NON-BANK FINANCIAL INTERMEDIATION

- A FOCUS ON SOUTH AFRICA

By

ESTI KEMP

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Co-Pierre Georg, Ph.D., Chair

To update, Ph.D.

To update, Ph.D.

Dedication

I dedicate this research to all students that venture into the world of shadow banking.

Declaration of Authorship

I, Esti Kemp, hereby declare that the work on which this dissertation/thesis is based is my original work (except where acknowledgements indicate otherwise) and that neither the whole work nor any part of it has been, is being, or is to be submitted for another degree in this or any other university. I empower the university to reproduce for the purpose of research either the whole or any portion of the contents in any manner whatsoever.

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Abstract

We measure the non-bank financial intermediation (NBFI) sector of South Africa over time, and how it is connected to the banking system. While the growth of the NBFI-sector has outpaced that of banks - driven mainly by collective investment schemes, banks continue to hold the largest share of financial assets. We show relatively high levels of interconnectedness between banks and non-banks, specifically investment funds. We also show high levels of portfolio overlap, or indirect interconnectedness, for money market funds (MMFs) registered in South Africa.

Given the limited academic work measuring interconnectedness beyond banks, as a second part of the work, a novel dataset is used to analyse the interconnectedness in South Africa in more detail. We propose a method to compute losses on the financial system as a result of a failure of the bank based on look-through exposures - i.e. those beyond the direct and indirect balance sheet links. Specifically, we show that the exposures of financial institutions in the SA financial system to the default of one one of its "big six" banks may be severely underestimated when only considering direct and indirect exposures. The default of one of the big six banks causes financial distress to spread throughout the system. Consequently, additional losses accumulate to institutions over time that are not covered by the

direct and indirect exposures. We introduce the *higher-order share of exposure* (HSE), which expresses what percentage of an exposure is overlooked when only considering direct and indirect exposures. We show that the HSE is close to 100% for a substantial part of the South African financial system, and that in other parts the HSE rises steeply during times of financial distress, when exposures matter most. We show that these higher order losses depend strongly on the network structure of the SA financial system and the robustness of its institutions. In a new domain of estimating exposures, we confirm an earlier established result, which finds that jointly including multiple asset classes and multiple types of financial exposures is requisite to avoid underestimating losses. This highlights the importance of granular data, and network-based modeling approaches that take advantage of these data to properly estimate exposures.

The third part of the work focuses on identifying and measuring the financial cycle in South Africa, using three different methodologies. The financial cycle is calculated using credit, house prices and equity prices as indicators, and estimated using traditional turning-point analysis, frequency-based filters and an unobserved components model-based approach. We then consider the financial cycle's main characteristics and examine its relationships with the business cycle. We confirm the presence of a financial cycle in South Africa that has a longer duration and a larger amplitude than the traditional business cycle. Developments in measures of credit and house prices are important indicators of the financial cycle, although the case for including equity prices in the measures is less certain. Periods where financial conditions are stressed are associated with peaks in the financial cycle, suggesting that the estimated financial cycle may have similar leading indicator properties to financial conditions or stress indices.

To determine the role of the NBFI sector in the financial cycle, in the final part of the work we also estimate the non-bank credit cycle. This methodology is applied to estimate the non-banking cycle of several economies, to gain insights into differences with the bank credit cycle. We find that the cyclical properties of non-bank credit cycles differ from those of bank credit: while the duration is similar, the amplitude of non-bank credit is relatively larger. The relationship between bank and non-bank credit is not stable and differs among jurisdictions, at a global level this relationship becomes less synchronised in the period leading up to the 2008 financial crisis. We argue that monitoring non-bank credit can bring additional information as a leading indicator for periods of financial instability, in particular currency crises. We complement the existing literature on leading indicators for financial crises by showing that bank credit is a useful indicator for systemic banking crises, while non-bank credit is helpful to predict currency crises, but not vice versa.

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Chapter One

Introduction

The role of non-bank financial intermediaries has increased over the past decade, both at a global level and also in South Africa (FSB, 2018). However, despite holding a larger share of the total financial assets, our understanding of these entities, their activities, and how they are connected within the financial system and thus could impact financial stability is limited. This dissertation addresses these gaps by first laying out the financial landscape of South Africa, measuring the size of the non-bank financial intermediation (NBFI) sector and exploring the direct links between banks and non-banks. Given the high level of direct and indirect interconnectedness observed among financial intermediaries, a measure is developed in the second part of this study to estimate the contagion effects of a bank failure. In the third part of the study the financial cycle of South Africa is estimated, and its properties are compared to the traditional business cycle. This is followed by an analysis of the non-bank financial cycle for South Africa and also for an additional 35 additional jurisdictions, to explore the cyclical properties of bank and non-bank credit and investigate the potential of using non-bank credit as a leading indicator for periods of financial instability.

