market failures identified in Section 5.2.2. It also helps regulators to delineate the impacts of the risks incurred by financial-sector entities into two broad categories: (1) those with direct adverse effects on the entities themselves and (2) those that spill over to others, in other words, externalities or systemic risk. While regulated entities have a natural incentive to identify and manage risks whose impacts have a direct effect on them, they do not have the same incentive to put time, effort and money into mitigation of the potential for externalities. This represents a key responsibility of regulation (S. Schwarcz 2008).

The South African Reserve Bank (SARB), operating as central bank and regulator of banks, also defines systemic risk in a manner that draws attention to the possibility of externalities and their impacts. A stable financial system is defined by the SARB in the following terms:

> [...] a financial system that is resilient to systemic shocks, facilitates efficient financial intermediation, and mitigates the macroeconomic costs of disruptions in such a way that confidence in the system is maintained. (SARB 2017a, inside cover page, no number)

Before turning to questions on the causes of systemic risk and the means typically utilised by regulators to mitigate systemic risk, it is appropriate to note the avenue of research that assesses the financial system as a network of connected entities. The nature of this network and the extent and form of its inter-connectedness are explored to shed light on the options available for mitigation of the potential of contagion, that is, the propagation of distress through the network.[19] South Africa's financial markets appear to show high levels of concentration and inter-connectedness (see discussion in Section 5.5.2), suggesting the possibility of fruitful further analysis in this regard (as considered in Section 5.7).

What are the sources of systemic risk? Of the authors consulted, Allen and Gu (2018) appear to consider these sources most widely. They list banking crises due to panic or to falling asset prices, contagion, the financial architecture itself, foreign exchange mismatches in the banking system and the behavioural impacts attributable to incomplete knowledge. SE Harrington (2009) suggests four, a spiral of falling asset prices, the domino effect of counterparty defaults, a loss of confidence resulting from opaque information on institutions and irrational withdrawals of funds. Others have taken a slightly different approach, distinguishing for example between direct financial exposures between banks and correlated exposure to a common asset (De Bandt and Hartmann 2000; Nier et al. 2007) and suggesting the following broad classification between sources:

- contagion attributable to the sale of assets at inopportune times, triggering a spiral of falling prices,[20]
- contagion caused by counterparty defaults, in turn resulting in the failure of others,
- contagion resulting from unclear information about institutions, provoking cautious unwillingness to engage financially with parties and a spiral of failures, and
- irrational contagion, typically resulting in withdrawal of funds by customers regardless of the financial strength of affected institutions.

How then might regulators mitigate or manage systemic risk? Notwithstanding the substantial weight of literature and policymaker focus on the problems associated with sys-

[19] Refer, for example, to Andries and Galasan (2020), Babus (2016), Caccioli, Barucca, and Kobayashi (2018), Chinazzi and Fagiolo (2013), Gai and Kapadia (2010), Georg (2013), Klinger and Teply (2015), Langfield and Soramäki (2014), Levy-Carciente et al. (2015), May and Arinaminpathy (2010), Rigobon (2016), Upper and Worms (2004) and, for application to South Africa's banking market, Walters et al. (2018).

[20] News of distress does not necessarily produce negative impacts in other market players. Brewer III and Jackson III (2002) show that such news can have positive impacts on the share prices of competitors that may stand to benefit from the financial distress of a market entity. Financial networks are complex.

temic risk, this remains a deeply challenging problem, beset by extraordinary complexity. It is clear that mistakes have been made in the past. The Group of Ten (2001), representing a gathering of central bankers and transnational financial institutions, while acknowledging signals of increasing risk, expressed itself satisfied that: "Existing policies appear adequate to contain individual firm and systemic risks both now and in the intermediate term" (Group of Ten 2001, p.7 and again on page 18). This thinking appears to have been overturned by the financial events of later that decade.

A number of improvements were implemented to regulatory systems across jurisdictions in response to the financial crisis of 2008–09.[21] Perhaps most notable of these was the implementation of special measures to address risks associated with those banks and insurers that became regarded as, in the popular parlance, 'too big to fail', which is considered in more detail in Section 5.4.3.

Yet questions remain about the framework that is now in place. May and Arinaminpathy (2010) ask whether the possibility of unintended consequences has been considered adequately, pointing out that the harmony underpinning the Basel accords, beneficial perhaps to individual institutions, may represent a concentration of risk to the system as a whole because it encourages herding of practices of risk- and solvency management. Concerns have been raised regarding regulatory approaches to increasing market complexity (Weber 2012). Furthermore, existing models, focused on the nature of the idiosyncratic risks of insurers and resting on a foundation of minimum capital requirements, may have underestimated the corresponding possibility of systemic risk, of regulation itself as a contributor to systemic risk and even of regulatory capture (D. Schwarcz and S. Schwarcz 2014; Smaga 2014; Weber 2010, 2011, 2012).[22] The discourse in Section 5.5.1 considers this and other criticism levelled on the Solvency II framework, upon which South Africa's approach is based, asking in particular whether that framework actively enhances systemic risk rather than mitigating it.

The discussion that follows considers the contribution of insurers to systemic risk and the next section tackles the tricky issue of regulating systemically significant entities. Regulatory approaches to Europe and South Africa are described in Section 5.5.

5.4.2 Insurers and systemic risk

A number of researchers have asked questions concerning the extent to which insurers contribute to systemic risk.[23] Though this work has a reasonable history (see, for example,

[21]A more complete treatment of the subject puts these responses in the context of the full suite of tools available under the general subject of macro-prudential policy along with their interaction with other central-bank tools such as monetary policy and micro-prudential regulation (Aikman, AG Haldane, and Kapadia 2013; Carreras, Davis, and Piggott 2019; Claessens 2015; ECB 2010; Galati and Moessner 2014; Lim et al. 2011; Shin 2013). This is included in the proposals for further research (Section 5.7).

[22]Coglianese and Lazer (2003) describe an alternative approach to regulation that seeks to impose on private-sector entities the obligation to achieve public-sector outcomes, leaving to them the freedom to determine how to do so. Most financial-sector regulators, in their defence, indeed aim to meet a set of social objectives. Those that are more transparent in their approaches also set out these objectives and demonstrate the extent to which they are measured.

[23]Helpful literature reviews are provided by Bierth, Irresberger, and GNF Weiß (2019), Benoit et al. (2017), H. Chen and Sun (2019), Eling and Pankoke (2016), Elyasiani, Staikouras, and Dontis-Charitos

Haley and Sigler 1996, which sought evidence for consumer panic linking four separate failures of insurance companies), it gained impetus following the rather public and very large bail-out of AIG during the financial crisis.

Before that time, one of the more high-profile studies of risk in the insurance industry was the so-called Sharma Report (EU 2002). The study was thorough, competent and highly influential in directing the course of insurance regulation in Europe, and across the world, putting risk management and its failures at the centre of its conclusions. Though it identified systemic risk as important, it did not place significant emphasis on those issues in insurers that might impact systemic risk.

A follow-up to the Sharma Report (EIOPA 2018) set out to explore the causes and contributing factors to all instances of insurer failures or near-failures in the EU over the period 1999 to 2016. The report confirmed the exposure of the insurance industry to the effects of the financial crisis, noting a clear peak in insurer malady corresponding to the period 2008 to 2009, during which time some 37 percent of all EU entities on the EIOPA database "suffered impairment or failure" (EIOPA 2018, p.3). Nevertheless, this adversity was not reported as an unavoidable consequence of widespread contagion, but rather of inadequate corporate governance, or of management inattention or ineptness:

> The two most common general causes of failure and near miss reported in the EIOPA database are linked to underlying internal risks of the insurer, namely: (1) the risk that management or staff lack the necessary skills, experience or professional qualities; and (2) the risk of inadequate or failed systems of corporate governance and overall control.(EIOPA 2018, p.3)

Concerning the financial crisis itself, while insurance group AIG gained a certain notoriety, not only for itself but for insurers in general, for the size of the bailouts received, it stood almost alone among insurers in this regard.[24] Total capital raised after the financial crisis was USD1 470bn for banks, 58 percent of shareholder equity, compared to USD170bn for insurers, 16 percent of shareholder equity (Geneva Association 2010b; Kessler 2014). While the Treasury Troubled Asset Relief Program (TARP) paid an initial amount of USD40bn to AIG, only two other insurers received financial support, to the total of USD4.35bn. This compares to USD245bn paid to 592 banking recipients, of which the largest ten received a total of USD190bn (SE Harrington 2009).[25] This is not to say that challenges to insurance markets do not occur.[26] The impact of the financial crisis on insurers, however,

(2015), Hauton and Héam (2015), Kanno (2016), Kaserer and C. Klein (2019) and Van Lelyveld, Liedorp, and Kampman (2019). The work of Eling and Pankoke (2016) is particularly noteworthy for its thoroughness in this regard.

[24]See SE Harrington (2009) for a detailed description of the events leading to AIG's financial challenges. The total amount authorised for financial support to AIG was USD182.3bn. The amount actually advanced amounted to USD134.9bn, USD81.9bn from the Federal Reserve Bank of New York and the balance from the US Treasury (SE Harrington 2009, p.795, possibly now dated).

[25]The amounts cited are until 16 July 2009 (SE Harrington 2009). AIG also received a commitment for an additional USD29.8bn.

[26]Some ten banking panics occurred in the US between 1873 and 1933 and in the third quarter of 2009, 50 US banks went bankrupt (Kessler 2014). A number of insurers went out of business in the US in the mid-1980s and the Lloyd's insurance market nearly went under in the early 1990s, but these have been isolated events rather than bearing the hallmarks of contagion (Baluch, Mutenga, and Parsons 2011). Such events are less common than for banks (Kessler 2014)

was considerably lower than on banks.[27]

> The insurance business model enabled the insurance sector to weather the effects of the crisis better than some other financial institutions. This is largely because the underwriting cycle is, in general, not correlated with the business cycle; in particular, the inverted production cycle—the upfront accumulation of premiums and the deferred nature of payment of liabilities—means that insurers are unlikely to fail in the same way as banks. However, where insurance groups engage in activities that expose them to active developments or movements in financial markets, they become more susceptible—and can indeed contribute—to systemic risk.[28]

The weight of studies of various kinds suggests that the overall contribution of insurers to systemic risk is small in comparison with the corresponding contribution of banks (Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; Billio et al. 2012; Bobtcheff, Chaney, and Gollier 2019; Eling and Pankoke 2016; Kaserer and C. Klein 2019; Van Lelyveld, Liedorp, and Kampman 2019). Banks appear to have a greater impact on insurers than the other way around (H. Chen, J. Cummins, et al. 2013). That insurers are expected, on the whole, to contribute less to systemic risk than banks is supported also by general argument (Bobtcheff, Chaney, and Gollier 2019; Kessler 2014) that insurers retain their risks on balance sheet, explicitly match assets to liabilities and outsource risk largely to reinsurers using a structure based on hierarchy rather than on peer-to-peer support. Systemic risk in reinsurance markets is also regarded as relatively limited, though in this case, the positive impacts of hierarchy are somewhat diluted by the network effect of reinsurers supporting one another (Kanno 2016).[29]

Against this are those who argue that the contribution of insurers to systemic risk is indeed significant. The list starts with those researchers who have pointed out the increase of this contribution during and following the financial crisis (Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; J. Cummins and Weiss 2014). The systemic risks attributable to insurance appear to be higher when insurers have strong bancassurance alliances or form part of financial groups (Baluch, Mutenga, and Parsons 2011; Hauton and Héam 2015). The Hauton and Héam (2015) study of the French market suggests that being part of a larger financial group improves the robustness of the insurer but increases overall levels of systemic risk, surely a warning for regulators of the possibility

[27] Studies of other aspects of insurers during the financial crisis appear to support this broad view. Berry-Stölzle, Nini, and Wende (2014) found that, notwithstanding losses experienced during the course of the crisis, insurers were, on the whole, easily able to raise new capital, unlike many of their peers in other parts of the financial sector. Paulson and Rosen (2016) explored the thesis that, under financial pressure, US insurers might sell corporate bonds in large number, triggering a downward price spiral. They found evidence that insurers indeed tend to absorb liquidity risk by purchasing bonds when these bonds are less liquid than average. This suggests the possibility of a counter-cyclical stabilising role for insurers. However, the authors found no evidence of increased buying or selling around the time of the crisis.

[28] Adams, J (2014), 'Global systemically important insurers: issues, policies and challenges after designation', Speech to The Geneva Association, published by the Bank of England, March.

[29] The technical arguments of sources such as the IAIS (2011, 2012b), the Geneva Association (2010a,b) and Rudolph (2017) are broadly supportive of these conclusions, but the sources should be considered less credible due to their positions in the market.

of an exchange of idiosyncratic risk for systemic risk in such instances.[30]

The contribution to systemic risk is particularly noteworthy in those instances in which insurers participate in ventures outside of core insurance activities (Baluch, Mutenga, and Parsons 2011; Bobtcheff, Chaney, and Gollier 2019; J. Cummins and Weiss 2014; Eling and Pankoke 2016; Koijen and Yogo 2017; Weiß and Mühlnickel 2014).[31] The logic underling this evidence is succinctly expressed by Catherine Bobtcheff and her colleagues:

> By the law of large numbers, traditional lines of insurance with idiosyncratic non-catastrophic risks cannot be systemic. On the contrary, undiversified insurers specialised in activities whose insured risks are highly correlated with GDP are systemic. (Bobtcheff, Chaney, and Gollier 2019, p.73)

Increased concentration of insurance markets appears to raise the corresponding propensity of these insurers to contribute to systemic risk, supporting the so-called "concentration-fragility" view (Shim 2017). Van Lelyveld, Liedorp, and Kampman (2019) finds little evidence of systemic risk across insurers in the Netherlands but raises concerns regarding the contagion risk associated with in-house reinsurance. Kanno (2016), studying global reinsurers, finds high levels of resilience but notes the importance to the network of a handful of highly connected entities.[32]

Insurers potentially contribute to systemic risk through policyholder behaviour, particular policy lapses and surrenders. Barsotti, Milhaud, and Salhi (2016) link policyholder behaviour to economic factors. Policy lapses tend to be highest at time of economic difficulty (Russell et al. 2013), exactly when the stress on insurers is likely to greatest. Barsotti, Milhaud, and Salhi (2016) conclude the possibility that typical stress-testing methodologies may under-estimate lapses under extreme economic scenarios. Insurers specialising in a single product type are more likely to provoke contagion should they fail than their diversified counterparts, particularly if operating in concentrated markets with poor substitutability (Geneva Association 2010b). The same applies to insurers operating in niche product lines that are poorly regulated (Rudolph 2017), though typically these lines are small and would not be expected to contribute substantially to systemic risk.

The most vehement warning against the position that insurers are unlikely to contribute materially to systemic risk, even in their core activity, is provided by Daniel and Steven Schwarcz (2014). Acknowledging efforts by US regulators, after the 2008–09 crisis, to manage the potential systemic risk of individual insurers, they warn that insufficient attention is given to the potential systemic correlations of risks across groups of insurers. As significant asset owners, as members of complex financial groups and as owners of significant tail risks, insurers, the authors argue, contribute significantly to systemic risk. This is not

[30] In related research that studies tie-ups of insurers and banks, the systemic risk of insurers after a deal appears to fall but the corresponding systemic risk of banks rises (Elyasiani, Staikouras, and Dontis-Charitos 2015).

[31] Refer, in addition, to Allen and Carletti (2006), who consider the systemic risks associated with the transfer of credit risk between banks and insurers.

[32] Related but slightly dated research is undertaken by Minderhoud (2003), who finds extreme co-movements of the share prices of financial institutions that suggest evidence for contagion, though correlation of share prices does not of itself constitute a strong case for systemic risk by insurers.

helped by the deep complexity of risks managed by insurers, the dependence of regulators on the work of rating agencies and the potential for errors in the calculation of reserves for liabilities. In this regard, the authors raise particular concerns around the incentives for insurers to under-reserve in periods of financial stress and the technical difficulties of reserving through the cycle of hard and soft markets in non-life insurance markets.

Policyholder interests are protected in a number of ways. Prominent among these is the imposition of minimum capital requirements on insurers. The models utilised to set these requirements have been rapidly improving (see the discussion of this development in Section 5.2.3) and are now based on frameworks that take into account the risks to which insurers are exposed. Serious concern has been raised, however, that efforts to establish minimum capital requirements based on the risk profile of insurers actively contribute to levels of systemic risk (refer to the discussion of the issue in Section 5.5.1).

Apart from these concerns, researchers have put forward a number of proposals for regulators in response to the potential contribution of insurers to systemic risk including (Ho, Palacios, and Stoll 2013; Hufeld, Koijen, and Thimann 2017; Kaserer and C. Klein 2019; R. Klein 2012b; Koijen and Yogo 2017):

- identifying and mitigating potential market failures in insurance, for example, the possibility of insurers taking excessive risk or engaging in activities that are harmful to customers,
- focusing on the resilience of the network rather than exclusively on the financial robustness of regulated entities,
- considering the activities in which entities engage and the potential for these activities to contribute to systemic risk,[33]
- enhancing market conduct, the transparency of market activity and the alignment of incentives, in the interests of better-informed customers and stronger competitive dynamics, and
- considering limits on certain market activities, or taxes on those activities that might contribute to the development of systemic risk.

In summary, notwithstanding a few high-profile insurer crashes during the financial crisis, the conventional wisdom is that insurers engaging in traditional insurance activity across a diversified portfolio are unlikely to contribute significantly to systemic risk. It follows from this that supervisory authorities should focus their attention on those insurers engaging in non-traditional non-insurance activity, those whose product lines are unique or difficult to replace and those forming parts of larger financial groups. The warnings of those who suggest that this strategy represents an unduly carefree approach to the potential for the aggregation of idiosyncratic insurer risk, however, should not be ignored.

[33] Considering the financial market as a network, entity-based regulation targets the nodes of the network, the insurers, and activity-based regulation focuses on the network edges, the activities that link these insurers (Kaserer and C. Klein 2019).

5.4.3 Regulating systemically significant entities

One of the results of the regulatory changes that followed the 2008–09 upheaval was the establishment of special regulatory requirements on those entities regarded as systemically significant. Identified as SIFIs (globally systemically important financial institutions) in the banking space and G-SIIs (globally systemically important insurers) in insurance, these entities fall into a group of those colloquially known as 'too big to fail'. The financial crisis appeared to confirm the willingness of authorities to step in to prevent the collapse of these entities (Ueda and Di Mauro 2013).

This raised a number of questions regarding the special status of these entities. Boyd and Heitz (2016) take the position that the cost to society of elevated systemic risk exceeds the benefit of the scale economy associated with these large entities. Others examine the significance of the moral hazard and potential for international externalities associated with these entities, calling for concerted international efforts to manage their corresponding systemic risk (Kim 2011; Ötker-Robe et al. 2011). A staff note of the International Monetary Fund (IMF) succinctly states the nature and scale of the problem:

> The unprecedented scope and intensity of the recent financial crisis underscored the too-important-to-fail (TITF) problem associated with systemically important financial institutions (SIFIs). Ahead of the crisis, implicit government backing permitted these institutions to take on greater risks without being adequately subject to market discipline and to enjoy a competitive advantage over systemically less important institutions. And when the crisis broke, their scale, complexity, and inter-connectedness, which had made them difficult to manage and supervise, also proved too significant to permit them to fail. (Ötker-Robe et al. 2011, p.2)

Perhaps unsurprisingly, financial markets seemed to regard 'too big to fail' as a label worth having. Share prices reflected perceptions of the designation as advantageous (Moenninghoff, Ongena, and Wieandt 2015). Entities falling into this group appeared to benefit from the special advantage of lower funding costs (Araten and Turner 2013) and evidence was produced that the margin in funding costs had further improved by the end of 2009 (Ueda and Di Mauro 2013).[34]

The financial crisis, however, or the actions of the authorities following the crisis, may have exacerbated the moral-hazard challenges:

> Yet, some SIFIs have already become bigger and even more complex following the crisis, and risky lending practices have begun to reappear. The restructuring following the crisis increased the level of concentration in many advanced economies' financial systems, with implications for stability and competitiveness. Policies are therefore needed to make financial institution failures less likely and less devastating when they occur, re-establish market discipline,

[34]Crawford (2017) calls for regulators to recognise the benefit of the credibility of loss among SIFI creditors, suggesting that it makes the damage caused by SIFI failure less severe when it happens but also less likely to occur in the first place.

> level the playing field, and spare governments and taxpayers the costs of future bailouts. (Ötker-Robe et al. 2011, p.2)

What followed was a process of improving the regulatory measures, both in banking and in insurance, that were applied to these entities. Regarding the insurers, policy measures to be applied to G-SIIs were first put forward in 2013 (IAIS 2013). These measures included special minimum capital requirements (Fung and Yeh 2018; IAIS 2013, 2015) and a detailed forward plan required of these entities in the event of financial distress (IAIS 2013). Significantly enhanced supervisory powers over the affected entities were also proposed, specifically with regard to systemic risk management planning and the treatment of non-traditional non-insurance activities (IAIS 2013).

The Financial Stability Board (FSB) identified nine insurers as falling into the category of G-SIIs, based on the methodology of the International Association of Insurance Supervisors (IAIS). The US Financial Stability Oversight Council followed the FSB recommendation, designating all three US-based insurers, AIG, Metlife and Prudential Financial as G-SIIs (H. Chen and Sun 2019). It is fair to say that the road has not been smooth since then, all three of these companies shedding their G-SII label following a successful ruling in favour of the Metlife appeal to have the status removed in 2016 (H. Chen and Sun 2019). In Europe, Assicurazioni Generali S.p.A. reduced the size of its business and sold reinsurance and banking units in a successful attempt to have itself removed from the list of G-SIIs.

A number of papers specific to insurers followed the announcement of these measures. On the one hand, the difference between the systemic risk of G-SIIs and other insurers, as measured by stock-market indicators, appeared to fall after the publication of policy measures (Fung and Yeh 2018), suggesting a broadly successful approach. On the other hand, the significance of the size of the insurer to systemic risk was said to be overstated and a number of factors utilised in the methodology were regarded as not statistically significant indicators of systemic risk (Weiß and Mühlnickel 2014). A few insurers that did not fall under the G-SII designation were found to contribute more to systemic risk than some of the G-SIIs, notwithstanding the finding that the G-SIIs were, on average, more systemically significant than those insurers falling outside of the G-SII group (H. Chen and Sun 2019). It was suggested that a stronger focus on country-specific attributes of insurers might be appropriate, with a particular focus on the risks associated with the non-traditional or non-insurance activities of the insurer (Jobst 2014).

The wisdom of the approach under which globally significant insurers are identified for special regulatory attention is not clear, particularly if this distracts regulators from the potential for the aggregation of risk from other insurance sources, in these and other insurers, that might have systemic impacts.

5.4.4 Concluding thoughts

The discussion in this section explores the nature of systemic risk in networks of interconnected financial markets and how this risk might be measured. It considers the sources of systemic risk and the broad options available for mitigating this risk. It investigates whether and how insurers might contribute to systemic risk. It summarises the approaches hitherto adopted in the regulation of those entities, banks and insurers, regarded as potentially contributing significantly to systemic risk.

Uncomfortable questions have been asked about the success of the approaches used. While the 2008–09 setbacks made clear the existence of systemic risk and the failure of regulatory models to manage this risk, it is not clear that the approaches adopted since then have been particularly effective either. In the discussion that follows, heading towards an assessment of the corresponding approaches used in South Africa, further questions are asked about aspects of the regulatory framework in Europe intended to unify country-specific approaches to enhanced stability and security of insurance markets.

5.5 Prudential Regulation of Insurers in South Africa

Like many countries around the world, South African policymakers have taken great strides forward in their efforts to improve the operation of insurance markets in this country. The prudential regulatory framework is described in Section 5.5.3. This is preceded by an assessment of the corresponding framework upon which this is built, Solvency II, and a summary of the nature of South Africa's insurance markets.

5.5.1 Solvency II: The modern model of insurance regulation

The discussion that follows summarises the system for regulating European insurers known as Solvency II. Motivation for this focus rests partly on the adoption by South Africa of the system in the development of its own risk-based regulatory model called the Solvency Assessment and Management (SAM) framework. Solvency II is also considered as part of this research because, notwithstanding significant criticism (see discussion that follows), it represents a significant improvement in existing arrangements in Europe (Doff 2016) and has exerted a strong influence on the corresponding regulatory systems elsewhere (Elderfield 2009).

Solvency II was developed over a number of years to improve its predecessor, Solvency I, by introducing principles of risk-based regulation. This did not happen in isolation: Canada and the United States implemented elements of risk-based capital in the early 1990s and they were followed by Japan, Australia, the United Kingdom and Switzerland, as part of a global process of standardisation (Elderfield 2009; Eling and Holzmüller 2008). Giving birth to Solvency II was not a straightforward process, however, starting with the establishment, on 17 July 2000, of the Committee of Wise Men on the Regulation of European Securities Markets, passing through two pieces of legislation (EU 2009, 2014) and the drafting of substantial technical specifications that led to implementation on 1 January 2016 (Rae et al. 2017). The stated objectives of Solvency II are to "deepen the integration of the EU insurance market; enhance the protection of policyholders and beneficiaries; improve the international competitiveness of EU insurers and reinsurers; and promote better regulation" (Doff 2016, p.588).

Solvency II, like its South African equivalent (NTSA 2011a, see Section 5.5.3) is based on rigorous management of risks by insurers, largely following the corresponding systems of banking regulation in the Basel system (DNB 2016)). Both systems are based on the three pillars that the Dutch Central Bank (DNB 2016)) refers to as risk quantification, risk management and transparency (see also IAIS 2018b). The second pillar calls for sound attention to minimum standards of corporate governance oversight. The third pillar requires high levels of technical disclosure to tight timescales, in the process testing the capacity of insurers to manage the risks to which they are exposed. For the purposes of this discussion, however, the focus falls on the first pillar, which sets standards of minimum capital for insurers.

The principles underpinning the minimum capital requirements in Solvency II utilise mark-to-market values and realistic projection assumptions to determine an appropriate capital buffer (DNB 2016). Insurers may use a standard formula for the solvency capital requirements (SCR), which combines a number of modules and sub-modules (T. Steffen 2008). This is supported by an absolute solvency floor called the Minimum Capital Requirement (MCR), easier to calculate (T. Steffen 2008). Insurers must also demonstrate, however, that the assumptions underpinning the SCR are appropriate to the insurer, failing which they must make adjustments to the standard formula or utilise an internal model, which is subject to separate regulatory approval (DNB 2016).

Two further principles underpinning Solvency II are worth noting before turning to an assessment of the methodology. The first is that Solvency II is essentially principles-based rather than rules-based (Elderfield 2009).[35] While rules exist, for example covering the SCR, boards of directors must apply their minds to the appropriateness of the level and quality of available capital to their current and projected financial position, under best-estimate and stressed conditions. The second is that the system is supported by considerable disclosure, both public and confidential to regulators (DNB 2016).

René Doff (2016), building on the corresponding assessment carried out prior to the finalisation of Solvency requirements (Doff 2008), provides a systemic assessment of Solvency II. His assessment is carried out against a defined set of 10 criteria from other sources, (J. Cummins, Harrington, and Niehous 1993; Holzmüller 2009) and two of his own, which are as follows:

- provide incentives to insurers to hold sufficient capital,
- reflect the risks to which insurers are exposed,
- calibrate the formula appropriately to weight risks in proportion to their impact on the risk of insolvency,
- prioritise those insurers most likely to cause the greatest damage to the economy,
- focus on realistic, economic values,
- discourage misreporting or other forms of distortion,

[35]Where rules apply, in any regulatory system, regulated entities are incentivised to take any advantage of leeway within those rules. See Becker and Ivashina (2015), for example, for evidence of such a tendency among US insurers.

- anticipate systemic risk and avoid causing insurers to fall into a downward spiral in time of crisis,
- take appropriately into account soft issues, such as the quality of management,
- ensure flexibility of the framework over time,
- strengthen the practices of risk management and transparency,
- provide appropriate powers of intervention, and
- ensure sufficient skills and capacity of the respective supervisory authorities.

Doff (2016) describes Solvency II as a considerable improvement on Solvency I, but raises a number of concerns. He suggests, for example, that operational risk (see also Eling and Holzmüller 2008) and liquidity risk are not managed sufficiently well under standard requirements, that the systemic risk contribution of large insurers is not appropriately recognised and that a commitment to economic values is not completely realised. He also points out that a great deal of responsibility for the success of Solvency II rests on the technical proficiency of supervisors and their ability to detect flaws in governance structures.

Comparisons of Solvency II with the corresponding systems in other countries (Eling and Holzmüller 2008; Holzmüller 2009; R. Klein 2012a; S. Liu et al. 2019) have cast the European framework in a broadly positive light. Nevertheless, criticism of a variety of types has been levelled.[36] These include:

- the need for more emphasis on appropriate governance (Eling, Schmeiser, and Schmit 2007; Gatzert and Wesker 2012),
- the risks associated with the use of internal models (Eling and Holzmüller 2008),
- the potential for review of technical aspects of the SCR (Cerchiara and Demarco 2016; Christiansen and Niemeyer 2014; Foroughi 2012; Frölich and Weng 2015, 2018),
- the concerns that interest-rate risk is significantly dependent on the choice of model (Martin 2013),
- the risk that flexible principles might shift to rigid rules over time (Gatzert and Wesker 2012),
- the possibility of regulatory arbitrage and related concerns of inconsistency with Basel requirements and variations in the outcomes of SCR calculations across countries (Laas and Siegel 2017; S. Liu et al. 2019; Martin 2013),[37]

[36] Sources in this list are, as far as can be seen, unbiased and subject to peer review. Industry comment is nevertheless interesting (Insurance Europe 2019). It suggests that a majority of insurers reported that Solvency II was inhibiting investment in the real economy and that insurers had shifted away from the provision of guarantees. These may be unforeseen consequences, but they are not necessarily wrong if they are the result of a more accurate assessment of the risk associated with these actions.

[37] S. Liu et al. (2019) point out the rational basis for the significant differences in SCR outcomes across countries. They explain their finding that the parameters used in specific jurisdictions tend to require higher capital for asset classes that exist in high volume and lines of business that are subject to greater volatility because of low volume. The risk of regulatory arbitrage surely still exists.

- the call for a model of improved market transparency to be considered as an alternative or complementary approach (Eling, Schmeiser, and Schmit 2007),
- the costs of implementation to insurers and supervisors that may raise barriers to entry, undermining the benefit of the approach (Swarup 2012), and
- undue complexity of approach, adding not only to cost but to the risk of arbitrage and supervisory ineffectiveness (Casarano et al. 2017; Eling, Schmeiser, and Schmit 2007; Gatzert and Wesker 2012; Swarup 2012).

Of greatest concern to this study, however, is criticism of the Solvency II framework for inadequate attention to the issue of systemic risk. This takes broadly two forms. Some critics adopt the position that the uniformity of the solvency framework would itself add to systemic risk because it incentivises behavioural herding or undue allocation of assets to sovereign debt (Al-Darwish et al. 2011; Floreani 2013; Rae et al. 2017; Swarup 2012). Consider, for example, the statement of the Institute and Faculty of Actuaries working party assessing the success of Solvency II:

> This concern around procyclicality is such that our working party is unanimous in its view that Solvency II has fallen short of its goal of aiding financial stability. (Rae et al. 2017, p.9)[38]

Others take issue with technical aspects of the Solvency II calculation, for example its dependence on value at risk as the primary determinant of the SCR rather than alternatives such as expected shortfall, which is the approach used in Switzerland and under Basel III (Barth 2000; Boonen 2017; Eling and Holzmüller 2008; J. Wagner 2014).[39]

The issue of value at risk as the central measure is not merely an issue of detail, with second- or third-order impacts. The SCR formula focuses on idiosyncratic risk, not the contribution of the insurer to systemic risk. It is not the only option. Alternatives to value at risk have been developed that have a specific focus on the contribution by the financial entity to systemic risk. Adrian and MK Brunnermeier (2016) propose a measure of systemic risk based on the impact in the value at risk of the entire financial system of the distress of a single institution relative to what they refer to as its median state. They refer to this as $\Delta CoVaR$, the change in the system-wide value at risk conditional on an institution being in a distressed state, in comparison with the corresponding value at risk with the institution in its median state. This approach has been thoroughly tested and expanded (Acharya, Pedersen, Philippon, and M. Richardson 2017; Z. Adams, Füss, and Gropp 2014; Bui, Scheule, and Wu 2017; Fong et al. 2009; Gauthier, Lehar, and Souissi

[38]Caruana (2010) points out that one way of dealing with systemic risk is to require higher margins of capital (and liquidity) during times of economic prosperity and permit some relaxation during times of stress.

[39]This is not a trivial matter but neither is the choice a simple one. Value-at-risk calculations are typically simpler than expected shortfall alternatives, but ignore tail risks (Boonen 2017; Yamai and Yoshiba 2004) besides other technical deficiencies (Boonen 2017). The expected shortfall approach had been considered by the designers of Solvency II (Boonen 2017) and appears to have been discarded on the grounds of additional complexity. It is pertinent to the issue of systemic risk, however. Companies, complying with solvency requirements based on value-at-risk measures, may be exposed to raised expected shortfall, in the process contributing to systemic risk (J. Wagner 2014).

2012; Hautsch, Schaumburg, and Schienle 2015; Sedunov 2016; Zhang et al. 2015).[40] A number of alternatives have been considered (Acharya, Engle, and M. Richardson 2012; Brownlees and Engle 2017; Giglio 2016; X. Huang, Zhou, and Zhu 2012a; Segoviano and Goodhart 2009).[41]

Leukes and Odei-Mensah (2019) report on their assessment of the contributions of a number of South African entities to systemic risk using a number of different tests. Some of their findings are intuitively comfortable. Banks contribute the most to systemic risk and then insurers. Contagion is more likely during distressed periods. Others are more difficult to swallow. Perhaps most concerning is the disparity of results between the ranking of institutions on the basis of CoVaR and the corresponding ranking based on a standard value-at-risk approach.

The use of value at risk as the primary measure of insurance risk in Solvency II appears to be a potentially problematic compromise. Not only might it underestimate the expected shortfall in the event of severe adversity because it does not consider the tail risk, it also appears to fall short on its capacity to identify an entity's contribution to systemic risk.[42]

At the heart of the matter is the profound problem that the pursuit of diversification by the entity tends to contribute to systemic risk (Acharya 2009; Allen and Carletti 2006; Checkley 2009; Ibragimov, Jaffee, and Walden 2011; W. Wagner 2010).[43] The benefits of diversification to individual entities, these authors contend, has led to its widespread encouragement in regulatory models, without appropriate consideration of the potential systemic impacts:

> While it is true that diversification reduces an institution's overall likelihood of failing, it also increases its inclination to fail at the same time as other institutions. Since externalities are typically associated with systemic failures rather than isolated institutional failures, our analysis suggests that there is hence a rationale for discouraging diversification. With respect to capital requirements this would imply that banks with more diversified portfolios should be subjected to higher capital charges. (W. Wagner 2010, p.374)

This begs the question of how the designers of the Solvency II framework intend to modify its approaches to risk management in future. The European Insurance and Occupational

[40] Both Sedunov (2016) and Zhang et al. (2015) present evidence that the CoVaR method of Adrian and MK Brunnermeier (2016) is better than its alternatives at identifying systemic risk, but Zhang et al. (2015) express concern that its predictive ability appears to be limited in instances outside of the crisis of 2008–09.

[41] SRISK, for example, is calculated as the shortfall experienced by a firm conditional on severe market conditions (Acharya, Engle, and M. Richardson 2012; Brownlees and Engle 2017), which is closely related to the Adrian and MK Brunnermeier (2016) CoVaR methodology. Giglio (2016) proposes a method based on the spreads on credit default swaps. Billio et al. (2012) test several different methods.

[42] This should perhaps not be surprising, given the concerns raised about the technical complexity of Solvency II. Much of the delay in the development of Solvency II, furthermore, was attributable to technical issues.

[43] This is not a criticism of diversification as a strategy for managing portfolio risk, as developed in the capital asset pricing model and many iterations of testing with which a number of readers are familiar (see, for example, F. Black 1972; F. Black, Jensen, and Scholes 1972; Fama and French 1993, 2004; Lakonishok and Shapiro 1984; Lintner 1965; Markowitz 1952; Roll 1978; Rossi 2016; Samuelson 1967; Sharpe 1964).

Pensions Authority (EIOPA) has acknowledged the need for additional regulatory tools to address macroprudential risk (EIOPA 2019a,b) following two discussion papers by the European Systemic Risk Board on the measures that may be available to address systemic risk in the insurance industry (ESRB 2018, 2020). In its comprehensive discussion of the issues, EIOPA (2019b) acknowledges the real potential for insurance to contribute to systemic risk, suggesting that these could arise from individual entities, activities across the industry and behaviour across the industry, particularly regarding herding by insurers in response to regulatory requirements.

> EIOPA is of the view that a comprehensive macroprudential framework addressing the specific sources of systemic risk identified for the insurance sector should be implemented in the context of the Solvency II review. (EIOPA 2019b, p.627)

EIOPA has identified a number of options for addressing macroprudential risks more explicitly, including a capital surcharge for systemic risk, concentration thresholds and expansion of the prudent person principle (EIOPA 2019b). The changes recommended are part of ongoing review of the Solvency II system.

5.5.2 The South African insurance market

By a number of measures, the South African insurance industry is large and sophisticated. The IMF (2014a) uses these words to describe South Africa's financial sector as a whole, pointing out that total industry assets, at just under three times GDP, are higher than the corresponding ratios of most emerging markets. The Prudential Authority (Prudential Authority 2019) reports the assets of South African insurers and reinsurers at just over R3 000 billion, some two-thirds of seasonally adjusted GDP,[44] and the corresponding assets of entities operating in the non-life industry at just under R200 billion. Global reinsurer Swiss Re describes South Africa's life insurance penetration in terms of premiums as a percentage of GDP as 10.3 percent, third in the world.[45] This is perhaps unlikely but the corresponding figure based on PA figures, 6.2 percent, would still put South Africa in the top ten countries in the world.[46] These figures may serve to illustrate the South African dichotomy of sophisticated financial services in an unequal society. They nevertheless confirm the significance of the industry.

The South African insurance industry is also concentrated. According to the IMF (2014a), the top five banks in 2013 held more than 90 percent of banking assets, well above the corresponding figures for the other BRICS countries, along with Chile, Mexico and Turkey. The top five insurers "account for 74 percent of the long-term insurance market" (IMF 2014a, p.10).[47] It is also highly interconnected (IMF 2008, 2014a). All of the largest

[44] South African Reserve Bank, 30 June 2019, R4 510 billion, accessed on 21 April 2020 from https://www.resbank.co.za/Research/Statistics/Pages/OnlineDownloadFacility.aspx. The quoted proportion of GDP in the text compares well to the 67.4 percent of GDP cited by the (IMF 2014a) for 2013.

[45] Swiss Re Institute, downloaded 21 April 2020 from www.sigma-explorer.com/, figures for 2018.

[46] Comparability must be regarded with care. Figures reported by the Prudential Authority (2019) are net premiums. As they include the corresponding net premium received by reinsurers, however, they may approximate the gross-of-reinsurance premiums received by insurers.

[47] This statement deserves more attention, in particular whether concentration might be growing or not.

banks are linked to insurers through direct ownership or holding companies, and the level of related-party transactions within financial groups is significant.[48]

This has implications for the regulatory framework:

> The large fiscal and current account deficits, a weak growth outlook, the reliance of banks on money market funds (MMFs) for short-term wholesale funding, and banks' active trading in the over-the-counter (OTC) derivatives market make South Africa susceptible to contagion and sudden stops of capital flows. This susceptibility and potential for spillovers have been exacerbated by the significant concentration and interconnections in the financial system, and the substantial expansion of South African banks into sub-Saharan Africa. (IMF 2014a, p.7)

Alongside broad commendation for the progress made in improving the regulatory framework for South Africa (IMF 2015a,b), the IMF recommends closer attention to liquidity risk (IMF 2015c) and a stronger approach in mitigation of the potential for systemic risk (IMF 2014a). Tools proposed in this regard included stronger powers of regulatory intervention and regular stress tests, across the system as a whole but also on systemically significant entities. While it expressed satisfaction with well-contained vulnerability to financial contagion throughout the transition of African Bank to curatorship in 2014, it nevertheless urged that the South African Reserve Bank devote additional resources to meeting its mandate as systemic regulator (IMF 2014a). While the IMF mentions the existence of asset-backed commercial paper issued by the securitisation vehicles established by banks, statistics from the Association for Savings and Investment South Africa (ASISA) suggest that life insurer involvement in investment vehicles outside of the mainstream is limited.[49] Finally, the IMF called for efforts to promote greater competition to reduce the adverse impacts of high levels of concentration.[50]

The Herfindahl–Hirschman Index is commonly used as a measure of industry concentration, for example, in numerous studies of fledgling insurance markets in Central and South-eastern Europe showing largely improving competition (Dimić et al. 2018; Kafková, Vološinová, and Bosáková 2005; Kostić, Maksimović, and Stojanović 2016; Kramaric and Kitić 2012; Tipurić, Bach, and Pavić 2008; World Bank 2020), improving competitive dynamics in Thailand (Sukpaiboonwat, Piputsitee, and Punyasavatsut 2014) and strong competition in Australia (Arych and Darcy 2020). The index is also commonly used to assess competitive dynamics in US health insurance markets (for example, in Dafny, Duggan, and Ramanarayanan 2012). A number of these authors utilise other measures of concentration. Alhassan and Biekpe (2019), analysing South Africa's non-life insurers, cite low Herfindahl–Hirschman Index values but, on the basis of the Lerner competitive index, express concerns regarding the high pricing power of these insurers, linking this pricing power to an increased probability of insurance insolvency.

[48] The IMF (2014a, p.16) specifically notes: "Substantial interconnectedness within the financial system could amplify risks. [...] A bank failure could have a significant impact on the asset quality of the affiliated NBFIs, while a sudden large withdrawal from NBFIs could cause liquidity stress for banks."

[49] The Association for Savings and Investment South Africa reports structured notes and collateralised securities at long-term insurers amounting to 0.62 percent of those assets linked to policy values and 4.38 percent of non-linked liabilities at the end of 2019 (ASISA Life Statistics, downloaded from https://www.asisa.org.za/statistics/long-term-insurance/ on 19 May 2020).

[50] This is echoed in policymaker calls for improved liquidity, competition and transparency of South African securities markets (NTSA 2018).

5.5.3 Prudential regulation of South African insurers

Having described the Solvency II system, upon which South Africa's framework is based, and set out the essential features of South Africa's insurance market, the discussion turns to that framework, its development and its detail.

South Africa commenced a comprehensive review of its financial sector regulatory framework in 2007, but expanded the scope of this review following the financial crisis of the next two years. Policymakers concluded that the key priorities for this framework were financial stability, consumer protection, access to financial services and combating financial crime (NTSA 2011a). The principles of risk-based supervision were introduced at the same time, with the launch of the SAM framework, based largely on the corresponding Solvency II approach (FSB 2010). The chosen structure of the regulatory framework followed the stated priorities, as recommended by the (OECD 2010).

Does the structure of the model of regulation and supervision make a difference to overall effectiveness? The issue has been subject to discussion for some time. Fay and Parent (2004) cite the seminal work of Goodhard et al. (1998) in support of their position that structure indeed has an impact on regulatory effectiveness. Schmulow (2015) considers some approaches better than others but Čihák and Podpiera (2006) express the view that no particular structure is inherently superior, each one bringing pros and cons. In the context of rapidly changing approaches in a number of countries, it is difficult to suggest clear direction (Čihák and Podpiera 2006; Group of Thirty 2008; Llewellyn 2006; Zimková and Vargová 2006). Policymakers have largely improved the extent to which structure follows purpose. The dominant models of the previous century, either institutional, in which oversight is allocated on the basis of legal status, or functional, where the responsibility for supervision follows the business transacted by the entity, have largely been replaced by more holistic models, integrating approaches across the available financial sectors. The key structural decisions now appear to be whether to combine all regulation under one body and how closely to integrate financial-sector regulation and the more traditional roles of central bankers (Di Noia and Di Giorgio 1999; Goodhart and Schoenmaker 1992; Schmulow 2015).

South African policymakers chose to split the oversight of insurers (and most other financial-sector institutions), along the respective lines of prudential- and market conduct supervision (NTSA 2011a, 2013b). The former is concerned largely with the financial security and stability of regulated entities, and the latter with the extent to which they meet the needs of their customers. Policymakers elected also to wrap the responsibility for prudential supervision into the central bank, the South African Reserve Bank (SARB), at the PA.[51] Concerns have been raised regarding the complexity and expense of the structure, suggesting that the rationale for the approach has been inadequately set out and that the expected benefits have not been weighed against the corresponding costs.[52]

[51]New Zealand has a similar structure (CFRNZ n.d.), notwithstanding the potential for conflicts of interest between the monetary and regulatory authorities in the central bank (Godwin and Schmulow 2015).

[52]Robert Vivian, Professor of Finance and Insurance, University of Witwatersrand, writing for the Free Market Foundation, 4 June 2016, accessed at http://www.freemarketfoundation.com/article-view/case-

The stated goals of the Prudential Authority (Prudential Authority 2018) include enhancing the soundness of financial institutions and the corresponding soundness of the market infrastructures within which these institutions fall, and protecting the customers of these institutions against the risk that they fail to meet their obligations to these customers. The goals also include assisting in the maintenance of financial stability, in other words mitigating systemic risks. At the heart of this paper is the question of how well it is able to do this with the tools currently at its disposal or in development.

Market conduct regulation is now the responsibility of the newly-created Financial Sector Conduct Authority (FSCA). The FSCA, seeded by the pre-existing Financial Services Board, whose mandate was dominated by prudential concerns, has also put out a paper describing its priorities (FSCA 2018). This includes a commitment to strengthening the efficiency and integrity of financial markets, but not (explicitly at least) to identifying and managing systemic risk. While the SARB has played a large part in addressing systemic risk (see SARB 2017c, for example), formal responsibility for managing the risk and effects of contagion now falls to the Financial Stability Oversight Committee (SARB 2017a).[53]

The discussion turns now to the principles underpinning the prudential regulation of South Africa's insurers, which has also been undergoing considerable change. The course of developing and implementing the SAM framework took a number of years and included dry runs and a full period of parallel processing of the old and new approaches. It was formally implemented on 1 July 2018, as evidenced by the effective date of all regulatory standards.[54] The methods underpinning the standard calculation, spanning dozens of discussion documents and position papers that have since been converted into the regulatory standards, largely follows the corresponding methodology of Solvency II, adapted to local conditions.[55]

As in Europe, the boards of directors of South African insurers are required, under the regulations supporting the Insurance Act, 2017, to:

- take full and direct responsibility for ensuring ongoing solvency of insurers in line with regulatory requirements, for putting in place and maintaining sound systems of risk management, and for meeting all standards of reporting to the regulatory authorities,

- establish a system of internal controls for the purpose of mitigating and managing risks that includes control functions focused on compliance, risk management,

against-introducing-the-twin-peaks-regulatory-system, on 5 February 2018.

[53]Attention to financial stability is not new. The Financial Stability Oversight Committee effectively replaces an earlier committee of the SARB, called the Financial Stability Committee, which was established in the year 2000 (SARB 2017a).

[54]Not included in the list of references to this paper are the regulatory requirements of the Prudential Authority that stipulate the requirements of governance, risk management and the valuation of assets and liabilities. These take the form of prescribed Standards or Guidance Notes, for example, 'Prudential Standard FSI 2.2: Valuation of Technical Provisions' and 'Prudential Standard GOI 3: Risk Management and Internal Controls for Insurers'.

[55]Closely following the Solvency II methodology is important if South African regulatory standards are to be regarded by regulators in other countries as achieving appropriate standards, in turn considered important to insurers regulated in South Africa that have any business in these countries.

actuarial risks and internal audit and headed by suitably qualified individuals,

- meet minimum solvency requirements that are governed by the detailed technical specifications underpinning the standard calculations, the Solvency Capital Requirement (SCR), and a sub-minimum, the Minimum Capital Requirement (MCR), and
- undertake all calculations on a best-estimate basis along with an explicit risk margin, taking into account all options, guarantees, policyholder behaviour, future discretionary benefits, management actions and the risk of counterparty default, and separately accounting for cashflows attributable to reinsurance arrangements, and
- carry out a rigorous process called the Own Risk and Solvency Assessment (ORSA), at least annually but also in the event of a significant change in the circumstances of the insurer, that involves assessing the current and likely future solvency of the insurer, under both best-estimate circumstances and a range of adverse scenarios, considering the implications of this assessment, writing a report regarding the assessment and its impacts on strategy and maintaining a record of the activities that went into the assessment for audit purposes.

While actuaries still have a degree of latitude in the calculation of technical provisions, the methodology underpinning the SCR is largely stipulated in regulation, leaving virtually no latitude for interpretation. The primary element of self-regulation left to the Actuarial Society of South Africa concerns the nature and responsibilities of the Head of the Actuarial Function, defined under Pillar II governance requirements as providing independent oversight on a number of issues of an actuarial nature (ASSA 2018, 2019).

South African insurers, like their counterparts in Europe, have the option of submitting an application to the regulatory authority to utilise an internal model in preference to the standard calculation. Unlike their European counterparts, however, it is understood that no more than a handful of insurers applied for permission to use such a model and that very few insurers are in the position of using such a model. All insurers, however, must demonstrate that they have considered the extent to which the actual risk profile of the insurer deviates from the corresponding profile implied by the standard calculation. They must also determine the impact that this difference has on the calculated MCR and SCR. Notwithstanding the provision of a standard formula, in other words, the boards of directors of all insurers must assess the risk profile of the insurer and consider the appropriateness of current and future capital in light of this profile.

As in Europe, sovereign debt is considered risk free:

> Unless otherwise approved by the Prudential Authority, insurers must use the government bond curve published by the Prudential Authority as the risk-free interest rate term structure to discount cash-flows for the purpose of valuing technical provisions. (PA, FSI2.2, paragraph 13.1)[56]

The solvency calculation includes an element of dependence on the views of ratings agen-

[56] Prudential Authority, 'Prudential Standard FSI 2.2: Valuation of Technical Provisions', page 17, July 2018

cies, as under Solvency II. The standard adjustment for counterparty default, for example, uses credit ratings to estimate the probability of default of that counterparty.

Perhaps the most significant difference between the requirements of Solvency II and the corresponding stipulations of SAM is that South African insurers are not (currently) required to publish a publicly-available version of the ORSA report as stipulated under Solvency II (see paragraph 5.1.5). EIOPA proposes not only to continue its requirement that insurers publish the Solvency and Financial Condition Report (SFCR) but to subject it to external audit and to split it between a short public-facing version and a more detailed version for the so-called professional public (EIOPA 2019b).

Observers have considered the possibility that developing accounting standards contribute to systemic risk by magnifying market movements (Ellul et al. 2014; Hufeld, Koijen, and Thimann 2017; Koijen and Yogo 2017). The approach underpinning calculations under the SAM methodology is largely consistent with the corresponding approach adopted under the accounting standards that are utilised in South Africa, the International Financial Reporting Standards (IFRS). IFRS17 is a forthcoming standard that is expected to increase significantly the complexity of accounting for insurance. It requires (1) a comprehensive assessment of the profitability of a contract when it is sold, on the basis of the expected future cashflow of that contract, and (2) an accounting, for the remaining life of the contract, of the profit as it emerges (IFRS Foundation 2017).[57] IFRS17 may prove helpful to assist insurers to understand and report more accurately on the risks to which they are exposed.

5.5.4 Concluding comments

South African policymakers have made substantial progress in implementing a framework of risk-based insurance regulation comparable to the corresponding systems in a number of advanced countries, notably Europe. Insurers are subject to a demanding set of requirements spanning reporting, governance, internal documentation and complex actuarial calculations. These are designed to enhance the soundness of these institutions, the protection provided to their customers and the financial stability of the system as a whole.

5.6 The South African regulatory model and systemic risk

The discussion that follows applies to the South African environment the thoughts of Section 5.5.1 regarding insurer contributions to systemic risk. It is sparingly referenced as it aims not to introduce new information. The enquiry starts by considering whether the rationale for the regulation of financial markets holds in this country and explores the legitimacy of the role of the South African insurance industry in meeting wider social and economic needs. It then turns to the potential contribution of South Africa's insurers

[57] Supporting information is available at Deloitte (2017a), 'Implementing IFRS17 in South Africa', Deloitte (2017b), 'IFRS17 – Insurance Contracts', Technical summary of IFRS17, EY (2018), 'Applying IFRS17: A closer look at the new Insurance Contracts Standard', May and PWC (2017), 'IFRS17 Marks a new epoch for insurance contract accounting', In Depth No. INT2017–04.

to systemic risk and investigates possibilities for new or modified forms of regulatory intervention.

5.6.1 The rationale for regulation of South Africa's insurers

The case for regulating financial markets in general and insurers in particular is strongly made (see Section 5.2.3), but do the arguments apply to this country? South Africa's insurance market is substantial, complex and concentrated. It is subject to high levels of inter-connectivity with other financial intermediaries (Section 5.5.2), particularly the banks which, it is generally accepted, are more prone to risks of contagion (Section 5.4.2). The consequences of a market failure depend significantly on the type and depth of the problem, but concerns regarding systemic risk are justifiable. Widespread contagion of the industry could have substantial knock-on effects on other parts of the financial market, potentially causing substantial hardship in the real economy.

It is submitted, in conclusion, that South Africa has extensive rationale for regulating insurers and associated intermediaries in the pursuit of the outcomes that it has put forward. These intended outcomes are (Section 5.5.3): to enhance the soundness of financial institutions, to improve the strength of the corresponding financial market infrastructure, to protect the customers of these institutions and to maintain financial stability. That the fourth outcome has been included is specifically noted.

Questions have been asked about the appropriateness of the chosen structure and its associated expense. Assessing the cost-benefit trade-offs of alternative regulatory frameworks is an intractable problem with a number of issues of great complexity (Section 5.2.1). Two particular difficulties are worth pointing out in the context of systemic risk for South Africa: first, quantifying the probability or consequences of a systemic event; and, second, putting a value to the impact of positive and negative externalities of the financial system, especially its ability to add to or detract from the imperatives of improving social cohesion and reducing economic inequality. Improving access to effective financial products and services is likely to be critical in this regard, as considered in the discussion that follows.

5.6.2 The economic and social contribution of insurance in South Africa

Research regarding the direction of influence between growth in the South African insurance market and the corresponding growth in the economy is inconclusive. This investigation suggests, for long-term insurance, that insurance growth follows economic growth, not the other way around. In the case of short-term insurance, it finds no evidence of a relationship (Section 5.3.2). It is nevertheless reasonable to posit, on the basis of theoretical work and household-level modelling, that insurance, appropriately utilised, provides significant microeconomic benefits to its customers and hence to society more widely (Section 5.3.1). Of course, in order for insurance to do so, it must meet the identified needs of customers, which is what South Africa's market-conduct framework seeks to ensure (Section 5.5.3).

More difficult to answer is the question of whether South Africa's insurance markets meets appropriate social objectives. The take-up of long-term insurance products by low-income customers appears to have increased rapidly in recent years (FMT 2015, 2018), but the increase appears to be limited to funeral products.[58] Short-term insurers, in particular, appear to have had little success in growing take-up among low-income customers, even in the largest consumer segments of motor and household risks,[59] let alone in agriculture where insurance has tremendous potential to support government policy (Section 5.3.1).[60]

South African policymakers have indicated their commitment to expanding access to insurance by lowering barriers to entry (NTSA 2011a). Regulatory commitment to transformation of the ownership patterns of insurers has also been made clear (FSCA 2018). Evidence for this is provided in the Prudential Authority stipulation that applications for converting the licences of insurers to the requirements of the Insurance Act, 2017, include plans for such transformation, failing which these applications are unlikely to be granted.

Considerable scope nevertheless remains for the insurance industry to contribute to meeting a wide range of social objectives. They could do so by providing products designed to meet the needs of low-income South Africans, perhaps focusing on economically or socially significant parts of the economy like small businesses and agriculture. Insurers could also devote a greater share of their assets to economic and social development. They could work alongside government to improve social cohesion through provision of disaster management services. If insurance has economic benefit, it would be helpful if the insurers themselves were to demonstrate this. Perhaps insurers could be called upon, under the terms of market conduct regulations, to report to FSCA their commitment to meeting specified social objectives and the progress that they have made in this regard. This information could be made public.

5.6.3 Potential for insurance-industry contribution to systemic risk in South Africa

What then is the potential contribution of South Africa's insurance industry to systemic risk? The discussion that follows utilises the evidence referred to in this paper and applies it to local insurers in the South African context. First, the 'case against' is considered, bringing to the fore all of the evidence suggesting that any contribution to systemic risk is not significant. The 'case in favour' then follows.

The rationale against a significant contribution to systemic risk by South African insurers is built on the following:

[58]Not all insurance products are beneficial to society. Thomson and Posel (2002), for example, express concern that the provision of funeral products to South Africa's low-income customers through funeral undertakers undermines the benefits of community-orientated burial societies.

[59]South African Insurance Association, 'Insights from the FinScope SA 2018 Study for non-life insurers', SAIA Bulletin, Jan 2019, accessed at https://saia.co.za/saia-news/2019/01/30/insightsfrom-the-fi/ on 23 April 2020.

[60]Among the sources cited in Section 5.3.1, a number confirm the benefits of insurance for agricultural risk, for example, H. Cai et al. (2015), J. Cai (2016), Cole, Gine, and Vickery (2013), Janzen and Carter (2018) and Karlan et al. (2014). The Land Bank and its insurance arm appear to be making progress in providing support for agricultural protection and development.

- these insurers have a long history of careful prudential management that is built on the foundation of (1) careful oversight by the most experienced members of the actuarial profession, and (2) a prudential regulatory framework inherited from the United Kingdom, itself marked by a careful and conservative approach to insurance markets;

- they have relatively little involvement in the non-traditional non-insurance activity and in the risky assets, credit default swaps for example, that were significant contributors to the downfall of insurers in the 2008–09 financial crisis in other parts of the world (Sections 5.4.2, 5.4.3 and 5.5.2);

- they have, over the last two or three decades, modified their products to share significant investment risk with their policyholders, initially through with-profit arrangements and subsequently through issuing unit-linked policies, and have much lower risk attributable to investments and to the provision of products with guaranteed returns than do their counterparts in many other parts of the world, Continental Europe, for example;[61]

- they have been subject to substantial recent improvements in the extent to which they are required (1) to meet risk-based capital requirements and (2) to demonstrate a serious and concerted effort to the identification and management of the risks to which they and their policyholders are exposed (Section 5.5.3); and,

- they have been subject to a gradually intensifying reporting regime that serves to improve the transparency with which they are viewed by the investment community and are soon to be subject to an intensive escalation in this process, through the imposition of international accounting standard IFRS17 (Section 5.5.3).

To this is added the widely-accepted point that insurers in general are less likely than other financial institutions, particularly banks, to contribute materially to systemic risk (Section 5.4.2).

That South African insurers indeed contribute significantly to system risk is supported by the following arguments:

- EOIPA recognises the potential for the contribution to systemic risk by insurers in Europe and is considering introducing significant changes to the Solvency II framework in order to improve the extent to which macroprudential protection may be enhanced (Section 5.5.1);

- the concentration levels of the industry, notably in the case of long-term insurance, are particularly high, as disclosed by international experts (Section 5.5.2), suggesting that industry exposure to any difficulties experienced by just one of the largest insurers is high;

- insurers have high levels of inter-relationships with other entities in financial markets,

[61] Beneficial to the management of risks for the insurer this may be, but whether it provides an appropriate service to the customer is surely questionable. A key role of the insurer is to take on risks that policyholders cannot easily mitigate themselves.

notably the banks, typically regarded as contributing significantly to systemic risk due to high levels of leverage and inter-dependence (Sections 5.4.2 and 5.5.2);

- with very large asset pools and similar liability profiles, the assets of South Africa's long-term insurers may be expected to be characterised by high levels of common holding, correlated exposure to the drivers of corporate value and a degree of direct investment in one another;

- as the value of insurance assets and liabilities are significantly tied to the discount rates available on sovereign bonds, long-term and short-term insurers are respectively subject to highly correlated exposure to the yields on these bonds though, in mitigation, assets and liabilities are effectively tied to the same rates through the solvency-assessment methodology;

- the products offered by the largest long-term insurers are not materially different from one another, increasing the risk of concentration of sources of risk on the liability side of balance sheets, similarly for the most significant short-term insurers;

- both types of insurers are strongly exposed to fluctuations in the economic cycle and to other types of business risks, though the avenues of transmission of risk are most likely different; and,

- insurers have common exposure to the potentially damaging behaviour of policyholders, linked to economic well-being, though the nature of the policies currently sold limits the extent of insurer exposure to policy lapses.[62]

To this list may be added the potential for contributions to systemic risk from specific sources, notably market risk, operational risk and liquidity risk. Perhaps the most prominent of these is the continued insistence by the authorities that investment in the sovereign bonds issued by the South African government are to be regarded as risk free.[63] Citing spreads in bond yields is risky at a time of high volatility but it is difficult to describe South Africa's bonds as risk free with all three of the major rating agencies, since March (SARB 2020c) taking the opposite position. South Africa's long-term insurers are reported as having relatively low allocations to government bonds.[64] Nevertheless, the SCR appears to include systemic under-estimation of the risk associated with investment in government bonds and all other asset types whose risks are determined with reference to government bonds. Concerns regarding the contribution to systemic risk arising from a distorted risk metric in the regulatory approach to minimum capital requirements deserve more attention.

[62] More generally, the events of 2020 may call for reconsideration of the assumed correlation between market risks and underwriting risks.

[63] "Unless otherwise approved by the Prudential Authority, insurers must use the government bond curve published by the Prudential Authority as the risk-free interest rate term structure to discount cash-flows for the purposes of valuing technical provisions." (Paragraph 13.1, Prudential Standard FSI 2.2: Valuation of Technical Provisions, Prudential Authority)

[64] The Association for Savings and Investment South Africa reports that 12.7 percent of the assets of long-term insurers were invested in government bonds (ASISA Life Statistics, downloaded from https://www.asisa.org.za/statistics/long-term-insurance/ on 19 May 2020). This considers only those assets outside of those allocated to investment funds and only those that are not linked explicitly to policyholder liabilities.

Operational risk, which encompasses a wide range of possibilities that can have considerable impact, forms a somewhat simplified part of the SCR calculation, and may merit further attention by insurers. Liquidity risk is identified by the IMF as requiring further attention (Section 5.5.2). Though the comment applies to banks, it may be appropriate for insurers more likely to experience liquidity stress to consider this risk more closely. Scenarios of liquidity stress should take into account the possibilities that the normal sources of emergency liquidity may not be available and that liquidity may be obtained from longer-term assets only at significant loss of value and the potential for a contribution to an asset spiral. Finally, the use of credit ratings in some parts of the technical specification may contribute to systemic risk.

Perhaps the most important source of concern lies in the deception of safety. The aftermath to the 2008–09 financial crisis was marked by an acknowledgement that financial markets were not as secure as regulators had thought they were. At this time, soon after formal implementation of the SAM system, complacency may represent a significant risk. Yet researchers have presented substantial evidence that the most significant contributor to systemic risk in a capital-management system such as Solvency II may lie in its key asset, the appearance of sophistication in its attention to idiosyncratic risk (Section 5.5.1).

5.6.4 Regulatory options

Financial-sector regulators have an enormously challenging task. Their reward is typically characterised by little upside, as commendation for establishing a stable environment is rare, and enormous downside, for they frequently attract a large share of the blame when things go wrong. For this reason, regulators are constantly on the watch for sources of systemic risk. The Prudential Authority, within the context of the South African Reserve Bank, is surely no exception to this. Lecturing the regulator on what it should be doing to address the potential for systemic risk is not the purpose of this paper. Thoughts for consideration are regarded as more appropriate.

The discussion that follows consists of a series of questions that decision-makers at the PA may wish to think about:

- Is the potential for systemic risk across the insurance industry a subject that should be taken more seriously by the regulatory authority? Is it worth exploring the appropriateness of the changes under consideration by EIOPA in advance of their potential implementation in Europe?

- Has sufficient attention been devoted to the possibility of correlated assets and liabilities across insurers of similar types? Could insurers themselves not be required to devote attention to this possibility, showing how their actions may contribute to systemic risk and how they have taken steps to mitigate this risk? Would a stronger emphasis on a realistically-determined economic capital requirement enhance the attention to systemic risk or might it merely improve insurers' assessments of their own risks at the cost of improved assessment of their contribution to systemic risk?

- How is model risk addressed? Is the appropriateness of the SCR calculation frequently reconsidered? Are alternatives to the value-at-risk approach evaluated for their potentially stronger indications of the entity contribution to systemic risk? Is the calibration of the model appropriate and is it reviewed from time to time? In particular, might the assumed correlations between elements of the calculation need to be reconsidered, in particular the link between market risk and underwriting risk? What might the impacts of treating government bonds as risk-free be on both idiosyncratic and systemic risks? Could elements of that calculation be improved to recognise differences in the attributes of insurers? Are approved internal models subject to regular testing and updated in response to evidence of the need for change? Are the skills available at the regulator sufficient to detect the potential for adverse impacts attributable to these models?

- How well is the potential for the propagation of risks within a financial group understood? The framework for group regulation exists but the nature of this propagation can be difficult to conceptualise. Are the current demands on boards of financial groups sufficient to mitigate this risk? How is the corresponding potential for the transfer of risk between entities with significant operational bonds that do not form part of the same group managed? Liquidity risk, for example, may not appear significant to insurers but, taking into account their relationships with other members of a group, could prove potentially problematic.

- More difficult, how well are the links between financial sectors understood, particularly where these links might facilitate the propagation of risks? Where the regulatory authorities may have developed robust views on the profile of risks across an industry sector, perhaps with the benefit of network modelling, have they been able to expand the concepts to take into consideration the links across industry clusters?

- Is sufficient attention given to those types of risks that typically fall outside of the realm of actuarial modelling but can have a significant impact on the risk profile of an organisation and its contribution to systemic risk? Operational and strategic risks fall into this category, as do other risks related to an organisation's internal culture.

- Are there ways to improve organisational transparency? These should not unnecessarily burden regulated entities. They should also not risk providing opportunities to mislead the public through issuing complex but unhelpful documents, which public-version ORSA reports could do?

- Having avoided the pitfalls of public declarations of too-big-to-fail, does the regulatory framework appropriately consider the potential contribution of entities to systemic risk to the extent that it is related to the size of these entities? Some suitably graduated approach that provides for responsibilities that increase with size or connectedness may be appropriate.

Perhaps it is appropriate to close with a reminder that what distinguishes systemic risk from idiosyncratic risk is the externality. Entities have a natural incentive to manage idiosyncratic risk because they would feel direct pain should it materialise. Systemic risk is different because the incentive to manage it is less likely to exist. Others get hurt. The regulatory authority has a key responsibility to do all that it can to avoid this propagation.

5.7 Further research

A number of areas for further research are touched upon through this paper. These thoughts are summarised in the list that follows.

5.7.1 Financial market networks

The excellent analysis of South Africa's banking network carried out by Dr Walters and her colleagues (Walters et al. 2018) may be taken forward in a number of ways. Tests of the sensitivity of results to assumptions would be helpful, but perhaps more insightful would be an examination of the effects of material changes to the nature of the network assumed. This could be supported by an empirical examination of the network attributes of the South African banking market. More ambitiously, extensions of the model to include insurers and to test the impacts on the economy are worth considering.

5.7.2 Benefits of insurance in South Africa

Further work on the economic and social benefits or harms of the South African insurance industry on the people of the country would be helpful. This research could be empirical or theoretical. It could include macroeconomic and microeconomic considerations or focus primarily on social impacts. It could allow more rigorously for the social and environmental costs of the profit- and growth-orientated thinking of neo-classical economics.

This type of work would be of great benefit to regulators and insurers interested to know where the positive effects and the potential for pitfalls are greatest. It may assist in the development of a sound framework of Regulatory Impact Analysis and help in the shaping of policy.

5.7.3 Empirical tests of the insurance industry

Research concerning aspects of the South African insurance industry in a number of respects may be fruitful. Possibilities include exploring the incidence of overlapping assets and liabilities across long-term and short-term entities in order to understand the potential for this overlap to contribute to systemic risk. The nature and impacts of intra-group relationships could fruitfully be explored. As touched upon in Section 5.5.2, the level and trends of concentration indices covering South Africa's insurance industry, and concerns over high levels of pricing power, could usefully be explored as these attributes may contribute to levels of systemic risk.

Technical tests could be undertaken regarding the impacts of changing the assumptions that underpin the existing solvency framework. How would minimum capital requirements change, for example, if government bonds were no longer treated as free of risk or if a higher correlation were assumed between market risk and underwriting risk? On the basis that a dependence on credit ratings may enhance the risk of systemic contagion to the system, it would be useful to understand what the extent of this dependence might be. A number of other tests are worth exploring.

Consideration could be given to the potential for a graduated regulatory approach to entities that, by virtue of their size or connectivity, might contribute more significantly to systemic risk. Ideally this approach should avoid splitting insurers into inflexible categories, based on size for example.

Finally, the available measures of entity-specific contributions to systemic risk tested elsewhere could be applied to South African insurers to test the possibility of a modified approach to minimum solvency requirements.

5.7.4 Contributions to strengthen the regulatory framework

South Africa's legislated and regulatory objectives appear to be sound. Further work may be helpful to motivate an improvement to the breadth of these objectives or the extent to which success could be demonstrated by defining impartial outcomes and publishing the extent to which these outcomes are achieved.

Options for an integrated approach to macroprudential regulation could be considered, bringing existing approaches to microprudential oversight, the disciplines of monetary policy and the alternative macroprudential tools together into a coherent whole.

A better articulated approach to Regulatory Impact Analysis in financial markets could be considered. As this paper shows, the obstacles are considerable. A framework would help, though, so that progress in any of the other research areas considered here might be fruitfully applied to improving the approach to the regulation of insurers and other financial entities.

5.8 Conclusion

Notwithstanding the significance of their contribution to an economy, financial markets are characterised by remarkable complexity and fragility. The challenges of regulating these markets to achieve a set of pre-defined objectives should not be understated.

Do South Africa's insurers contribute materially to the country's systemic risk? On the face of it, this contribution appears to be relatively low. For regulators to adopt this position would be irresponsible, however, given the potential consequences of financial contagion on the market, its customers and the economy more widely.

Recent efforts to improve the awareness, measurement and management of risk in South Africa's insurers represent substantial movement in the right direction. Two concerns are raised in this paper regarding these steps, however, and the illusion of security that they might create. First, care needs to be exercised to understand tail risks at entity-level, recognising that these tail risks may be correlated across market players, contributing to systemic risk. Second, the pursuit of an improved assessment of entity-specific risk may actively contribute to the incidence of poorly-recognised systemic risk. Measures may need to be considered to overcome this potential weakness in the regulatory system.

It is hoped that the thoughts set out in this paper prove useful to policymakers, regulators and participants in South Africa's insurance market.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Chapter 6

The Contribution of Insurers to Systemic Risk: A practical framework for regulators

While insurers are not typically the most significant contributors to systemic risk, their actions and behaviour may materially contribute to such risk. This study considers the models that may be used to detect systemic risk originating in the insurance market and proposes a framework for identifying and classifying the sources of systemic risk attributable to insurers. It applies this framework to the insurance market in South Africa, in the process providing practical recommendations for consideration by all regulators.

JEL classification: C19, C63, D62, G22, G28

6.1 Introduction

Systemic risk is the possibility of weakness of or contagion within the financial system, with potential spillover into the wider economy (Acharya, Pedersen, Philippon, and M. Richardson 2017; Bisias et al. 2012; Kessler 2014; Weiß and Mühlnickel 2014). Financial-sector regulators typically include among their objectives the goal of identifying and mitigating the potential for systemic risk (Brunnermeier et al. 2009; IMF 2018; NTSA 2011a). South Africa's framework for regulating financial-sector entities is generally strong (IMF 2022a), but exposure to systemic risk is nevertheless high (IMF 2022a,e).

Insurers are generally regarded as unlikely to contribute as much to systemic risk as their banking counterparts, largely on the basis that insurers do not engage in peer-to-peer transactions to the same extent as banks (refer to the summary of the literature in Section 6.2). The potential for insurers to be systemically risky entities is nevertheless not immaterial (Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; J. Cummins and Weiss 2014; Eling and Pankoke 2016; D. Schwarcz and S. Schwarcz 2014, for example, refer to Section 6.2.3) and should be guarded against by regulators.

The South African Reserve Bank includes observations on the potential contribution by the insurance sector in its reviews of financial stability (see SARB 2021b, 2022a, for example). In the United Kingdom, a spike in government bond yields led to severe liquidity pressure on liability-driven investment arrangements, some of which were managed by insurers, triggering Bank of England intervention (R. Chen and Kemp 2023; Financial Stability Committee 2022; Pinter 2023). These events, following shortly after the generally positive views of the IMF regarding the capacity of the insurance sector to absorb even large increases to interest rates (IMF 2022b), serve to illuminate the systemic significance of insurance markets, as part of the wider non-bank financial sector.

This chapter proposes an approach to identifying the sources of systemic risk arising in the insurance sector. The approach is based on a classification system that is developed from a survey of the available literature and examination of the corresponding frameworks proposed by others. It contributes to the literature on systemic risk attributable to insurers by proposing a practical approach to identifying the sources of such risk arising in insurers across the market. It applies this approach to the South African insurance environment by considering those sources of risk that have been acknowledged by several insurers and recommending regulatory action to detect the possibility of other sources of systemic risk across the framework.

Several quantitative approaches to assessing levels of systemic risk have been developed (see Section 6.3.3, in particular the literature summaries by W. Silva, Herbert, and Vinicius (2017) and Ellis, Sharma, and Brzeszczyński (2022)). Practical constraints limit the effectiveness with which such approaches may be applied to insurers (refer to the considerations set out in Section 6.4.4). This study aims to provide pragmatic approaches to insurance regulators to mitigate these constraints. Improving the effectiveness of the available qualitative approaches for identifying the sources of systemic risk attributable to insurers contributes to a more robust understanding of the nature of this risk that might be supported by such modelling.

Section 6.2 describes the objectives-based approach to financial-sector regulation and summarises the literature on the question of the insurer contribution to systemic risk. It also describes South Africa's insurance market. Section 6.3 sets out the methodology underpinning the research. It describes the development of the framework proposed for identifying and classifying the sources of systemic risk attributable to insurers. It also summarises the financial models available for detecting such risk quantitatively and considers the appropriateness of these models to meeting regulatory objectives. Section 6.4 summarises the results of the analysis. It demonstrates how this framework may be utilised by describing a survey of South Africa's insurers to identify the extent to which some of these sources of risk have been acknowledged already. Section 6.5 concludes, setting out thoughts on potential supporting research.

6.2 Background

The discussion in this section provides a foundation to the analysis that follows. It describes the widely-adopted position of financial-sector regulators that their approach should be directed by a set of regulatory objectives, one of which should be to mitigate the impacts of systemic risk. It then turns to the question of whether insurers contribute materially to systemic risk and how they might do so. The section closes with a description of South Africa's insurance market.

6.2.1 Objectives-based financial-sector regulation

Financial-sector regulation has been subject to significant development over the last two or three decades (Atack 2009; J. Black 2004; FSA 2006, 2007; Llewellyn 1999). Some of these changes have been stimulated by contemporary events such as the 2007-09 financial upheaval. The crisis drew considerable attention to the challenges of systemic risk and the inadequacy of the regulatory response to it (Grochulski and Morrison 2014; OECD 2010; S. Schwarcz 2019).

Several regulators have adopted an objectives-based model to determine their priorities, for instance, those in Australia, the United Kingdom, Singapore and South Africa (APRA 2014; FSA 2007; MAS 2015; NTSA 2011a). Under this approach, regulators identify the objectives of their intervention in financial markets and determine the actions considered most effective at meeting these objectives, taking into account the risks that regulation seeks to mitigate (Armour et al. 2016; Baldwin and J. Black 2016; J. Black and Baldwin 2010, 2012; Knot 2014; Michael, S, and Osaulenko 2010; Sinha 2012).[1]

The success or failure of this approach could prove highly significant to the financial sectors and wider economies of the countries served by such regulations. Financial markets are critically important to the economies they serve (Merton 1995; OECD 2010; World Bank 2012), but they are also characteristically complex, fragile and changeable (ADB 2017; ECB 2012; Erskine 2014; Schmukler 2004; Tagoe 2016).

6.2.2 Defining systemic risk

A well-established objective in many markets is the prevention or mitigation of systemic risk (Brunnermeier et al. 2009; Carvajal et al. 2009; Grochulski and Morrison 2014; IMF 2013, 2014b, 2018). Achieving this objective calls for a strong understanding of the nature of the risk, its origins and its channels of propagation. It also requires sound comprehension of the way alternative forms of intervention might prevent the occurrence of this risk or mitigate its effects (Baldwin and J. Black 2016; EIOPA 2017, 2019a,b; OECD 2010), helping regulators to understand which of their available actions might best meet their stated objectives.

Since one of the objectives of financial-sector regulation is to mitigate the impacts of systemic risk, defining this risk unambiguously is important. Several researchers have

[1] Refer to Rusconi (2020) for a summary of the primary reasons for employing an objectives-based regulatory framework.

grappled with this problem, with limited success (Claessens 2015; ECB 2010; Eling and Pankoke 2016; Galati and Moessner 2014; Hansen 2013). A joint statement of the International Monetary Fund, Bank for International Settlements and Financial Stability Board to the G20 (IMF et al. 2009, p. 2) describes systemic risk as "a risk of disruption to financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences for the real economy."

The following characteristics might be considered to represent broad consensus on the attributes of systemic risk (Acharya, Pedersen, Philippon, and M. Richardson 2017; Bisias et al. 2012; J. Cummins and Weiss 2014; De Bandt and Hartmann 2000; Eling and Pankoke 2016; Georg 2011; SE Harrington 2009; Kessler 2014; Nier et al. 2007; Safa, Hassan, and Maroney 2013; Weiß and Mühlnickel 2014): (1) preconditions of widespread market connectedness or interdependence, (2) substantial loss of confidence leading to economic losses, (3) extensive adverse impacts on financial entities and (4) market failure, often resulting in considerable adverse impact on the wider economy. Underpinning this paper is the view that regulators should strive to understand the dynamics of systemic risk in their markets and to enhance their ability to detect any warning signs that such risk may be rising.

6.2.3 Insurer contribution to systemic risk

The discussion turns next to the question of whether insurers, individually or collectively, contribute substantially to systemic risk.[2]

It is widely accepted that the contribution to systemic risk by insurers is generally weaker than the corresponding contribution by banks. The primary reasons for this are that insurers are less likely to provide and demand financial support from peers and insurers typically retain on their balance sheets, hence transparently report, potentially risky financial activities (Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; Billio et al. 2012; Bobtcheff, Chaney, and Gollier 2019; Eling and Pankoke 2016; Kaserer and C. Klein 2019; Kessler 2014; Van Lelyveld, Liedorp, and Kampman 2019).

Several other reasons for this position may be added to these. Insurers are generally well regulated (J. Cummins and Weiss 2014). Claims are typically dependent on random events rather than on customer behaviour (Baluch, Mutenga, and Parsons 2011; J. Cummins and Weiss 2014; Kessler 2014) and are payable over an extended period (J. Cummins and Weiss 2014; IAIS 2011; Kessler 2014; Trichet 2005). Premiums are largely payable in advance (J. Cummins and Weiss 2014; Kessler 2014; Trichet 2005). Fees on lapses mitigate the risk of customer runs attributable to deteriorating confidence (Kessler 2014). Product substitutability is generally high (J. Cummins and Weiss 2013, 2014), business lines are separable and entity risks are typically idiosyncratic and uncorrelated (IAIS 2011). Interconnectedness between insurers is low (Baluch, Mutenga, and Parsons 2011; J. Cummins

[2] Eling and Pankoke (2016) provide a thorough meta-analysis of the literature concerned with the contribution of insurers to systemic risk. Refer to Rusconi (2020) for a more detailed consideration of the contribution by insurers to systemic risk with particular application to South Africa.

and Weiss 2013; Grace, Rauch, and Wende 2013; IAIS 2011; Kessler 2014; Trichet 2005), risk transfer is typically hierarchical, not peer-based (Baluch, Mutenga, and Parsons 2011; Besar et al. 2011; IAIS 2011), external funding is available (Berry-Stölzle, Nini, and Wende 2014) and reinsurance bankruptcy can be absorbed (S. Park and Xie 2014; Van Lelyveld, Liedorp, and Kampman 2019). Insurer wind-up is generally a lengthy, orderly process (IAIS 2009, 2010) because the liabilities in specific business lines can be isolated for sale or running down (IAIS 2011). Finally, the insurance industry is more robust to economic adversity, in contrast to the corresponding experience of the banking industry (Berry-Stölzle, Nini, and Wende 2014).

Notwithstanding these mitigating factors, the contribution to systemic risk by insurers is potentially significant (Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; J. Cummins and Weiss 2014; D. Schwarcz and S. Schwarcz 2014) and should not be ignored. This contribution, furthermore, may be exacerbated by the attributes, business activities or behaviour of insurers (Baluch, Mutenga, and Parsons 2011; Bobtcheff, Chaney, and Gollier 2019; J. Cummins and Weiss 2014; EIOPA 2017; Eling and Pankoke 2016; Koijen and Yogo 2017; Weiß and Mühlnickel 2014). These attributes, activities and behaviour represent the focus of this research, considering both the literature (Section 6.3) and evidence from the market (Section 6.4).

Furthermore, even if insurers do not originate systemic risk, they may propagate or magnify it, typically through collective reactions or decisions (EIOPA 2017; IAIS 2019). These might include the sale of assets that intensify market movements and contribute to volatility, transfers of losses to other market participants or the interruption of a critical function, in this case the insurance service, in the process exacerbating distress elsewhere in the economy (IAIS 2019).

Insurers that form part of a financial group are generally more likely to contribute to systemic risk, particularly if one or more banks are also members of the group (Baluch, Mutenga, and Parsons 2011; Hauton and Héam 2015). Insurers are also impacted by their customers. They may contribute to systemic risk through the behaviour of policyholders, which is linked to the state of the economy or the condition of other financial institutions (Barsotti, Milhaud, and Salhi 2016; R. Klein 2012b; Russell et al. 2013).

For the purpose of managing systemic risk, regulators must take care not to depend on even soundly-established micro-prudential regulatory methods. These methods focus considerable attention on idiosyncratic risk at regulated entities, but may contribute to behavioural herding that could paradoxically increase systemic risk (Al-Darwish et al. 2011; Floreani 2013; Rae et al. 2017; Swarup 2012). Furthermore, the pursuit of diversification at entity level, encouraged by micro-prudential regulatory methods, could contribute to systemic risk (Acharya 2009; Allen and Carletti 2006; Checkley 2009; Ibragimov, Jaffee, and Walden 2011; W. Wagner 2010).

In summary, though insurance is typically less systemically risky than banking, regulators should be aware that insurers can indeed contribute to systemic risk. They may originate systemic risk through their attributes or activities. They may contribute to the propagation of systemic risk through their collective reactions to adverse events. They may exacerbate systemic risk through their links to other financial-sector entities, particularly banks.

Finally, scope remains for quantitative assessment of the respective contributions to systemic risk by individual entities (Acharya, Engle, and M. Richardson 2012; Acharya, Pedersen, Philippon, and M. Richardson 2017; Z. Adams, Füss, and Gropp 2014; Adrian and MK Brunnermeier 2016; Brownlees and Engle 2017; Bui, Scheule, and Wu 2017; Fong et al. 2009; Gauthier, Lehar, and Souissi 2012; Giglio 2016; Hautsch, Schaumburg, and Schienle 2015; X. Huang, Zhou, and Zhu 2012b; Sedunov 2016; Zhang et al. 2015), taking care to understand the drivers and transmission channels of systemic risk (EIOPA 2017). However, attention should be given to the effectiveness with which the methods used to assess banks could be applied to insurers. This also forms part of the assessment described in this chapter (see Section 6.3.3 and its application in Section 6.4.4).

6.2.4 South Africa's insurance market

South Africa's financial sector is large and sophisticated (IMF 2014a, 2022a) with significant assets assessed against gross domestic product (IMF 2014a). It is also complex, however, and concentrated, with high levels of inter-connectedness between banks and other financial institutions (IMF 2008, 2014a, 2022a). Prudential regulation of financial-sector entities falls under the responsibility of the Prudential Authority, a division of the South African Reserve Bank (SARB). The Prudential Authority acknowledges explicitly its responsibility to identify and mitigate potential contributions to systemic risk, as part of the SARB and in partnership with the market-conduct regulator, the Financial Sector Conduct Authority (Prudential Authority 2021).

The insurance sector is similarly large and complex, but it is also competitive, with a diverse range of business models (IMF 2022e). Assets in life insurers (also termed long-term insurers) amount to some two-thirds of annual gross domestic product (Prudential Authority 2019; Rusconi 2020) and the non-life (short-term) insurance market is large and competitive (KPMG 2022; Rusconi 2020). The insurance industry is generally well regulated, implementing several significant recent enhancements (IMF 2022a,e), has high levels of solvency (IMF 2022e) and weathered the storm of the COVID pandemic relatively well (IMF 2022a).

International observers have nevertheless noted several systemic risks related to South Africa's insurance sector. Among them are: considerable inter-connectedness of financial entitles (IMF 2022e), dependence by banks on the liquidity provided by non-bank institutions (IMF 2022a), large equity holdings by insurers (IMF 2022e), high rates of lapses and surrenders by policyholders (IMF 2022e), high dependence on the accuracy of the assumptions underlying the modelling of idiosyncratic risk in insurers (IMF 2022e) and, together with other financial institutions, relatively high holdings of sovereign debt (IMF 2022f). The IMF notes as well concerns regarding inadequate transparency of the Financial Stability Committee (IMF 2022a,c) and the potentially adverse impacts of systemic governance weaknesses uncovered in the public- and private sectors (IMF 2022d).

6.3 Descriptive framework

The literature exploring the nature of systemic risk and the manner of its propagation (see Section 6.2) suggests that the contribution of banks to systemic risk is generally greater than that of insurers. By the nature of the financial interactions between entities, the banking system both propagates and absorbs risk. Insurers typically do not operate in this manner. They absorb risk from their customers, but they redistribute this risk in a hierarchical structure, commonly through reinsurers. They are required to hold capital that is more than sufficient to back this risk and they typically retain all of their risk on their balance sheets.