This chapter provides an overview of the main research questions and the methodological approach. Following a brief problem statement, we will highlight the scope and contributions of the dissertation and give an outline of the chapters that follow.

1.1 Background and problem statement

Globally, non-bank financial intermediation has existed for several years prior to the 2008 financial crisis; however, given the role that these entities played in the 2008 crisis and their relative size in the financial system, the NBFI sector has become an increasing focal area. The need to better understand the linkages and dependencies in the financial system in addition to the vulnerabilities within the non-bank financial intermediaries was again demonstrated in March 2020 when stress in certain investment funds, including money market funds, only abated after the official sector in some jurisdictions took steps to support market liquidity (Li et al., 2020, Eren et al., 2020).

Similar to banks, entities in the NBFI sector engage in financial intermediation – i.e., channelling funds between ultimate savers and ultimate borrowers. However in contrast to banks, the NBFI sector is made up of a heterogeneous set of agents. Even though some of these entities conduct activities that involve risks similar to those of a bank, including credit intermediation, maturity transformation, liquidity transformation and leverage (Claessens and Ratnovski, 2014), NBFI-sector entities neither accept deposits and thus are not subject to the same regulations, nor have access to the same government safety nets as banks, such as deposit insurance and lender of last resort facilities by the central bank.

The focus of this study is the NBFI sector, including the activities within the NBFI sector that pose bank-like financial stability risks as a result of the bank-like activities that they conduct. Examples of NBFI entities are pension funds, insurance corporations, investment funds, finance companies, broker dealers and special purpose vehicles (SPVs). These intermediaries not only play a complementary role to commercial banks by providing additional services, but also compete with commercial banks and thus force these banks to improve their efficiency and response to the needs of their customers (Vittas, 2016). These institutions matter not only from a regulatory but also from an economic perspective and activities that they conduct can give rise to financial stability risks. In addition to maturity-liquidity- and credit transformation as well as leverage, these entities are linked among each other and to banks and as such could give rise to systemic risk. Given that they perform these activities that are similar to banks, there is the potential for regulatory arbitrage. Moreover the non-banking space is an important channel for capital flows and given their role in the economy they can impact the monetary policy transmission channel.

1.2 Scope and contribution of study

The main research questions addressed in this study are as follows:

- How large is the NBFI sector in South Africa, what are the largest components of this sector and which entities have the most potential to impact financial stability and systemic risk?
- What percentage of exposure in South Africa's financial system is overlooked when only focussing on direct and indirect links; are direct and indirect exposure data sufficient to estimate the impact of a default of a large financial institution on the rest of the financial system?
- What are the characteristics of South Africa's financial cycle and how is the financial cycle in South Africa related to the business cycle?
- What are the cyclical properties of the non-bank financial credit cycle and how can the non-bank credit cycle be used as a leading indicator for financial instability?

This study quantifies the NBFI sector in South Africa, based on the Financial Stability Board's methodology, and takes stock of the regulations that they adhere to. We then measure the sector's direct links with the banking sector. We also estimate the indirect links, or the portfolio overlap, of MMFs in South Africa. Given the relatively high levels of direct linkages observed, we then develop a model to improve the understanding of how contagion can spread through the South African financial system. Financial distress caused by the default of an institution may be propagated by the system, causing further losses down the line through write-downs/offs of assets that do not generate direct or indirect exposures to the defaulted institution. We refer to these as Higher-Order Exposures.This work is driven by the observation that an institution's exposure to another is not limited to direct and indirect exposures. We propose that traditional estimates of counterparty exposures (see e.g. L. S. Allen, 2003; Canabarro et al., 2014; C. Bluhm et al., 2016) - here meaning the exposure between two institutions in the financial system – should include direct, indirect and higher-order exposures to properly account for the loss that an institution i is exposed to upon institution j's default. As far as we are aware, we are the first to propose this and offer a method to compute it.

Given that financial cycles provide a broad indication of the changes in risks to financial stability and therefore provide an important monitoring tool for policy-makers, we then estimate the financial cycle in South Africa using three different approaches, namely turning point analysis, frequency domain analysis using band-pass filters and a multivariate model-based approach to extract cycles using unobserved components time series models. We use a parsimonious specification that included credit, property prices and equity prices. We then estimate and compare the cycles of bank and non-bank credit to better understand the role of credit provided by non-bank specifically,

This study has three main aims. The first is to measure the part of the NBFI sector that perform bank-like activities but are not subject to bank-like regulation and under normal circumstances are not backed by the central bank, and to analyse how this part of the NBFI sector has changed over time. The second aim is to develop a concept to measure exposures beyond direct and indirect exposures *higher-order exposures*, taking into account the various assets included in the South African financial system. The third is to explore analysis of credit extension while focusing on the role of non-banks and determining the role of non-bank financing in the economy. To do this, the traditional financial cycle is identified and compared to the traditional business cycle. For context, the non-bank financial cycle is estimated for several countries and compared with the respective banking cycles to better understand the relationship between bank credit and credit provided by non-banks over time.