The insurer contribution to systemic risk, however, is not immaterial, as summarised in Section 6.2 and discussed in more detail in this section. As regulated entities do not have the same economic incentives to mitigate externalities as they do to manage the risks that would impact their businesses directly (S. Schwarcz 2008), regulators have the responsibility to mitigate systemic risk arising from these entities. In order to do this, they should seek to understand the nature of the contribution by insurers to systemic risk, through their attributes, business activities or behaviour, in the process identifying and mitigating this contribution to systemic risk. This is the subject of this article.

A survey of the literature exploring the contribution of insurers to systemic risk was undertaken. This utilised available literature reviews (notably (J. Cummins and Weiss 2014; Eling and Pankoke 2016), but original sources were scrutinised to ensure a sound understanding of the identified risk. The primary difficulty encountered was making sense of these risks by classifying them in a coherent form. The discussion that follows describes efforts to understand qualitatively the nature of this contribution and considers existing approaches to classifying these risks. It then proposes an alternative system of classification that could enhance the effectiveness by regulators of the management of systemic risk originating at or propagated by insurers. The final part of this section describes the corresponding quantitative methods available for assessing these risks and considers some of the difficulties of these methods.

6.3.1 Qualitative analysis: existing models

The European Insurance and Occupational Pensions Authority (EIOPA 2017) suggests that systemic risk events and their impacts should be considered in two broad ways. Systemic risk may be introduced to markets directly, typically because of the failure of a significant insurer or group of insurers. This may be referred to as an entity-based source. Alternatively, it may be indirect, activity-based or behaviour-based, under which the risks triggered by an outside set of events are propagated through the system by insurers either through their activities or through their reaction to events or the actions of others.

Entity-based risks are managed through existing micro-prudential approaches that are designed to identify and mitigate weaknesses in the risk-management systems of individual insurers. Several researchers have questioned the effectiveness of existing largely micro-prudential approaches for identifying systemic risks, in some cases arguing that these approaches stimulate herding behaviour that magnifies systemic risk (Al-Darwish et al. 2011; Floreani 2013; Rae et al. 2017; Swarup 2012). This, however, is only one part of the EIOPA (2017) approach.

Examples of indirect activity-based sources identified by EIOPA (2017) include financial guarantees to customers, securities lending and derivative trading not concerned with hedging risk. Widespread use of strategies such as these should be a signal to regulators of elevated levels of systemic risk. Behaviour-based sources of risk under the EIOPA (2017) framework include (1) collective behaviour, like fire sales or herding, that may sharpen movements in market prices, (2) imprudent risk-taking or concentration of assets or liabilities, and (3) inadequate provisioning or under-pricing, typically under pressure by competitors. Adding to systemic tendency, these behaviours may be linked to market conditions like elevated competition, a search for yield or other asset-side herding behaviour, and moral hazard problems such as the too-big-to-fail risk.

The EIOPA (2017) model focuses not just on the sources of systemic risk, but the channels of transmission. These channels serve to amplify the propagation of systemic risk through financial markets. Such channels include linkages to banks and other financial institutions, asset liquidation risks and the use of bank-like products such as investment guarantees and options embedded in insurance products.

An effort was made to allocate all of the insurance-related risks identified in the literature to the EIOPA framework by identifying a type (entity, activity or behaviour) and nature (driver or transmitter). This proved difficult. Some risks impact insurers but originate outside of the insurance industry. Climate change, which impacts asset prices and insurance liabilities, is an example of such a risk. These risks could be excluded from the framework. Alternatively, to capture risks like this, the EIOPA framework could be modified to include, under the type, an impact, and, under the nature, a contributor. In other cases, choosing the most appropriate type or nature was difficult. Though a mapping of all of the risks identified in the literature (refer to Table 13 in the Appendix) to the modified EIOPA framework was completed, the consistency and reliability of the approach was considered unsatisfactory.

The International Association of Insurance Supervisors (IAIS) utilises a similar model, considering the origination and propagation of risks separately (IAIS 2019). It identifies the primary sources of systemic risk in the insurance industry and the channels through which this risk may be transmitted to the wider economy. The most significant sources noted by the IAIS are (1) liquidity risk, (2) exposure to economic factors and to counterparties and (3) the effects of limited substitutability of essential products or services of one or more insurers. The transmission channels considered by the IAIS include (1) depressed asset values resulting from fire sales, (2) economic impacts, through direct holdings in other financial entities or correlated experience with other institutions and (3) the interruption of critical functions.

An attempt was made to allocation each of the risks identified in the literature to the categories proposed by the IAIS, but this also proved challenging. In this case, the main problem experienced was that the IAIS categories are designed to incorporate the most significant systemic risks originated in or transmitted through the insurance industry. This made it inappropriate for the purpose of allocating a complete set of risks to these categories as several of the identified risks did not suit any of the available categories.

In view of the difficulties in allocating the identified risks to the categories proposed by either EIOPA or IAIS, an alternative classification system was developed.

6.3.2 Qualitative analysis: identifying and classifying insurance risks

The discussion that follows describes efforts to identify and classify the sources of systemic risk arising in or propagated by the insurance industry. This is undertaken through (1) a review of the literature to identify such sources and (2) an approach to classifying them into categories that would assist in the process of identifying any additional sources of or contributors to systemic risk.

Overall approach

Classification takes place in two stages. The first of these results from a survey of the literature and results in a broad set of categories. The output of this approach is set out in Table 13 in the Appendix. The second represents a more concise categorisation which is used to organise risks identified in annual reports by South African insurers. This is described in the next part of the chapter, Section 6.4.

In the assessment of the sources of systemic risk attributable to insurers, no distinction is made between origination and transmission, primarily because of the overlap between the factors respectively impacting origination and transmission. Furthermore, no attempt is made to prioritise these factors. The intention, rather, is to assist the insurance regulator by providing a framework for identifying such factors. With this in mind, the approach aims to be collectively exhaustive, by exploring possibilities across as a wide front as possible, and mutually exclusive, by allocating factors to distinct categories.

Sources utilised

The sources considered include academic literature and publications by regulators, like the SARB, or regulatory umbrella organisations, such as the IAIS. Sources of systemic risk identified by international or regional bodies like the IAIS or EIOPA are considered sufficiently broad for general application, but locally identified risks should be reviewed as part of a study of country-specific sources of systemic risk. This explains the inclusion of sources identified by the SARB. In most cases, these add descriptive detail to risks already noted in the literature without materially adding to the list. They are also typically mirrored by the corresponding sources of risk identified by insurers, as described in Section 6.4.

Meta-analysis is also utilised, referring to the corresponding literature reviews of authors such as Eling and Pankoke (2016) and J. Cummins and Weiss (2014). All references to the potential sources of systemic risk attributable to insurers, or factors exacerbating the transmission of systemic risk are noted. Efforts to evaluate the significance of a risk are not captured on the basis of the subjectivity of approach. For the same reason, the frequency with which risks are mentioned is not recorded, the main difficulty in this case being the variations in wording that make it difficult to establish whether different risks are identified or the same risk repeated.

Approach to classifying systemic risks

As described in Section 6.3.1, difficulties were experienced in arranging and classifying the risks identified in the literature using available classification models and it was considered better to develop an alternative approach, with typical regulator approaches to identifying risks in mind. The approach proposed aims to assist regulators by aligning with existing methods for managing and mitigating insurance risk, categorising these risks first by balance sheet sector and then by the type of risk.

There are disadvantages to developing an approach similar to existing methods, the most important of which is that these methods are typically developed for micro-prudential purposes. Concerns are expressed by several researchers that the tendency of existing regulatory approaches to focus on idiosyncratic insurer-specific risk, not systemic risk, can exacerbate problems of systemic risk (Al-Darwish et al. 2011; Floreani 2013; Ibragimov, Jaffee, and Walden 2011; Rae et al. 2017; Swarup 2012; W. Wagner 2010). This is mitigated by limiting the risks included in the framework to those identified as potentially systemic by credible sources in the literature. Significant overlap of these risks with the corresponding set of idiosyncratic risks is nevertheless likely, as many risks with potentially systemic attributes are also specific to individual insurers and could be identified and mitigated by these insurers.

The advantage of the proposed approach is that it is practical, fitting in with the existing framework and assisting regulators to extend that framework to identify and mitigate risks that may be systemic in their impacts.

Categories selected

Risk categories are chosen on two levels: that part of the balance sheet most impacted by the risk and the broad form that the risk takes. Under the first of these, five alternatives are used. These are assets, liabilities, asset-liability management (ALM), solvency and a general category. The first two are used respectively to classify risks that operate primarily to affect the assets or liabilities of an insurer. The investment of assets and its impact on investment returns is an example of the first type and concentration of insured risks of the second. The ALM category is used for risks that affect the balance between assets and liabilities. For example, an excessive reliability on short-term funding in the context of long-term liabilities can introduce or exacerbate a mismatch of assets to liabilities. Solvency is used to capture risks that most directly impact the financial viability of the insurer. The general category is used to capture risks that do not readily fall into other categories, typically covering risks of a strategic nature.

The second level of risk categories considers the broad type of risk: concentration of risk, a mismatch of the risk to its mitigation strategy, poor quality in product or investment, strategic risks, operational risks and general risks that do not fall into another category.

This approach aims to achieve objectives of collective exhaustion and mutual exclusivity most effectively, but it is affected by subjectivity. The meaning of researchers in characterising a risk could be misinterpreted. Two writers referring to the same risk may use different words, or the same terminology may be applied to risks that are actually distinct in their attributes. Subtle differences in wording can lead to misinterpretation regarding the nature of a risk or its application to different parts of a balance sheet. Some writers describe a risk in broad terms and others apply it more precisely to a specific area.

Consider the example of the substitutability of products, that is the breadth with which a particular offering is available across the market. This is identified by some writers in general terms (J. Cummins and Weiss 2014; IAIS 2018a), while others note the impact of poor substitutability on industry capacity (IAIS 2011) or consider the issue in specific classes of business (IAIS 2019). It is at least clear that this is a risk concerned with concentration of liabilities. In other instances, it is not obvious whether a risk is more concerned with assets, in the case of structured securities, say, or ALM. For example, risks related to embedded investment guarantees in long-term insurance products may be allocated to liabilities, ALM or solvency. The broad approach employed in instances of doubt is to allocate risks first to assets or liabilities, then to ALM and then to solvency or to general risks.

Notwithstanding these concerns, the framework is regarded as helpful to regulators as an approach to categorise risks and to find areas of risk that have not yet been identified. Not all combinations of the categories used at the two levels are populated with identified risks, but these combinations could be used by regulators to identify possibilities not hitherto considered.

Allocating risks to categories

Classification is undertaken in two stages. The first stage aims for collective exhaustion at the risk of some overlap or confusion of categories. This is used to classify the risks attributable to insurers that are identified in the literature. The second targets mutual exclusion by limiting the possibility of incorrectly allocating the risks identified by insurers. This is used to assess the risks reported by insurers themselves.

First, examples identified in the literature are classified broadly, keeping separate risks that may have distinct attributes. This potentially overstates the number of distinct categories of risk, but it allows others to interpret these categories as they wish, perhaps consolidating them or reorganising them to suit their purposes. This information is summarised in Table 13 in the Appendix.

Second, categories that appear similar are consolidated for the purposes of categorising risks identified by South African insurers, the results of which are shown in Figure 6.1 and discussed in Section 6.4. This consolidation makes it easier to allocate these risks on a consistent basis. This process is also prone to subjectivity, as judgement is required on appropriate consolidation of the categories identified in the literature. The number of categories, 50 in total, is small enough to facilitate reasonable classification of risks identified through the market survey, but sufficiently large to distinguish appropriately between these risks and hence between the corresponding strategies to mitigate them.

The process of classifying risks and consolidating them into a more concise set of categories was completed prior to considering the evidence for each of the identified risk types, described in Section 6.4.

6.3.3 Quantitative analysis

Significant research has been undertaken to quantify the impacts of poor market conditions on individual entities and, in turn, the extent to which the collapse of individual companies might affect their peers and the broader market. Such work is hampered by the absence of consensus on what constitutes systemic risk (see Section 6.2.2) but it does encourage the use of a wide range of approaches, helpfully assessed and classified by W. Silva, Herbert, and Vinicius (2017) and Ellis, Sharma, and Brzeszczyński (2022).

A summary of several studies of quantitative methods for assessing systemic risk is provided in Table 14 in the Appendix, drawing on the classification system proposed by Ellis, Sharma, and Brzeszczyński (2022). Measures of solvency include SRISK, the capital shortfall of an entity conditional on a crisis (Acharya, Engle, and M. Richardson 2012; Brownlees and Engle 2017) and Delta CoVaR, the marginal change in the value-at-risk of the system conditional on the distress of an entity (Z. Adams, Füss, and Gropp 2014; Adrian and MK Brunnermeier 2016). While SRISK explores the possibility of market impacts on an entity and Delta CoVaR the corresponding impacts that an entity may have on the market, not all methods seek evidence of direction of effect. Alternative approaches include models of joint probabilities of default (Segoviano and Goodhart 2009), Granger causality studies (Billio et al. 2012) and a variety of network models (Hautsch, Schaumburg, and Schienle 2015; S. Lee 2013; Martinez-Jaramillo et al. 2015; Poledna et al. 2015).

The methods also have different data requirements. With the exception of S. Lee (2013), all of the studies listed in Table 14 utilise quoted market data, either stock returns or credit default swap (CDS) prices. Several of them also use accounting information, which is typically available at significantly lower frequency than the market data, calling for a blended approach to data from different sources. Refer to Adrian and MK Brunnermeier (2016) for a thorough explanation of the challenges involved.

On the whole, not a great deal of attention has been given to quantitative studies of systemic risk involving insurers. Exceptions to this include Weiß and Mühlnickel (2014), who report evidence that insurers materially contributed to instability of the financial system in the 2007-09 crisis, and Leukes and Odei-Mensah (2019), who include insurers alongside other financial-market entities in their study of systemic risk in South Africa.

While the continued use of such modelling in the insurance sphere is encouraged, its challenges should not be understated. First, market prices are not necessarily representative of the insurer. This would be the case where the group holding company rather than the insurer itself is listed on the stock exchange. Second, not all countries have sufficient depth of CDS markets to enable these methods to be used with reliability: South Africa suffers this difficulty. Third, book values are typically available infrequently and are often delayed.[3] Fourth, some methods call for comparison of a single entity with the market as a whole. Data challenges are often particularly acute for smaller entities. Though they do not contribute a great deal to aggregate market figures, these entities often bring unusual features to the market, so it can be difficult to claim that the market is adequately represented if smaller entities are not included in the available data. Both the market and accounting data of these entities are likely to be more difficult to obtain with accuracy than for their larger counterparts.

While some of these problems could apply to all financial-sector entities, they could be particularly acute for insurers. In South Africa, for example, while monthly bank accounting figures are centrally published in standard format with a delay of a few weeks, no such equivalent information is available on insurers. This means that information would need to be manually extracted from published reports, which are available quarterly at best and may be subject to inconsistency of definition and interpretation.[4]

The appropriateness of quantitative methods to analysing the contribution of South Africa's insurance industry to sysemic risk is considered in Section 6.4.4, the last part of the discussion that follows.

6.4 Application to South African insurers

The discussion turns now to the application of the method of classifying insurance-related systemic risk to South Africa's marketplace, supported by the summary of the market set out in Section 6.2.4. This starts with a description of the analytical approach. It is followed by a discussion of the findings and consideration of the regulatory methodology that may be utilised in response to poorly-reported risks. The discussion closes with a reflection of the potential for quantitative methods in this environment.

6.4.1 Analytical approach

Section 6.3.2 describes the process of consolidating the broad system for classifying the sources of systemic risk attributable to insurers into a more manageable set of risks arranged into two types of categories. The first of these is that part of the balance sheet

[3] The authors recently conducted an assessment of the relationship between the adverse experience of South African banks and the market as a whole. Monthly accounting data was used and quantile regression methods were employed, in line with the Delta CoVaR method of Adrian and MK Brunnermeier (2016), but using the accounting data only, not the market data in addition. Detecting stable patterns in the tails of the distribution on the basis of monthly banking data proved challenging.

[4] In such instances, the regulatory authority typically has information of better quality than is publicly available. The Prudential Authority requires all registered insurers to submit returns on a standard format, which facilitates the extraction and analysis of industry data. This was required monthly during the economic difficulties associated with the COVID pandemic in 2020 and 2021, but the frequency with which these must be submitted has since reverted to quarterly.

most affected by the risk. The second is the broad form that the risk takes. The discussion that follows explains how evidence for the existence of each of these risks may be identified from within the insurance industry.

Entities quoted on the Johannesburg Stock Exchange publish annual reports meeting listing requirements. These reports include a description of the most significant risks that the entities are exposed to. In the interest of transparency, some companies issue several reports covering the listed entity and its subsidiaries. In some instances, unlisted entities publish similarly comprehensive reports. The analysis summarised in this discussion and in Figure 6.1 covers the last five years' reports of the seven financial groups that include the five largest life insurers by assets (Deloitte 2022; Prudential Authority 2022a) and the five most significant non-life insurers by premium volume (KPMG 2022; Prudential Authority 2022c). The value of assets of these groups (Deloitte 2022, Hollard 2021a, Outsurance 2021) amounts to some 89 percent of industry assets (Prudential Authority 2022b).[5] The groups included in this analysis are, in alphabetical order, Discovery, Hollard, Liberty, Momentum Metropolitan, Old Mutual, Outsurance and Sanlam. Not all of the group entities issue separate reports for their life and non-life subsidiaries but, in most cases, the corresponding group reports identify risks relevant to these subsidiaries. Some 78 reports are included in the study, listed in Section A.7 of the Appendix. Though all the annual reports and financial statements issued in the last five years were studied, in several cases the risks noted in these reports do not vary significantly from year to year.

Figure 6.1 maps the risks reported by South African insurers to the framework of systemic risks described in Section 6.3. Each of the the risks identified in published reports is allocated to one of the categories. The reported or implied significance of each risk is not captured, either in terms of its likelihood or potential financial impact. There were several reasons for this, the most important of which is that the reports typically do not disclose this information. Even if some of them did, it is not considered possible to capture this data on a consistent, objective basis. Multiple mentions of the same risk type are also not captured, whether these occur in a single report or repeatedly over several years, again on the basis that it is difficult to do so without introducing an element of subjectivity.

As noted in 6.3.2 significant overlap with idiosyncratic risks is expected. Insurers are more likely to be focused on idiosyncratic risks, for their own purposes, then their systemic counterparts. Allocating the identified risks to categories identified in the literature as potentially systemic, however, allows the regulator to map the potential for systemic risk using these reports as one source of information.

Other risks of subjectivity remain, notably in the interpretation of the text and allocation of the risk to the available categories. Some risks are also less likely to be disclosed by insurers, even if they exist. This may be because insurers are typically focused on idiosyncratic risks rather than those with systemic qualities or because the risks disclosed are those more likely to be of interest to readers of the report, among them the regulator. It may also reflect internal blind spots. Insurers are unlikely, for example, to identify

[5] Hollard and Outsurance assets are for June not December, but contribute a small proportion to the total.

and disclose economic exposure through speculative derivatives or risks associated with governance inadequacy. Both of these require an element of judgement and are difficult to describe dispassionately. Ambiguous disclosure could be detrimental. Transparent communication in matters such as these should nevertheless exist between the entity and the regulatory authority. The hope underpinning this research is to facilitate regulatory identification of such matters.

The resulting output (see Figure 6.1) is a scatter plot showing the extent to which risks falling into each of the categories are disclosed by insurers and their group holding companies in their financial reports. Summaries of the frequencies with which risks are reported that fall respectively into each balance sheet category and risk type are shown in Table 6.1 and Table 6.2 and discussed below.

6.4.2 Discussion of findings

The bottom rows of Tables 1 and 2 show the overall frequency with which risks falling into the identified sub-categories are reported for each type of company. This frequency, averaging 0.28 across all entities, is highest for holding companies (0.33), followed by long-term insurers (0.28) and short-term insurers (0.21). This is consistent with the expectation that holding companies have a broader perspective on risks that could be systemic in nature and that systemic risk is more likely to originate in or be propagated by long-term insurers than by their short-term counterparts (S. Park and Xie 2014, for example).

	Holding companies	Long-term insurers	Short-term insurers	Average
Assets	0.45	0.19	0.16	0.28
Liabilities	0.33	0.35	0.23	0.30
ALM	0.38	0.31	0.25	0.32
Solvency	0.14	0.25	0.21	0.20
General	0.20	0.00	0.00	0.08
Average	0.33	0.28	0.21	0.28

Table 6.1: Insurer risk identification by balance sheet category
The table shows the frequency with which risks of each balance sheet category are reported in the annual financial statements and supporting published documents of entities of different type. ALM refers to asset-liability management.

Table 6.1 indicates that risks concerning the allocation of assets, which includes asset-liability management, and risks of a general nature are most frequently disclosed and managed at holding-company level, where strategic decisions are more likely than at the level of the subsidiary. In contrast, risks focused on insurance liabilities and on solvency are more frequently noted at the level of the insurance licence, where the attention to these issues is likely to be more acute. The differences between long-term and short-term insurers are greatest for those risks impacting liabilities, solvency and asset-liability management. This is consistent with the higher likelihood of a duration mismatch between assets and liabilities at long-term insurers than at their short-term counterparts.

Figure 6.1: Systemic risks identified for large South African insurers

Balance sheet element	Risk type	Risk form	SARB	Total	Grp	LTI	STI	Mitigation
Assets	Concentration	Economic, policy and governance impacts on assets		9	5	2	2	
		Impacts of climate change on asset values		3	3			Scrutiny of impacts and potential concentration of risk
		Interconnected stock market performance		1	1			Stress tests and capital buffers
		Investment in banks and the real economy or direct banking business		4	3	1		
	Quality	Counterparty exposures		10	4	3	3	
		Investment through unregulated subsidiaries						**Regulatory scrutiny and focus on group risk**
		Non-traditional investment activities						**Regulatory analytics and detailed probes**
		Complex structured securities, CDSs and others		2	2			Analysis of derivative holdings and their purpose
Liabilities	Concentration	Catastrophe risk		9	3	3	3	
		Impacts on climate change on liaibilities		5	4		1	
		Correlated product classes		4		2	2	
		Limited substitutability and capacity: general						**Concentration studies and care over barriers to entry**
		Substitutability limitations: class-specific concerns						**Focused market-sector analysis**
		Exposure to social issues and the broader economy		9	5	1	3	
		Insurer concentration and interconnectedness		2	1	1		Concentration and interdependency studies
		Reinsurance with limited risk transfer		2		1	1	Registration of financial reinsurance schemes, with monitoring
	Mismatch	Products with guarantees and embedded options		6	3	3		
		Savings and investment in long-term insurance		5	1	4		
		Policyholder lapses and surrenders		8	3	4	1	
	Quality	Product complexity		1		1		Market conduct focus
		Bank-like product design						**Product definition and control measures**
	Strategic	Distribution through banks		3	1	1	1	
		Credit protection and economic exposure		12	5	3	4	
		Exposure to burden of disease and economic impacts		6	3	2	1	
		Exposure to fraudulent activity		1		1		Focus on operational risk management
		Insurer provides critical function with few substitutes						**Class-by-class identification of potential for concentration**
		Third-party asset management						**Minimum governance standards**
	Operational	Cyber risk		6	4	1	1	
ALM	Mismatch	Asset lending and associated liquidity risk		2	2			Standard regulatory reporting
		Liquidity risks attributable to constrained funding, asset volatility or derivative exposure		9	3	3	3	
		Reliance on short-term financing						**Liquidity modelling and occasional focused studies**
		High exposure to equity investments		13	5	4	4	
		Maturity mismatches		2	2			Liquidity modelling and stress tests
		Economic exposure attributable to speculative derivatives						**Liquidity modelling, regulatory disclosure and special studies**
	Quality	Counterparty exposure, particularly from reinsurance		11	4	4	3	
		Alternative risk transfer, banking, hedge fund and synthetic investments		4	2	1	1	
		Property management risk		7	3	3	1	
	Strategic	Business model risks and interconnectedness		1	1			Occasional focus on strategic risk management
		Non-core activities and unusual exposures		1	1			Systematic disclosure framework covering assets and liabilities
		Insurance-linked securities						**Identification and assessment**
Solvency	Concentration	Risk exposures attributable to links with reinsurers		1	1			Reinsurer solvency and analysis of concentration risks
		Losses tranfered to other participants		1		1		Assessment of inward reinsurance arrangements
	Mismatch	Leverage		1		1		Microprudential tools and shock testing
	Quality	Funding structures		3	1	1	1	
	Strategic	Unduly rapid growth		1	1			Scenario testing and focus on identified insurers
	Operational	Inadequate pricing and provisioning		3		1	2	
		Operational liquidity risk and limited fungibility within groups		8	2	3	3	
General	General	Policy and regulation not geared towards reducing systemic risk		2	2			Increasing regulatory focus on systemic risk
		Panic run possible		1	1			Scenerio testing and care over product design
		Inadequate governance						**Minimum standards at regulated entities**

The figure (1) synthesises the risk forms identified in the literature and set out in Table 13, (2) indicates those risks reported by seven South African insurance groups and their subsidiaries and (3) summarises the proposed mitigation strategy for those reported with poor frequency (normal text) or not identified at all (bold text). Background to the analysis is available in Section 6.4. The numbers in the table denote the number of entities identifying each risk as applicable to them. Sources are as follows: 'Grp' indicates the group or holding company, 'LTI' a long-term insurer and 'STI' a short-term insurer. The reports assessed are listed in Section A.7 of the Appendix. Not all entities publish group reports and only some of them have both long- and short-term insurers in the group.

	Holding companies	Long-term insurers	Short-term insurers	Average
Concentration	0.37	0.21	0.21	0.27
Mismatch	0.38	0.48	0.20	0.35
Quality	0.32	0.33	0.23	0.29
Strategic	0.24	0.18	0.15	0.19
Operational	0.40	0.42	0.50	0.44
General	0.20	0.00	0.00	0.08
Average	0.33	0.28	0.21	0.28

Table 6.2: Insurer risk identification by risk type

The table shows the frequency with which risks of each broad type are reported in the annual financial statements and supporting published documents of insurers and their holding companies.

Similar patterns are observed concerning the frequency with which risks are identified by category, shown in Table 6.2. Groups more frequently report on concentration-, strategic- and general risks than their insurance subsidiaries, consistent with the high-level perspective of these entities. Long-term insurers note risks of mismatching more often than their short-term counterparts, in line with the duration-based complexity of both their assets and their liabilities. Both holding companies and long-term insurers report risks of quality with relatively high frequency. These risks typically concern counterparty risks, alternative risk transfer, property management risk and product complexity. Short-term insurers identify operational risk more frequently than their long-term and holding-company counterparts. Though this is based on a sample cluster of risks, it is consistent with the generally higher operational intensity of short-term insurers and the competitiveness of their pricing in many product categories.

The discussion turns now to the frequency with which risks in each sub-category are reported (refer to the blue and green columns in Figure 6.1) and the overlap with those risks identified by the SARB in its financial stability reviews (refer to the column labelled 'SARB'). Those risks most consistently noted by insurers include exposure to counterparties, including reinsurers, to stock market volatility and to risks concerned with uncertainty in social and economic conditions and government policy. Several insurers also identify catastrophe risk, lapses and surrenders by policyholders and liquidity risk as potentially significant contributors to adverse experience.

While some overlap of these risks with those noted by the SARB in its focus on systemic risk exists, such overlap is not particularly strong. The SARB, for example, has not identified counterparty risk or equity exposure as material systemic risks in its financial stability reports of the last few years, perhaps on the basis that it regards these risks as broadly under control. Furthermore, some of the risks noted by the SARB have not been identified by insurers with high frequency. These include the impacts of climate change, insurer concentration and exposure to fraudulent activity. This may indicate that they are limited to pockets of insurers. It may instead illustrate the difference in perspective between the regulator, which is concerned about systemic risk, and the regulated entities that have a limited incentive to manage risks whose impacts could be widely felt but might not directly impact the entities themselves (S. Schwarcz 2008). Climate change and insurer concentration are examples of such risks.

6.4.3 Risks infrequently reported by insurers

The focus of the discussion turns now to those risks of a systemic nature that are infrequently identified by insurers, or not at all. The possibility of bias in the source data is acknowledged. Insurers and their holding companies are unlikely to report risks judged likely to have little impact on their operations or financial positions, even if these risks have potential systemic effects. Their absence from the annual financial reports of the largest insurers and their holding companies cannot be construed either as poor identification by these entities or that the risk is not relevant to the South African environment.

No instances were found, for example, of insurers identifying the risks associated with investment through unregulated subsidiaries or any non-traditional investment activities. There are good reasons for this. In the first instance, if insurers were using unregulated subsidiaries to channel investment, the status of such entities as unregulated would most likely not be highlighted in annual reports. Insurers are required to submit detailed charts of group organisational structures to the regulator, however, facilitating the identification of such subsidiaries outside of the public domain. This is consistent with regulatory focus on group risk. In the second instance, the term 'non-traditional' is subjective. Several insurers disclose investment in derivative structures to match their liabilities. Whether this match is perfect or whether some of these derivative arrangements are motivated by the pursuit of return rather than the management of risk is difficult to determine but would also be expected to form part of regulatory scrutiny.

In each case of risk sub-categories with no reporting or sparse reporting by insurers, further analysis is warranted to determine the likelihood that the risk exists and the extent of its potential impact on the financial system. This is most appropriately carried out by the regulator, in discussion with the insurers. Brief thoughts regarding the approach to each of these risks are indicated in the right-most column of Figure 6.1, in bold text where no instances of the risk are reported. With reference to the examples mentioned in the previous paragraph, for instance, the regulator is in a strong position to scrutinise group structures and probe the investment activity of insurers, using standardised reporting information and supporting this with more detailed investigation where appropriate. These examples call for detailed analysis at insurer or group level.

Some risks require investigation that is technically complex or must be carried out across the industry. A few examples are considered in the discussion that follows. Investigation of insurer concentration is relatively straightforward where it is limited to the proportion of assets or premium income attributable to the largest insurers, but product substitutability concerns require a more nuanced and detailed understanding that may prove beyond the means of the analysis of the standardised annual or quarterly regulatory insurance returns. Investigation of reinsurance arrangements with limited transfer of risk, or product complexity or of bank-like products offered by insurers all require technical knowledge and judgement. Expertise in governance and risk management is required to assess the risks of inadequacy in leadership or the effectiveness with which board policies are drafted and implemented.

Different approaches may be required at group level, where the respective attributes of distinct types of entities in the group may be considered, along with the potential for a contribution to systemic risk arising from interaction between these entities. A useful start to this process could be to consider whether, for each of the risk sub-types listed in this framework, the potential for risk magnification may exist as a result of attributes of the group and its relationships.

Most of the interaction and correspondence between the regulator and the entities that it oversees is not in the public domain. The summarised findings of this interaction, however, are frequently published in order to enhance awareness and influence behaviour. The categories and sub-categories used in this study to describe the types of systemic risks that might originate at or be propagated by insurers are designed to assist regulators to identify and manage these risks and to publicise the extent to which it is doing so. It should link this explicitly to its regulatory objectives.

Through their micro-prudential oversight, regulators expect to have a strong understanding of the idiosyncratic risk profile of supervised entities. The approach proposed aims to assist regulators to convert this insight into an analysis of the potential for these risks to become systemic in nature. It is hoped that this framework would assist South Africa's Prudential Authority and regulators in other jurisdictions not only to identify and manage systemic risk in their insurance markets but also to plan their resourcing requirements. How they might respond to risks needs to be appropriate to the circumstances. Identified instances of systemic risk call for case-specific responses, some of which need to be coordinated across entities. Such interventions may range from requirements of entities to mitigate specified risks or improve solvency levels to industry-wide initiatives to raise organisational resilience to uncertainty.

6.4.4 Quantitative analysis in practice

Some of the models used to assess the contribution of banks and insurers to systemic risk are summarised in Section 6.3.3. The most significant limitations of these models and some of the challenges concerning the data that they require are also considered in that discussion.

Notwithstanding these limitations, ongoing quantitative analysis of the systemic risk indicators and the drivers of systemic risk should be undertaken. The regulatory authority is typically in the strongest position to model systemic risk on the basis that it has the best access to the information required to do so. Where such information is desirable, but not currently available, consideration should be given to requesting regulated entities to submit this to the regulator. Where quarterly reports are submitted under the existing regulatory framework, for example, consideration should be given to the need for monthly information, possibly with backdated information to establish a history. For the purposes of this analysis, a significantly simplified version of the standard reporting template may be sufficient.

It is recommended that consideration be given to the appropriateness of several alternative models, such as Delta CoVaR, SRISK, Marginal Expected Shortfall and Systemic Expected Shortfall. Where alternative methods are possible, under each of these models, these should be actively investigated, preferably by constructing several of these alternatives and studying the reasons for differences in the results. Consideration of the detail underlying the models is likely to prove more helpful to an understanding of systemic risk than a blind acceptance of the outputs from just one model.

In time, the insights gained from this process could be shared with industry participants, with invitation to comment, potentially justifying the need for more frequent or more detailed information.

6.5 Concluding comments

Identifying and mitigating instances of systemic risk in the financial sector are priorities for regulatory authorities around the world. It is broadly agreed that banking contributes to systemic risk by virtue of the inter-linkages between entities. The nature of the corresponding contribution by insurers is not as obvious. This article proposes a framework for classifying the sources of systemic risk attributable to insurers. The thorough approach to classification aims also to improve detection and identification of risk sources. It applies this framework to the insurance market in South Africa, in the process providing practical recommendations for consideration by all regulators.

While several approaches have been developed for assessing quantitatively the contribution to systemic risk by individual entities, practical constraints inhibit the application of quantitative methods to insurers, particularly in countries like South Africa with data limitations. Regulators are encouraged to explore the merit of these methods and to call for the data required to support this exploration. The framework presented herein aims to assist regulators to build a coherent understanding of the potential for systemic risk of various kinds arising from the insurers that fall under its responsibility, in turn contributing to efforts to develop supporting quantitative methods.

The discussion concludes with possibilities for further research. Possibilities for further exploration of a qualitative nature include the following. First, deeper engagement with insurers could be considered to understand their risk profiles in more detail. This might be conducted through structured interviews or an analysis of their management accounts or product ranges. Second, the risk sub-types defined in the literature and classified in two stages in this study could be more precisely defined, perhaps with the attributes of insurers or their activities that regulators should look out for to identify evidence for each risk. Third, further study of insurance groups could be conducted in order to apply the methodology proposed in this chapter to complex entities of various kinds. Fourth, cross-country studies could be considered that aim to identify systemic risks that are similar across jurisdictions or distinct to particular markets, in the process assisting in the development of appropriate responses to regulators. Finally, engagement with regulators might be considered, across countries or through regulatory associations, to gain insight into their perspective on the risks most commonly encountered and the most effective corresponding mitigating actions.

Several avenues could also be considered for further research of a quantitative nature. A detailed assessment of the alternative approaches that may be used for modelling in a particular country could be carried out. This could take into account the nature of the risks that characterise the insurance market in that country and the type and accuracy of data available. The models considered in this chapter typically have several components. Consideration of the insights available from each of these components might be assessed and described.

The question of whether insurers might contribute to systemic risk is not a simple one. It is nevertheless a question that deserves the consideration of financial-sector regulators within the framework of their regulatory objectives. This chapter aims to provide a practical framework within which regulators might identify and categorise the sources of systemic risk arising in insurers with a view to monitoring and mitigating such risk.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Chapter 7

Conclusion

> "Systemic risk increased during the period under review, mainly due to further monetary policy tightening, global banking turmoil, volatile financial markets and downward revisions of growth projections, both for major economies and South Africa. Lingering recession fears and geopolitical tensions contributed to heightened systemic risk over the review period." (SARB 2023, p.31)

Systemic risk is topical, not just in the financial sector. South Africans are only too well aware of systemic risk in power generation, for example (refer to the introduction in Chapter 1). If the system fails, the consequences for the country, its economy and its people would be felt much more widely than in the immediately consequences of cold and darkness. Externalities would abound.

The same applies to systemic risk in the financial sector. The failure of an entity can have substantial effects on the rest of the sector and on society at large. For this reason, Banks and insurers must meet minimum capital and liquidity requirements. They must demonstrate their preparedness for adversity and they must show a strong understanding of their exposure to risk. Still, while entities have financial incentives to identify and manage risks that has a direct impact on them, they do not have the same incentives to mitigate risk that does not directly impact them but might affect others (S. Schwarcz 2008). For this reason, regulators have a special responsibility to manage systemic risk, imposing additional requirements on regulated entities to do so.

The research set out in this thesis aims to provide several tools to assist regulators in executing on this responsibility. This concluding discussion is arranged as follows. Section 7.1 considers the extent to which objectives are met. Section 7.2 summarises the possibilities for further research. Section 7.3 concludes.

7.1 Review of objectives

The discussion that follows summarises the manner in which the study meets its goals with reference to the objectives set out in Chapter 1, the introduction to this thesis. Text extracted from that chapter is in italic typeface.

7.1.1 Overall objective

The overarching objective of the research described in this thesis is to enhance the understanding of policymakers and regulators concerning the nature of systemic risk in South Africa's banking and insurance markets. Each study aims to assist decision-makers in practical ways, thereby contributing to more rapid identification of early warning signs and more effective mitigation of potential systemic risks.

The thesis meets this objective by focusing on practical results that could applied by the Prudential Authority (PA), regulator of banks and insurers in South Africa, to achieve its regulatory objectives more effectively. In particular, the findings help the PA to improve:

- its understanding of systemic risk originating in the banks and insurers that fall under its jurisdiction, along with any signs that such risk may be tending higher or lower at any time,
- the tools available to identify early warnings of elevated levels of systemic risk in regulated entities and hence to mitigate the potential impacts of these risks, and
- its ability to recognise market activities or entity behaviour that may contribute to increased systemic risk through herding or other mechanisms.

These are designed to assist the regulator to identify signs of elevated systemic risk and mitigate the potential impacts of such risk.

7.1.2 Banking networks

This objective is achieved by applying quantitative modelling techniques to questions of systemic risk arising in banking networks, suggesting the possibility of disproportionate contributions to systemic risk by large banks (Chapter 2) and of tipping points in ambient levels of systemic risk (Chapter 3);

Chapter 1 introduces the principles of network modelling. Chapter 2 uses network modelling on monthly balance sheet data for banks across the South African market. It confirms the findings of Walters et al. (2018), extending the period of analysis from two years to five and a half. The method proves helpful to identify periods of elevated systemic risk, but it may also be applied to understand the tendency for certain banks to contribute more to this risk than others.

That in turn allows testing of the relative contribution of certain banks to systemic risk by assessing market conditions were they hypothetically removed from the network. The analysis suggests that larger banks in South Africa contribute disproportionately to systemic risk. This has practical implications for the manner in which these banks are regulated. It also shows differences between these contributions by channels of contagion, in turn helping the regulator to understand which channels and which conditions might be more favourable for risk events of a systemic nature and which banks are more likely to contribute to such elevated risk.

Chapter 3 uses similar methods to assess the sensitivity of levels of ambient risk to changes in the assumptions governing the model. The study concludes that such risk levels may be impacted in unexpected ways by market conditions and may be subject to tipping points that could result in a significant elevation in risk levels in response to small changes in the parameters that describe these conditions.

Tipping points are identified in the sensitivity of systemic risk indicators to changes in the liquidity indicator and the sentiment factor. The liquidity indicator is the extent to which a shock impacts the values of assets of other banks and the sentiment indicator is the corresponding impact on the asset value of those banks assumed to be closely related to the shocked entity. The results are robust to changes in the nature of the assumed market network model. These insights are of practical value to policymakers, suggesting that more information regarding the likely values of these indicators at any time would be useful to understand the possibility of conditions approaching these identified tipping points.

7.1.3 Conditional value at risk

This objective is achieved by [...] assessing alternative approaches to measuring the contribution to systemic risk by individual entities in both banking and insurance (Chapter 4);

The approach utilised in the third study is applied to banks but it is relevant to both banking and insurance. A method of assessing tail-risk correlations between individual entities and the market as a whole is well-established in the literature but somewhat complex to implement in practice. The method is called $\Delta CoVaR$. It aims to estimate the value at risk of the market, conditional on adverse conditions at a particular entity.

The complexity arises from two sources. First, the method typically uses of a combination of market and book data, which must be blended. Market data is typically available at daily or weekly intervals, however, and book data only at monthly or quarterly intervals. Second, the method filters market data using state variables to remove the impacts of market noise and allow time-wise variations in the parameters estimated. It is not clear how much the choice of state variables might impact the results of the analysis.

The approach proposed in Chapter 4 is a simplified method of calculating $\Delta CoVaR$ using only monthly book values. The simplicity of calculation is helpful, but the key advantage of this approach is the ease with which it may be illustrated graphically. This adds intuitive insights to regulators regarding the strength and persistence of tail relationships between each entity and the market.

The primary disadvantage of the approach is that, notwithstanding its simplicity in comparison to the classical $\Delta CoVaR$ method, it is data intensive, leading to results using monthly data that are unstable over time. The approach is nevertheless practical. It is easily adapted to other data available in bank balance sheets. Subject to the availability of monthly data, it could be applied also to insurers.

It is recommended that such analysis forms part of the tool set of policymakers in banking and, subject to available data, also to insurance.

7.1.4 Systemic risk in insurance

This objective is achieved by [...] asking broad questions regarding the possibility of systemic risk arising in insurers through a detailed enquiry of the literature (Chapter 5);

The fourth study focuses attention more closely on insurance markets, undertaking a thorough review of the literature concerning these markets. This review aims to determine the extent to which insurers might contribute to systemic risk. It then applies this to South Africa's insurers, considering how aspects of the regulatory framework, the insurers themselves and their relationships with other entities might contribute to or exacerbate systemic risk. It cautiously concludes that, despite several mitigating factors, a contribution by these insurers to systemic risk is a possibility.

The practical value of this paper lies in the wide-ranging assessment of the nature of the insurance industry, including its contribution to economic growth and social welfare, and the range and details of the concerns raised by researchers and industry bodies regarding the insurance industry, some of which could give rise to systemic risk or propagate it more effectively.

This objective is achieved by [...] putting forward a coherent framework for classifying and hence identifying the sources of insurance-related systemic risk and applying this to South Africa's insurers through a survey of publicly-available information (Chapter 6);

The final study builds on the possibility of systemic risk arising in insurers in two ways. First, having surveyed the literature to identify insurance-related sources of systemic risk, or contributions to the propagation of this risk, it proposes a classification system for these sources or propagators. The practical benefits of this work include a thorough examination of the ways in which insurers might originate or propagate systemic risk and the arrangement of these possibilities into a practical framework. This helps not only to classify risks but to identify risks that may otherwise have gone unnoticed were it not for the framework that indicates the possibility of their existence.

Second, it applies this system to South African insurers with reference to risks disclosed by two sources:

- The country's largest insurers offering products in both long-term and short-term categories disclose and discuss the key risks to which they are exposed in their annual reports.
- The South African Reserve Bank, effectively the parent entity of the PA, regularly publishes an analysis of the state of systemic risk and the corresponding contributions to such risks of South Africa's primary economic sectors, including banking and insurance.

The result is not so much an analysis of the most common sources and propagators of systemic risk in South African insurers, but a practical framework to identify, in a systematic manner, potentially hidden contributors to the systemic risk environment. The method aims to assist regulators, which have access to more detailed internal assessments than are reflected in insurers' financial reports, with the process of identifying and mitigating sources of systemic risk in insurance.

7.2 Possibilities for further research

Research is an ongoing process. The studies in this thesis aim to provide a foundation for practical implementation and further enquiry. Each of the chapters identifies several further possibilities for investigation. The discussion that follows summarises these, identifying possibilities in common across chapters and emphasising practical possibilities.

7.2.1 Banking networks

Chapter 2 presents evidence that South Africa's large banks may contribute disproportionately to systemic risk. It does so by hypothetically removing the large banks from the network model and noting the significantly reduced systemic risk indicator following their removal than when all banks are assumed to form part of the network.

Scrutiny of the attributes of the medium-sized banks may reveal further detail on the reasons for this reduction in the modelled (hypothetical) level of systemic risk. The sensitivity of the systemic risk indicator to changes in solvency or cash levels, for example, would help regulators to understand the potential benefits from an alternative approach to minimum capital or liquidity requirements. Other characteristics of these banks could be investigated to assess the sensitivity of results to changes in these characteristics.

The study assumes that, when larger banks are removed from the market, the other banks do not respond to this disappearance by modifying their financial management strategies. This may not be realistic. They may regard it as appropriate, for example, to reduce their capital levels in response to the hypothetical increase in their market share or indeed in pursuit of further growth. Sensitivity of results to alternative counterfactuals could be explored.

Chapter 3 continues the approach of modelling the banking market as a network of interlinked entities. It notes tipping points in the sensitivity of the systemic risk indicator to changes in two of the assumptions underpinning this modelling. Tests of the robustness of this result to changes in assumptions are recommended in that chapter along with examination of the sensitivity of results to alternative network models.

Several options for further research of these results exist that may equally be applied to the large-bank impacts described in Chapter 2. These include the following possibilities:

- assess the sensitivity of results to variations in bank-specific attributes such as the solvency level or the spread of assets over the term spectrum,

- explore the expected costs and benefits of regulatory intervention, starting with alternative minimum capital or liquidity stipulations,
- analyse different formulations of the channels of contagion, for example, under the credit shock approach, alternatives to the assumed equal proportional reduction to the assets of surviving banks in response to a shock to a peer,
- assess the likelihood that each of the three modelled channels of contagion exist, or the relative influence that the channels might exert on the network in practice,
- examine empirically the dynamics of the network to estimate the most likely values taken by the assumptions underpinning each of the modelled channels of contagion, and
- assess the attributes of the South African banking market to determine the network models that most closely describe the nature of existing market relationships, perhaps also assessing the possibility that these relationships may change over time.

In the interest of practical insights, it would be helpful also to study the attributes of balance sheets that most easily contribute to or detract from the likelihood of collapse in response to a shock assuming different channels of contagion. This would facilitate regulatory action, specific to prevailing conditions, to reduce this probability.

7.2.2 Conditional value at risk

Chapter 4 proposes a simplified approach to the calculation of $\Delta CoVaR$, a widely-used method of estimating tail dependency between adverse circumstances at a bank and for the market as a whole. The results of this approach are not stable over time, suggesting that monthly data is not sufficiently granular or that the method is too simplified to detect bank attributes with reliability.

Several avenues for further research may be considered. Some of these explore the possibilities for bridging to existing methods to adjust for the possibility of an over-simplified approach, for example:

- consider alternative approaches to adjusting book values to capture the information available in market values, which is available at greater frequency, and
- explore the sensitivity of results to changes in the set of state variables that are used to filter noise in market data.

Further options could be considered to assess other aspects of the relationships between variables:

- scrutinise the attributes of banks over shorter sub-periods to identify the most significant drivers of tail correlations with the market,
- examine the impacts on the results of removing outlier periods, such as March 2020, characterised by exceptional market conditions that are unlikely to be repeated, at the same time scrutinising the attributes of balance sheets over these periods

to understand the extent of co-movements during these potentially unique market events,

- consider alternative metrics to return on assets to determine whether co-movements are more easily detected and explained for these alternatives, such as solvency, or for measures that consider contributory factors to these metrics, such as increases in the values of assets or liabilities in sub-categories, and
- subject to available data, extend the method and its alternatives to other types of entities, considering also the possibilities of applying the method to identify tail co-movements between members of the same financial group.

Insights gained should contribute to regulatory efforts to monitor and manage systemic risk more effectively.

7.2.3 Insurer contribution to systemic risk

Chapter 5 assesses the possibility of systemic risk originating in or propagated by the South African insurance industry and Chapter 6 proposes a framework for classifying the types of risk in an effort to assist regulatory detection and mitigation of such risk. Taken together, possibilities for further research may be divided into extensions of banking network models to insurance, empirical tests of the insurance industry and improvements to the regulatory process.

Insights from the banking environment may be extended and applied to insurance in several ways:

- alternative network models for banking, as described in Chapter 2 and Chapter 3, could be fitted to the South African experience, first in the banking market and then in other financial-sector markets,
- network alternatives could be extended to financial-sector groups, formulating the nature of these networks, perhaps in the forms of clusters of entities, and empirically testing the attributes of the market against these models,
- empirical systemic risk indicators such as $\Delta CoVaR$ could be applied to insurers or insurance groups to examine their attributes in comparison to the banks, considering alternative approaches to the challenges of defining the market against which to assess these entities, and
- such approaches could be extended to examine tail co-movements in financial-sector groups and the potential for magnified contributions to systemic risk from these groups.

The appropriateness of alternative empirical approaches in different countries could be explored, considering the attributes of the market and the corresponding regulatory environment in each of these marketplaces.

Empirical tests of the insurance industry could include assessing the potential for overlapping assets or liabilities across entities, mapping intra-group relationships between entities and developing indices of industry concentration. Using the framework described in Chapter 6, regulators could engage with insurers to understand more clearly the nature of the risks within these categories, along with the potential for correlated exposure to these risks across the industry. Regulators are likely to have deeper insights available to them through their engagement with market entities. Cross-country studies may be useful in this instance as well, potentially enhancing levels of cooperation between regulators across jurisdictions.

Other possibilities that have been identified through this work include:

- technical tests of the effectiveness of the existing prudential regulatory framework, particularly of the tendency of the micro-prudential approach to encourage herding, in turn stimulating systemic risk,
- possibilities for improving the effectiveness of the regulatory framework by deploying a graduated approach to regulatory requirements that vary by size or by other entity attributes,
- specifying regulatory objectives to mitigate and manage systemic risk and measuring and publishing the effectiveness with which these objectives are met, shaping short-term regulatory goals and developing options for an integrated approach to macro-prudential regulation in the process, and
- improving the articulation of the approach to regulatory impact assessment, with particular respect to the risk of systemic events.

Finally, the effort in Chapter 6 to classifying potentially systemic risks into a mutually exclusive and collectively exhaustive framework represents a first step. Further effort to improve this framework is encouraged, either by identifying other types of risk or by sub-dividing the available risk categories to identify risks in finer detail.

7.3 Concluding comments

Financial-sector regulators typically work to a range of objectives, for example, aiming for well-managed, solvent entities and customers whose financial needs are soundly met. A systemic event, under which financial difficulty at one entity leads to a domino effect that impacts several other entities and their customers, potentially undermining an entire economy, is typically very high on the list of risks to be managed and mitigated by regulators. It can severely undermine confidence in the financial system, and indeed in its regulation, for some time to come.

This research provides several tools to assist regulators to meet the objective of reducing and managing systemic risk. By studying banking networks it draws attention to the possibility of disproportional contributions to systemic risk by large banks and to the potential for small changes in external circumstances to trigger substantial increases to systemic risk levels. By exploring the possibility of simplifying a well-established approach to detecting tail co-movement between entities and the market, it adds to the set of quantitative indicators available to regulators. It poses the possibility that South African insurers may contribute materially to systemic risk and recommends a framework for classifying the manner in which they might originate or propagate systemic risk. This in turn should assist regulators to identify potential contributions and manage their impacts on the market.

Systemic risk is difficult to define and recognise, but the consequences of an event with systemic attributes are potentially substantial. This research, it is hoped, makes a contribution to ongoing efforts to understanding the signs of systemic risk and mitigating their impacts.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Appendices

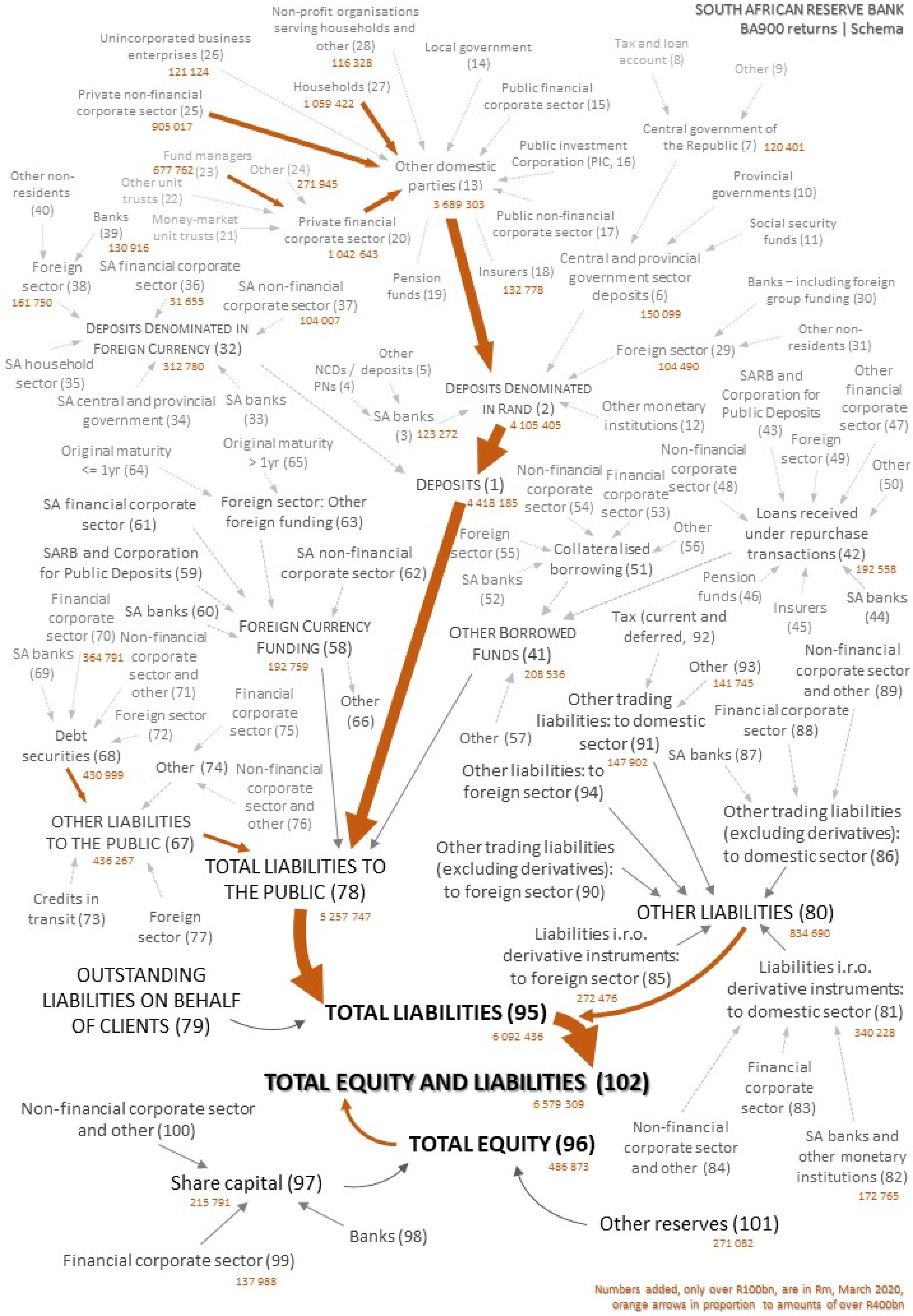
A.1 Summary of banking statistics, Chapters 2 and 3

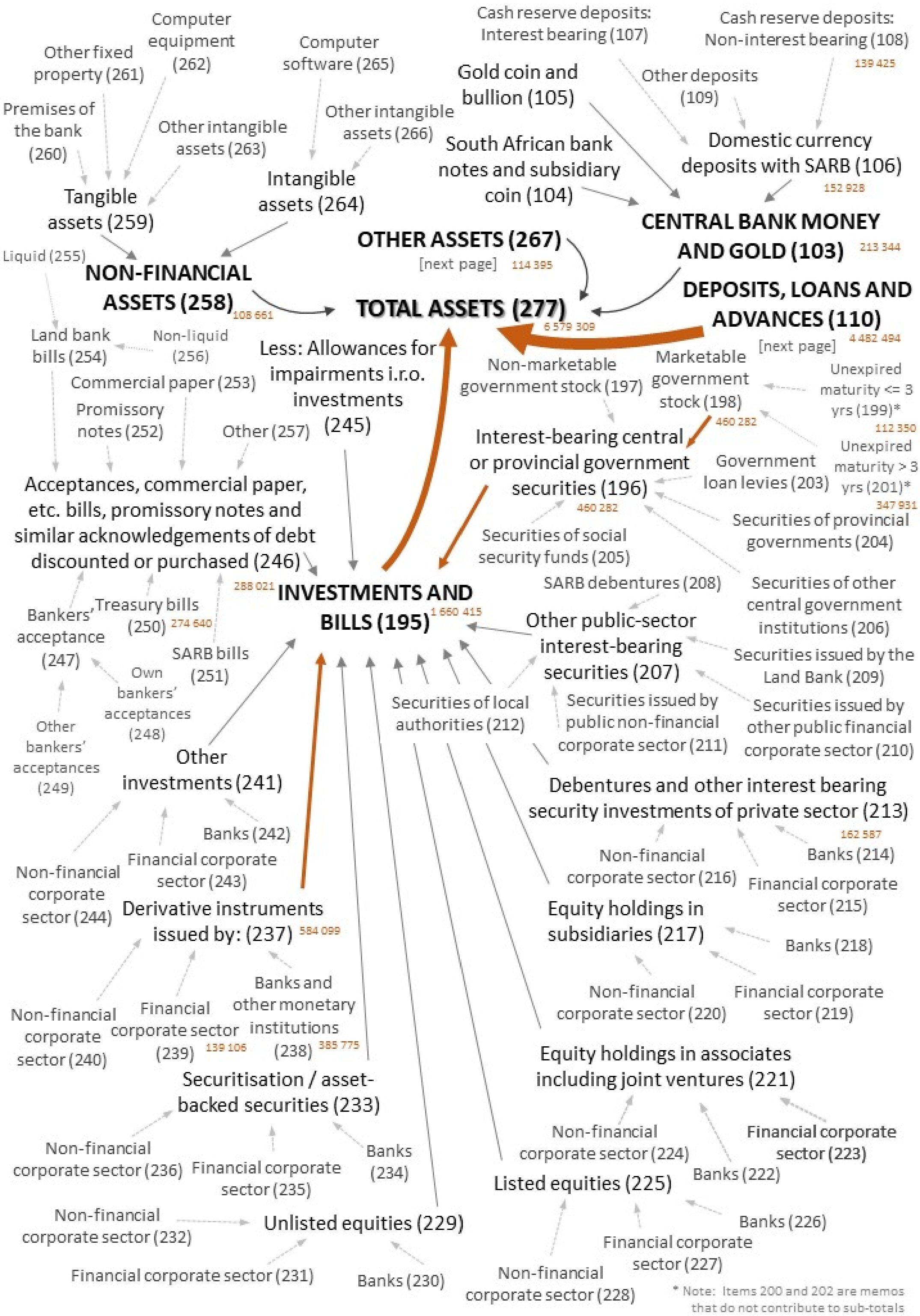
	Label in tables	Mean assets (Rm)	Asset mix (%) short	mid	long	CET1 stats mean	std dev
The Standard Bank of SA	Bank 1	1 292 626	0.19	0.31	0.50	0.055	0.002
Firstrand Bank	Bank 2	1 115 949	0.14	0.39	0.47	0.069	0.001
ABSA Bank	Bank 3	1 026 968	0.20	0.38	0.41	0.060	0.007
Nedbank	Bank 4	920 315	0.11	0.41	0.48	0.056	0.003
Investec Bank	Bank 5	420 857	0.16	0.32	0.53	0.082	0.003
Capitec Bank	Bank 6	88 656	0.35	0.60	0.05	0.199	0.002
Citibank NA	Bank 7	64 791	0.35	0.44	0.21	0.104	0.019
HSBC Bank	Bank 8	52 877	0.50	0.49	0.01	0.092	0.012
JP Morgan Chase Bank	Bank 9	49 507	0.17	0.23	0.60	0.115	0.039
Bank of China	Bank 10	43 005	0.54	0.42	0.04	0.124	0.024
China Construction Bank	Bank 11	35 452	0.54	0.25	0.21	0.103	0.033
Standard Chartered Bank	Bank 12	34 996	0.43	0.49	0.08	0.100	0.010
Mercantile Bank	Bank 13	12 769	0.18	0.40	0.42	0.170	0.013
Grindrod Bank	Bank 14	12 562	0.32	0.33	0.35	0.073	0.016
Deutsche Bank AG	Bank 15	12 545	0.18	0.33	0.49	0.089	0.021
Bidvest Bank	Bank 16	8 436	0.35	0.29	0.36	0.205	0.023
Sasfin Bank	Bank 17	7 697	0.12	0.74	0.14	0.124	0.026
Albaraka Bank	Bank 18	6 187	0.21	0.20	0.59	0.100	0.007
Ubank	Bank 19	5 264	0.11	0.81	0.08	0.089	0.009
HBZ Bank	Bank 20	4 892	0.44	0.32	0.23	0.074	0.004
Bank of Athens / Grobank	Bank 21	2 603	0.16	0.25	0.60	0.087	0.012
Finbond Mutual Bank	Bank 22	1 573	0.18	0.34	0.48	0.184	0.050
Habib Overseas Bank	Bank 23	1 249	0.50	0.48	0.02	0.086	0.010

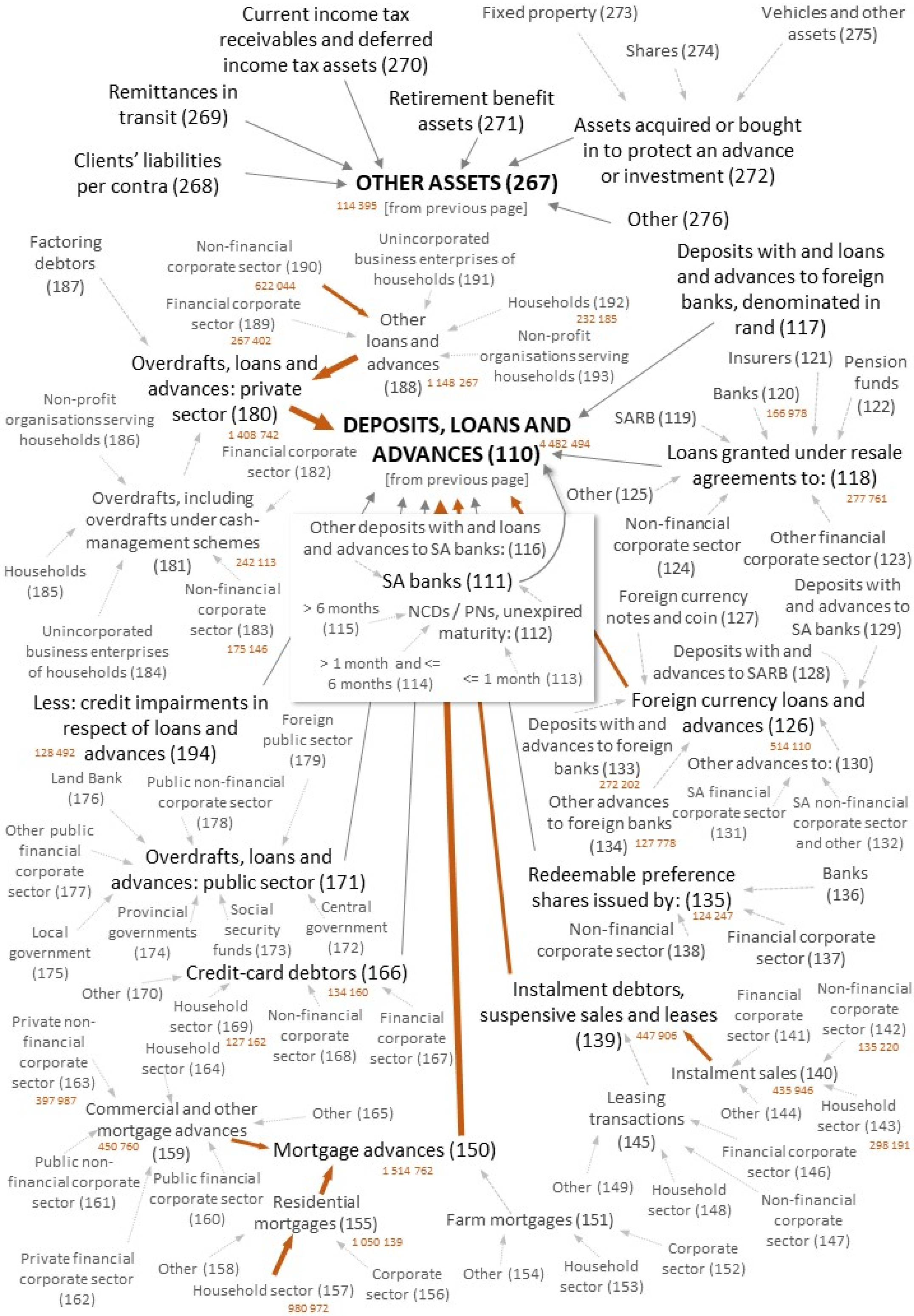
Table 1: Banks included in Chapter 2 & Chapter 3: summary statistics
The CET1 mean is the proportion of total assets of the bank attributable to CET1, averaged over the study period. The 'std dev' is the sample standard deviation of this proportion over the period.

A.2 Summary of South African Reserve Bank BA900 content

The images that follow describe the content of the standardised bank balance sheets available from the South African Reserve Bank.




Computer equipment (262)
Other fixed property (261)
Computer software (265)
Cash reserve deposits: Interest bearing (107)
Cash reserve deposits: Non-interest bearing (108)
139 425
Premises of the bank (260)
Other intangible assets (263)
Other intangible assets (266)
Gold coin and bullion (105)
Other deposits (109)
Domestic currency deposits with SARB (106)
152 928
Tangible assets (259)
Intangible assets (264)
South African bank notes and subsidiary coin (104)
CENTRAL BANK MONEY AND GOLD (103)
213 344
OTHER ASSETS (267)
[next page]
114 395
Liquid (255)
NON-FINANCIAL ASSETS (258)
108 661
TOTAL ASSETS (277)
6 579 309
DEPOSITS, LOANS AND ADVANCES (110)
4 482 494
[next page]
Land bank bills (254)
Non-liquid (256)
Less: Allowances for impairments i.r.o. investments (245)
Non-marketable government stock (197)
Marketable government stock (198)
460 282
Unexpired maturity <= 3 yrs (199)*
112 350
Commercial paper (253)
Promissory notes (252)
Other (257)
Interest-bearing central or provincial government securities (196)
460 282
Government loan levies (203)
Unexpired maturity > 3 yrs (201)*
347 931
Acceptances, commercial paper, etc. bills, promissory notes and similar acknowledgements of debt discounted or purchased (246)
288 021
Securities of social security funds (205)
Securities of provincial governments (204)
SARB debentures (208)
Securities of other central government institutions (206)
Bankers' acceptance (247)
Treasury bills (250)
274 640
INVESTMENTS AND BILLS (195)
1 660 415
Other public-sector interest-bearing securities (207)
SARB bills (251)
Own bankers' acceptances (248)
Securities issued by the Land Bank (209)
Other bankers' acceptances (249)
Other investments (241)
Securities of local authorities (212)
Securities issued by public non-financial corporate sector (211)
Securities issued by other public financial corporate sector (210)
Debentures and other interest bearing security investments of private sector (213)
162 587
Banks (242)
Non-financial corporate sector (244)
Financial corporate sector (243)
Non-financial corporate sector (216)
Banks (214)
Financial corporate sector (215)
Derivative instruments issued by: (237)
584 099
Equity holdings in subsidiaries (217)
Banks (218)
Non-financial corporate sector (240)
Financial corporate sector (239)
139 106
Banks and other monetary institutions (238)
385 775
Non-financial corporate sector (220)
Financial corporate sector (219)
Securitisation / asset-backed securities (233)
Equity holdings in associates including joint ventures (221)
Non-financial corporate sector (236)
Financial corporate sector (235)
Banks (234)
Non-financial corporate sector (224)
Financial corporate sector (223)
Banks (222)
Listed equities (225)
Non-financial corporate sector (232)
Unlisted equities (229)
Banks (226)
Financial corporate sector (227)
Financial corporate sector (231)
Banks (230)
Non-financial corporate sector (228)
* Note: Items 200 and 202 are memos that do not contribute to sub-totals


Current income tax receivables and deferred income tax assets (270)
Fixed property (273)
Vehicles and other assets (275)
Shares (274)
Remittances in transit (269)
Retirement benefit assets (271)
Assets acquired or bought in to protect an advance or investment (272)
Clients' liabilities per contra (268)
OTHER ASSETS (267)
114 395 [from previous page]
Other (276)
Factoring debtors (187)
Non-financial corporate sector (190)
622 044
Unincorporated business enterprises of households (191)
Deposits with and loans and advances to foreign banks, denominated in rand (117)
Financial corporate sector (189)
267 402
Other loans and advances (188) 1 148 267
Households (192)
232 185
Non-profit organisations serving households (193)
Insurers (121)
Pension funds (122)
Overdrafts, loans and advances: private sector (180)
1 408 742
Banks (120)
166 978
Non-profit organisations serving households (186)
SARB (119)
DEPOSITS, LOANS AND ADVANCES (110)
4 482 494
[from previous page]
Financial corporate sector (182)
Loans granted under resale agreements to: (118)
277 761
Other (125)
Overdrafts, including overdrafts under cash-management schemes (181)
242 113
Other deposits with and loans and advances to SA banks: (116)
Non-financial corporate sector (124)
Other financial corporate sector (123)
Households (185)
SA banks (111)
Non-financial corporate sector (183)
175 146
> 6 months (115)
NCDs / PNs, unexpired maturity: (112)
Foreign currency notes and coin (127)
Deposits with and advances to SA banks (129)
Unincorporated business enterprises of households (184)
> 1 month and <= 6 months (114)
<= 1 month (113)
Deposits with and advances to SARB (128)
Less: credit impairments in respect of loans and advances (194)
128 492
Foreign public sector (179)
Foreign currency loans and advances (126)
514 110
Deposits with and advances to foreign banks (133)
272 202
Other advances to: (130)
Land Bank (176)
Public non-financial corporate sector (178)
Other advances to foreign banks (134) 127 778
SA financial corporate sector (131)
SA non-financial corporate sector and other (132)
Other public financial corporate sector (177)
Overdrafts, loans and advances: public sector (171)
Redeemable preference shares issued by: (135)
124 247
Banks (136)
Local government (175)
Provincial governments (174)
Social security funds (173)
Central government (172)
Non-financial corporate sector (138)
Financial corporate sector (137)
Other (170)
Credit-card debtors (166)
134 160
Instalment debtors, suspensive sales and leases (139)
447 906
Financial corporate sector (141)
Non-financial corporate sector (142)
135 220
Private non-financial corporate sector (163)
397 987
Household sector (169)
127 162
Household sector (164)
Non-financial corporate sector (168)
Financial corporate sector (167)
Instalment sales (140)
435 946
Commercial and other mortgage advances (159)
450 760
Other (165)
Leasing transactions (145)
Other (144)
Household sector (143)
298 191
Mortgage advances (150)
1 514 762
Financial corporate sector (146)
Public non-financial corporate sector (161)
Public financial corporate sector (160)
Residential mortgages (155)
1 050 139
Other (149)
Household sector (148)
Non-financial corporate sector (147)
Farm mortgages (151)
Corporate sector (152)
Private financial corporate sector (162)
Other (158)
Household sector (157)
980 972
Corporate sector (156)
Other (154)
Household sector (153)

A.3 Supplementary results to Large Banks, Chapter 2

The tables that follow show bank-specific average probabilities of default for alternative network models and assumption sets. Later tables also show the impacts of removing the largest banks from the network model.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18	Bank 19	Bank 20	Bank 21	Bank 22	Bank 23
Bank 1	1	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28	.28
Bank 2	.42	1	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41
Bank 3	.42	.41	1	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41
Bank 4	.42	.41	.41	1	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41
Bank 5	.36	.36	.36	.36	1	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36	.36
Bank 6	.42	.41	.41	.41	.42	1	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.42	.41	.41	.41	.41	.41
Bank 7	.42	.41	.41	.41	.41	.41	1	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41
Bank 8	.42	.41	.41	.41	.41	.41	.41	1	.41	.41	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41
Bank 9	.42	.41	.41	.41	.41	.41	.41	.41	1	.41	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41
Bank 10	.42	.41	.41	.41	.42	.41	.41	.41	.41	1	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41
Bank 11	.40	.39	.39	.39	.40	.39	.39	.39	.39	.39	1	.39	.39	.39	.40	.39	.39	.40	.39	.39	.39	.39	.39
Bank 12	.42	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	1	.41	.41	.42	.41	.41	.42	.41	.41	.41	.41	.41
Bank 13	.42	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	1	.41	.42	.41	.41	.42	.41	.41	.41	.41	.41
Bank 14	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	1	.42	.41	.41	.41	.41	.41	.41	.41	.41
Bank 15	.33	.32	.32	.32	.32	.32	.32	.32	.32	.32	.32	.32	.32	.32	1	.32	.32	.32	.32	.32	.32	.32	.32
Bank 16	.42	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	1	.41	.42	.41	.41	.41	.41	.41
Bank 17	.42	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	1	.42	.41	.41	.41	.41	.41
Bank 18	.39	.38	.38	.38	.38	.38	.38	.38	.38	.38	.38	.38	.38	.38	.39	.38	.38	1	.38	.38	.38	.38	.38
Bank 19	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.41	1	.41	.41	.41	.41
Bank 20	.42	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.42	.41	1	.41	.41	.41
Bank 21	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	1	.41	.41
Bank 22	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	1	.41
Bank 23	.42	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.41	.42	.41	.41	.41	.41	.41	.41	.41	1

Table 2: Bank-specific average probabilities of default: *Assumption Set 2*, proximity shock only, random connections

Note. This table shows, for each combination of shocked banks and impacted banks the probability of bank default across the study period, assuming only proximity shock, with a probability of interbank connection of 0.2 and a shock factor of 0.06. The Erdös-Rényi network structure is assumed.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18	Bank 19	Bank 20	Bank 21	Bank 22	Bank 23
Bank 1	1	.55	.56	.56	.49	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.45	.45
Bank 2	.87	1	.87	.87	.77	.73	.73	.73	.73	.73	.73	.73	.73	.73	.73	.73	.73	.73	.73	.73	.72	.71	.69
Bank 3	.82	.81	1	.82	.72	.68	.69	.69	.69	.69	.69	.69	.69	.69	.69	.69	.69	.69	.69	.69	.68	.66	.65
Bank 4	.72	.71	.71	1	.63	.60	.60	.60	.60	.60	.60	.60	.60	.60	.60	.60	.60	.60	.60	.60	.60	.58	.57
Bank 5	.54	.54	.54	.54	1	.46	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.47	.46	.45	.44
Bank 6	.22	.22	.22	.22	.20	1	.22	.22	.22	.22	.22	.22	.22	.22	.22	.22	.22	.22	.22	.22	.22	.21	.21
Bank 7	.19	.19	.19	.19	.18	.19	1	.19	.19	.19	.19	.19	.19	.20	.19	.19	.19	.19	.19	.19	.19	.19	.18
Bank 8	.19	.19	.20	.19	.18	.21	.21	1	.21	.21	.21	.21	.21	.22	.21	.21	.21	.21	.21	.21	.20	.20	.20
Bank 9	.22	.22	.22	.22	.21	.23	.24	.24	1	.24	.24	.24	.24	.25	.24	.24	.24	.24	.24	.24	.23	.23	.22
Bank 10	.22	.22	.22	.22	.21	.24	.24	.24	.24	1	.24	.24	.24	.25	.24	.24	.24	.24	.24	.24	.24	.24	.23
Bank 11	.11	.11	.11	.11	.10	.11	.11	.11	.11	.11	1	.11	.11	.12	.11	.11	.11	.11	.11	.11	.11	.11	.11
Bank 12	.21	.22	.22	.22	.21	.24	.24	.24	.24	.24	.24	1	.24	.25	.24	.24	.24	.24	.24	.24	.24	.23	.23
Bank 13	.17	.17	.17	.17	.16	.19	.19	.19	.19	.19	.19	.19	1	.21	.19	.19	.19	.19	.19	.19	.19	.19	.18
Bank 14	.06	.06	.06	.06	.06	.07	.07	.07	.07	.07	.07	.07	.07	1	.07	.07	.07	.07	.07	.07	.07	.07	.07
Bank 15	.19	.19	.20	.19	.19	.22	.22	.22	.22	.22	.22	.22	.22	.24	1	.22	.22	.22	.22	.22	.22	.22	.21
Bank 16	.12	.12	.12	.12	.11	.13	.13	.13	.13	.13	.13	.13	.13	.14	.13	1	.13	.13	.13	.13	.13	.13	.12
Bank 17	.11	.11	.11	.11	.11	.12	.13	.13	.13	.13	.13	.13	.13	.13	.13	.13	1	.13	.13	.13	.12	.12	.12
Bank 18	.09	.09	.09	.09	.09	.10	.10	.10	.10	.10	.10	.10	.10	.11	.10	.10	.10	1	.10	.10	.10	.10	.10
Bank 19	.08	.08	.08	.08	.08	.09	.09	.09	.09	.09	.09	.09	.09	.10	.09	.09	.09	.09	1	.09	.09	.09	.09
Bank 20	.07	.07	.07	.07	.06	.07	.07	.07	.07	.07	.07	.07	.07	.09	.07	.07	.07	.07	.07	1	.07	.07	.07
Bank 21	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.04	.05	.04	.04	.04	.04	.04	.04	1	.04	.04
Bank 22	.02	.02	.02	.02	.02	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03	.03	1	.03
Bank 23	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	.02	1

Table 3: Bank-specific average probabilities of default: *Assumption Set 2*, proximity shock only, Assortativeness network
Note. This table shows, for each combination of shocked banks and impacted banks the probability of bank default across the study period, assuming only proximity shock, with a probability of interbank connection of 0.2 and a shock factor of 0.06, under the Assortativeness market network.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18	Bank 19	Bank 20	Bank 21
Bank 3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Bank 4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Bank 5	.49	.49	1	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49	.49
Bank 6	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 7	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 8	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 9	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 10	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 11	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 12	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 13	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 14	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 15	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00
Bank 16	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00
Bank 17	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00
Bank 18	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00
Bank 19	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00
Bank 20	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00
Bank 21	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00
Bank 22	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00
Bank 23	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1

Table 4: Bank-specific average probabilities of default: *Assumption Set 1*, random connections, 2 banks removed

Note. This table shows, for each combination of shocked banks and impacted banks the probability of bank default across the study period. It is based on *Assumption Set 1*, which combines all channels of contagion, but it removes the two largest banks from the data set. The Erdös-Rényi network structure is assumed. The banks are ranked in decreasing order of assets at the end of the study period.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18
Bank 6	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 7	.01	1	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
Bank 8	.05	.05	1	.05	.05	.05	.05	.05	.05	.05	.05	.05	.05	.05	.05	.05	.05	.05
Bank 9	.01	.01	.01	1	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
Bank 10	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 11	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 12	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 13	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 14	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 15	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00
Bank 16	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00
Bank 17	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00
Bank 18	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00
Bank 19	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00	.00
Bank 20	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00	.00
Bank 21	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00	.00
Bank 22	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1	.00
Bank 23	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	1

Table 5: Bank-specific average probabilities of default: *Assumption Set 1*, random connections, 5 banks removed
small Note. This table shows, for each combination of shocked banks and impacted banks the probability of bank default across the study period. It is based on *Assumption Set 1*, which combines all channels of contagion, but it removes the five largest banks from the data set. The Erdös-Rényi network structure is assumed. The banks are ranked in decreasing order of assets at the end of the study period.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18
Bank 6	1	.18	.18	.18	.18	.21	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18
Bank 7	.17	1	.17	.17	.17	.19	.17	.17	.17	.17	.17	.17	.17	.17	.17	.17	.17	.17
Bank 8	.18	.18	1	.18	.18	.20	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18
Bank 9	.17	.18	.17	1	.17	.20	.17	.17	.17	.17	.18	.17	.17	.18	.17	.18	.17	.18
Bank 10	.18	.18	.18	.18	1	.20	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18
Bank 11	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 12	.18	.18	.19	.18	.18	.21	1	.18	.19	.18	.18	.19	.18	.18	.18	.18	.18	.18
Bank 13	.18	.18	.18	.18	.18	.20	.18	1	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18
Bank 14	.18	.17	.18	.18	.18	.20	.18	.18	1	.17	.18	.18	.18	.18	.18	.18	.17	.18
Bank 15	.17	.18	.18	.18	.18	.19	.18	.18	.18	1	.18	.18	.18	.18	.18	.18	.17	.18
Bank 16	.18	.18	.18	.18	.18	.21	.18	.18	.18	.18	1	.18	.18	.18	.18	.18	.18	.18
Bank 17	.18	.18	.18	.18	.18	.20	.18	.18	.18	.18	.18	1	.18	.18	.18	.18	.18	.18
Bank 18	.18	.18	.18	.18	.18	.20	.18	.18	.18	.18	.18	.18	1	.18	.18	.18	.18	.18
Bank 19	.17	.17	.17	.18	.17	.20	.17	.17	.18	.18	.17	.17	.17	1	.17	.17	.17	.18
Bank 20	.17	.17	.17	.17	.17	.20	.17	.17	.18	.17	.18	.17	.17	.17	1	.18	.17	.17
Bank 21	.18	.18	.18	.18	.18	.20	.18	.18	.18	.18	.18	.18	.18	.18	.18	1	.18	.18
Bank 22	.18	.18	.18	.18	.18	.20	.18	.18	.18	.18	.18	.18	.18	.18	.18	.18	1	.18
Bank 23	.17	.17	.17	.17	.18	.20	.17	.17	.18	.17	.17	.18	.17	.17	.18	.18	.17	1

Table 6: Bank-specific average probabilities of default: *Assumption Set 2*, random connections, 5 banks removed

Note. This table shows, for each combination of shocked banks and impacted banks the probability of bank default across the study period, assuming only proximity shock, with a probability of interbank connection of 0.2 and a shock factor of 0.06, under the Erdös-Rényi market network, but with the largest five banks removed.

	Bank 1	Bank 2	Bank 3	Bank 4	Bank 5	Bank 6	Bank 7	Bank 8	Bank 9	Bank 10	Bank 11	Bank 12	Bank 13	Bank 14	Bank 15	Bank 16	Bank 17	Bank 18
Bank 6	1	.42	.42	.42	.41	.43	.41	.39	.40	.38	.41	.38	.38	.38	.38	.37	.36	.37
Bank 7	.32	1	.32	.32	.32	.33	.32	.30	.30	.29	.31	.29	.29	.29	.29	.28	.28	.28
Bank 8	.38	.38	1	.38	.37	.39	.38	.35	.36	.35	.37	.34	.34	.34	.34	.34	.33	.33
Bank 9	.38	.38	.38	1	.38	.40	.38	.36	.36	.35	.38	.35	.35	.35	.35	.34	.34	.34
Bank 10	.27	.27	.27	.27	1	.28	.26	.25	.25	.24	.26	.24	.24	.24	.24	.24	.23	.23
Bank 11	.00	.00	.00	.00	.00	1	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
Bank 12	.29	.29	.29	.29	.29	.30	1	.27	.28	.27	.29	.27	.27	.26	.26	.26	.26	.26
Bank 13	.17	.17	.17	.17	.17	.18	.17	1	.16	.16	.17	.16	.16	.15	.16	.15	.15	.15
Bank 14	.18	.18	.18	.18	.18	.19	.18	.17	1	.16	.18	.16	.16	.16	.16	.16	.15	.16
Bank 15	.15	.15	.15	.15	.15	.16	.15	.14	.15	1	.15	.14	.14	.14	.14	.13	.13	.14
Bank 16	.22	.22	.22	.22	.22	.24	.22	.21	.21	.20	1	.20	.20	.21	.20	.20	.20	.20
Bank 17	.16	.16	.16	.16	.16	.17	.16	.15	.15	.14	.15	1	.14	.14	.14	.14	.14	.14
Bank 18	.15	.15	.15	.15	.15	.16	.15	.14	.14	.14	.15	.14	1	.14	.14	.13	.13	.13
Bank 19	.15	.15	.15	.15	.14	.16	.15	.14	.14	.13	.14	.13	.13	1	.13	.13	.13	.13
Bank 20	.14	.14	.14	.14	.14	.15	.14	.13	.13	.13	.14	.13	.13	.13	1	.12	.12	.12
Bank 21	.14	.14	.14	.14	.14	.15	.14	.13	.13	.13	.13	.13	.13	.12	.13	1	.12	.12
Bank 22	.14	.14	.14	.14	.14	.15	.14	.13	.13	.12	.13	.13	.12	.12	.13	.12	1	.12
Bank 23	.14	.14	.14	.14	.14	.15	.14	.13	.13	.13	.14	.12	.13	.12	.13	.12	.12	1

Table 7: Bank-specific average probabilities of default: *Assumption Set 2*, Tiered Type I structure, 5 banks removed
Note. This table shows, for each combination of shocked banks and impacted banks the probability of bank default across the study period, assuming only proximity shock, with a probability of interbank connection of 0.2 and a shock factor of 0.06, under the Tiered Type I structure market network, but with the largest five banks removed.

A.4 Code generating Large Banks analysis, Chapter 2

The text that follows is the Matlab code used to generate the results set out in Chapter 2. Comments and unused code have been retained in the interests of transparency.