1.3 Organisation of study

This study is divided into four parts. In the first part, we give an overview of the relevant literature on NBFI and how it has evolved since the 2008 financial crisis; interconnectedness measures as well as the importance of the financial cycle for financial stability. In the second part we focus on the non-bank financial landscape in South Africa and the current data gaps faced. In the third part of the study, We focus on interconnectedness and show that the exposures of financial institutions in the SA financial system, to the default of one one of its "big six" banks, may be severely underestimated when only considering direct and indirect exposures. In the fourth part, we estimate the financial cycle in South Africa using first the credit extended by banks and then comparing this to the traditional business cycle. To complement this work, the non-bank financial cycle and its relationship to the traditional financial cycle is estimated for 36 global jurisdictions - including South Africa.

Chapter Two

Literature review

This chapter reviews the relevant literature with the aim of providing an overview of NBFI in South Africa, in the context of global developments. It includes approaches to defining and measuring non-banks' activity and how these entities are linked to the rest of the financial system. While non-bank financial intermediaries are generally regulated from a micro-prudential perspective, there are often limited tools available for the NBFI-sector in the macroprudential framework. In Section 2.3 we discuss the importance of systemic risk, specifically for the NBFI-sector, and modelling techniques used to determine such risk. In Section 2.4, we discuss how financial cycles are measured and how the traditional measures can be extended to take the non-bank financial cycle into account.

2.1 Overview of the NBFI sector

2.1.1 What are non-bank financial intermediaries?

To shed light on and better understand the intricacies of *shadow banks* or non-bank financial intermediaries, one needs to keep the role of the traditional banking system and the role it performs in the economy in mind.

Banks are financial intermediaries that make long(er)-term loans which are funded by short-term deposits (Edwards et al., 1995). Their traditional role results in banks undertaking maturity-, liquidity- and credit transformation (Luttrell et al., 2012). Banks perform **maturity transformation** as a result of the maturity mismatch between short-term deposits and longer-term loans. Similarly, given that the liabilities (i.e. deposits, which are available at any time) of a bank is more liquid than its assets (i.e. loans which often have a fixed term) it offers - banks also perform **liquidity transformation**. Finally, bank assets is typically more risky than its liabilities - thus banks perform **credit transformation**.

As a result of these activities, banks face several risks. One of these is a depositor run, where depositors withdraw their money from a bank on short notice and banks have to liquidate assets to meet the demand. Banks might then become insolvent - i.e. their liabilities would become larger than the value of its assets. Banks also have access to the central bank who will act as a lender of last resort to prevent a bank becoming illiquid. The risk that banks face are well documented (see for example Linsley et al., 2005 and Fiordelisi et al., 2013, and confidence in the bank is key. For example. Diamond et al., 1983 show how banks' liquidity liabilities (i.e. deposits) and illiquid assets (longer-term loans) can result in self-fulfilling panics and ultimately bank failures. Moreover, risk-taking and the ultimate failure of a bank could lead to a loss of deposits. Therefore banks are regulated to protect depositors and ensure confidence in the system - without confidence in the system banks would not be able to function.

Similar to banks. entities in the NBFI sector engage in financial intermediation – i.e., channelling funds between ultimate savers and ultimate borrowers. However in contrast to banks, the NBFI sector is made up of a heterogeneous set of agents. Even though some of these entities conduct activities that involve risks similar to those of a bank, including credit intermediation, maturity transformation, liquidity transformation and leverage (Claessens and Ratnovski, 2014), NBFI-sector entities neither accept deposits and thus are not subject to the same regulations, nor have access to the same government safety nets as banks, such as deposit insurance and lender of last resort facilities by the central bank. Examples of NBFI entities are pension funds, insurance corporations, investment funds, finance companies, broker dealers and special purpose vehicles (SPVs). These intermediaries not only play a complementary role to commercial banks by providing additional services but also compete with commercial banks and thus force these banks to improve their efficiency and response to the needs of their customers

(Vittas, 2016). As such, these institutions matter not only from a regulatory but also from an economic perspective.

2.1.2 The rise of shadow banking in the United States (US)

The NBFI-sector became more prominent as a result of its role in the 2008 financial crisis. The rise of *shadow banking* in the US is discussed below to provide context for this shift in intermediation activities.