Primary code

```
clear vars;
tic
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %Initialize parameters
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%Set to low-risk parameters and moderate interconnectedness
sim = 100;%changed from 20000;         %Number of simulations to run
av_p = 0.5;%0.15      %The average probability of a directed edge existing
    between any two nodes
g_s = 0.015;%0.015%  %Reduction factor associated with short term assets
g_m = 0.015;%0.015%  %Reduction factor associated with medium term assets
g_l = 0.03;%0.03%    %Reduction factor associated with long term assets
PS = 0.015;%0.015%   %Proximity shock reduction
n_months = 66;         %Number of months to take
shock_prop = 0.4;     %0.4 %Proportion of external assets to wipe out as a
    result of initial shock
cap_thrs = 1;         %Capital threshold (% of capital) that determines when
     a bank is regarded as having defaulted
direct_loss = 0.3;    %0.3 %Proportion of loss absorbed by remaining banks
networks = 6;         %The number of networks in the model - extend 6 to 9
    if including bank pairs or testing alternative comparators
av_default = zeros(n_months,networks); %Key output: per-month per-network
    probability of default across all banks
cap_lost = zeros(n_months,networks); %Key output: per-month per-network
    proportion of capital lost across all banks
bank_count = 23;      %Number of banks; only used to establish the magnitude
     of the next three matrices
fail_distribution_month = zeros(bank_count,bank_count,networks); %Count of
    bank fails, by causing bank, failing bank and network types
fail_distribution_total = zeros(bank_count,bank_count,networks); %Count of
    bank fails, by causing bank, failing bank and network types, across
    months
fail_distribution_average = zeros(bank_count,bank_count,networks); %To
    average the distribution of bank failures across all months
external_correlates = xlsread('C:\Users\robr\Dropbox\Regulation research\
    Research\Networks\MATLAB material\Analysis\Final Monthly Data RR
    202102.xlsx','Correlates','C3:AC68'); %Candidates for testing the
    correlation of results against external factors
corr_matrix = zeros(n_months,27+2*networks); %Matrix prepared for
    correlation tests - 27 outside factors, one for av_default and cap_lost
     for each network model
output_file_chart_defprob = append('C:\Users\robr\Dropbox\Regulation
    research\Research\Networks\MATLAB material\Analysis\Results\DefProb_','
    av_p',num2str(av_p),'_g_s',num2str(g_s),'_g_m',num2str(g_m),'_g_l',
    num2str(g_l),'_PS',num2str(PS),'_shockprop',num2str(shock_prop),'
    _capthrs',num2str(cap_thrs),'_directloss',num2str(direct_loss),'.fig');
```

```
output_file_chart_caplost = append('C:\Users\robr\Dropbox\Regulation
    research\Research\Networks\MATLAB material\Analysis\Results\CapLost_','
    av_p',num2str(av_p),'_g_s',num2str(g_s),'_g_m',num2str(g_m),'_g_l',
    num2str(g_l),'_PS',num2str(PS),'_shockprop',num2str(shock_prop),'
    _capthrs',num2str(cap_thrs),'_directloss',num2str(direct_loss),'.fig');
output_file_sheet = append('C:\Users\robr\Dropbox\Regulation research\
    Research\Networks\MATLAB material\Analysis\Results\Defaults_','av_p',
    num2str(av_p),'_g_s',num2str(g_s),'_g_m',num2str(g_m),'_g_l',num2str(
    g_l),'_PS',num2str(PS),'_shockprop',num2str(shock_prop),'_capthrs',
    num2str(cap_thrs),'_directloss',num2str(direct_loss),'.xls');

for month = 1:n_months %Function changed from parfor

    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %Import data and set balance sheets
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

        %Path changed from original to match my path
    BS_data = xlsread('C:\Users\robr\Dropbox\Regulation research\Research\
        Networks\MATLAB material\Analysis\Final Monthly Data RR 202101
        sorted.xlsx',n_months+1-month,'B3:E25');     %Import the asset and
        CET1 data from excel
    Support_data = xlsread('C:\Users\robr\Dropbox\Regulation research\
        Research\Networks\MATLAB material\Analysis\Final Monthly Data RR
        202102.xlsx',n_months+1-month,'Q3:V25');     %Import the other
        supporting data from excel
    BS_data(BS_data<0)=0;    %Ensure that there are no negative values;

    % Import asset and CET1 data and set up variables
    N = numel(BS_data(:,1));     %Number of banks in the network
    %M = numel(Support_data(:,1))     %Number of banks in the network
    %E = BS_data(:,1);              %Total interbank assets of each bank
    AssetpBank = zeros(3,N);       %Amount of each asset category held by
        each bank
    SupportDataBank = zeros(6,N); %Supporting data, six categories
    AssetpBank(1,:) = transpose(BS_data(:,1));  %Short term assets of each
        bank
    AssetpBank(2,:) = transpose(BS_data(:,2));  %Medium term assets of each
         bank
    AssetpBank(3,:) = transpose(BS_data(:,3));  %Long term assets of each
        bank
    cap = BS_data(:,4); %The capital held by each bank
    a = transpose(sum(AssetpBank));      %Total assets of each bank

    % Import support data, 6 x N, used for covariate assets or liabilities
        and set up variables
    % Support_data(:,1)
    SupportDataBank(1,:) = transpose(Support_data(:,1));  %Mortgage
        advances of each bank
    SupportDataBank(2,:) = transpose(Support_data(:,2));  %Overdrafts and
        loans of each bank
    SupportDataBank(3,:) = transpose(Support_data(:,3));  %Derivative
        instruments of each bank
```

```
SupportDataBank(4,:) = transpose(Support_data(:,4));  %Household
    deposits of each bank
SupportDataBank(5,:) = transpose(Support_data(:,5));  %Non-financial
    corporate deposits of each bank
SupportDataBank(6,:) = transpose(Support_data(:,6));  %Financial
    corporate deposits of each bank

av_def = zeros(networks,sim);          %Average defaults for each
    simulation
lost = zeros(networks,sim);      %To contain the average proportion of
    capital lost for each parameter value, structure and simulation
fail_distribution_month = zeros(bank_count,bank_count,networks); %Reset
     to zero for the month in question

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
    %Determine the probability of links between banks
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for Network_Type = 0:networks-1     %0:5 usually, zero to select only
    the random case; indicates which type of network structure is to be
     assumed.
     p_ij = Network_Struct_reorganised(Network_Type,N,a,SupportDataBank
        );  %Matrix of probabilities where (i,j) is the probability
        that i has lent to j
     p_ij = Scale_p_ij(av_p,p_ij);  %Scale the probabilities to make
        structures comparable
     F2 = zeros(N,N);   %Matrix capturing all failures, across all sims
         with rows for shocked banks and columns for those whose
        failure is caused

    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
                        %Start the simulations
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

    for m=1:sim

        default = 0;        %To count the number of defaults for each
            simulation

        %The links between the banks (i,j)=1 means i is linked to j
        links = Link_Sim_SAnew_NoAdjustments(p_ij,ones(N,1));

        %Determine shortest paths between banks, considering only
            incoming
        %links
        Edges = zeros(sum(sum(links)),2);   %To store the edges
        count_edge = 1; %Keep track of number of edges below
        for i = 1:N
            for j = 1:N
                if links(i,j) == 1
                    %Remember that head and tail nodes need to be
                        swopped
                    %because of the direction of lending
                    Edges(count_edge,1) = j;
                    Edges(count_edge,2) = i;
```

```
                count_edge = count_edge + 1;
            end
        end
    end
    short_path = ShortestPathFloydWarshal(Edges,N);
    short_path(short_path == Inf) = 0;
    max_prox = max(max(short_path));    %Maximum shortest path
        between banks

    %Plot network for single simulation
    if sim == 1
        GraphLayout = PlotNetwork(links,a,0.001);
    end

    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        %Shocking the system
    %%%%%%%%%%%%%%%%%%%%%%%%%%%%%

    shock = a*shock_prop; %Vector containing the size of the shock
        for each bank

    %To remember the initial balance sheet entries
    Initial_cap = cap;
    InitialAssetpBank = AssetpBank;

    for n=1:N                           %Bank to be shocked
        F = zeros(1,N);                 %Vector indicating which banks
            have failed
        s_next = zeros(N,1);            %Vector to contain the shocks
            for the next round
        AssetpBank(:,n) = AssetpBank(:,n)*(1-shock_prop);   %Reduce
             external assets of shocked bank

        %%%%The initial shock to the system
        if shock(n) > cap(n)*cap_thrs%     %Bank n fails
            F(1,n) = 1;                 %Indicate that bank n has
                failed
            F2(n,n) = F2(n,n) + 1;      %Add to running total of banks
                that have failed
            if shock(n) > cap(n)        %Bank n's creditors suffer
                losses
                for i=1:N
                        s_next(i) = direct_loss*(shock(n) - cap(n
                            ,1))*a(i)/sum(a);       %Shocks on
                            banks for the next round
                end
            end
            %Add Liquidity shocks
            Ext_asset_loss = [AssetpBank(1,:).*(1-exp(-g_s));
                AssetpBank(2,:).*(1-exp(-g_m)); AssetpBank(3,:)
                .*(1-exp(-g_l))];
            s_next = s_next + sum(Ext_asset_loss).';

            %Proximity liquidity shock
```

```
        for prox = 1:max_prox
            for j = 1:N
                if short_path(n,j) == prox
                    s_next(j) = s_next(j) + sum(AssetpBank(:,j)
                        ).*(1-exp(-PS/prox));
                    AssetpBank(:,j) = AssetpBank(:,j).*exp(-PS/
                        prox); %Adjust external assets
                end
            end
        end
        AssetpBank = AssetpBank - Ext_asset_loss;   %Adjust
            external assets
        cap(n,1) = max([0 cap(n,1)-shock(n)]);
    else
        cap(n,1) = cap(n,1) - shock(n);
        %GraphPlotGraphLayoutTest(GraphLayout,F);
    end

    %%%Subsequent rounds of default
    while any(s_next) == true
        %rounds(n,m) = rounds(n,m)+1;
        s_next0 = zeros(N,1);        %Vector to contain the
            shocks for the next round
        AssetpBank0 = AssetpBank;   %Keep track of original
            matrix for liquidity reduction calculation, so that
             proximity factor does not influence it
        for j=1:N
            if s_next(j) > cap(j)*cap_thrs && F(1,j) == 0
                F(1,j) = 1;                %Indicate that bank j
                    has failed
                F2(n,j) = F2(n,j) + 1;  %Adds to the counter of
                     the shocked bank (bank n) and the
                    resulting failure (bank j)
                if s_next(j) > cap(j)
                    for i=1:N
                        s_next0(i) = s_next0(i) + direct_loss*(
                            s_next(j) - cap(j))*a(i)/sum(a);  %
                            Shocks on banks for the next round
                    end
                end
                %Add Liquidity shocks
                Ext_asset_loss = [AssetpBank0(1,:).*(1-exp(-g_s
                    ));AssetpBank0(2,:).*(1-exp(-g_m));
                    AssetpBank0(3,:).*(1-exp(-g_l))];
                s_next0 = s_next0 + sum(Ext_asset_loss).';
                AssetpBank = AssetpBank - Ext_asset_loss;

                %Proximity liquidity shock
                for prox = 1:max_prox
                    for ii = 1:N
                        if short_path(j,ii) == prox
                            s_next0(ii) = s_next0(ii) + sum(
                                AssetpBank0(:,ii)).*(1-exp(-PS/
                                prox));
```

```
                                        AssetpBank(:,ii) = AssetpBank(:,ii)
                                            -AssetpBank0(:,ii).*(1-exp(-PS/
                                            prox));
                                    end
                                end
                            end
                            cap(j) = max([0 cap(j,1)-s_next(j)]);
                        elseif s_next(j) > 0 && F(1,j) == 0 %If capital of
                            j is not depleted and j has not defaulted
                            before
                            cap(j) = cap(j) - s_next(j);            %If bank
                                survived, an_djust its capital to reflect
                                loss
                        end
                    end
                    s_next = s_next0;
                end
                %Calculate proportion of capital lost by the system
                lost(Network_Type+1,m) = lost(Network_Type+1,m) + sum(
                    Initial_cap-cap)/sum(Initial_cap);

                %Reset balance sheet entries
                cap = Initial_cap;
                AssetpBank = InitialAssetpBank;

                %Add defaults
                default = default + sum(F);

            end
            av_def(Network_Type+1,m) = default/(N*(N));
            % Code that follows checks F2 every simulation
               % sheetnum = (month-1)*sim + m
               % writematrix(F2,output_file_sheet,'Sheet',sheetnum)
        end
        %Add to the 26x26x6 fails total that part relevant to this
        %particular simulation and network
        fail_distribution_month(:,:,Network_Type+1) =
            fail_distribution_month(:,:,Network_Type+1) + F2/sim;

    end

    %Write to spreadsheet file for the month and add to running total
    %sheet = month;
    writematrix(fail_distribution_month,output_file_sheet,'Sheet',month)
    fail_distribution_total = fail_distribution_total +
        fail_distribution_month;

    %Complete other calculations for the month
    lost = lost/N;
    av_default(month,:) = mean(av_def,2).';
    cap_lost(month,:) = mean(lost,2).';
    month
end
```

```
%Divide all fails by the number of months, across all network types
fail_distribution_average = fail_distribution_total / n_months;

%Put together the matrix of results with correlation factors and then
    calculate the correlation matrix
corr_matrix = [av_default cap_lost external_correlates];  % this is a
    matrix concetenating the outputs and external correlates
[r,p] = corrcoef(corr_matrix); %r provides correlations and p the
    equivalent p-values
% r_lag_default_business_cycle = xcorr(corr_matrix(:,1),corr_matrix(:,13)
    ,12,'normalized'); % test of lags
% r_lag_capitalloss_consumder_confidence = xcorr(corr_matrix(:,7),
    corr_matrix(:,38),12,'normalized'); % test of lags

%Calculate quantitative regression of the loss probability outputs and one
    of the correlates
%Currently doesn't find a solution, possibly because iterations don't %
    converge (but it may just be the confidence interval that is the
    problem
%[p50,stats50]=quantreg(corr_matrix(:,1),corr_matrix(:,13),.50,3);
%[p90,stats90]=quantreg(corr_matrix(:,1),corr_matrix(:,13),.90,3);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
            % Charting preparation and layout
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%av_default_prob = sum(av_default,3)/sim
toc;
startDate = datenum('04-30-2015');
endDate = datenum('09-30-2020');
xData = linspace(startDate,endDate,n_months);

figure('Name',strcat('DefProb_',num2str(sim)));

plot1 = plot(xData,av_default);
set(gca,'Position',[0.105 0.11 0.851 0.815],'FontSize',14,'XTick', xData,'
    XGrid','on','YGrid','on',...
     'XTick',...
     [736084 736114.461538462 736144.923076923 736175.384615385
        736205.846153846 736236.307692308 736266.769230769 736297.230769231
         736327.692307692 736358.153846154 736388.615384615
        736419.076923077 736449.538461538 736480.000000000 736510.461538462
         736540.923076923 736571.384615385 736601.846153846
        736632.307692308 736662.769230769 736693.230769231 736723.692307692
         736754.153846154 736784.615384615 736815.076923077
        736845.538461538 736876 736906.461538462 736936.923076923
        736967.384615385 736997.846153846 737028.307692308 737058.769230769
         737089.230769231 737119.692307692 737150.153846154
        737180.615384615 737211.076923077 737241.538461538 737272
        737302.461538462 737332.923076923 737363.384615385 737393.846153846
         737424.307692308 737454.769230769 737485.230769231
        737515.692307692 737546.153846154 737576.615384615 737607.076923077
         737637.538461538 737668 737698.461538462 737728.923076923
        737759.384615385 737789.846153846 737820.307692308 737850.769230769
```

```
         737881.230769231 737911.692307692 737942.153846154
        737972.615384615 738003.076923077 738033.538461538 738064],...
    'XTickLabel',...
    {'','','Jun-15','','','','','','Dec-15','','','','','','Jun-16','','','
        ','','','Dec-16','','','','','','Jun-17','','','','','','Dec-17',''
        ,'','','','','Jun-18','','','','','','Dec-18','','','','','','Jun
        -19','','','','','','Dec-19','','','','','','Jun-20','','',''});
%datetick('x','mmm-yy','keepticks')
set(plot1(1),'Color',[0 0 0],'LineWidth',1.5,'DisplayName','Erd\"{o}s-R\''{
    e}nyi');
set(plot1(2),'Color',[0 0 0],'Linestyle','-.','LineWidth',1.5,'DisplayName'
    ,'Disassortativeness');
set(plot1(3),'Color',[0 0 0],'Linestyle','--','LineWidth',1.5,'DisplayName'
    ,'Assortativeness');
set(plot1(4),'Color',[0.6 0.6 0.6],'Linestyle','--','LineWidth',1.5,'
    DisplayName','Attraction to size');
set(plot1(5),'Color',[0.6 0.6 0.6],'Linestyle','-','LineWidth',1.5,'
    DisplayName','Tiered type I');
set(plot1(6),'Color',[0 0 0],'Linestyle',':','LineWidth',1.5,'DisplayName',
    'Tiered type II');
xlabel('Month','Interpreter','latex','FontSize',20);
ylabel('Systemic default indicator','Interpreter','latex','FontSize',20);
set(gca,'XLim',[736084 738064]);
legend1 = legend(gca,'show','Location','southwest');
set(legend1,'Interpreter','latex');
propedit
saveas(gcf,strcat(output_file_chart_defprob));

figure('Name',strcat('Cap_Lost_',num2str(sim)));
%set(gca,'YLim',[0,0.5]);

plot2 = plot(xData,cap_lost);
set(gca,'Position',[0.105 0.11 0.851 0.815],'FontSize',14,'XTick', xData,'
    XGrid','on','YGrid','on',...
    'XTick',...
    [736084 736114.461538462 736144.923076923 736175.384615385
        736205.846153846 736236.307692308 736266.769230769 736297.230769231
         736327.692307692 736358.153846154 736388.615384615
        736419.076923077 736449.538461538 736480.000000000 736510.461538462
         736540.923076923 736571.384615385 736601.846153846
        736632.307692308 736662.769230769 736693.230769231 736723.692307692
         736754.153846154 736784.615384615 736815.076923077
        736845.538461538 736876 736906.461538462 736936.923076923
        736967.384615385 736997.846153846 737028.307692308 737058.769230769
         737089.230769231 737119.692307692 737150.153846154
        737180.615384615 737211.076923077 737241.538461538 737272
        737302.461538462 737332.923076923 737363.384615385 737393.846153846
         737424.307692308 737454.769230769 737485.230769231
        737515.692307692 737546.153846154 737576.615384615 737607.076923077
         737637.538461538 737668 737698.461538462 737728.923076923
        737759.384615385 737789.846153846 737820.307692308 737850.769230769
         737881.230769231 737911.692307692 737942.153846154
        737972.615384615 738003.076923077 738033.538461538 738064],...
    'XTickLabel',...
```

```
    {'','','Jun-15','','','','','','Dec-15','','','','','','Jun-16','','','
       ','','','Dec-16','','','','','','Jun-17','','','','','','Dec-17',''
       ,'','','','','Jun-18','','','','','','Dec-18','','','','','','Jun
       -19','','','','','','Dec-19','','','','','','Jun-20','','',''});
%datetick('x','mmm-yy','keepticks')

set(plot2(1),'Color',[0 0 0],'LineWidth',1.5,'DisplayName','Erd\"{o}s-R\''{
    e}nyi');
set(plot2(2),'Color',[0 0 0],'Linestyle','-.','LineWidth',1.5,'DisplayName'
    ,'Disassortativeness');
set(plot2(3),'Color',[0 0 0],'Linestyle','--','LineWidth',1.5,'DisplayName'
    ,'Assortativeness');
set(plot2(4),'Color',[0.6 0.6 0.6],'Linestyle','--','LineWidth',1.5,'
    DisplayName','Attraction to size');
set(plot2(5),'Color',[0.6 0.6 0.6],'Linestyle','-','LineWidth',1.5,'
    DisplayName','Tiered type I');
set(plot2(6),'Color',[0 0 0],'Linestyle',':','LineWidth',1.5,'DisplayName',
    'Tiered type II');
xlabel('Month','Interpreter','latex','FontSize',20);
ylabel('Average CRR','Interpreter','latex','FontSize',20);
set(gca,'XLim',[736084 738064]);
legend2 = legend(gca,'show','Location','best');
set(legend2,'Interpreter','latex');
propedit
saveas(gcf,strcat(output_file_chart_caplost));

% Separately plot output of the quantitative regression
%plot(corr_matrix(:,1),corr_matrix(:,13),corr_matrix(:,1),polyval(p50,
    corr_matrix(:,1)),polyval(p90,corr_matrix(:,1)),'k:')
%legend('default probability vs business cycle','3nd order 50th percentile
    fit','3nd order 90th percentile fit','location','best')

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
            % Writing outputs to spreadsheets
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

% writematrix(fail_distribution_total,output_file_sheet)
writematrix(fail_distribution_total,output_file_sheet,'Sheet','Fail totals'
    )
writematrix(fail_distribution_average,output_file_sheet,'Sheet','Fail
    averages')
writematrix(r,output_file_sheet,'Sheet','Correlation matrix')
writematrix(p,output_file_sheet,'Sheet','Correlation p values')
% writematrix(r_lag_default_business_cycle,output_file_sheet,'Sheet','
    Random default v business cycle')
% writematrix(r_lag_capitalloss_consumder_confidence,output_file_sheet,'
    Sheet','Random capital loss v cons conf')
```

Sub-routines

```
function p_ij = Network_Struct(Type,N,a,SupportDataBank)
%Network_Struct
    %Determines the matrix p_ij for different network types, where there
```

```
%are N banks in the system.

p_ij = zeros(N);     %Matrix of probabilities where entry (i,j) is the
                %probability that bank i has lent to bank j
switch Type
    case 0  %If Erdos-Renji assumption holds
        %By default the Erdos-Renji probability is set to 0.5.
        %Keep in mind that the main program is designed in such a way
        %that the user selects a desired average for the p_ij probabilities,
        %and that the program then scales the probabilities so that they
        %have the desired average. Therefore the actual value chosen
        %for the Erdos-Renji case here is actually irrelevant.
        p_ij = 0.5*ones(N);
        for i=1:N
            p_ij(i,i) = 0;
        end

    case 3  %Flight to quality (If p_ij varies linearly with a(j))
        for i=1:N
            for j=1:N
                if i ~= j
                    %p_ij higher for larger banks j reflecting creditworthiness
                    p_ij(i,j) = a(j)/max(a);
                end
            end
        end

    case 1  %Disassortativeness
        a_max = max(a);
        a_min = min(a);
        for i=1:N
            for j=1:N
               if i ~= j
                    p_ij(i,j) = (max(a(i)/a(j),a(j)/a(i)))/(a_max/a_min);
                end
            end
        end

    case 2  %Assortativeness
        for i=1:N
            for j=1:N
                if i ~= j
                    p_ij(i,j) = min(a(i),a(j))/max(a(i),a(j));
                end
            end
        end

    case 1  %Selective assortativeness/disassortativenes type I (small banks
        generally don't lend to each other)
        a_desc = sort(a,'descend');
        for i=1:N
            for j=1:N
                if i ~= j
                    p_ij(i,j) = (a(i)+a(j))/(a_desc(1)+a_desc(2));
                end
            end
        end

    case 2  %Selective assortativeness/disassortativeness (hierarchical network
        )
        for i=1:N
            for j=1:N
```

```
                    if i ~= j
                        p_ij(i,j) = (a(i)+a(j) + max(a(i)-a(j),0))/(3*max(a));
                    end
                end
            end

%         case 1  %Pairwise links between large and small banks, otherwise uniform
    probabilities
%                      p_ij = xlsread('C:\Users\robr\Dropbox\Regulation research\
    Research\Networks\MATLAB material\Analysis\Final Monthly Data RR 202102.xlsx','
    Links LS','B2:X24');
%         case 2  %Pairwise links between medium and small banks, otherwise uniform
    probabilities
%                      p_ij = xlsread('C:\Users\robr\Dropbox\Regulation research\
    Research\Networks\MATLAB material\Analysis\Final Monthly Data RR 202102.xlsx','
    Links MS','B2:X24');
%         case 3  %Pairwise links between large and medium banks, otherwise uniform
    probabilities
%                     p_ij = xlsread('C:\Users\robr\Dropbox\Regulation research\
    Research\Networks\MATLAB material\Analysis\Final Monthly Data RR 202102.xlsx','
    Links LM','B2:X24');

%         case 3  %Used to test alternative methods of connecting banks, through the
     support data on an alternative balance sheet items
%                 %Can only operate on one of the six rows available in
    SuppportDataBank and the row is determined manually by
%                 %specifying it to the variable Covariate; method used to determine
     links between banks is the same as Tiered Type I,
%                 %the sum of the relevant measure across the pair of banks
%             covariate = SupportDataBank(4,:);
%             covariate_desc = sort(covariate,'descend');
%             for i=1:N
%                 for j=1:N
%                     if i ~= j
%                         p_ij(i,j) = (covariate(i)+covariate(j))/(covariate_desc(1)
    +covariate_desc(2));
%                     end
%                 end
%             end
%         case 4  %Also used to test connection through a balance sheet item #2;
    also Tiered Type I, the sum of the measures
%             covariate = SupportDataBank(5,:);
%             covariate_desc = sort(covariate,'descend');
%             for i=1:N
%                 for j=1:N
%                     if i ~= j
%                         p_ij(i,j) = (covariate(i)+covariate(j))/(covariate_desc(1)
    +covariate_desc(2));
%                     end
%                 end
%             end
%         case 5  %Also used to test connection through a balance sheet item #8;
    also Tiered Type I, the sum of the measures
%             covariate = SupportDataBank(6,:);
%             covariate_desc = sort(covariate,'descend');
%             for i=1:N
%                 for j=1:N
%                     if i ~= j
%                         p_ij(i,j) = (covariate(i)+covariate(j))/(covariate_desc(1)
    +covariate_desc(2));
%                     end
%                 end
```

```
%              end
    end
end

function p_ij_new = Scale_p_ij(new_av,p_ij_old)
%Scale_p_ij
    %Scales the connection probabilities contained in the matrix p_ij in
    %order to obtain the desired average probability of an edge existing in the
    %network. The new average connection probability is new_av, which is a
    %scalar contained in the range [0,1].

    %Calculate the average of the existing probabilities p_ij (excluding
    %the cases where i=j)
    N = length(p_ij_old);
    old_av = sum(sum(p_ij_old))/(N^2-N);

    if old_av < new_av
        p_ij_new = 1 - (1 - p_ij_old).*(1 - new_av)./(1 - old_av);

        %Correct the diagonal entries
        p_ij_new = p_ij_new .* (ones(N)-diag(ones(N,1)));

    elseif old_av > new_av
        p_ij_new = p_ij_old .* (new_av)./(old_av);

        %Correct the diagonal entries
        p_ij_new = p_ij_new .* (ones(N)-diag(ones(N,1)));

    else
        p_ij_new = p_ij_old;
    end
end

function links = Link_Sim_SAnew_NoAdjustments(p_ij,b)
%Link_Sim
%   Simulates links for a given matrix p_ij, and given interbank borrowings
%   Assumes the sum of all the loans equals the sum of all the borrowings.
%   Produces another matrix each time it is used, since it simulates links
%   between banks based on p_ij.

    N = numel(b);
    links = zeros(N,N);
    %Assign the links between the banks
    for i=1:N
        for j=1:N
            if i~=j && b(j)~=0
                uni = rand(1);
                if uni <= p_ij(i,j)
                    links(i,j) = 1; %Link(i,j)=1 if i has lent to j, and zero
                        otherwise
                end
            end
        end
    end

    %Ensure that each row has at least one non-zero entry
%     for i=1:N
%         while sum(links(i,:)) == 0
%             for j=1:N
%                 if i~=j && b(j)~=0
%                     uni = rand(1);
%                     if uni <= p_ij(i,j)
```

```
%                           links(i,j) = 1;
%                       end
%                   end
%               end
%           end
%       end

%       %Ensure that each column has at least one non-zero entry (except for
%       %banks with no interbank liabilities)
%       for j=1:N
%           while sum(links(:,j)) == 0 && b(j) ~= 0
%               for i=1:N
%                   if i~=j && b(j)~=0
%                       uni = rand(1);
%                       if uni <= p_ij(i,j)
%                           links(i,j) = 1;
%                       end
%                   end
%               end
%           end
%       end

end

function d = ShortestPathFloydWarshal(Edges,n)
%Floyd-Warshal algorithm for finding the shortest path between nodes.
%   Edges   -   Matrix with dimensions NEdges x 2: NEdges is the number of edges in
    the
%               system. Each row represents an edge. The first column is
%               the head vertices and the second column is the tail. For
%               example if an edge starts at node i and ends at j, its row
%               will be represented by [i j]
%   n       -   Scalar: the number of nodes in the system

NEdges = length(Edges); %Number of edges. Assumes at least two edges in system
d = Inf*ones(n,n);      %To contain shortest paths between nodes
for v = 1:n
    d(v,v) = 0;
end
for e = 1:NEdges
    u = Edges(e,1);
    v = Edges(e,2);
    d(u,v) = 1;
end

for k = 1:n
    for i = 1:n
        for j = 1:n
            if d(i,j) > d(i,k) + d(k,j);
                d(i,j) = d(i,k) + d(k,j);
            end
        end
    end
end
end
```

A.5 Supplementary results to Tipping Points, Chapter 3

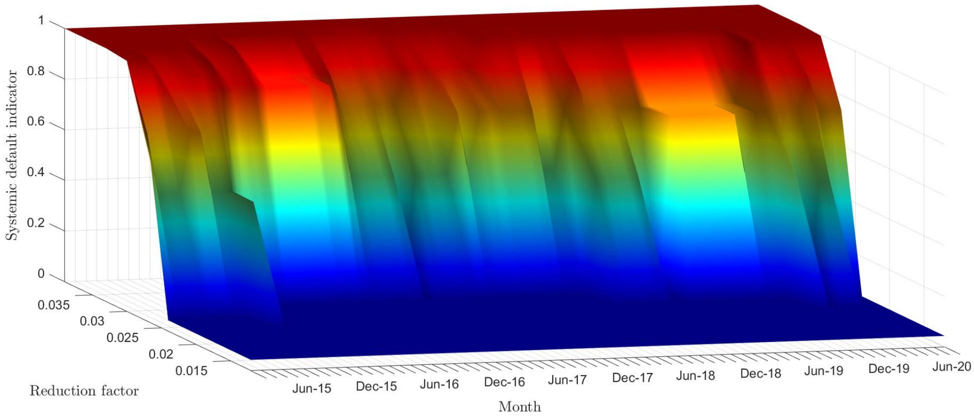


Figure 1: Systemic default indicator, liquidity shock variations with proximity shock present

The chart shows the systemic default indicator, considering variations in the liquidity shock parameters, but with allowance also for the proximity shock mechanism. The indicated reduction factor applies to the first two of the liquidity shock parameters, $\eta^{(s)}$ and $\eta^{(m)}$, while the value of the third, $\eta^{(l)}$, is equal to double each of the others at all times. The proximity shock sentiment factor, α, takes the value of 0.015 and the average probability of connections between pairs of banks, $\overline{p}$ is 0.5. The size initial shock parameter, S, is 0.4.

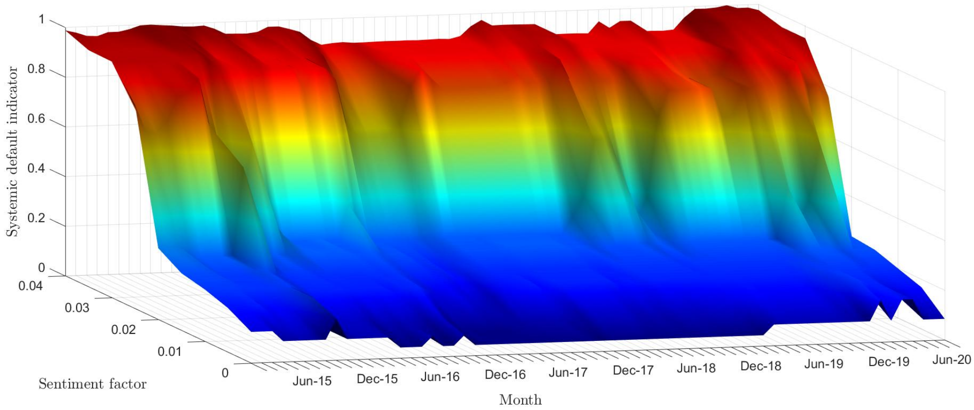


Figure 2: Systemic default indicator, proximity shock variation with liquidity shock present
The chart shows the systemic default indicator, considering variations in the proximity shock sentiment factor, α, with allowance also for the liquidity shock mechanism. The average probability of connections between pairs of banks, $\overline{p}$ is 0.5. The respective liquidity shock parameters, $\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$ take the values 0.02, 0.02 and 0.04. The initial shock parameter, S, is 0.4.

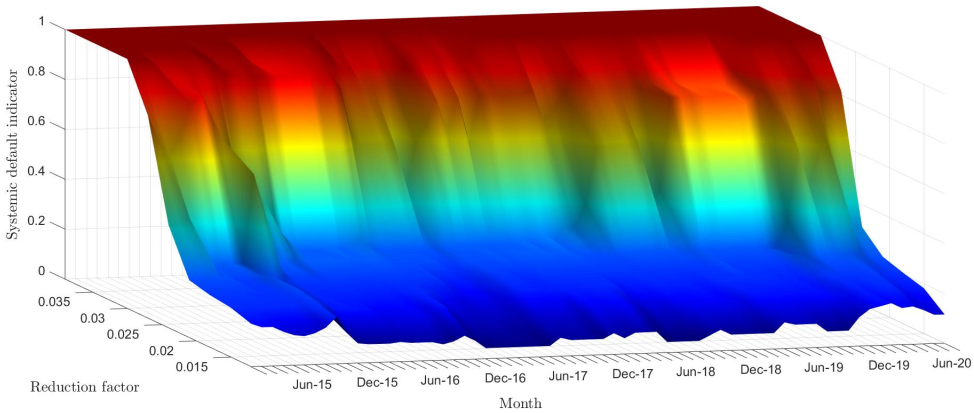


Figure 3: Systemic default indicator, liquidity shock variations with credit and proximity shocks
The chart shows the systemic default indicator, considering variations in the liquidity shock parameters, but with allowance also for the credit shock and proximity shock mechanisms. The indicated reduction factor applies to the first two of the liquidity shock parameters, $\eta^{(s)}$ and $\eta^{(m)}$. The value of the third, $\eta^{(l)}$, is equal to double the others at all times. The initial shock parameter, S, is 0.4. The loss shared as a proportion of the losses experienced by the shocked bank, u, is 0.3. The proximity shock sentiment factor, α, takes the value of 0.015 and the average probability of connections between pairs of banks, $\overline{p}$ is 0.5.

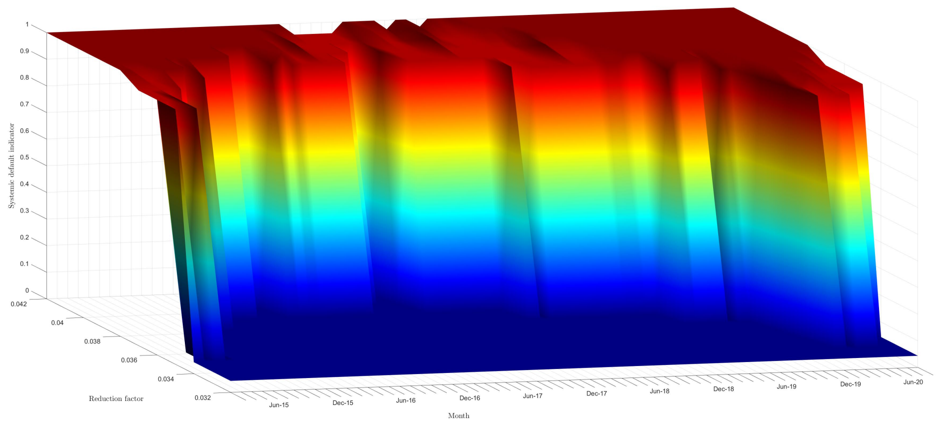


Figure 4: Systemic default indicator, liquidity shock only, attraction to size network model
The chart shows the systemic default indicator, considering only the liquidity shock contagion mechanism, at varying levels of the respective liquidity shock parameters, $\eta^{(s)}$, $\eta^{(m)}$ and $\eta^{(l)}$. The indicated reduction factor applies to the first two of these, $\eta^{(s)}$ and $\eta^{(m)}$, while the value of the third, $\eta^{(l)}$, is equal to double each of the others at all times. The size of the initial shock as a proportion of the assets of the shocked bank, S, is 0.4. It assumes an attraction to size network model rather than the standard Erdös-Rényi network model.

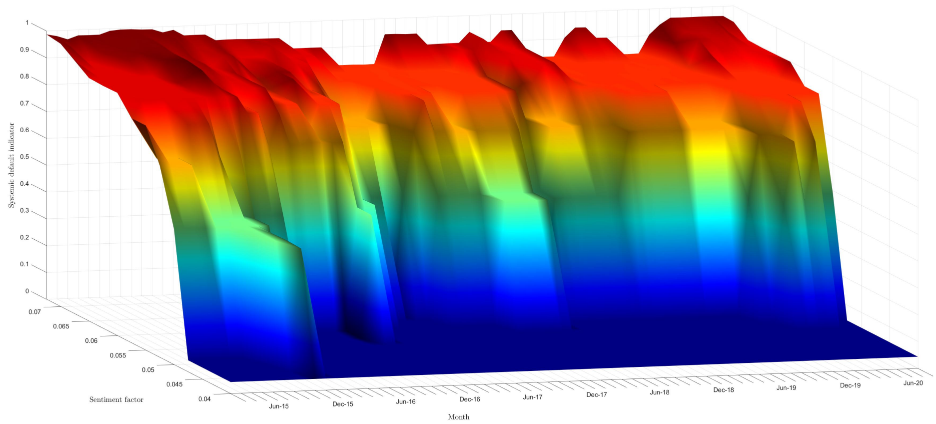


Figure 5: Systemic default indicator, proximity shock only, attraction to size network model
The chart shows the systemic default indicator, considering only the proximity shock contagion mechanism, at varying levels of the shock, α, with a constant probability of links between banks, $\overline{p}$, of 0.5. The size of the initial shock as a proportion of the assets of the shocked bank, S, is 0.4. It assumes an attraction to size network model rather than the standard Erdös-Rényi network model.

A.6 Supplementary results to CoVaR, Chapter 4

The charts below illustrate the modelling for three different banks covering the full period of investigation, using a linear fit, and for Standard Bank using a quadratic fit. The tables that follow set out the modelling results for each of four non-overlapping five-year periods, in aggregate covering the full period of investigation.

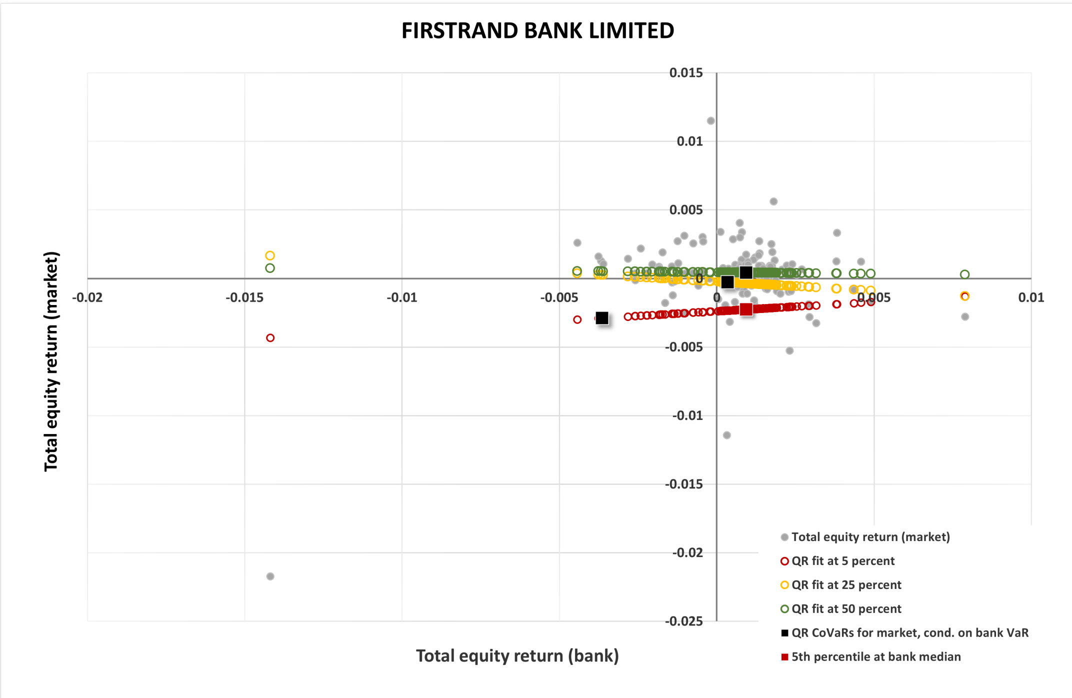


Figure 6: $\Delta CoVaR$ calculation, First Rand
The chart shows the data underpinning the calculation of $\Delta CoVaR$, using data for First Rand covering the full period of investigation.

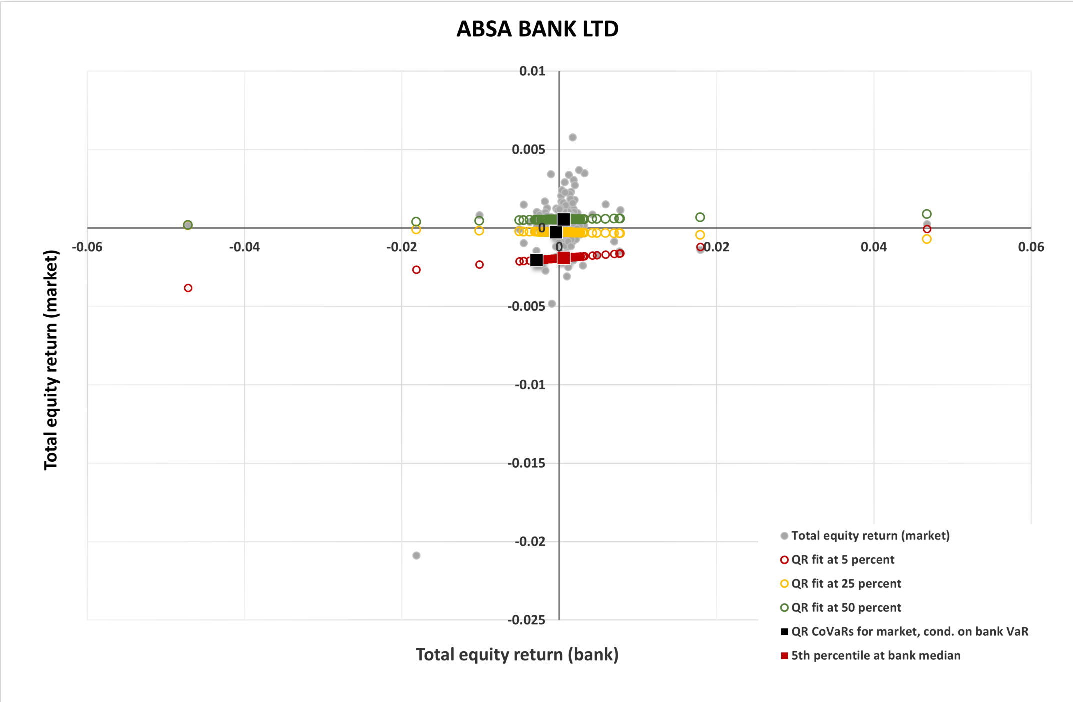


Figure 7: $\Delta CoVaR$ calculation, ABSA
The chart shows the data underpinning the calculation of $\Delta CoVaR$, using data for ABSA covering the full period of investigation.

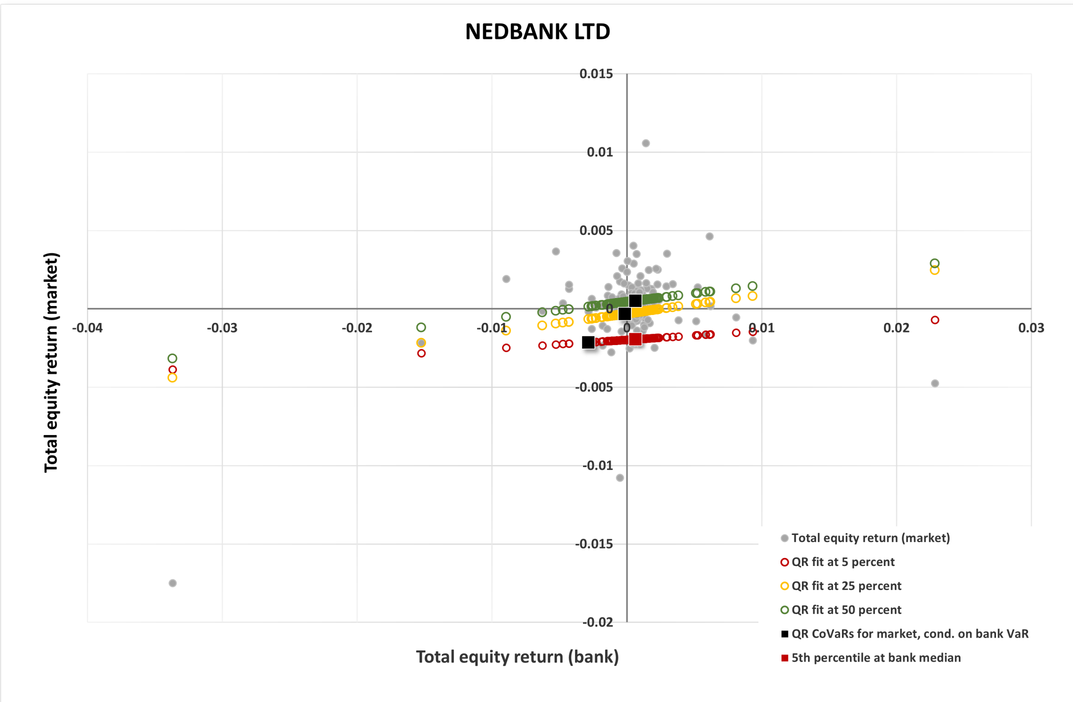


Figure 8: $\Delta CoVaR$ calculation, Nedbank
The chart shows the data underpinning the calculation of $\Delta CoVaR$, using data for Nedbank covering the full period of investigation.

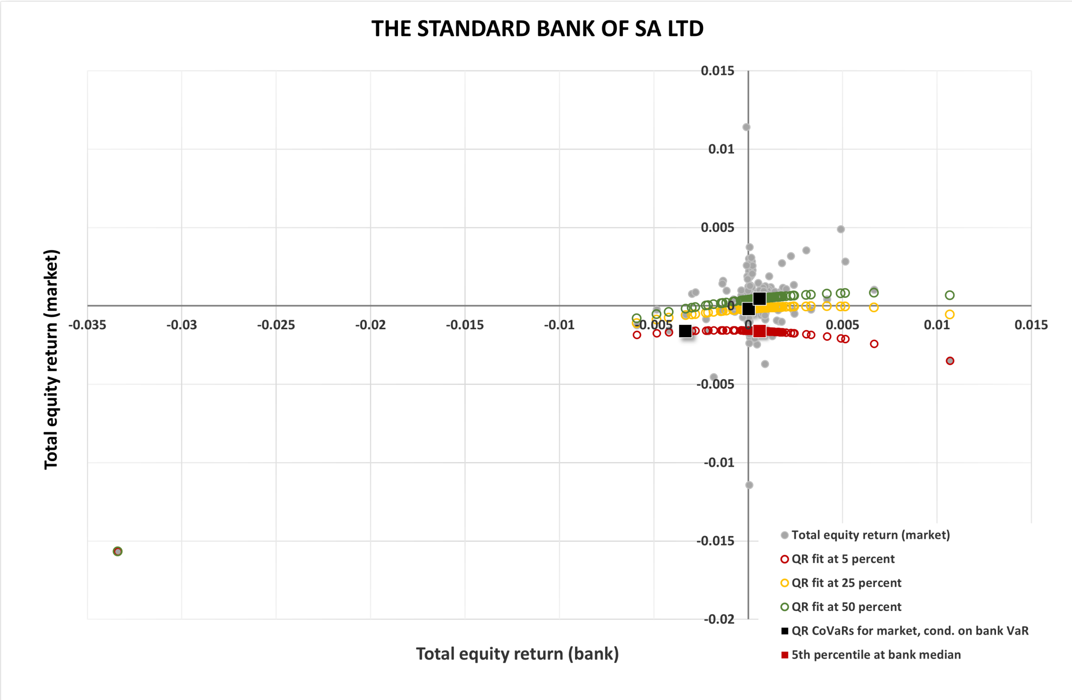


Figure 9: $\Delta CoVaR$ calculation, quadratic quantile fit, Standard Bank
The chart shows the data underpinning the calculation of $\Delta CoVaR$, limited to second-order polynomials, using data for Standard Bank covering the full period of investigation.

	$CoVaR^i_{0.50}$ monthly	$CoVaR^i_{0.05}$ monthly	$\Delta CoVaR^i_{0.05}$ annualised	$\Delta^R CoVaR^i_{0.05}$ R'000
B of Taiwan	-0.00155	-0.00401	0.0300	18 951
B of China	-0.00235	-0.00473	0.0290	8 987
Bidvest	-0.00222	-0.00395	0.0209	7 513
Sasfin	-0.00213	-0.00250	0.0044	4 022
HBZ	-0.00207	-0.00241	0.0041	4 124
Investec	-0.00152	-0.00173	0.0025	249 282
Citibank	-0.00159	-0.00179	0.0024	78 863
ABSA	-0.00192	-0.00207	0.0018	666 697
B of Athens	-0.00163	-0.00153	-0.0012	-809
Albaraka	-0.00215	-0.00203	-0.0014	-1 604
Standard	-0.00206	-0.00183	-0.0028	-1 243 531
Grindrod	-0.00242	-0.00216	-0.0030	-2 363
Capitec	-0.00205	-0.00175	-0.0036	-4 224
China Constr.	-0.00210	-0.00170	-0.0047	-3 263
Nedbank	-0.00256	-0.00201	-0.0066	-2 057 969
Deutsche	-0.00216	-0.00144	-0.0086	-137 727
Habib	-0.00187	-0.00106	-0.0097	-3 918
UBank	-0.00234	-0.00129	-0.0125	-27 558
B of India	-0.00277	-0.00010	-0.0316	-18 954
First Rand	-0.00238	0.00095	-0.0393	-12 222 462

Table 8: Results for February 2001 - January 2006
Notes: $CoVaR^i_{0.50}$ is the system value at risk conditional on the median monthly return for bank i and $CoVaR^i_{0.05}$ is the corresponding system value at risk for the 5th percentile of bank i returns. The difference between these, annualised, is $\Delta CoVaR^i_{0.05}$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR^i_{0.05}$.

	$CoVaR^i_{0.50}$ monthly	$CoVaR^i_{0.05}$ monthly	$\Delta CoVaR^i_{0.05}$ annualised	$\Delta^R CoVaR^i_{0.05}$ R'000
First Rand	-0.00276	-0.00641	0.0447	26 581 699
ABSA	-0.00245	-0.00607	0.0443	29 362 064
Sasfin	-0.00223	-0.00357	0.0161	33 304
B of China	-0.00166	-0.00281	0.0139	64 775
Nedbank	-0.00220	-0.00315	0.0114	6 151 518
Investec	-0.00221	-0.00313	0.0112	2 394 436
Standard	-0.00231	-0.00311	0.0095	7 378 015
Habib	-0.00177	-0.00225	0.0058	4 429
Grindrod	-0.00178	-0.00219	0.0049	12 462
Capitec	-0.00181	-0.00202	0.0026	36 850
Albaraka	-0.00178	-0.00195	0.0020	5 698
Bidvest	-0.00179	-0.00185	0.0008	2 093
B of Taiwan	-0.00176	-0.00178	0.0002	148
China Constr.	-0.00177	-0.00176	-0.0001	-995
B of India	-0.00177	-0.00176	-0.0002	-364
B of Athens	-0.00173	-0.00164	-0.0010	-1 291
UBank	-0.00175	-0.00145	-0.0037	-12 652
HBZ	-0.00177	-0.00140	-0.0044	-11 932
Deutsche	-0.00187	-0.00110	-0.0091	-353 763
Citibank	-0.00174	0.00000	-0.0206	-935 756

Table 9: Results for February 2006 - January 2011

Notes: $CoVaR^i_{0.50}$ is the system value at risk conditional on the median monthly return for bank i and $CoVaR^i_{0.05}$ is the corresponding system value at risk for the 5th percentile of bank i returns. The difference between these, annualised, is $\Delta CoVaR^i_{0.05}$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR^i_{0.05}$.

	$CoVaR^i_{0.50}$ monthly	$CoVaR^i_{0.05}$ monthly	$\Delta CoVaR^i_{0.05}$ annualised	$\Delta^R CoVaR^i_{0.05}$ R'000
Nedbank	-0.00098	-0.00283	0.0224	18 078 126
First Rand	-0.00183	-0.00304	0.0146	14 094 868
Albaraka	-0.00144	-0.00255	0.0134	67 871
Standard	-0.00071	-0.00140	0.0083	10 332 465
Capitec	-0.00113	-0.00170	0.0069	429 416
Grindrod	-0.00113	-0.00154	0.0049	44 603
Sasfin	-0.00144	-0.00162	0.0022	12 241
China Constr.	-0.00134	-0.00143	0.0011	35 464
B of India	-0.00144	-0.00145	0.0001	944
B of Athens	-0.00137	-0.00137	0.0000	-97
Citibank	-0.00145	-0.00140	-0.0006	-44 628
HBZ	-0.00145	-0.00126	-0.0022	-9 389
B of China	-0.00133	-0.00109	-0.0028	-94 582
Bidvest	-0.00146	-0.00119	-0.0032	-19 362
Deutsche	-0.00143	-0.00112	-0.0037	-73 300
ABSA	-0.00163	-0.00122	-0.0049	-4 537 697
UBank	-0.00140	-0.00082	-0.0069	-32 138
B of Taiwan	-0.00144	-0.00057	-0.0104	-15 491
Investec	-0.00160	-0.00035	-0.0149	-5 780 466
Habib	-0.00140	0.00058	-0.0234	-30 998

Table 10: Results for February 2011 - January 2016

Notes: $CoVaR^i_{0.50}$ is the system value at risk conditional on the median monthly return for bank i and $CoVaR^i_{0.05}$ is the corresponding system value at risk for the 5th percentile of bank i returns. The difference between these, annualised, is $\Delta CoVaR^i_{0.05}$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR^i_{0.05}$.

	$CoVaR^i_{0.50}$ monthly	$CoVaR^i_{0.05}$ monthly	$\Delta CoVaR^i_{0.05}$ annualised	$\Delta^R CoVaR^i_{0.05}$ R'000
Nedbank	-0.00104	-0.00316	0.0257	28 399 951
Bidvest	-0.00116	-0.00236	0.0145	177 421
Capitec	-0.00125	-0.00212	0.0106	1 652 024
ABSA	-0.00177	-0.00256	0.0095	12 437 378
UBank	-0.00163	-0.00228	0.0078	44 642
Standard	-0.00094	-0.00157	0.0076	11 800 553
B of Athens	-0.00152	-0.00204	0.0062	18 209
Deutsche	-0.00144	-0.00195	0.0061	103 169
B of Taiwan	-0.00137	-0.00183	0.0054	13 395
HBZ	-0.00153	-0.00190	0.0045	30 323
B of India	-0.00176	-0.00165	-0.0013	-15 964
Investec	-0.00172	-0.00161	-0.0013	-665 619
Sasfin	-0.00169	-0.00155	-0.0016	-13 169
B of China	-0.00165	-0.00134	-0.0037	-183 825
Grindrod	-0.00184	-0.00142	-0.0051	-62 005
Habib	-0.00184	-0.00137	-0.0056	-5 818
Citibank	-0.00190	-0.00141	-0.0058	-499 590
China Constr.	-0.00152	-0.00078	-0.0089	-338 806
First Rand	-0.00203	-0.00111	-0.0110	-15 244 409
Albaraka	-0.00178	-0.00017	-0.0192	-162 394

Table 11: Results for February 2016 - February 2021

Notes: $CoVaR^i_{0.50}$ is the system value at risk conditional on the median monthly return for bank i and $CoVaR^i_{0.05}$ is the corresponding system value at risk for the 5th percentile of bank i returns. The difference between these, annualised, is $\Delta CoVaR^i_{0.05}$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR^i_{0.05}$.

	$CoVaR^i_{0.50}$ monthly	$CoVaR^i_{0.05}$ monthly	$\Delta CoVaR^i_{0.05}$ annualised	$\Delta^R CoVaR^i_{0.05}$ R'000
Citibank	-0.00259	-0.00476	0.0263	2 265 459
Standard	-0.00295	-0.00504	0.0253	39 312 329
First Rand	-0.00282	-0.00373	0.0109	15 132 215
B of China	-0.00239	-0.00320	0.0098	479 577
Nedbank	-0.00254	-0.00312	0.0069	7 629 062
ABSA	-0.00226	-0.00281	0.0066	8 613 091
Deutsche	-0.00236	-0.00267	0.0037	63 042
UBank	-0.00255	-0.00280	0.0030	17 283
Investec	-0.00238	-0.00260	0.0026	1 334 875
Grindrod	-0.00250	-0.00259	0.0011	13 348
B of Athens	-0.00258	-0.00264	0.0008	2 312
China Constr.	-0.00001	-0.00003	0.0003	11 449
Sasfin	-0.00001	-0.00002	0.0001	1 099
Capitec	-0.00002	-0.00002	0.0000	-809
Bidvest	-0.00001	-0.00001	0.0000	-335
Albaraka	-0.00001	-0.00001	0.0000	-280
HBZ	-0.00250	-0.00241	-0.0011	-7 565
B of Taiwan	-0.00255	-0.00243	-0.0014	-3 453
Habib	-0.00251	-0.00235	-0.0019	-1 938
B of India	-0.00246	-0.00187	-0.0071	-87 187

Table 12: Results for February 2001 - February 2021 based on solvency metric

Notes: The solvency metric used is the change in the ratio of equity to assets from the corresponding ratio the previous month. $CoVaR^i_{0.50}$ is the system value at risk conditional on the median solvency metric for bank i and $CoVaR^i_{0.05}$ is the corresponding system value at risk for the 5th percentile of bank i solvency metrics. The difference between these, annualised, is $\Delta CoVaR^i_{0.05}$. This is scaled by bank assets at the end of the calculation period to produce $\Delta^R CoVaR^i_{0.05}$.

A.7 Financial reports consulted, Chapter 6

Discovery (2018a). *Annual Financial Statements for the year ended 30 June 2018*, Discovery Limited.

Discovery (2018b). *Integrated Annual Report for the year ended 30 June 2018*, Discovery Limited.

Discovery (2019a). *Annual Financial Statements for the year ended 30 June 2019*, Discovery Limited.

Discovery (2019b). *Integrated Annual Report for the year ended 30 June 2019*, Discovery Limited.

Discovery (2020a). *Annual Financial Statements for the year ended 30 June 2020*, Discovery Limited.

Discovery (2020b). *Integrated Annual Report for the year ended 30 June 2020*, Discovery Limited.

Discovery (2021a). *Annual Financial Statements for the year ended 30 June 2021*, Discovery Limited.

Discovery (2021b). *Integrated Annual Report for the year ended 30 June 2021*, Discovery Limited.

Discovery (2022a). *Annual Financial Statements for the year ended 30 June 2022*, Discovery Limited.

Discovery (2022b). *Integrated Annual Report for the year ended 30 June 2022*, Discovery Limited.

Hollard (2017a). *Audited consolidated annual financial statements for the year ended 30 June 2017*, The Hollard Insurance Company Limited.

Hollard (2018a). *Audited consolidated annual financial statements for the year ended 30 June 2018*, The Hollard Insurance Company Limited.

Hollard (2019a). *Audited consolidated annual financial statements for the year ended 30 June 2019*, The Hollard Insurance Company Limited.

Hollard (2020a). *Audited consolidated annual financial statements for the year ended 30 June 2020*, The Hollard Insurance Company Limited.

Hollard (2021a). *Audited consolidated annual financial statements for the year ended 30 June 2021*, The Hollard Insurance Company Limited.

Hollard Life (2017b). *Audited consolidated annual financial statements for the year ended 30 June 2017*, Hollard Life Insurance Company Limited.

Hollard Life (2018b). *Audited consolidated annual financial statements for the year ended 30 June 2018*, Hollard Life Insurance Company Limited.

Hollard Life (2019b). *Audited consolidated annual financial statements for the year ended 30 June 2019*, Hollard Life Insurance Company Limited.

Hollard Life (2020b). *Audited consolidated annual financial statements for the year ended 30 June 2020*, Hollard Life Insurance Company Limited.

Hollard Life (2021b). *Audited consolidated annual financial statements for the year ended 30 June 2021*, Hollard Life Insurance Company Limited.

Hollard Specialist (2019c). *Audited consolidated annual financial statements for the year ended 30 June 2019*, Hollard Specialist Insurance Company Limited.

Hollard Specialist (2020c). *Audited consolidated annual financial statements for the year ended 30 June 2020*, Hollard Specialist Insurance Company Limited.

Hollard Specialist (2021c). *Audited consolidated annual financial statements for the year ended 30*

June 2021, Hollard Specialist Insurance Company Limited.

Liberty (2018a). *Annual Financial Statements for the year ended 31 December 2017*, Liberty Holdings Limited.

Liberty (2018b). *Group and Company annual financial statements for the year ended 31 December 2017*, Liberty Group Limited.

Liberty (2018c). *Integrated report for the year ended 31 December 2017*, Liberty Holdings Limited.

Liberty (2019a). *Annual Financial Statements for the year ended 31 December 2018*, Liberty Holdings Limited.

Liberty (2019b). *Group and Company annual financial statements for the year ended 31 December 2018*, Liberty Group Limited.

Liberty (2020a). *Annual Financial Statements for the year ended 31 December 2019*, Liberty Holdings Limited.

Liberty (2020b). *Group and Company annual financial statements for the year ended 31 December 2019*, Liberty Group Limited.

Liberty (2021a). *Annual Report for the year ended 31 December 2020*, Liberty Holdings Limited.

Liberty (2021b). *Annual Financial Statements for the year ended 31 December 2020*, Liberty Holdings Limited.

Liberty (2022a). *Annual Report for the year ended 31 December 2021*, Liberty Holdings.

Liberty (2022b). *Annual Financial Statements for the year ended 31 December 2021*, Liberty Group Limited.

Liberty (2022c). *Annual Financial Statements for the year ended 31 December 2021*, Liberty Holdings Limited.

MMI Holdings (2017). *Advancing MMI's Strategy: Financial Results 2017*, MMI Holdings Group.

MMI Holdings (2018). *Reset and Grow: Results for the year ended June 2018*, MMI Holdings Group.

Momentum (2019). *Summary of Financial Information: Audited results for the year ended June 2019*, Momentum Metropolitan.

Momentum (2020). *Group Annual Financial Statements: Audited results for the year ended June 2020*, Momentum Metropolitan.

Momentum (2021a). *Group Annual Financial Statements: Audited results for the year ended June 2021*, Momentum Metropolitan.

Momentum (2021b). *Integrated report 2021*, Momentum Metropolitan.

Momentum (2022a). *Group Annual Financial Statements: Audited results for the year ended June 2022*, Momentum Metropolitan.

Momentum (2022b). *Integrated report 2022*, Momentum Metropolitan.

Old Mutual (2020). *Integrated Report 2019*, Old Mutual Limited.

Old Mutual (2021). *Integrated Report 2020*, Old Mutual Limited.

Old Mutual (2019a). *Integrated Report 2018*, Old Mutual Limited.

Old Mutual (2019b). *Annual Financial Statements for the year ended 31 December 2018*, Old Mutual Limited.

Old Mutual (2022a). *Annual Financial Statements, consolidated and separate, for the year ended 31 December 2021.*

Old Mutual (2022b). *Integrated Report 2021*, Old Mutual Limited.

OMI (2018). *Annual Report 2017*, Old Mutual Insure Limited.

OMI (2019). *Annual Report 2018*, Old Mutual Insure Limited.

OMI (2020). *Annual Report 2019*, Old Mutual Insure Limited.

OMI (2021). *Annual Report 2020*, Old Mutual Insure Limited.

OMI (2022). *Annual Report 2021*, Old Mutual Insure Limited.

OMLACSA (2018). *Separate and Consolidated Annual Financial Statements for the year ended 31 December 2017*, Old Mutual Life Assurance Company (South Africa) Ltd.

OMLACSA (2019). *Annual Financial Statements for the year ended 31 December 2018*, Old Mutual Life Assurance Company (South Africa) Ltd.

OUTsurance (2017). *Annual report 2017*, OUTsurance Holdings Limited.

OUTsurance (2018). *Annual report 2018*, OUTsurance Holdings Limited.

OUTsurance (2019). *Annual report 2019*, OUTsurance Holdings Limited.

OUTsurance (2020). *Annual report 2020*, OUTsurance Holdings Limited.

OUTsurance (2021). *Annual report 2021*, OUTsurance Holdings Limited.

Sanlam (2018a). *Integrated Report 2017*, Sanlam.

Sanlam (2018b). *Audited Annual Results 2017*, Sanlam.

Sanlam (2019a). *Integrated Report 2018*, Sanlam.

Sanlam (2019b). *Audited Annual Results 2018*, Sanlam.

Sanlam (2020a). *Integrated Report 2019*, Sanlam.

Sanlam (2020b). *Audited Annual Results 2019*, Sanlam.

Sanlam (2021a). *Integrated Report 2020*, Sanlam.

Sanlam (2021b). *Audited Annual Results 2020*, Sanlam.

Sanlam (2022a). *Integrated Report 2021*, Sanlam.

Sanlam (2022b). *Audited Annual Results 2021*, Sanlam.

Sanlam Life (2018). *Annual Financial Statements 2017*, Sanlam Life Insurance Limited.

Sanlam Life (2019). *Annual Financial Statements 2018*, Sanlam Life Insurance Limited.

Sanlam Life (2020). *Annual Financial Statements 2019*, Sanlam Life Insurance Limited.

Sanlam Life (2021). *Annual Financial Statements 2020*, Sanlam Life Insurance Limited.

Sanlam Life (2022). *Annual Financial Statements 2021*, Sanlam Life Insurance Limited.

Santam (2021). *Annual Financial Statements 2020*, Santam.

Santam (2022). *Annual Financial Statements 2021*, Santam.

A.8 Supporting information, SA insurers, Chapter 6

Table 13: High-level classification of insurer contributions to systemic risk

Balance sheet element	Risk type	Detail and references
Assets	Concentration	Climate change and impact on asset prices (SARB 2019) Exposure through investments (IAIS 2011) Exposure to policy and governance (SARB 2020a) Exposure to the economy (SARB 2020a) Impact of investment returns on insurers (SARB 2020b) Increasingly interconnected stock market performance (Acharya, J. Biggs, et al. 2011; Acharya, Pedersen, Philippon, and Richardon 2010; Baluch, Mutenga, and Parsons 2011; Bierth, Irresberger, and GNF Weiß 2019; Billio et al. 2012; J. Cummins and Weiss 2013; D. Schwarcz and S. Schwarcz 2014) Investment in banks and the real economy (SARB 2017a, 2020a)
	Quality	Structured securities: liquidity and systemic impacts (Baluch, Mutenga, and Parsons 2011; Baranoff 2012; H. Chen, J. Cummins, et al. 2013; J. Cummins and Weiss 2013, 2014; Geneva Association 2010b; R. Klein 2013; Trichet 2005) Counterparty exposures (assets) (IAIS 2018a) Exploiting unregulated subsidiaries and information asymmetries (Acharya, J. Biggs, et al. 2011; Baranoff 2012; SE Harrington 2009; IAIS 2011) Investing in complex structured securities (J. Cummins and Weiss 2014) Non-traditional activities drive systemic risk (J. Cummins and Weiss 2013; Neale et al. 2012)
Liabilities	Concentration	Catastrophe risk (S. Park and Xie 2014) Impact of climate change on liabilities (SARB 2020a) Correlated product classes (IAIS 2011) Export credit insurance (poor substitutability) (IAIS 2019) Exposure to business interruption claims (SARB 2021b) Exposure to civil unrest (SARB 2021b) Exposure to the economy (SARB 2017b) Industry-loss warranties (IAIS 2012b) Insurer concentration (SARB 2020a, 2021b) Insurer interconnectedness (SARB 2018b) Poor substitutability (J. Cummins and Weiss 2014; IAIS 2018a) Poor substitutability and capacity concerns (IAIS 2011) Poor substitutability: marine and aviation classes (IAIS 2019) Poor substitutability: mortgage insurance class (IAIS 2019) Reinsurance with limited or no risk transfer (IAIS 2011)
	Mismatch	Annuities with options and guarantees (J. Cummins and Weiss 2013) Embedded options (early surrender, liquidity risk) (IAIS 2019) Financial guarantees: liquidity impacts (J. Cummins and Weiss 2013, 2014; Geneva Association 2010b; IAIS 2011) Fixed-benefit guarantees (macro-economic exposure) (IAIS 2019) Guarantee funds (J. Cummins and Weiss 2014) Guaranteed returns on saving products (IAIS 2018a) Guarantees without matching (IAIS 2018a) Policyholder lapses and surrenders (SARB 2018a, 2020a,b) Products with guarantees (Geneva Association 2011) Providing financial guarantees (J. Cummins and Weiss 2014) Saving and investment in long-term insurance (IAIS 2011)
	Quality	Complexity (J. Cummins and Weiss 2014) Complexity (low for non-life insurers) (S. Park and Xie 2014) Product design more like banks (IAIS 2011)
	Strategic	Bancassurance (IAIS 2011) Credit protection and associated macro-economic exposure (IAIS 2019) Exposure to burden of disease and economic impacts (SARB 2021a) Exposure to business interruption claims (SARB 2020b) Exposure to fraudulent activity (SARB 2021b) Functions critical to the financial sector (IAIS 2018a) Insurance provides critical function with few substitutes (IAIS 2019) Third-party asset management (IAIS 2011)
	Operational	Cyber risk (IAIS 2018a)
ALM	Mismatch	Asset lending (Acharya, J. Biggs, et al. 2011; Besar et al. 2011; J. Cummins and Weiss 2014; IAIS 2018a) Asset lending: liquidity risk (IAIS 2018a) Asset liquidation (IAIS 2018a) Constraining funding or liquidity (exposure channel) (IAIS 2019) Contributing to asset volatility (asset liquidation) (IAIS 2019) Derivatives (liquidity risk) (IAIS 2018a, 2019) Exacerbating market movements (asset liquidation) (IAIS 2019) Excessive reliance on short-term financing (J. Cummins and Weiss 2014) High equity levels in life insurance (H. Chen, J. Cummins, et al. 2013; SE Harrington 2009; IMF 2009) Liquidity risks (J. Cummins and Weiss 2014) Liquidity: backing liquid liabilities with illiquid assets (IAIS 2018a) Maturity mismatches (J. Cummins and Weiss 2014) Securities lending (liquidity risk) (IAIS 2019) Short-term funding potentially leading to fire sales (Acharya, J. Biggs, et al. 2011; Besar et al. 2011; Geneva Association 2010a,b; Jobst 2014; D. Schwarcz and S. Schwarcz 2014) Speculative derivatives (macro-economic exposure) (IAIS 2019) Counterparty exposures (reinsurers) (IAIS 2019)
	Quality	Alternative risk transfer (J. Cummins and Weiss 2009; IAIS 2011)

Table 13: High-level classification of insurer contributions to systemic risk

Balance sheet element	Risk type	Detail and references
		Asset concentration (counterparty exposure) (IAIS 2019) Banking and hedge fund activities (IAIS 2011) Derivatives (liquidity risk) (IAIS 2011) Lending interaction (counterparty exposure) (IAIS 2019) Property management (IAIS 2011) Synthetic investment portfolios (IAIS 2011) Business model: mix of risks (IAIS 2011)
	Strategic	Growth in non-core activities (Baluch, Mutenga, and Parsons 2011) Insurance-linked securities (IAIS 2011) Interconnectedness of various types (J. Cummins and Weiss 2014) Size of exposures (J. Cummins and Weiss 2014) Hierarchical link to reinsurers insufficient (IAIS 2012a; S. Park and Xie 2014)
Solvency	Concentration	Transferring losses to other participants (exposure channel) (IAIS 2019) Leverage (IMF 2009)
	Mismatch	Funding structure (IMF 2009)
	Quality	Rapid growth (IAIS 2011)
	Strategic	Deficient provisioning and inadequate pricing (IAIS 2011)
	Operational	Limited fungibility within insurance groups (Baranoff 2012; Radice 2010) Under-reserving or under-pricing (IAIS 2018a) Government policy and regulation (J. Cummins and Weiss 2014)
General	General	Interconnectedness higher than previously thought (Acharya, Pedersen, Philippon, and Richardon 2010; Billio et al. 2012) Life insurance more concentrated (IAIS 2011) Panic run possible (Acharya and M. Richardson 2014) Regulation: not primarily to reduce systemic risk (IAIS 2011) Regulation: disadvantages of convergence (IAIS 2011) Inadequate governance (IMF 2022d)

Table 14: Selection of approaches to modelling systemic risk

Ellis type*	Summary of approach	Contagion direction	Data sources
Capital	Propensity to be under-capitalised when the system is under-capitalised (Acharya, Pedersen, Philippon, and Richardon 2010)	Market to entity	Book & market
	Capital shortfall of a company conditional on a market crisis (Acharya, Engle, and M. Richardson 2012)	Market to entity	Book & market
	State-dependent sensitivity VaR to show dependence on state of financial markets (Z. Adams, Füss, and Gropp 2014)	Entity to market	Market
	Impact of entity distress on the value at risk of the financial system (Adrian and MK Brunnermeier 2016)	Entity to market	Book & market
	Capital shortfall of a company conditional on a market crisis (Brownlees and Engle 2017)	Market to entity	Book & market
	Joint probability of default: system tail risk, based on CDS data (Segoviano and Goodhart 2009)	No direction implied	Market
	Various approaches to study insurance contribution to systemic risk (Weiß and Mühlnickel 2014)	Several approaches	Book & market
	Based on sovereign CDS in Asia-Pacific, shows inter-connectedness between countries (Wong and Fong 2010)	Entity to market	Market
Contagion	Econometric connectedness on principal component analysis and Granger causality networks (Billio et al. 2012)	Between entities	Market
	Granger causality between banks and insurers using market and CDS prices (H. Chen, J. Cummins, et al. 2013)	Between entities	Market
Early warning	Granger causality between market returns of entities (Billio et al. 2012)	Between entities	Market
	Systemic risk metrics derived from CDS prices (Giglio 2016)	No direction implied	Market
	Price of insurance against financial distress using CDS and equity price co-movements (X. Huang, Zhou, and Zhu 2012b)	Entity to market	Market
Liquidity	Impact of shocks on individual banks and the system using Bayesian VaR (Aikman, Alessandri, et al. 2011)	Market to entity	Book & market
	Several approaches to marginal impact of liquidity shortfall on market statistics (Jobst 2014)	Entity to market	Book & market
Liquidity / Network	Liquidity shortages due to bank inter-connectedness: six network structures (S. Lee 2013)	Between entities	Simulated
Network	Time-varying marginal effect of firm's VaR on system VaR, allowing for system interdependence (Hautsch, Schaumburg, and Schienle 2015)	Entity to market	Book & market
	Study of dynamics of interbank exposures and payment system networks (Martinez-Jaramillo et al. 2015)	Between entities	Book & market
	Quantify contribution to systemic risk from four distinct types of financial exposure (Poledna et al. 2015)	Between entities	Book & market

Notes: The Ellis type follows the classification system proposed by Ellis, Sharma, and Brzeszczyński (2022). The acronym VaR in the summary of approach denotes Value at Risk. Contagion direction describes the nature of the relationship between individual entities and the market as a whole that the modelling aims to demonstrate. Market information is from quoted stock-price or CDS data and book values are obtained from accounting information.

This page is intentionally left blank so that all new sections start on the right-hand page using double-sided printing

Bibliography

Acharya, VV (2009). “A Theory of Systemic Risk and Design of Prudential Bank Regulation”. In: *Journal of Financial Stability* 5, pp. 224–255.

Acharya, VV, J Biggs, M Richardson, and S Ryan (2011). “Systemic Risk and the Regulation of Insurance Companies”. In: *Regulating Wall Street - The Dodd-Frank Act and the New Architecture of Global Finance*. Ed. by VV Acharya, TF Cooley, M Richardson, and I Walter. Hoboken, NJ: John Wiley & Sons, pp. 241–301.

Acharya, VV, TF Cooley, M Richardson, and I Walter (2011). *Market Failures and Regulatory Failures: Lessons from Past and Present Financial Crises*. ADBI Working Paper Series No. 264. Asian Development Bank Institute.

Acharya, VV, RF Engle, and M Richardson (2012). “Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks”. In: *American Economic Review* 102.3, pp. 59–64.

Acharya, VV, LH Pedersen, T Philippon, and M Richardon (2010). *Measuring Systemic Risk*. Working Paper. Federal Reserve Bank of Cleveland.

Acharya, VV, LH Pedersen, T Philippon, and M Richardson (2017). “Measuring Systemic Risk”. In: *The Review of Financial Studies* 30.1, pp. 2–47.

Acharya, VV and M Richardson (2014). “Is the Insurance Industry Systemically Risky?” In: *Modernizing Insurance Regulation*. Ed. by JH Biggs and M Richardson. 1st ed. Hoboken, NJ: John Wiley & Sons, pp. 151–179.

Adams, M, J Andersson, L Andersson, and M Lindmark (2008). *Commercial Banking, Insurance and Economic Growth in Sweden between 1830 and 1998*. Working Paper, SBE 2008/1, School of Business & Economics, Swansea University.

Adams, Z, R Füss, and R Gropp (2014). “Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk Approach”. In: *Journal of Financial and Quantitative Analysis* 49.3, pp. 575–598.

ADB (2017). *Asian Economic Integration Report*. Asian Development Bank.

Adelle, C, D Macrae, A Marusic, and F Naru (2015). “New Development: Regulatory Impact Assessment in Developing Countries – Tales from the Road to Good Governance”. In: *Public Money & Management* 35.3, pp. 233–238.

Adelle, C, S Weiland, J Dick, D González, J Marquart, G Rots, J Wübbeke, and I Zasada (2016). "Regulatory Impact Assessment: A Survey of Selected Developing and Emerging Economies". In: *Public Money & Management* 36.2, pp. 89–96.

Adrian, T and MK Brunnermeier (2008). *CoVaR*. Staff Report No. 348. Federal Reserve Bank of New York.

— (2011). *COVAR*. Working Paper 17454. National Bureau of Economic Research.

— (2016). "CoVaR". In: *American Economic Review* 106.7, pp. 1705–1741.

Aikman, D, P Alessandri, B Eklund, P Gai, S Kapadia, E Martin, N Mora, G Sterne, and M Willison (2011). "Funding Liquidity Risk in a Quantitative Model of Systemic Stability". In: *Financial Stability, Monetary Policy, and Central Banking*. Ed. by R Alfaro. Vol. 15. Central Banking, Analysis, and Economic Policies Book Series. Central Bank of Chile. Chap. 12, pp. 371–410.

Aikman, D, AG Haldane, and S Kapadia (2013). *Operationalising a Macroprudential Regime: Goals, Tools and Open Issues*. Estabilidad Financiera, Núm 24. Banco de España.

Akinlo, T and OT Apanisile (2014). "Relationship between Insurance and Economic Growth in Sub-Saharan Africa: A Panel Data Analysis". In: *Modern Economy* 5, pp. 122–129.

Al-Darwish, A, M Hafeman, G Impavido, M Kemp, and P O'Malley (2011). *Possible Unintended Consequences of Basel III and Solvency II*. Working Paper WP/11/187. International Monetary Fund.

Alhassan, AL and N Biekpe (2019). "Pricing Power in Insurance Markets: Evidence from South Africa". In: *International Journal of Bank Marketing* 37.5, pp. 1371–1392.

Allen, F and E Carletti (2006). "Credit Risk Transfer and Contagion". In: *Journal of Monetary Economics* 55, pp. 89–111.

Allen, F and D Gale (2000). "Financial Contagion". In: *Journal of Political Economy* 108.1, pp. 1–33.

Allen, F and X Gu (2018). "The Interplay between Regulations and Financial Stability". In: *Journal of Financial Services Research* 53, pp. 233–248.

Anand, K, P Gai, and M Marsili (2012). "Rollover risk, network structure and systemic financial crises". In: *Journal of Economic Dynamics & Control* 36, pp. 1088–1100.

Andries, AN and E Galasan (2020). "Measuring Financial Contagion and Spillover Effects with a State-Dependent Sensitivity Value-at-Risk Model". In: *Risks* 8.5, 10.3390/risks8010005.

APRA (2014). *Annual Report 2014*. Australian Prudential Regulation Authority.

Araten, M and C Turner (2013). "Understanding the funding cost differences between global systemically important banks and non-G-SIBs in the USA". In: *Journal of Risk Management in Financial Institutions* 6, pp. 387–410.

Arena, M (2008). "Does Insurance Market Activity Promote Economic Growth? A Cross-country Study for Industrialized and Developing Countries". In: *Journal of Risk and Insurance* 75.4, pp. 921–946.

Armour, J, D Awrey, P Davies, L Enriques, JN Gordon, C Mayer, and J Payne (2016). "The Goals and Strategies of Financial Regulation". In: *Principles of Financial Regulation*. Ed. by J Armour, D Awrey, P Davies, L Enriques, JN Gordon, C Mayer, and J Payne. London, United Kingdom: Oxford University Press, pp. 51–79. ISBN: 9780198786474.

Arthur, T and P Booth (2010). *Does Britain Need a Financial Regulator? Statutory Regulation, Private Regulation and Financial Markets*. The Institute of Economic Affairs in association with Profile Books, London.

Arych, M and W Darcy (2020). "General Trends and Competitiveness of Australian Life Insurance Industry". In: *Journal of International Studies* 13.1, pp. 212–233.

Ashwin, P, S Wieczorek, R Vitolo, and P Cox (2012). "Tipping Points in Open Systems: Bifurcation, Noise-induced and Rate-dependent Examples in the Climate System". In: *Philosophical Transactions of the Royal Society* 370, pp. 1166–1184.

ASSA (2018). *APN 106/403: Head of Actuarial Function for South African Insurers*. Advisory Practice Note. Actuarial Society of South Africa.

— (2019). *APN 111/404: Head of Actuarial Function for South African Insurance Groups*. Advisory Practice Note. Actuarial Society of South Africa.

Aswathy, RK and S Mathew (2016). "On Different Forms of Self Similarity". In: *Chaos, Solitons & Fractals* 87, pp. 102–108.

Atack, J (2009). "Financial Innovation and Crises: The View Backwards from Northern Rock". In: *The Origins and Development of Financial Markets and Institutions: From the Seventeenth Century to the Present*. Ed. by J Atack and L Neal. Cambridge: Cambridge University Press.

Australian Government (1997). *Financial System Inquiry Final Report*. The Wallis Inquiry. Commonwealth of Australia.

— (2014). *Financial System Inquiry: Final Report*. Commonwealth of Australia.

Babus, A (2016). "The Formation of Financial Networks". In: *RAND Journal of Economics* 47.2, pp. 239–272.

Bajar, S and M Rajeev (2015). *The Impact of Infrastructure Provisioning on Inequality: Evidence from India*. Working Paper No. 35, Global Labour University. International Labour Organization.

Baldwin, R and J Black (2016). "Driving Priorities in Risk-based Regulation: What's the Problem?" In: *Journal of Law and Society* 43.4, pp. 565–595.

Baluch, F, S Mutenga, and C Parsons (2011). "Insurance, Systemic Risk and the Financial Crisis". In: *The Geneva Papers* 36, pp. 126–163.

Baranoff, E (2012). "An Analysis of the AIG Case: Understanding Systemic Risk and Its Relation to Insurance". In: *Journal of Insurance Regulation; Kansas City* 31.1, pp. 243–270.

Bargigli, L, L Riccetti, A Russo, and M Gallegati (2020). "Network Calibration and Metamodeling of a Financial Accelerator Agent Based Model". In: *Journal of Economic Interaction and Coordination* 15, pp. 413–440.

Barr, N and P Diamond (2006). "The Economics of Pensions". In: *Oxford Review of Economic Policy* 22.1, pp. 15–39.

Barsotti, F, X Milhaud, and Y Salhi (2016). "Lapse Risk in Life Insurance: Correlation and Contagion Effects among Policyholders' Behaviors". In: *Insurance: Mathematics and Economics* 71, pp. 317–331.

Barth, MM (2000). "A Comparison of Risk-based Capital Standards under the Expected Policyholder Deficit and Probability of Ruin Approaches". In: *Journal of Risk and Insurance* 67.3, pp. 397–413.

Bartlett III, RP (2014). "The Institutional Framework for Cost-Benefit Analysis in Financial Regulation: A Tale of Four Paradigms?" In: *The Journal of Legal Studies* 43.S2, S379–S405.

Bats, J and A Houben (2017). *Bank-based versus Market-based Financing: Implications for Systemic Risk*. DNB Working Paper No. 577. De Nederlandsche Bank.

Battiston, S, JD Farmer, A Flache, D Garlaschelli, AG Haldane, H Heesterbeek, Hommes C, Jaeger C, May R, and Scheffer M (2016). "Complexity Theory and Financial Regulation". In: *Science* 6275, pp. 818–819.

BDI (2016). *An Innovation Check for Regulatory Impact Assessment: Making regulation innovation friendly*. BDI Publication No. 053. Federation of German Industries (BDI) with Kienbaum Management Consultants GmbH.

Beaugrand, G (2004). "The North Sea Regime Shift: Evidence, Causes, Mechanisms and Consequences". In: *Progress in Oceanography* 60, pp. 245–262.

Becker, B and V Ivashina (2015). "Reaching for Yield in the Bond Market". In: *Journal of Finance* 70.5, pp. 1863–1901.

Benartzi, S and RH Thaler (1995). "Myopic Loss Aversion and the Equity Premium Puzzle". In: *The Quarterly Journal of Economics* 110.1, pp. 73–92.

— (2007). "Heuristics and Biases in Retirement Savings Behaviour". In: *Journal of Economic Perspectives* 21.3, pp. 81–104.

Benoit, S, J Colliard, C Hurlin, and C Pérignon (2017). "Where the Risks Lie: A Survey on Systemic Risk". In: *Review of Finance* 21.1, pp. 109–152.

Bentley, RA et al. (2014). "Social Tipping Points and Earth Systems Dynamics". In: *Frontiers in Environmental Science* 2.Article 35.

Berry-Stölzle, TR, GP Nini, and S Wende (2014). "External Financing in the Life Insurance Industry: Evidence From the Financial Crisis". In: *Journal of Risk and Insurance* 81.3, pp. 529–562.

Besar, D, P Booth, Chan KK, KL Milne, and J Picklles (2011). "Systemic Risk in Financial Services". In: *British Actuarial Journal* 16.2, pp. 195–300.

Bierth, C, F Irresberger, and GNF Weiß (2019). "Systemic Risk of Insurers around the Globe". In: *Journal of Banking and Finance* 55, pp. 232–245.

Billio, M, M Getmansky, AW Lo, and L Pelizzon (2012). "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors". In: *Journal of Financial Economics* 104, pp. 535–559.

Bisias, D, M Flood, AW Lo, and S Valavanis (2012). "A Survey of Systemic Risk Analytics". In: *Annual Review of Financial Economics* 4.1, pp. 255–296.

Black, F (1972). "Capital Market Equilibrium with Restricted Borrowing". In: *Journal of Business* 45.3, pp. 444–455.

Black, F, MC Jensen, and M Scholes (1972). "The Capital Asset Pricing Model: Some Empirical Tests". In: *Studies in the Theory of Capital Markets*. Ed. by MC Jensen. New York: Praeger, pp. 79–124.

Black, J (2004). *The Development of Risk Based Regulation in Financial Services: Canada, the UK and Australia.* A Research Report, ESRC Centre for the Analysis of Risk and Regulation. London School of Economics and Political Science.

— (2012). *Calling Regulators to Account: Challenges, Capacities and Prospects.* Society and Economy Working Papers 15/2012, LSE Law. London School of Economics and Political Science.

— (2013). "Reconceiving Financial Markets – From the Economic to the Social". In: *Journal of Corporate Law Studies* 13.2, pp. 401–442.

Black, J and R Baldwin (2010). "Really Responsive Risk-based Regulation". In: *Law and Policy* 32.2.

— (2012). "When Risk-based Regulation Aims Low: A Strategic Framework". In: *Law and Policy* 6.2, pp. 131–148.

Bobtcheff, C, T Chaney, and C Gollier (2019). "Analysis of Systemic Risk in the Insurance Industry". In: *The Geneva Papers* 41, pp. 73–106.

Boonen, TJ (2017). "Solvency II Solvency Capital Requirements for Life Insurance Companies based on Expected Shortfall". In: *European Actuarial Journal* 7, pp. 405–434.

Borensztein, E, E Cavallo, and O Leanne (2017). "The Welfare Gains from Macro-insurance against Natural Disasters". In: *Journal of Development Economics* 124, pp. 142–156.

Borges, MR, L Ulica, and M Gubareva (2020). "Systemic risk in the Angolan interbank payment system - a network approach". In: *Applied Economics* 52.45, pp. 4900–4912.

Boss, M, H Elsinger, M Summer, and S Thurner (2004). "Network topology of the interbank market". In: *Quantitative Finance* 4.6, pp. 677–684.

Boyd, JH and A Heitz (2016). "The Social Costs and Benefits of Too-big-to-fail Banks: A 'Bounding' Exercise". In: *Journal of Banking & Finance* 68, pp. 251–265.

Brainard, L (2008). *What is the Role of Insurance in Economic Development.* Zurich Financial Services.

Brandsma, GJ and T Schillemans (2012). "The Accountability Cube: Measuring Accountability". In: *Journal of Public Administration Research and Theory* 23, pp. 953–975.

Brewer III, E and WE Jackson III (2002). *Inter-industry Contagion and the Competitive Effects of Financial Distress Announcements: Evidence from Commercial Banks and Life Insurance Companies.* Working Paper WP 2002–23. Federal Reserve Bank of Chicago.

Brownlees, CT and RF Engle (2017). "SRISK: A Conditional Capital Shortfall Measure of Systemic Risk". In: *Review of Financial Studies* 30.1, pp. 48–79.

Bruce, AD and RA Cowley (1981). *Structural phase transitions.* London: Taylor & Francis.

Brunnermeier, M, A Crocket, C Goodhart, AD Persaud, and H Shin (2009). *The Fundamental Principles of Financial Regulation.* Geneva Reports on the World Economy 11. International Center for Monetary, Banking Studies, and the Centre for Economic Policy Research.

Brusco, S and F Castiglionesi (2007). "Liquidity Coinsurance, Moral Hazard, and Financial Contagion". In: *The Journal of Finance* 62.5, pp. 2275–2302.

Bui, C, H Scheule, and E Wu (2017). "The Value of Bank Capital Buffers in Maintaining Financial System Resilience". In: *Journal of Financial Stability* 33, pp. 23–40.

Caccioli, F, P Barucca, and T Kobayashi (2018). "Network models of financial systemic risk: a review". In: *Journal of Computational Social Science* 1.1, pp. 81–114.

Caccioli, F, M Shrestha, C Moore, and J Doyne Farmer (2014). "Stability analysis of financial contagion due to overlapping portfolios". In: *Journal of Banking & Finance* 46, pp. 233–245.

Cai, H, Y Chen, H Fang, and L Zhou (2015). "The Effect of Microinsurance on Economic Activities: Evidence from a Randomized Field Experiment". In: *The Review of Economics and Statistics* 97.2, pp. 287–300.

Cai, J (2016). "The Impact of Insurance Provision on Household Production and Financial Decisions". In: *American Economic Journal: Economic Policy* 8.2, pp. 44–88.

Campbell, JY, AW Lo, and AC MacKinlay (1996). *The Econometrics of Financial Markets*. Princeton: Princeton University Press.

Carreras, O, EP Davis, and R Piggott (2019). "Assessing Macroprudential Tools in OECD Countries within a Cointegration Framework". In: *Journal of Financial Stability* 37, pp. 112–130.

Carter, MR and CB Barrett (2006). "The Economics of Poverty Traps and Persistent Poverty: An Asset-based Approach". In: *Journal of Development Studies* 42.2, pp. 178–199.

Caruana, J (2010). *Systemic risk: how to deal with it?* Discussion Paper. Bank for International Settlements.

Carvajal, A, R Dodd, M Moore, E Nier, I Tower, and L Zanforlin (2009). *The Perimeter of Financial Regulation*. IMF Staff Position Note SPN/09/07. International Monetary Fund.

Casarano, G, G Castellani, L Passalacqua, F Perla, and P Zanetti (2017). "Relevant Applications of Monte Carlo Simulation in Solvency II". In: *Soft Compulting* 21, pp. 1181–1192.

Cerchiara, RR and V Demarco (2016). "Undertaking Specific Parameters under Solvency II: Reduction of Capital Requirements or Not?" In: *European Actuarial Journal* 6, pp. 351–376.

Cerra, V and SC Saxena (2017). *Booms, Crises, and Recoveries: A New Paradigm of the Business Cycle and Its Policy Implications*. IMF Working Paper, WP/17/250. International Monetary Fund.

CFRNZ (n.d.). *Regulatory Charter: Financial Markets Regulatory System*. New Zealand Council of Financial Regulators.

Chamberlain, D, A Camargo, and W Coetzee (2017). *Funding the Frontier: The Link Between Inclusive Insurance Market, Growth and Poverty Reduction in Africa*. Centre for Financial Regulation and Inclusion, published with FSDAfrica.

Chan-Lau, J, MA Espinosa-Vega, K Giesecke, and J Solé (2009). "Assessing the Systemic Implications of Financial Linkages". In: Global Financial Stability Report: Responding to the Financial Crisis and Measuring Systemic Risk, International Monetary Fund. Chap. 2.

Chang, T, C Lee, and C Chang (2014). "Does Insurance Activity Promote Economic Growth? Further Evidence Based on Bootstrap Panel Granger Causality Test". In: *The European Journal of Finance* 20.12, pp. 1187–1210.

Chatterjee, S and M Sing (2021). *Measuring Systemic Risk in South African Banks*. Working Paper Series WP/21/04. South African Reserve Bank.

Chatterjee, S and SJ Turnovsky (2012). "Infrastructure and Inequality". In: *European Economic Review* 56, pp. 1730–1745.

Checkley, MS (2009). "Inadvertent Systemic Risk in Financial Networks: Venture Capital and Institutional Funds". In: *Long Range Planning* 42.3, pp. 341–358.

Chen, H, JD Cummins, KS Viswanathan, and MA Weiss (2013). "Systemic Risk and the Interconnectedness between Banks and Insurers: An Econometric Analysis". In: *Journal of Risk and Insurance* 81.3, pp. 623–652.

Chen, H and T Sun (2019). "Tail Risk Networks of Insurers Around the World: An Empirical Examination of Systematic Risk for G-SIIs vs Non-G-SIIs". In: *Journal of Risk and Insurance* 86.1, pp. 1–345.

Chen, R and E Kemp (2023). *Lessons sfrom the United Kingdom's Liability-Driven Investment (LDI) Crisis*. Selected Issues Paper SIP/2023/049. International Monetary Fund.

Chen, S and S Desiderio (2022). "A Regression-Based Calibration Method for Agent-Based Models". In: *Computational Economics* 59, pp. 687–700.

Chen, Y (2014). "The Spatial Meaning of Pareto's Scaling Exponent of City-size Distributions". In: *Fractals* 22.1. 1450001–117.

Chen, Y and B Jiang (2014). "Hierarchical Scaling in Systems of Natural Cities". In: *Entropy* 20.6, pp. 432–488.

Chenyu, B, Y Haomiao, and Z Ning (2019). "How does the Supervision Stringency Affect Systemic Risk based on the Differential Dynamic Model?" In: *Systems Science & Control Engineering* 1.1, pp. 357–368.

Chinazzi, M and G Fagiolo (2013). *Systemic Risk, Contagion, and Financial Networks: A Survey*. LEM Working Paper Series, No. 2013/08, Scuola Superiore Sant'Anna. Laboratory of Economics and Management.

Christiansen, MC and A Niemeyer (2014). "Fundamental Definition of the Solvency Capital Requirement in Solvency II". In: *Astin Bulletin* 44.3, pp. 501–533.

Chuah, S and J Devlin (2011). "Behavioural Economics and Financial Services Marketing: A Review". In: *International Journal of Bank Marketing* 29.6, pp. 456–469.

Churchill, C (2008). "What is Insurance for the Poor?" In: *Protecting the Poor: A Microinsurance Compendium*. Ed. by C Churchill. New Delhi: International Labour Organization and The Academic Foundation, pp. 12–24.

Churchill, C and MJ McCord (2012). "Current Trends in Microinsurance". In: *Protecting the Poor: A Microinsurance Compendium, Volume II*. Ed. by C Churchill and M Matul. Geneva: International Labour Organization, pp. 8–39.

Čihák, M and R Podpiera (2006). *Is One Watchdog Better Than Three? International Experience with Integrated Financial Sector Supervision*. Working Paper 06/57. International Monetary Fund.

Cimini, G, T Squartini, N Musmeci, M Puliga, A Gabrielli, D Garlaschelli, S Battiston, and G Caldarelli (2015). "Reconstructing Topological Properties of Complex Networks using the Fitness Model". In: *Social Informatics. SocInfo 2014. Lecture Notes* *in Computer Science*. Ed. by L Aiello and D McFarland. Vol. 8852. Springer. DOI: 10.1007/978-3-319-15168-7_41.

Civan, Z, GG Simsek, and EC Akay (2020). "Identifying the systemically important banks of Turkey with the CoVaR method". In: *Heliyon* 6, e04790.

Claessens, S (2015). "An Overview of Macroprudential Policy Tools". In: *Annual Review of Financial Economics* 7, pp. 397–422.

Clarke DJ amd Mahul, O, R Poulter, and T The (2017). "Evaluating Sovereign Disaster Risk Finance Strategies: A Framework". In: *The Geneva Papers* 42, pp. 565–584.

Coates, JC (2015). "Cost-benefit Analysis of Financial Regulation: Case Studies and Implications". In: *The Yale Law Journal* 124, pp. 882–1011.

Cocco, JF, FJ Gomes, and NC Martins (2009). "Lending relationships in the interbank market". In: *Journal of Financial Intermediation* 18.1, pp. 24–48.

Cochrane, JC (2014). "Challenges for Cost-Benefit Analysis of Financial Regulation". In: *Journal of Legal Studies* 43, S63–S105.

Coglianese, C and D Lazer (2003). "Management-Based Regulation: Prescribing Private Management to Achieve Public Goals". In: *Law & Society Review* 37.4, pp. 691–730.

Cohen, M and J Sebstad (2008). "The Demand for Microinsurance". In: *Protecting the Poor: A Microinsurance Compendium*. Ed. by C Churchill. New Delhi: International Labour Organization and The Academic Foundation, pp. 25–44.

Cole, S, X Gine, and J Vickery (2013). *How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment*. Working Paper No. 13-080. Harvard Business School.

Colliard, J and C Georg (2020). *Measuring Regulatory Complexity*. HEC Paris Research Paper No. FIN-2020-1358. available at SSRN: https://ssrn.com/abstract=3523824.

Courtney, M, H Jiao, N Spellmeyer, and D Kleppner (1995). "Closed Orbit Bifurcations in Continuum Stark Spectra". In: *Physical Review Letters* 74.9, pp. 1538–1541.

Crawford, J (2017). "Credible Losers: A Regulatory Design for Prudent Market Discipline". In: *American Business Law Journal* 54.1, pp. 107–159.

Crawford, JD (1991). "Introduction to Bifurcation Theory". In: *Reviews of Modern Physics* 63.4, pp. 991–1037.

Crovelli, RA and CC Barton (1995). "Fractals and the Pareto Distribution Applied to Petroleum Accumulation-Size Distributions". In: *Fractals in Petroleum Geology and Earth Processes*. Ed. by CC Barton and PR Pointe. New York: Springer.

Cummins, D, M Cragg, B Zhou, and J De Fonseka (2018). *The Social and Economic Contributions of the Life Insurance Industry*. The Brattle Group.

Cummins, JD, S Harrington, and G Niehous (1993). "An Economic Overview of Risk-based Capital Requirements for the Property-liability Insurance Industry". In: *Journal of Insurance Regulation* 11.4, pp. 427–447.

Cummins, JD and MA Weiss (2009). "Convergence of Insurance and Financial Markets: Hybrid and Securitized Risk-Transfer Solutions". In: *Journal of Risk and Insurance* 76.3, pp. 493–554.

— (2013). *Systemic Risk and Regulation of the US Insurance Industry*. Working Paper. Temple University, Philadelphia.

— (2014). "Systemic Risk and the US Insurance Sector". In: *Journal of Risk and Insurance* 81.3, pp. 489–527.

Dafny, L, M Duggan, and S Ramanarayanan (2012). "Paying a Premium on Your Premium? Consolidation in the US Health Insurance Industry". In: *American Economic Review* 102.2, pp. 1161–1185.

Dash, S, RP Pradhan, RP Maradana, K Gaurav, DB Zaki, and M Jayakumar (2018). "Insurance Market Penetration and Economic Growth in Eurozone Countries: Time Series Evidence on Causality". In: *Future Business Journal* 4, pp. 50–67.

De Bandt, O and P Hartmann (2000). *Systemic Risk: A Survey.* Working Paper No. 35. European Central Bank.

De la Dehesa, G (2010). *Twelve Market and Government Failures Leading to the 2008–09 Financial Crisis.* Occasional Paper 80. Group of 30.

Deblon, Y and M Loewe (2012). "The Potential of Microinsurance for Social Protection". In: *Protecting the Poor: A Microinsurance Compendium, Volume II.* Ed. by C Churchill and M Matul. Geneva: International Labour Organization, pp. 40–58.

Dekker, E (2018). "Schumpeter: Theorist of the Avant-garde, The Embrace of the New in Schumpeter's Original Theory of Economic Development". In: *Review of Austrian Economics* 31, pp. 177–194.

Deloitte (2022). *Africa Insurance Outlook 2022: Navigating the Insurance Landscape.* Deloitte South Africa.

Demirgüç-Kunt, A and RE Levine (1999). *Bank-based and Market-based Financial Systems: Cross-country Comparisons.* Policy Research Working Paper No. 2143. World Bank.

Dercon, S and L Christiaensen (2007). *Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia.* Policy Research Working Paper 4257. World Bank.

Detzer, D (2014). *The German Financial System and the Financial Crisis.* Financial Systems in Financial Crisis – An Analysis of Banking Systems in the EU, Intereconomics 2014 (2). ZBW – Leibniz Information Centre for Economics.

Di Gangi, D, F Lillo, and D Pirino (2018). "Assessing Systemic Risk due to Fire Sales Spillover through Maximum Entropy Network Reconstruction". In: *Journal of Economic Dynamica and Control* 94, pp. 117–141.

Di Noia, C and G Di Giorgio (1999). "Should Banking Supervision and Monetary Policy Tasks be Given to Different Agencies?" In: *International Finance* 2.3, pp. 361–378.

Dickinson, G (1998). "The Economic Role of the Insurance Sector in the Risk Transfer-Capital Market Nexus". In: *The Geneva Papers* 23, pp. 519–529.

Dijkman, M (2010). *A Framework for Assessing Systemic Risk.* Policy Research Working Paper 5282. World Bank.

Dimić, M, L Barkajtarović, O Arsenijević, Šprajcm P, and J Zirovnik (2018). "Measuring the Concentration of Insurance Sector – the Case of Southeastern European Countries". In: *Organizacija* 51.1, pp. 50–64.

Din, SMU, A Abu-Bakar, and A Regupathi (2017). "Does Insurance Promote Economic Growth: A Comparative Study of Developed and Emerging/Developing Economies". In: *Cogent Economics and Finance* 5, 1390029.

DNB (2016). *Solvency II: A New Framework for Prudential Supervision of Insurance Companies*. De Nederlandse Bank.

Doff, R (2008). "A Critical Analysis of the Solvency II Proposals". In: *The Geneva Papers* 33, pp. 193–206.

— (2016). "The Final Solvency II Framework: Will it be Effective?" In: *The Geneva Papers* 41, pp. 587–607.

Drijfhout, S, S Bathiany, C Beaulieu, V Brovkin, M Claussen, C Huntingford, M Scheffer, G Sgubin, and D Swingedouw (2015). "Abrupt Shifts in IPCC climate models". In: *Proceedings of the National Academy of Sciences* 112.43, E5777–E5786.

ECB (2010). *Macro-prudential Policy Objectives and Tools*. Financial Stability Review. European Central Bank, pp. 129–137.

— (2012). *The Interplay of Financial Intermediaries and its impact on Monetary Analysis*. Monthly Bulletin. European Central Bank, pp. 59–73.

Ehlers, T and A Villar (2015). "The Role of Banks". In: *What do New Forms of Finance Mean for EM Central Banks*. BIS Papers, No. 83. Bank for International Settlements, pp. 9–40.

EIOPA (2017). *The Interplay of Financial Intermediaries and its impact on Monetary Analysis*. European Insurance and Occupational Pensions Authority, Publications Office of the European Union.

— (2018). *Failures and Near Misses in Insurance: Overview of the Causes and Early Identification*. European Insurance and Occupational Pensions Authority, Publications Office of the European Union.

— (2019a). *2020 Review of Solvency II*. European Insurance and Occupational Pensions Authority, Publications Office of the European Union.

— (2019b). *Consultation Paper on the Opinion on the 2020 Review of Solvency II*. European Insurance and Occupational Pensions Authority, Publications Office of the European Union.

Elderfield, M (2009). "Solvency II: Setting the Pace for Regulatory Change". In: *The Geneva Papers* 34, pp. 35–41.

Eling, M and I Holzmüller (2008). "An Overview and Comparison of Risk-based Capital Standards". In: *Journal of Insurance Regulation* 26.4, pp. 31–60.

Eling, M and DA Pankoke (2016). "Systemic Risk in the Insurance Sector: A Review and Directions for Future Research". In: *Risk Management and Insurance Review* 19.2, pp. 249–284.

Eling, M, H Schmeiser, and JT Schmit (2007). "The Solvency II Process: Overview and Critical Analysis". In: *Risk Management and Insurance Review* 10.1, pp. 69–85.

Ellis, S, S Sharma, and J Brzeszczyński (2022). "Systemic Risk Measures and Regulatory Challenges". In: *Journal of Financial Stability* 61, 100960.

Ellul, A, C Jotikasthira, CT Lundblad, and Wang Y (2014). "Mark-to-market Accounting and Systemic Risk: Evidence from the Insurance Industry". In: *Economic Policy* 29.78, pp. 297–341.

Elyasiani, E, SK Staikouras, and P Dontis-Charitos (2015). "Cross-industry Product Diversification and Contagion in Risk and Return: The Case of Bank-Insurance and Insurance-Bank Takeovers". In: *Journal of Risk and Insurance* 83.3, 681–718.

Enz, R (2010). "The S-Curve Relation Between Per-capita Income and Insurance Penetration". In: *The Geneva Papers* 25.3, pp. 396–406.

Erdös, P and A Rényi (1959). "On random graphs". In: *Publicationes Mathematicae* 6, pp. 290–297.

Erskine, A (2014). *Regulating the Australian Financial System.* Funding Australia's Future. Australian Centre for Financial Studies.

ESRB (2018). *Macroprudential Provisions, Measures and Instruments for Insurance.* European Systemic Risk Board, European System of Financial Supervision, November.

— (2020). *Enhancing the Macroprudential Dimension of Solvency II.* European Systemic Risk Board, European System of Financial Supervision, November.

EU (2002). *Prudential Supervision of Insurance Undertakings.* Conference of the Insurance Supervisory Services of the Member States of the European Union, prepared under the chairmanship of Paul Sharma, Head of the Prudential Risks Department of the United Kingdom Financial Services Authority. European Union.

— (2009). *Directive 2009/138/EC of the European Parliament and of the Council.* 25 November 2009, on the taking-up and pursuit of the business of Insurance and Reinsurance (Solvency II). Official Journal of the European Union.

— (2014). *Directive 2014/51/EU of the European Parliament and of the Council.* 6 April 2014, amending Directives 2003/71/EC and 2009/138/EC and Regulations (EC) No 1060/2009, (EU) No 1094/2010 and (EU) No 1095/2010 in respect of the powers of EIOPA and ESMA. Official Journal of the European Union.

Falconer, K (2014). *Fractal Geometry: Mathematical Foundations and Applications.* New York Academy of Sciences Series. Nework: John Wiley Sons.

Falkena, H, R Bamber, D Llewellyn, and T Store (2001). *Financial Regulation in South Africa.* South African Financial Sector Forum.

Fama, EF and KR French (1993). "Common Risk Factors in the Returns on Stocks and Bonds". In: *Journal of Financial Economics* 33.1, pp. 3–56.

— (2004). "The Capital Asset Pricing Model: Theory and Evidence". In: *Journal of Economic Perspectives* 18.3, pp. 25–46.

Fay, C and N Parent (2004). "The Organizational Structure of Financial Market Regulation: Highlights from the Literature". In: *Financial System Review* June 2004, pp. 53–60.

FCA (2013). *How the Financial Conduct Authority will investigate and report on regulatory failure.* Financial Conduct Authority, United Kingdom.

Feasibility (2010). *Treating Customers Fairly: A Discussion Paper Prepared for the Financial Services Board.* Financial Services Board, South Africa.

Fell, J and G Schinasi (2005). "Assessing Financial Stability: Exploring the Boundaries of Analysis". In: *National Institute Economic Review* 192, pp. 102–117.

Fidrmuc, J and R Lind (2018). "Macroeconomic Impact of Basel III: Evidence from a Meta-analysis". In: *Journal of Banking and Finance* 55, pp. 234–245.

Financial Stability Committee (2022). *Financial Stability Report: December 2022.* Bank of England.

Floreani, A (2013). "Risk Measures and Capital Requirements: A Critique of the Solvency II Approach". In: *The Geneva Papers* 38, pp. 189–212.

FMT (2015). *FinScope South Africa 2015*. FinMark Trust, South Africa.

— (2018). *How South Africans are Leveraging Informal and Formal Financial Markets*. FinMark Trust, South Africa.

Foggitt, GM, A Heymans, GW Van Vuuren, and A Pretorius (2017). "Measuring the systemic risk in the South African banking sector". In: *South African Journal of Economic and Management Sciences* 20.1, a1619.

Fohlin, C (2014). *Financial Systems and Economic Development in Historical Perspective*. available at ssrn.com/abstract=2524109, published in 2016 as Diebolt, C and Haupert, M (Eds.) 'Financial Systems', in 'Handbook of Cliometrics', Springer-Verlag, Berlin, Heidelberg.

Fong, T, L Fung, Lam L, and I Yu (2009). *Measuring the Interdependence of Banks in Hong Kong*. Working Paper 19/2009. Hong Kong Monetary Authority.

Foroughi, K (2012). "Market-consistent Valuations and Solvency II: Implications of the Recent Financial Crisis". In: *British Actuarial Journal* 17.1, pp. 18–65.

Founargiotakis, M, SC Farantos, Ch Skokos, and G Contopoulos (1997). "Bifurcation Diagrams of Periodic Orbits for Unbound Molecular Systems: FH_2". In: *Chemical Physics Letters* 277, pp. 456–464.

Freixas, X, BM Parigi, and J Rochet (2000). "Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank". In: *Journal of Money, Credit and Banking* 32.3, pp. 611–638.

Fricke, D and T Lux (2015). "Core-periphery structure in the overnight money market: evidence from the e-MID trading platform". In: *Computational Economics* 45.3, pp. 359–395.

Frölich, A and A Weng (2015). "Modelling Parameter Uncertainty for Risk Capital Calculation". In: *European Actuarial Journal* 5, pp. 79–112.

— (2018). "Parameter Uncertainty and Reserve Risk under Solvency II". In: *Insurance: Mathematics and Economics* 81, pp. 130–141.

FSA (2006). *A Guide to Market Failure Analysis and High Level Cost Benefit Analysis*. Financial Services Authority, United Kingdom.

— (2007). *Principles-based regulation: Focusing on the outcomes that matter*. Financial Services Authority, United Kingdom.

— (2012). *Journey to the FCA: To Make Financial Markets Work Well so Customers get a Fair Deal*. Financial Services Authority, United Kingdom.

FSB (2010). *Solvency Assessment and Management Roadmap, version 1*. Financial Services Board, South Africa.

— (2020). *Peer Review of South Africa: Review Report*. Financial Stability Board.

FSCA (2018). *Regulatory Strategy of the Financial Sector Conduct Authority: October 2018 to September 2021*. Financial Sector Conduct Authority, South Africa.

Fung, DWH and JJH Yeh (2018). "Is the New Regulation Successful in Reducing Systemic Risk of Global Systemically Important Insurers? Empirical Evidence from Insurers around the Globe". In: *Journal of Insurance Issues* 41.1, pp. 1–54.

Furceri, D and A Mourougane (2009). *Financial Crises: Past Lessons and Policy Implications*. OECD Economics Department Working Papers 668. OECD Publishing.

Gai, P, A Haldane, and S Kapadia (2010). “Complexity, concentration and contagion”. In: *Journal of Monetary Economics* 58.5, pp. 453–470.

Gai, P and S Kapadia (2010). “Contagion in Financial Networks”. In: *Proceedings of the Royal Society of London: Mathematical, Physical and Engineering Sciences* 466.2120, pp. 2401–2423.

Galati, G and R Moessner (2014). *What do we know about the Effects of Macroprudential Policy?* DNB Working Paper No. 440. DeNederlandscheBank.

Garcia, MTM (2012). “Determinants of the Property-liability Insurance Market: Evidence from Portugal”. In: *Journal of Economic Studies* 39.4, pp. 440–450.

Garratt, RJ, L Mahadeva, and K Svirydzenka (2011). *Mapping systemic risk in the international banking network*. Working Paper No. 413. Bank of England.

Gatzert, N and H Wesker (2012). “A Comparative Assessment of Basel II/III and Solvency II”. In: *The Geneva Papers* 37, pp. 539–570.

Gauthier, C, A Lehar, and M Souissi (2012). “Macroprudential capital requirements and systemic risk”. In: *Journal of Financial Intermediation* 21, pp. 594–618.

Geneva Association (2010a). *An Account of the Geneva Association’s Ongoing Dialogue on Systemic Risk with Regulators and Policymakers*. Special Report of The Geneva Association Systemic Risk Working Group. The Geneva Association.

— (2010b). *Systemic Risk in Insurance: An Analysis of Insurance and Financial Stability*. Special Report of The Geneva Association Systemic Risk Working Group. The Geneva Association.

— (2011). *Variable Annuities with Guarantees and Use of Hedging*. The Geneva Association.

Georg, C (2011). *Basel III and Systemic Risk Regulation - What Way Forward?* Working Papers on Global Financial Markets No. 17. Universität Jena und Universität Halle-Wittenberg.

— (2013). “The Effect of the Interbank Network Structure on Contagion and Common Shocks”. In: *Journal of Banking & Finance* 37, pp. 2216–2228.

Georg, C and N Brink (2011). *Note on interlinkages in the South African interbank system*. Financial Stability Review, March 2011. South African Reserve Bank.

Ghosh, A (2013). “Does Life Insurance Activity Promote Economic Development in India: An Empirical Analysis”. In: *Journal of Asia Business Studies* 7.1, pp. 31–43.

Giglio, S (2016). *Credit Default Swap Spreads and Systemic Financial Risk*. Working Paper Series No. 15.

Gilligan, G (1992). “Historical Touchstones in the Regulation of the Financial Services Sector: The Evolution of Financial Services Regulation”. In: *Journal of Financial Regulation and Compliance* 1.1, pp. 63–71.

Gillingham, K and J Sweeney (2010). “Market Failure and the Structure of Externalities”. In: *Harnessing Renewable Energy in Electric Power Systems: Theory, Practice & Policy*. Ed. by B Moselle, J Padilla, and R Schmalensee. Abingdon and New York: Taylor & Francis.

Gintis, H (1981). *Game Theory Evolving: A Problem-Centred Introduction to Modelling Strategic Interaction*. 2nd ed. Princeton, Oxford: Princeton University Press.

Gladwell, M (2000). *The Tipping Point: How Little Things can Make a Big Difference*. Little, Brown: New York.

Godwin, AJ and A Schmulow (2015). "Financial Sector Regulation Bill in South Africa, Second Draft: Lessons from Australia". In: *The South African Law Journal* 132.4, pp. 756–768.

Goodhard, C, P Hartmann, D Llewellyn, L Rojas-Suarez, and S Welsbrod (1998). *Financial Regulation Why, How and Where Now?* London: Routledge.

Goodhart, C and D Schoenmaker (1992). "Institutional Separation between Supervisory and Monetary Agencies". In: *Giornale degli Economisti e Annali di Economia* 9, pp. 353–439.

Gordon, JN (2014). "The Empty Call for Benefit-Cost Analysis in Financial Regulation". In: *The Journal of Legal Studies* 43.S2, S351–S378.

Grace, MF, J Rauch, and S Wende (2013). *Systemic Risk and Interconnectedness in the Financial Industry: Implications on Regulation of Financial Conglomerates*. Working Paper. Georgia State University, Atlanta.

Grant, E (2012). *The Social and Economic Value of Insurance*. The Geneva Association.

Grochulski, B and W Morrison (2014). *Understanding Market Failure in the 2007-08 Crisis*. Economic Brief 14-12. Federal Reserve Bank of Richmond.

Group of Ten (2001). *Report on Consolidation in the Financial Sector*. Group of Ten, Bank for International Settlements, International Monetary Fund, the Organisation for Economic Cooperation & Development.

Group of Thirty (2008). *The Structure of Financial Supervision: Approaches and Challenges in a Global Marketplace*. Group of Thirty, Washinton, D.C.

Guleva, VY (2020). *Estimation of Tipping Poitns for Critical and Transitional Regimes in the Evolution of Complex Interbank Network*. LNCS12137. International Conference on Computational Science, pp. 432–444.

Guochen, PAN and SU Chi Wei (2012). *The Relationship between Insurance Development and Economic Growth: A Cross-Region Study for China*. China International Conference on Insurance and Risk Management, July 18-21, Qingdao, China.

Gyong, JE (2011). "Good Governance and Accountability in a Democracy". In: *European Scientific Journal* 7.12, pp. 71–89.

Haiss, P and K Sümegi (2008). "The Relationship between Insurance and Economic Growth in Europe: A Theoretical and Empirical Analysis". In: *Empirica* 35, pp. 405–431.

Haley, JD and KJ Sigler (1996). "Contagion Effects in the Life Insurance Industry Spring and Summer 1991". In: *Managerial Finance* 22.3, pp. 11–27.

Han, L, D Li, F Moshirian, and Y Tian (2010). "Insurance Development and Economic Growth". In: *The Geneva Papers* 35, pp. 183–199.

Hansen, LP (2013). *Challenges in Identifying and Measuring Systemic Risk*. BFI Working Paper Series No. 2012-012. Becker Friedman Institute for Research in Economics, University of Chicago.

Harrington, SE (2009). "The Financial Crisis, Systemic Risk, and the Future of Insurance Regulation". In: *Journal of Risk and Insurance* 76.4, pp. 785–819.

Hauton, G and J Héam (2015). "Interconnectedness of Financial Conglomerates". In: *Risk* 3, pp. 139–163.

Hautsch, N, J Schaumburg, and M Schienle (2015). "Financial Network Systemic Risk Contributions". In: *Review of Finance* 19.2, pp. 685–738.

He, X, X Pan, KM Tan, and W Zhou (2023). "Smoothed Quantile Regression with Large-scale Inference". In: *Journal of Econometrics* 232, pp. 367–388.

Healy, PM and KG Palepu (2001). "Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure Literature". In: *Journal of Accounting and Economics* 31, pp. 405–440.

Ho, TSY, M Palacios, and HR Stoll (2013). *Dynamic Financial System: Complexity, Fragility and Regulatory Principles*. Financial Markets, Institutions & Instruments, Topics in Financial Intermediation. New York University Salomon Center, with Wiley Periodicals.

Hoadley, JC (1884). "A Tilting Water Meter for Purposes of Experiment". In: *Journal of The Franklin Institute* 117, pp. 273–78.

Holling, CS (1973). "Resilience and Stability of Ecological Systems". In: *Annual Review of Ecology and Systematics* 4, pp. 1–23.

Holzmüller, I (2009). "The United States RBC Standards, Solvency II and the Swiss Solvency Test: A Comparative Assessment". In: *The Geneva Papers* 39, pp. 56–77.

Huang, X, H Zhou, and H Zhu (2012a). "Assessing the systemic risk of a heterogeneous portfolio of banks during the recent financial crisis". In: *Journal of Financial Stability* 8.3, pp. 193–205.

— (2012b). "Systemic Risk Contributions". In: *Journal of Financial Services Research* 42, pp. 55–83.

Hufeld, F, RSJ Koijen, and C Thimann (2017). *The Invisible Service: The Economics, Regulation and Systemic Risk of Insurance Markets*. VOX. CEPR Policy Portal.

Hüser, A (2016). *Too Interconnected to Fail: A Survey of the Interbank Networks Literature*. SAFE Working Paper Series 91. Leibniz Institute for Financial Research.

Hussels, S, D Ward, and R Zurbruegg (2005). "Stimulating the Demand for Insurance". In: *Risk Management and Insurance Review* 8.2, pp. 257–278.

IAIS (2009). *Systemic Risk and the Insurance Sector*. International Association of Insurance Supervisors.

— (2010). *Position Statement on Key Financial Stability Issues*. International Association of Insurance Supervisors.

— (2011). *Insurance and Financial Stability*. International Association of Insurance Supervisors.

— (2012a). *Globally Systemically Important Insurers: Proposed Assessment Methodology*. International Association of Insurance Supervisors.

— (2012b). *Reinsurance and Financial Stability*. International Association of Insurance Supervisors.

— (2013). *Globally Systemically Important Insurers: Policy Measures*. International Association of Insurance Supervisors.

IAIS (2015). *Capital Requirements for Global Systemically Important Insurers: Basic Capital Requirements and Higher Loss Absorbency*. International Association of Insurance Supervisors.

— (2018a). *Holistic Framework for Systemic Risk in the Insurance Sector, Public Consultation Document*. International Association of Insurance Supervisors.

— (2018b). *IAIS Global Insurance Market Report 2017*. International Association of Insurance Supervisors.

— (2019). *Holistic Framework for Systemic Risk in the Insurance Sector*. International Association of Insurance Supervisors.

Ibragimov, R, D Jaffee, and J Walden (2011). "Diversification Disasters". In: *Journal of Financial Economics* 99, pp. 333–348.

Idier, J, G Lamé, and J Mésonnier (2014). "How useful is the Marginal Expected Shortfall for the measurement of systemic exposure? A practical assessment". In: *Journal of Banking & Finance* 47, pp. 134–146.

IFRS Foundation (2017). *IFRS17: Insurance Contracts*. International Accounting Standards Board.

IMF (2008). *South Africa: Financial System Stability Assessment*. Country Report No. 08/349, including report on the observance of standards and codes on the following topic: Securities Regulation. International Monetary Fund.

— (2009). *Global Financial Stability Report: Responding to the Financial Crisis and Measuring Systemic Risks*. International Monetary Fund.

— (2013). *Key Aspects of Macroprudential Policy*. International Monetary Fund.

— (2014a). *South Africa Financial System Stability Assessment*. Country Report No. 14/340. International Monetary Fund.

— (2014b). *Staff Guidance Note on Macroprudential Policy*. International Monetary Fund.

— (2015a). *South Africa Financial Sector Assessment Program: Detailed Assessment of Compliance on the Basel Core Principles for Effective Banking Supervision*. Country Report No. 15/55. International Monetary Fund.

— (2015b). *South Africa Financial Sector Assessment Program: Detailed Assessment of Observance on the Insurance Core Principles*. Country Report No. 15/56. International Monetary Fund.

— (2015c). *South Africa Financial Sector Assessment Program: Stress Testing the Financial System–Technical Note*. Country Report No. 15/54. International Monetary Fund.

— (2018). *The IMF's Annual Macroprudential Policy Survey – Objectives, Design and Country Responses*. International Monetary Fund.

— (2022a). *2021 Article IV Consultation - Press Release; Staff Report and Statement by the Executive Director for South Africa*. Country Report No. 22/37. International Monetary Fund.

— (2022b). *Detailed Assessment of Observance of Insurance Core Principles Issued by the International Association of Insurance Supervisors*. United Kingdom Country Report No. 22/109, Financial Sector Assessment Program. International Monetary Fund.

— (2022c). *South Africa 2021 Article IV Consultation - Press Release; Staff Report; and Statement by the Executive Director for South Africa*. Country Report No. 22/37. International Monetary Fund.

— (2022d). *South Africa Financial Sector Assessment Program: Technical Note on Banking Regulation and Supervision*. Country Report No. 22/184. International Monetary Fund.

— (2022e). *South Africa Financial Sector Assessment Program: Technical Note on Systemic Risk Oversight and Macroprudential Policy*. Country Report No. 22/186. International Monetary Fund.

— (2022f). *South Africa Financial System Stability Assessment*. Country Report No. 22/39. International Monetary Fund.

IMF et al. (2009). *Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations, Report to the G-20 Finance Ministers and Central Bank Governors*. International Monetary Fund, the Bank for International Settlements, and the Secretariat of the Financial Stability Board.

In't Veld, D and I Van Lelyveld (2014). "Finding the core: Network structure in interbank markets". In: *Journal of Banking & Finance* 49, pp. 27–40.

Inaoka, H, Ninomiya T, K Taniguchi, T Shimizu, and H Takayasu (2004). *Fractal Network derived from banking transaction - An analysis of network structures formed by financial institutions*. Working Paper Series No. 04-E-04. Bank of Japan.

Insurance Europe (2019). *Annual Report 2018-2019*. Insurance Europe.

Iori, G, G De Masi, OV Precup, Gabbi G, and G Caldarelli (2008). "A network analysis of the Italian overnight money market". In: *Journal of Economic Dynamics & Control* 32.1, pp. 259–278.

Jacquier, C, G Ramm, P Marcadent, and V Schmitt-Diabate (2008). "The Social Protection Perspective on Microinsurance". In: *Protecting the Poor: A Microinsurance Compendium*. Ed. by C Churchill. New Delhi: International Labour Organization and The Academic Foundation, pp. 45–64.

Janzen, SA and MR Carter (2018). "After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection". In: *American Journal of Agricultural Economics* 101.3, pp. 651–671.

Jobst, AA (2014). "Systemic Risk in the Insurance Sector: A Review of Current Assessment Approaches". In: *The Geneva Papers* 39, pp. 440–470.

Johnson, EJ, J Hershey, J Meszaros, and H Kunreuther (1993). "Framing, Probability Distortions and Insurance Decisions". In: *Journal of Risk and Uncertainty* 7, pp. 35–51.

Kafková, E, D Vološinová, and Z Bosáková (2005). "Development of Key Macroeconomic Indicators and Commercial Insurance in V4 Countries in 1995-2004, Part 2, Slovak Republic". In: *BIATEC* 13.9, pp. 16–20.

Kämpke, T (2015). "Pareto Distribution, Self-similarity and Empirics". In: *Income Modeling and Balancing: A Rigorous Treatment of Distribution Patterns*. Ed. by T Kämpke and FJ Radermacher. Springer Cham, pp. 103–128. DOI: 10.1007/978-3-319-13224-2.

Kanno, M (2016). "The Network Structure and Systemic Risk in the Global Non-life Insurance Market". In: *Insurance: Mathematics and Economics* 67, pp. 38–53.

Karagueuziah, HS, H Stepanyan, and WJ Mandel (2013). "Bifurcation Theory and Cardiac Arrhythmias". In: *American Journal of Cardiovascular Disease* 3.1, pp. 1–16.

Karlan, D, R Osei, I Osei-Akoto, and C Udry (2014). "Agricultural Decisions after Relaxing Credit and Risk Constraints". In: *Quarterly Journal of Economics* 129.2, pp. 597–652.

Kaserer, C and C Klein (2019). "Systemic Risk in Financial Markets: How Systemically Important are Insurers?" In: *Journal of Risk and Insurance* 86.3, pp. 729–759.

Kessler, D (2014). "Why (Re)insurance is Not Systemic". In: *Journal of Risk and Insurance* 81.3, pp. 477–487.

Kessler, D, A De Montchalin, and C Thimann (2016). *Insurance and Economic Development: Growth, Stabilization and Distribution*. Impact Insurance, Paper No. 46. Internal Labour Organization.

Khwaja, AI and A Mian (2011). "Rent Seeking and Corruption in Financial Markets". In: *Annual Review of Economics* 3, 579600.

Kim, Y (2011). "International Policy Coordination Mechanism with respect to the Moral Hazards of Financial Intermediaries". In: *Economic Modelling* 28, pp. 1914–1922.

Klein, RW (2012a). *Insurance Regulation and the Challenge of Solvency II: Modernizing the System of US Solvency Regulation*. National Association of Mutual Insurance Companies.

— (2012b). "Principles for Insurance Regulation: An Evaluation of Current Practices and Potential Reforms". In: *The Geneva Papers* 37, pp. 175–199.

— (2013). "Insurance Market Regulation: Catastrophe Risk, Competition and Systemic Risk". In: *Handbook of Insurance*. Ed. by G Dionne. 2nd ed. New York: Springer, pp. 909–939.

Klinger, T and P Teply (2015). "The Nexus Between Systemic Risk and Sovereign Crises". In: *Journal of Economics and Finance* 66.1, pp. 50–69.

Knot, K (2014). *Governance of Macroeconomic Policy*. Macroprudential Policies: Implementation and Interactions, Financial Stability Review. Banque de France.

Koenker, R (2005). *Quantile Regression*. Cambridge University Press.

Koenker, R and JAF Machado (1999). "Goodness of Fit and Related Inference Processes for Quantile Regression". In: *Journal of the American Statistical Association* 94.448, pp. 1296–1310.

Koijen, RSJ and M Yogo (2017). *Risk of Life Insurers: Recent Trends and Transmission Mechanisms*. Working Paper No. 23365. National Bureau of Economic Research.

Komai, A and G Richardson (2011). *A Brief History of Regulations Regarding Financial Markets in the United States 1789 to 2009*. Working Paper 17443. National Bureau of Economic Research, Cambriedge, MA.

Kostanjcar, Z, S Begusic, HE Stankey, and B Podobnik (2016). "Estimating Tipping Points in Feedback-Driven Financial Networks". In: *IEEE Journal of Selected Topics in Signal Processing* 10.6, pp. 1040–1052.

Kostić, M, L Maksimović, and B Stojanović (2016). "The Limitations of Competition in the Insurance Markets of Slovenia, Croatia and Serbia". In: *Economic Research-Ekonomska Istraživanja* 29.1, pp. 395–418.

KPMG (2022). *The South African Insurance Industry Survey 2022*. KPMG South Africa.

Kramaric, TP and M Kitić (2012). "Comparative Analysis of Concentration in Insurance Markets in New EU Member States". In: *World Academy of Science, Engineering and Technology, International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering* 6, pp. 1322–1326.

Krause, A and S Giansante (2012). "Interbank lending and the spread of bank failures: A network model of systemic risk". In: *Journal of Economic Behaviour & Organization* 83.3, pp. 583–608.

Kugler, M and R Ofoghi (2005). *Does Insurance Promote Economic Growth? Evidence from the UK*. Paper presented at the Money Macro and Finance Research Group Conference, United Kingdom.

Kuznetsov, YA (1997). *Elements of Applied Bifurcation Theory*. Springer-Verlag: New York.

Laas, D and C Siegel (2017). "Basel Accords versus Solvency II: An Analysis of Regulatory Consistency under the new Capital Standards". In: *Journal of Risk and Insurance* 84.4, pp. 1231–1267.

Laffont, J and D Martimort (2002). *The Theory of Incentives – The Principal-Agent Model*. Princeton: Princeton University Press.

Lakonishok, J and A Shapiro (1984). "Stock Returns, Beta, Variance and Size: An Empirical Analysis". In: *Financial Analysts Journal* 40.3, pp. 36–41.

Landau, L (1936). "The Theory of Phase Transitions". In: *Nature* 138, pp. 840–841.

Langfield, S and K Soramäki (2014). "Interbank Exposure Networks". In: *Computational Economics* 47, pp. 3–17.

Lee, C, W Huang, and C Yin (2013). "The Dynamic Interactions among the Stock, Bond and Insurance Markets". In: *North American Journal of Economics and Finance* 26, pp. 28–52.

Lee, SH (2013). "Systemic liquidity shortages and interbank network structures". In: *Journal of Financial Stability* 9.1, pp. 1–12.

Leitner, Y (2005). "Financial Networks: Contagion, Commitment, and Private Sector Bailouts". In: *The Journal of Finance* 60.6, pp. 2925–2953.

Leland, WE, MS Taqqu, W Willinger, and DV Wilson (1994). "On the Self-similar Nature of Ethernet Traffic (extended version)". In: *IEEE/ACM Transactions on Networking* 2, pp. 1–15.

Lenton, TM (2013). "Environmental Tipping Points". In: *Annual Review of Environment and Resources* 38, pp. 1–29.

Lenton, TM, H Held, E Kriegler, JW Hall, W Lucht, S Rahmstorf, and HJ Schellnhuber (2008). "Tipping Elements in the Earth's Climate System". In: *Proceedings of the National Academy of Sciences* 105.6, pp. 1786–1793.

Lenton, TM, J Rockstrom, O Gaffney, S Rahmsdorf, K Richardson, W Steffen, and HJ Schellnhuber (2019). "Climate Tipping Points - Too Risky to Bet Against". In: *Nature* 575, pp. 592–595.

Lenzu, S and G Tedeschi (2012). "Systemic risk on different interbank network topologies". In: *Physica A: Statistical Mechanics and its Applications* 391.18, pp. 4331–4341.

Leukes, C and J Odei-Mensah (2019). "Systemic risk contribution of financial institutions in South Africa". In: *African Review of Economics and Finance* 11.2, pp. 188–218.

Levine, R (2002). *Bank-based or Market-based Financial Systems: Which is Better?* Working Paper 9138. National Bureau of Economic Research.

Levy-Carciente, S, DY Kenett, A Avakian, HE Stanley, and S Havlin (2015). "Dynamical Macroprudential Stress Testing using Network Theory". In: *Journal of Banking & Finance* 59, pp. 164–181.

Li, D, F Moshirian, P Nguyen, and T Wee (2007). "The Demand for LIfe Insurance in OECD Countries". In: *Journal of Risk and Insurance* 74.3, pp. 637–652.

Liedtke, PM (2007). "What's Insurance to a Modern Economy?" In: *The Geneva Papers* 32.2, pp. 211–221.

Lim, C, F Columba, A Costa, P Kongsamut, A Otani, M Saiyid, T Wezel, and X Wu (2011). *Macroprudential Policy: What Instruments and How to Use Them?* Working Paper, WP/11/238. International Monetary Fund.

Lintner, J (1965). "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets". In: *Review of Economics and Statistics* 47.1, pp. 13–37.

Liu, G, L He, Y Yue, and J Wang (2014). "The Linkage between Insurance Activity and Banking Credit: Some Evidence from Dynamic Analysis". In: *North American Journal of Economics and Finance* 29, pp. 239–265.

Liu, S, R Jia, Y Zhao, and Q Sun (2019). "Global Consistent or Market-orientated? A Quantitative Assessment of RBC Standards, Solvency II and C-ROSS". In: *Pacific-Basin Finance Journal* 57, 101073.

Llewellyn, DT (1999). *The Economic Rationale for Financial Regulation*. Occasional Paper Series No. 1. Financial Services Authority.

— (2006). *Institutional Structure of Financial Regulation and Supervision: The Basic Issues*. World Bank seminar: Aligning Supervisory Structures with Country Needs.

Lopreato, J (1973). "Notes on the Work of Vilfredo Pareto". In: *Social Science Quarterly;* 54.3, pp. 451–468.

Lucas, RE (1988). "On the Mechanics of Economic Development". In: *Journal of Monetary Economics* 22, pp. 3–42.

Mandelbrot, B (1963). "The Variation of Certain Speculative Prices". In: *Journal of Business of the University of Chicago* 36, pp. 394–411.

— (1965). "Self-similar Error Clusters in Communication Svstems and the Concept of Conditional Stationarity". In: *IEEE Transactions on Communication Technology* 13, pp. 71–90.

— (1967). "How Long is the Coast of Britain? Statistical Self-Similarity and Fractional Dimension". In: *Science* 156.3775, pp. 636–638.

— (1981). "Fractals and Self Similarity". In: *Indiana University Mathematics Journal* 30.5, pp. 713–747.

— (1983). *The Fractal Geometry of Nature*. New York: WH Freeman.

Manguzvane, M and JWM Mwamba (2019). "Modelling systemic risk in the South African banking sector using CoVaR". In: *International Review of Applied Economics* 33.5, pp. 624–641.

Markham, J (2000). "Banking Regulation: Its History and Future". In: *North Carolina Banking Institute* 4.1, pp. 211–286.

Markowitz, H (1952). "Portfolio Selection". In: *Journal of Finance* 7.1, pp. 77–91.

Martin, M (2013). "Assessing the Model Risk with Respect to the Interest Rate Term Structure under Solvency II". In: *Journal of Risk Finance* 14.3, pp. 200–233.

Martínez-Alier, J (2012). "Social Metabolism, Environmental Cost-Shifting and Valuation Languages". In: *Towards an Integrated Paradigm in Heterodox Economics*. Ed. by Gerber JF and R Steppacher. London: Palgrave Macmillan.

Martinez-Jaramillo, S, B Alexandrova-Kabadjova, B Bravo-Benitez, and JP Solórzano-Margain (2015). "An empirical study of the Mexican banking system's network and its implications for systemic risk". In: *Journal of Economic Dynamics & Control* 20, pp. 70–81.

MAS (2015). *Objectives and Principles of Financial Supervision in Singapore*. April 2004, revised in September 2015. Monetary Authority of Singapore.

May, RM and N Arinaminpathy (2010). "Systemic Risk: The Dynamics of Model Banking Systems". In: *Journal of the Royal Society Interface* 7, pp. 823–838.

McLeod, HD (2005). "Mutuality and Solidarity in Healthcare in South Africa". In: *South African Actuarial Journal* 5, pp. 135–167.

Merton, RC (1995). "A Functional Perspective of Financial Intermediation". In: *Financial Management* 24.2, pp. 23–41.

Michael, B, Goo S, and S Osaulenko (2010). "Does Objectives-based Financial Regulation Imply a Rethink of Legislatively Mandated Economic Regulation? A Literature Review". In: *Journal of Legislation* 46.2, pp. 245–275.

Milkoreit, M, J Hodbod, J Baggio, K Benessaiah, R Calderón-Contreras, JF Donges, D Mathias, JC Rocha, M Schoon, and SE Werners (2018). "Defining Tipping Points for Social-ecological Systems Scholarship - An Interdisciplinary Literature Review". In: *Environmental Research Letters* 13.033005.

Minderhoud, K (2003). *Extreme Stock Return Co-movements of Financial Institutions: Contagion or Interdependence?* MEB Serie No. 2003-16. De Nederlandsche Bank.

Minoiu, C, C Kang, VS Subrahmanian, and Berea A (2013). *Does Financial Connectedness Predict Crises?* IMF Working Paper WP/13/267. International Monetary Fund.

Mistrulli, PE (2011). "Assessing Contagion in the Interbank Market: Maximum Entropy versus Observed Interbank Lending Patterns". In: *Journal of Banking and Finance* 35.5, pp. 1114–1127.

Mlambo, K and M Ncube (2011). "Competition and Efficiency in the Banking Sector in South African". In: *African Development Review* 23.1, pp. 4–15.

Moenninghoff, SC, S Ongena, and A Wieandt (2015). "The Perennial Challenge to Counter Too-Big-to-Fail in Banking: Empirical Evidence from the new International Regulation Dealing with Global Systemically Important Banks". In: *Journal of Banking and Finance* 61, pp. 221–236.

Moyo, B (2018). "An Analysis of Competition, Efficiency and Soundness in the South African Banking Sector". In: *South African Journal of Economic and Management* 21.1, e1–e14.

Muharam, H and E Erwin (2017). “Measuring Systemic Risk of Banking in Indonesia: Conditional Value at Risk Model Application”. In: *Signifikan: Jurnal Ilmu Ekonomi* 6.2, pp. 301–318.

Murray, N, AK Manrai, and LA Manrai (2017). “The Financial Services Industry and Society: The Role of Incentives/Punishments, Moral Hazard, and Conflicts of Interests in the 2008 Financial Crisis”. In: *Journal of Economics, Finance and Administrative Science* 22.43, pp. 168–190.

Musmeci, N, S Battiston, G Caldarelli, M Puliga, and A Gabrielli (2013). “Bootstrapping Topological Properties and Systemic Risk of Complex Networks Using the Fitness Model”. In: *Journal of Statistical Physics* 151, pp. 720–734.

Ndalu, C (2016). “Financial Deepening of Insurance and Economic Growth in Kenya”. In: *International Journal of Academic Research in Acocunting, Finance and Management Sciences* 6.1, pp. 7–14.

Neale, FR, PP Drake, P Schorno, and E Semaan (2012). *Insurance and Interconnectedness in the Financial Services Industry*. Working Paper. UNC Charlotte.

Nektarios, M (2010). “A Growth Theory for the Insurance Industry”. In: *Risk Management and Insurance Review* 13.1, pp. 45–60.

Neveu, AR (2018). “A Survey of Network-based Analysis and Systemic Risk Measurement”. In: *Journal of Economic Interaction and Coordination* 13.2, pp. 241–281.

Newberry, MG and VM Savage (2019). “Self-Similar Processes Follow a Power Law in Discrete Logarithmic Space”. In: *Physical Review Letters* 122. 158303-1.

Newman, MEJ (2005). “Power Laws, Pareto Distributions and Zipf’s Law”. In: *Contemporary Physics* 46.5, pp. 323–351.

Nier, E, J Yang, T Yorulmazer, and A Alentorn (2007). “Network Models and Financial Stability”. In: *Journal of Economic Dynamics and Control* 31, pp. 2033–2060.

Njegomir, V and D Stojić (2010). “Does Insurance Promote Economic Growth: The Evidence from Ex-Yugoslavia Region”. In: *Economic Thought and Practice* 19, pp. 31–48.

NTSA (2011a). *A Safer Financial Sector to Serve South Africa Better*. Policy Document. National Treasury, Government of South Africa.

— (2011b). *Reviewing the Regulation of Financial Markets in South Africa*. Policy document explaining the Financial Markets Bill, 2011. National Treasury, Government of South Africa.

— (2012). *Enabling a Better Income in Retirement*. Technical Discussion Paper B for Public Comment. National Treasury, Government of South Africa.

— (2013a). *Charges in South African Retirement Funds*. Technical Discussion Paper A for Public Comment. National Treasury, Government of South Africa.

— (2013b). *Implementing a Twin Peaks Model of Financial Regulation in South Africa*. Policy Document. Financial Regulatory Reform Steering Committee, a partnership of the National Treasury, South African Reserve Bank and Financial Services Board, South Africa.

— (2018). *2018 Financial Markets Review*. National Treasury, published with the Financial Markets Review Committee of the South African Reserve Bank, in cooperation with the Financial Sector Conduct Authority and the National Planning Commission.

OECD (2009). *Regulatory Impact Analysis: A Tool for Policy Coherence.* OECD Reviews of Regulatory Reform. Organisation for Economic Cooperation and Development Publishing, Paris.

— (2010). *Policy Framework for Effective and Efficient Financial Regulation: General Guidance and High-level Checklist.* Organisation for Economic Cooperation and Development Publishing, Paris.

Olayungbo, DO (2015). "Insurance and Economic Growth in Nigeria: Asymmetric Non-Linear Relationship under Heterogeneous Agents". In: *African Development Review* 27.3, pp. 248–261.

Olayungbo, DO and AE Akinlo (2016). "Insurance Penetration and Economic Growth in Africa: Dynamic Effects Analysis using Bayesian TVP-VAR Approach". In: *Cogent Economics and Finance* 4, 1150390.

Oosterloo, S and J De Haan (2003). *A Survey of Institutional Frameworks for Financial Stability.* Occasional Studies Vol. 1, No. 4. De Nederlandsche Bank.

Ötker-Robe, I, A Narain, A Ilyina, and J Surti (2011). *The Too-Important-to-Fail Conundrum: Impossible to Ignore and Difficult to Resolve.* IMF Staff Discussion Note SDN/11/12. International Monetary Fund.

Outreville, JF (1990). "The Economic Significance of Insurance Markets in Developing Countries". In: *Journal of Risk and Insurance* 57.3, pp. 487–498.

— (1996). "Life Insurance Markets in Developing Countries". In: *Journal of Risk and Insurance* 63.2, pp. 263–278.

— (2013). "The Relationship between Insurance and Economic Development: 85 Empirical Papers for a Review of the Literature". In: *Risk Management and Insurance Review* 16.1, pp. 71–122.

Park, K and W Willinger (2000). "Self-Similar Network Traffic: An Overview". In: *Self-Similar Network Traffic and Performance Evaluation.* Ed. by K Park and W Willinger. New York: John Wiley Sons, pp. 1–38. DOI: 10.1002/047120644X.ch1.

Park, SC and X Xie (2014). "Reinsurance and Systemic Risk: The Impact of Reinsurer Downgrading on Property-Casualty Insurers". In: *Journal of Risk and Insurance,* 81.3, pp. 587–622.

Parker, D (2002). "Economic Regulation: A Review of Issues". In: *Annals of Public and Cooperative Economics,* 73.4, pp. 493–519.

Paulson, A and R Rosen (2016). "The Life Insurance Industry and Systemic Risk: A Bond Market Perspective". In: *Annual Review of Financial Economics* 8, pp. 155–174.

Peleckienė, V, K Peleckis, G Dudzevičiūtė, and KK Peleckis (2019). "The relationship between insurance and economic growth: evidence from the European Union countries". In: *Economic Research-Ekonomska Istraživanja* 32.1, pp. 1138–1151.

Perelman, M (1995). "Retrospectives: Schumpeter, David Wells and Creative Destruction". In: *Journal of Economic Perspectives* 9.3, pp. 189–197.

Peters, AD and C Jaffé (1994). "Quantum Manifestations of Bifurcations of Classical Orbits: An Exactly Solvable Model". In: *Physical Review Letters* 73.21, pp. 2825–2829.

Pinter, G (2023). *An Anatomy of the 2022 Gilt Market Crisis.* Staff Working Paper No. 1 019. Bank of England.

Poincaré, H (1885). “Sur l’équilibre d’une masse fluide animée d’un mouvement de rotation”. In: *Acta Mathematica* 7, pp. 259–380.

Poledna, S, JL Molina-Borboa, S Martínez-Jaramillo, M Van der Leij, and S Thurner (2015). “The multi-layer network nature of systemic risk and its implications for the costs of financial crises”. In: *Journal of Financial Stability* 20, pp. 70–81.

Posner, E and EG Weyl (2013a). “Benefit-Cost Analysis for Financial Regulation”. In: *American Economic Review: Papers and Proceedings* 103.3, pp. 393–397.

— (2013b). *Benefit-Cost Paradigms in Financial Regulation*. Working Paper No. 660. Coase-Sandor Institute for Law & Economics.

— (2015). “Cost-Benefit Analysis of Financial Regulations: A Response to Criticism”. In: *The Yale Law Journal Forum* 124, pp. 246–262.

Pradhan, RP, MB Arvin, S Bahmani, SE Bennett, and JH Hall (2016). “Insurance-growth Nexus and Macroconomic Determinants: Evidence from Middle-income Countries”. In: *Empirical Economics* 52, pp. 1337–1366.

Pradhan, RP, MB Arvin, and NR Norman (2015). “Insurance Development and the Finance-growth Nexus: Evidence from 34 OECD Countries”. In: *Journal of Multinational Financial Management* 31, pp. 1–22.

Pradhan, RP, S Dash, RP Maradana, M Jayakumar, and K Gaurav (2017). “Insurance market density and economic growth in Eurozone countries: the Granger Causality Approach”. In: *Financial Innovation* 3, pp. 17–40.

Prudential Authority (2018). *Regulatory Strategy 2018–2021*. Prudential Authority, South African Reserve Bank.

— (2019). *Annual Report 2018/19*. Prudential Authority, South African Reserve Bank.

— (2021). *Regulatory Strategy 2021-2024*. Prudential Authority, South African Reserve Bank.

— (2022a). *2021 Life Insurance Industry Experience*. Prudential Authority, South African Reserve Bank.

— (2022b). *Annual Report 2021/22*. Prudential Authority, South African Reserve Bank.

— (2022c). *Non-Life Industry Experience 2022*. Prudential Authority, South African Reserve Bank.

— (2023a). *Flavour-of-the-year topic Communication to Insurers*. Prudential Communication 1 of 2023. Prudential Authority, South African Reserve Bank.

— (2023b). *Principles for Operational Resilience*. Proposed Directive issued in terms of section 6(6) of the Banks Act, 1990. Prudential Authority, South African Reserve Bank.

Quinn, S and W Roberds (2009). “An Economic Explanation of the Early Bank of Amsterdam, Debasement, Bills of Exchange and the Emergence of the First Central Bank”. In: *The Origins and Development of Financial Markets and Institutions: From the Seventeenth Century to the Present*. Ed. by J Atack and L Neal. Cambridge: Cambridge University Press.

Radaelli, CM (2005). *What Does Regulatory Impact Assessment Mean in Europe*. Related Publication 05-02. AEI-Brookings Joint Center for Regulatory Studies.

Radermacher, R, H McGowan, and S Dercon (2012). “What is the Impact of Microinsurance?” In: *Protecting the Poor: A Microinsurance Compendium, Volume II*. Ed. by C Churchill and M Matul. Geneva: International Labour Organization, pp. 59–82.

Radice, MP (2010). *Assessing the Potential for Systemic Risks in the Insurance Sector: Considerations on Insurance in Switzerland.* Working Paper June/2010. FINMA: Swiss Financial Market Supervisory Authority.

Rae, RA, A Barrett, D Brooks, MA Chotai, AJ Pelkiewicz, and C Wang (2017). *A Review of Solvency II: Has it met its Objectives?* Solvency II Working Party, Presented at Edinburgh, May. Institute and Faculty of Actuaries.

Ramoutar, RS (2020). "The Effects of Insurances, Pensions and Mutual Funds on Economic Growth". In: *Journal of Economics and Public Finance* 6.1, pp. 17–27.

Randaldi, M (2023). *Fractal Theory of Income Distribution.* Working Paper Series No. 62. Stone Center on Socio-economic Inequality, The Graduate Center, City University of New York.

Reid, R (2010). *Financial Development: A Broader Perspective.* ADBI Working Paper Series No. 258. Asian Development Bank Institute.

Reinhart, CM and KS Rogoff (2008). "Is the 2007 US Sub-prime Financial Crisis so Different? An International Historical Comparison". In: *American Economic Review* 98.2, pp. 339–344.

— (2011). *This Time Is Different: Eight Centuries of Financial Folly.* Princeton: Princeton University Press.

Ren, H and D Watts (2015). "Early Warning Signals for Critical Transitions in Power Systems". In: *Electric Power Systems Research* 124, pp. 173–180.

Reverz, RL (2016). *Cost-Benefit Analysis and the Structure of the Administrative State: The Case of Financial Services Regulation.* Working Paper No. 2016/2. Institute for Policy Integrity.

Richterková, Z and P Koráb (2013). "Impact of Insurance Sector Activity on Economic Growth - A Meta-Analysis". In: *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis* 59.7, pp. 2677–2683.

Rigobon, R (2016). *Contagion, Spillover and Interdependence.* Staff Working Paper No. 607. Bank of England.

Rocha, JC, GD Peterson, and R Biggs (2015). "Regime Shifts in the Anthropocene: Drivers, Risks and Resilience". In: *PLOS ONE* 10.8, e0134639.

Rocha, JC, GD Peterson, O Bodin, and S Levin (2018). "Cascading Regime Shifts Within and Across Scales". In: *Science* 362, pp. 1379–1383.

Rodriguez, RN and Y Yao (2017). *Five Things You Should Know about Quantile Regression.* Paper SAS525-2017. SAS Institute Inc.

Roll, R (1978). "Ambiguity when Performance is Measured by the Securities Market Line". In: *Journal of Finance* 33.4, pp. 1051–1069.

Rørdam, KB and ML Bech (2009). "The topology of Danish interbank money flows". In: *Bank and Bank Systems* 4.4, pp. 48–65.

Rose, P and CJ Walker (2013). *The Importance of Cost-Benefit Analysis in Financial Regulation.* Center for Capital Markets Competitiveness. United States Chamber of Commerce.

Rossi, M (2016). "The Capital Asset Pricing Model: A Critical Literature Review". In: *Global Business and Economics Review* 18.5, pp. 604–617.

Roukny, T, H Bersini, H Pirotte, G Caldarelli, and S Battiston (2013). "Default Cascades in Complex Networks: Topology and Systemic Risk". In: *Scientific Reports* 3.2759, pp. 1–8.

Rudolph, MJ (2017). *Reviewing Systemic Risk within the Insurance Industry*. Society of Actuaries.

Rusconi, RD (2020). "The Contribution of South Africa's Insurers to Systemic Risk: Thoughts for Policymakers". In: *South African Actuarial Journal* 20, pp. 149–210.

Russell, DT, SG Fier, JM Carson, and RE Dumm (2013). "An Empirical Analysis of Life Insurance Policy Surrender Activity". In: *Journal of Insurance Issues* 36.1, pp. 35–57.

Safa, MF, MK Hassan, and NC Maroney (2013). "AIG's Announcements, Fed's Innovation, Contagion and Systemic Risk in the Financial Industries". In: *Applied Financial Economics* 23.16, pp. 1337–1348.

Samuelson, PA (1967). "General Proof that Diversification Pays". In: *Journal of Financial and Quantitative Analysis* 2.1, pp. 1–13.

Saramäki, K, ML Bech, J Arnold, RJ Glass, and WE Beyeler (2007). "The topology of interbank payment flows". In: *Physica A* 379.1, pp. 317–333.

SARB (2017a). *Financial Stability Review 2017: First Edition*. South African Reserve Bank.

— (2017b). *Financial Stability Review 2017: Second Edition*. South African Reserve Bank.

— (2017c). *Promoting the Economic Well-being of South Africans: Annual Report 2016/17*. South African Reserve Bank.

— (2018a). *Financial Stability Review 2018: First Edition*. South African Reserve Bank.

— (2018b). *Financial Stability Review 2018: Second Edition*. South African Reserve Bank.

— (2019). *Financial Stability Review 2019: Second Edition*. South African Reserve Bank.

— (2020a). *Financial Stability Review 2020: First Edition*. South African Reserve Bank.

— (2020b). *Financial Stability Review 2020: Second Edition*. South African Reserve Bank.

— (2020c). *Quarterly Bulletin: June 2020*. South African Reserve Bank.

— (2021a). *Financial Stability Review 2021: First Edition*. South African Reserve Bank.

— (2021b). *Financial Stability Review 2021: Second Edition*. South African Reserve Bank.

— (2022a). *Financial Stability Review 2022: First Edition*. South African Reserve Bank.

— (2022b). *Ubank Limited Statement by Governor Kganyago, May*. South African Reserve Bank.

— (2023). *Financial Stability Review 2023: First Edition*. South African Reserve Bank.

Sarkar, AE (2009). *The Crises of Capitalism: A Different Study of Political Economy*. Berkeley, California: Counterpoint.

Sarkar, S (2012). "The New Mode of Public Governance and Public Accountability in Developing Countries: An Analysis with Particular Reference to Bangladesh". In: *International Journal of Public Administration* 32.13, pp. 1101–1123.

Scheffer, M, J Bascompte, WA Brock, V Brovkin, SR Carpenter, V Dakos, H Held, EH Van Nes, M Rietkerk, and G Sugihara (2009). "Early-warning Signals for Critical Transitions". In: *Nature* 461, pp. 53–59.

Scheffer, M, SR Carpenter, TM Lenton, J Bascompte, WA Brock, V Dakos, J Van de Koppel, IA Van de Leemput, SA Levin, EH Van Nes, M Pascual, and J Vandermeer (2012). "Anticipating Critical Transitions". In: *Science* 338.6105, pp. 344–348.

Schelling, TC (1971). “Dynamic Models of Segregation”. In: *Journal of Mathematical Sociology* 1, pp. 143–168.
Schmukler, S (2004). *Benefits and Risks of Financial Globalization: Challenges for Developing Countries*. Development Research Group. The World Bank.
Schmulow, A (2015). “The Four Methods of Financial System Regulation: An International Comparative Survey”. In: *Journal of Banking and Finance Law and Practice* 26, pp. 151–172.
Schneider, T, CM Kaul, and KG Pressel (2019). “Possible Climate Transitions from Breakup of Stratocumulus Decks under Greenhouse Warming”. In: *Nature Geoscience* 12, pp. 163–167.
Schumpeter, JA (1949). “Vilfredo Pareto (1848-1923)”. In: *The Quarterly Journal of Economics* 63.2, pp. 147–173.
Schwarcz, D and SL Schwarcz (2014). “Regulating Systemic Risk in Insurance”. In: *University of Chicago Law Review* 81, pp. 1569–1640.
Schwarcz, SL (2008). “Systemic Risk”. In: *Georgetown Law Journal* 97, pp. 193–248.
— (2019). “Systematic Regulation of Systemic Risk”. In: *Wisconsin Law Review* 2019, pp. 1–53.
Sedunov, J (2016). “What is the Systemic Risk Exposure of Financial Institutions?” In: *Journal of Financial Stability* 24, pp. 71–87.
Segoviano, MA and C Goodhart (2009). *Banking Stability Measures*. Working Paper 09/04. International Monetary Fund.
Sharpe, WF (1964). “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk”. In: *Journal of Finance* 19.3, pp. 425–442.
Shea, GS (2009). “Sir George Caswall vs. the Duke of Portland: Financial Contracts and Litigation in the Wake of the South Sea Bubble”. In: *The Origins and Development of Financial Markets and Institutions: From the Seventeenth Century to the Present*. Ed. by J Atack and L Neal. Cambridge: Cambridge University Press.
Shim, J (2017). “An Investigation of Market Concentration and Financial Stability in Property-liability Insurance Industry”. In: *Journal of Risk and Insurance* 84.2, pp. 567–597.
Shin, HS (2013). “Adapting Macro Prudential Approaches to Emerging and Developing Economies”. In: *Dealing with the Challenges of Macro Financial Linkages in Emerging Markets*. Ed. by O Canuto and SR Ghosh. Washington, DC: World Bank.
Sibindi, AB and NJ Godi (2014). “Insurance Sector Development and Economic Growth: Evidence from South Africa”. In: *Corporate Ownership and Control* 11.4, pp. 530–538.
Silva, TC, SR Stancato de Souza, and BM Tabak (2016). “Network structure analysis of the Brazilian interbank market”. In: *Emerging Markets Review* 26, pp. 130–152.
Silva, W, R Herbert, and AS Vinicius (2017). “An Analysis of the Literature on Systemic Financial Risk: A Survey”. In: *Journal of Financial Stability* 28, pp. 91–114.
Simatele, M (2015). “Market Structure and Competition in the South African Banking Sector”. In: *Procedia Economics and Finance* 30, pp. 825–835.
Simbanegavia, W, JB Greenberg, and T Gwatidzo (2015). “Testing for Competition in the South African Banking Sector”. In: *Journal of African Economies* 24.3, pp. 303–324.

Sinha, A (2012). *Financial Sector Regulation and Implications for Growth*. BIS Papers No. 62. Bank for International Settlements.

Skipper, HD (1997). *Foreign Insurers in Emerging Markets: Issues and Concerns*. IIF Occasional Paper, No. 1. Washington, DC: International Insurance Foundation.

Smaga, P (2014). *The Concept of Systemic Risk*. Systemic Risk Centre Special Paper No. 5. The London School of Economics and Political Science.

Smart, B (2012). “Fiscal Crisis and Creative Destruction: Critical Reflections on Schumpeter’s Contemporary Relevance”. In: *Journal of Classical Sociology* 12.3-4, pp. 526–543.

Solé, RV (2011). *Phase Transitions*. Primers in Complex Systems. Princeton University Press: Princeton, NJ.

Spaiser, V, P Hedström, S Ranganathan, K Jansson, MK Nordvik, and DJT Sumpter (2018). “Identifying Complex Dynamics in Social Systems: A New Methodological Approach Applied to Study School Segregation”. In: *Sociological Methods & Research* 47.2, pp. 103–135.

Spash, C (2019). *Making Pollution into a Market Failure Rather than a Cost-shifting Success: The Suppression of Revolutionary Change in Economics*. SRE-Discussion Papers 2019/06. WU Vienna University of Economics and Business.

Steffen, T (2008). “Solvency II and the Work of CEIOPS”. In: *The Geneva Papers* 33, pp. 60–65.

Steffen, W et al. (2018). “Trajectories of the Earth System in the Anthropocene”. In: *Proceedings of the National Academy of Sciences* 115.33, pp. 8252–8259.

Sternfors, A, E Clark, I Farahani, Hansen AL, and Passarella M (2014). *The Swedish Financial System*. Studies in Financial Systems No. 13. FESSUD - Financialisation, Economy, Society and Sustainable Development.

Stinchcombe, RB (1988). “Phase Transitions”. In: *Order and Chaos in Nonlinear Physical Systems. Physics of Solids and Liquids*. Ed. by S Lundqvist, NH March, and MP Tosi. New York: Springer. ISBN: 978-1-4899-2058-4.

Stojaković, A and L Jeremić (2016). “Development of the Insurance Sector and Economic Growth in Countries in Transition”. In: *Megatrend Revija* 13, pp. 83–106.

Stolbova, V, I Monasterolo, and S Battiston (2018). “A Financial Macro-Network Approach to Climate Policy Evaluation”. In: *Ecological Economics* 149, pp. 239–253.

Sukpaiboonwat, S, C Piputsitee, and A Punyasavatsut (2014). “Measuring the Degree of Market Concentration in Thailand Insurance Industry”. In: *Asian Social Science* 10.4, pp. 214–232.

Sunstein, CR (2015). “Financial Regulation and Cost-Benefit Analysis”. In: *The Yale Law Journal Forum* 24, pp. 270–279.

Swaney, JA and MA Evers (1989). “The Social Cost Concepts of K. William Kapp and Karl Polanyi”. In: *Journal of Economic Issues* 23.1, pp. 7–34.

Swarup, A (2012). “A well-intentioned folly: The macroeconomic implications of Solvency II”. In: *Economic Affairs* 32.3, pp. 17–23.

Syll, LP (2010). “What is (wrong with) economic theory?” In: *Real-world Economics Review* 55, pp. 23–57.

Tabak, BM, IB Dalla Riva e Silva, and TC Silva (2016). "Analysis of Connectivity between the World's Banking Markets: The COVID-19 Global Pandemic Shock". In: *Quarterly Review of Economics and Finance* 84, pp. 324–336.

Tagoe, NA (2016). "The Emerging Role of Financial Intermediaries in the Financial Market of Ghana". In: *Business and Economics Journal* 7.4, 1000253.

Tasca, P, P Mavrodiev, and F Schweitzer (2014). "Quantifying the impact of leveraging and diversification on systemic risk". In: *Journal of Financial Stability* 15, pp. 43–52.

Teteryatnikova, M (2014). "Systemic risk in banking networks: Advantages of 'tiered' banking systems". In: *Journal of Economic Dynamics & Control* 47.1, pp. 186–210.

Thom, M, C Hougaard, J Gray, B Msulwa, K Rinehart-Smit, and J De Waal (2019). *Insurance for Inclusive and Sustainable Growth: Imperatives for Action from a Four-country Synthesis*. Centre for Financial Regulation and Inclusion, published with FSDAfrica.

Thompson, JMT and J Sieber (2011). "Climate Tipping as a Noisy Bifurcation: A Predictive Technique". In: *IMA Journal of Applied Mathematics (Institute of Mathematics and its Applications)* 76.1, pp. 27–46.

Thomson, R and DB Posel (2002). "The Management of Risk by Burial Societies in South Africa". In: *South African Actuarial Journal* 2, pp. 83–128.

Tien, JJ and SS Yang (2014). "The Determinants of Life Insurer's Growth for a Developing Insurance Market: Domestic v Foreign Insurance Firms". In: *The Geneva Papers* 39, pp. 1–24.

Tipurić, D, MP Bach, and T Pavić (2008). "Concentration of the Insurance Industry in Selected Transition Countries of Central and Eastern Europe, 1998-2006". In: *Post-Communist Economies* 20.1, pp. 97–118.

Trichet, JC (2005). "Financial Stability and the Insurance Sector". In: *Geneva Papers on Risk and Insurance - Issues and Practice* 30, pp. 65–71.

Troger, H and A Steindl (1991). *Nonlinear Stability and Bifurcation Theory: An Introduction for Engineers and Applied Scientists*. Vienna: Springer.

Tversky, A and D Kahneman (1991). "Loss Aversion in Riskless Choice: A Reference-Dependent Model". In: *The Quarterly Journal of Economics* 106.4, pp. 1039–1061.

Ueda, K and BW Di Mauro (2013). "Quantifying Structural Subsidy Values for Systemically Important Financial Institutions". In: *Journal of Banking & Finance* 37, pp. 3830–3842.

UNCTAD (1964). *Proceedings of the United Nations Conference on Trade and Development, Geneva, 23 March - 16 June 1964, Volume I, Final Act and Report*. United Nations.

— (2015). *Mobilizing Investment for Sustainable Development: Background Information and Considerations Pertinent to the Third International Conference on Financing for Development*. Investment, Enterprise and Development Commission, United Nations Conference on Trade and Development, Geneva. United Nations.

UNEPFI (2014). *Harnessing the Full Potential of the Insurance Industry in Disaster Risk Management*. Principles for Sustainable Insurance, United Nations Environment Programme Finance Initiative. United Nations.

Upper, C (2011). "Simulation methods to assess the danger of contagion in interbank markets". In: *Journal of Financial Stability* 7.3, pp. 111–125.

Upper, C and A Worms (2004). "Estimating bilateral exposures in the German interbank market: Is there a danger of contagion?" In: *European Economic Review* 48.4, pp. 827–849.

Vallascas, F and K Keasey (2012). "Bank resilience to systemic shocks and the stability of banking systems: Small is beautiful". In: *Journal of International Money and Finance* 31.6, pp. 1745–1776.

Van Lelyveld, I, F Liedorp, and M Kampman (2019). "An Empirical Assessment of Reinsurance Risk". In: *Journal of Financial Stability* 7, pp. 191–203.

Velde, FR (2009). "Was John Law's System a Bubble? The Mississippi Bubble Revisited". In: *The Origins and Development of Financial Markets and Institutions: From the Seventeenth Century to the Present*. Ed. by J Atack and L Neal. Cambridge: Cambridge University Press.

Verma, A and R Bala (2013). "The Relationship between Life Insurance and Economic Growth: Evidence from India". In: *Global Journal of Management and Business Studies* 3.4, pp. 413–422.

Verma, P, A Kienle, D Flockerzi, and D Ramkrishna (2020). "Using Bifurcation Theory for Exploring Pain". In: *Industrial & Engineering Chemistry Research* 59.6, pp. 2524–2535.

Vitols, S (2001). *The Origins of Bank-based and Market-based Financial Systems: Germany, Japan and the United States*. Discussion Paper FS 01-302. WZB Berlin Social Science Center.

Wagner, J (2014). "A Note on the Appropriate Choice of Risk Measures in the Solvency Assessment of Insurance Companies". In: *Journal of Risk Finance* 15.2, pp. 110–130.

Wagner, W (2010). "Diversification at Financial Institutions and Systemic Crises". In: *Journal of Financial Intermediation* 19, pp. 373–386.

Walters, NM, FJC Beyers, AJ Van Zyl, and Van den Heever RJ (2018). "A Framework for Simulating Systemic Risk and its Application to the South African Banking Sector". In: *South African Actuarial Journal* 18, pp. 99–133.

Wang, G, Y Feng, Y Xiao, Y Zhu, and X Chi (2022). "Connectedness and Systemic Risk of the Banking Industry along the Belt and Road". In: *Journal of Management Science and Engineering* 7, pp. 303–329.

Ward, D and R Zurbruegg (2000). "Does Insurance Promote Economic Growth? Evidence from OECD Countries". In: *Journal of Risk & Insurance* 67.4, pp. 489–506.

Webb, IP, MF Grace, and HD Skipper (2002). *The Effect of Banking and Insurance on the Growth of Capital and Output*. Working Paper 02-1, Center for Risk Management and Insurance, Robinson College of Business. Georgia State University.

Weber, RF (2010). "New Governance, Financial Regulation and Challenges to Legitimacy: The Example of the Internal Models Approach to Capital Adequacy Regulation". In: *Administrative Law Review* 62.3, pp. 783–869.

— (2011). "Combating the Teleological Drift of Life Insurance Solvency Regulation: The Case for a Meta-Risk Management Approach to Principles-Based Reserving". In: *Berkeley Business Law Journal* 8, pp. 35–115.

— (2012). "Structural Regulation as Antidote to Complexity Capture". In: *American Business Law Journal* 49.3, pp. 643–738.

Weisbart, S (2018). *How Insurance Drives Economic Growth*. Insurance Information institute.

Weiß, G, D Boxtandzic, and S Neumann (2014). "What Factors Drive Systemic Risk During International Financial Crises?" In: *Journal of Banking & Finance* 41, pp. 78–96.

Weiß, G and J Mühlnickel (2014). "Why do Some Insurers Become Systemically Relevant?" In: *Journal of Financial Stability* 13, pp. 95–117.

Wells, S (2004). *Financial Interlinkages in the United Kingdom: Interbank Market and the Risk of Contagion*. Working Paper No. 230. Bank of England.

Whitehead, CK (2012). "The Goldilocks Approach: Financial Risk and Staged Regulation". In: *Cornell Law Review* 97.5, pp. 1267–1308.

Wieczorek, S, P Ashwim, CM Luke, and PM Cox (2011). "Excitability in Ramped Systems: The Compost-Bomb Instability". In: *Proceedings Royal Society A* 467, pp. 1243–1269.

Wieczorek, S, B Krauskopf, Simpson TB, and D Lenstra (2005). "The Dynamical Complexity of Optically Injected Semiconductor Lasers". In: *Physics Report* 416, pp. 1–128.

Winkler, A (1998). *The Dual Role of Financial Markets in Economic Development: Engine of Growth and Source of Instability, A Survey of Economic Theory with Reflections on the East Asian Financial Crisis*. IPC Working Paper No. 18. Internationale Projekt Consult GmbH.

Winston, C (2006). *Government Failure versus Market Failure: Microeconomics Policy Research and Government Performance*. AEI-Brookings Joint Center for Regulatory Studies.

Wolpert, D and W Macready (1998). "Self-Dissimilarity: An Empirical Measure of Complexity". In: *Unifying Themes in Complex Systems*. Ed. by Y Bar-yam. Vol. 1. Boca Raton: CRC Press. DOI: 10.1201/9780429503344.

Wong, A and T Fong (2010). *Analysing Interconnectivity Among Economies*. Working Paper 03/2010. Hong Kong Monetary Authority.

World Bank (2012). *Rethinking the Role of the State in Finance*. Global Financial Development Report 2013. The World Bank.

— (2020). *Albania: Insurance Market Development*. World Bank, in cooperation the First Initiative 2.0, UKAid and the Centre for Global Disaster Protection.

Yamai, Y and T Yoshiba (2004). "Value-at-risk versus Expected Shortfall: A Practical Perspective". In: *Journal of Banking and Finance* 29, pp. 997–1015.

Yinusa, O and T Akinlo (2013). "Insurance Development and Economic Growth in Nigeria, 1986-2010". In: *Journal of Economics and International Finance* 5.5, pp. 218–224.

Yu, K, Zudi Lu, and J Stander (2003). "Quantile Regression: Applications and Current Research Areas". In: *The Statistician* 52.3, pp. 331–350.

Zerbe Jr, RO and H McCurdy (2000). "The End of Market Failure". In: *Regulation* 23.2, pp. 10–14.

Zhang, Q, F Vallascas, K Keasey, and CX Cai (2015). "Are Market-Based Measures of Global Systemic Importance of Financial Institutions Useful to Regulators and Supervisors?" In: *Journal of Money, Credit and Banking* 47.7, pp. 1403–1442.

Zilgalvis, P (2014). "The Need for an Innovation Principle in Regulatory Impact Assessment: The Case of Finance and Innovation in Europe". In: *Policy and Internet* 6.4, pp. 377–392.

Zimková, E and V Vargová (2006). "Trends in institutional Structure of Financial Regulation and Supervision in the European Union". In: *BIATEC* XIV.5, pp. 18–21.