After depositor-runs on several banks, the US Federal Reserve (Fed) was created in 1913 to act as the lender of last resort, and the Glass–Steagall Act was passed by Congress in 1933, which established the Federal Deposit Insurance Corporation (FDIC) (Bernanke, 2013). Deposit insurance meant that depositors no longer had to be the first in line to withdraw money from a bank if that particular bank ran into trouble, while the Fed would ensure that banks do not fail because of a liquidity crisis. With taxpayers' money now at risk, Congress proceeded to restrict banks' activities, in order to discourage excessive risk taking, furthermore the Fed capped the interest rates that banks could pay depositors with the ultimate aim of keeping institutions safe by making sure that competition for banks as deposit-takers did not get out of hand. This rule, known as 'Regulation Q', was not perceived as a problem in a low-inflation environment; however, when inflation started increasing, investors started seeking alternatives to traditional deposit accounts.

In the late 1970s Merrill Lynch, Fidelity, Vanguard and others created money-market mutual funds (MMMFs) and attracted businesses and consumers away from banks by offering them higher returns (Edwards et al., 1995). The MMMFs invested depositors' money in short-term securities that were perceived to be safe, and which paid higher interest rates than banks. These funds functioned similar to bank accounts, except customers bought shares that were redeemable daily at a stable value. After Merrill Lynch introduced 'cash management accounts' in 1977, other MMMFs quickly followed. One of the most important distinctions between these funds and bank deposits was that they were not protected by deposit insurance. However, even without insurance, these funds were considered almost as safe as bank deposits (Commission et al., 2011). Furthermore, consumers enjoyed relatively higher interest rates and the funds implicitly promised to maintain the full asset value of the shares by maintaining a constant net asset value.

In the 1980s and 1990s, the less regulated market for capital grew rapidly next to the traditional banking system (Edwards et al., 1995). In the search for safe, high-quality assets, money-market funds (MMFs) developed an appetite for the 'commercial paper' and 'repurchase' (repo) markets. Regulatory arbitrage was possible because investment banks set up special purpose vehicles (SPVs) to do the actual securitization and endowed them with liquidity guarantees. Since these guarantees had much lower risk weights than the mortgages that were transferred to the SPVs, investment banks were able to leverage much more than otherwise possible. This led to a rapid expansion in non-bank financing activities, at the expense of traditional commercial banks, because financing was provided cheaper (with commercial paper and repos) and returns for investors (by MMMFs) were higher. Some regulators became concerned since it eroded the competitive positions of banks and left them vulnerable.[1] Grievances were taken to Congress, and long-standing restrictions were slowly removed.[2] US regulators generally supported and encouraged this shift toward deregulated financial markets, arguing that financial institutions had sufficiently strong incentives to protect their own shareholders, thus the financial institutions would therefore regulate themselves through improved risk management (Yeoh, 2011).

Following deregulations, banks in the US started to extend higher-risk loans with higher interest payments, and large commercial banks even lent money to companies and governments in emerging markets which resulted in higher

[1] Alan Blinder, Vice Chairperson of the Federal Reserve (1994–1996), expressed concern regarding the competitive position of banks since competition was coming from a variety of non-bank institutions (mainly from Wall Street firms) that were receiving deposits and entering into the loan business. This was expected to decrease the competitiveness of banks and could ultimately threaten banks' safety and soundness.

[2] These reforms included the Depository Institutions Deregulation and Monetary Control Act (1980), which rescinded the limits on the interest rates that depository institutions could offer on deposits, as well as the Garn-St. Germain Act (1982), which broadened the types of loans and investments that banks could make and also gave broader scope in the mortgage market.

profits, but added significantly to their risk profile. Amid the Savings and Loan crisis of the 1980s the trend towards deregulation continued, focusing in part on the continued dismantling of regulations that limited depository institutions' activities in capital markets.[3] This resulted in two parallel financial intermediation systems of enormous scale, which lowered mortgage costs significantly. The funding available in the so-called shadow banking system in the US steadily gained ground on the traditional banking sector and surpassed the banking sector briefly in around 2000 and again between 2005 and 2007.[4] It was believed that large well-run commercial banks that are well capitalised and well regulated, would be able to provide support should any problems emerge in the shadow banking system (Yeoh, 2011).

The shadow banking system in the US, with relatively less supervision and regulation, grew to rival the commercial banking system. This system was fragile due to high leverage, risky assets, short-term funding, inadequate liquidity, and the lack of a Federal backstop. Edwards et al., 1995 noted that while the traditional role of banks had declined amid reduced profitability, their off-balance sheet assets in fact had increased (see also Boyd et al., 1994 and Kaufman and Mote, 1994).

At the onset of the great financial crisis of 2007/08, the US mortgage market collapsed and financial firms began to discard the commercial paper and repo lending markets. Some institutions that relied on them for funding their operations failed or had to be rescued. Interconnections created contagion, and the crisis spread to markets and firms that had little or no direct exposure to the mortgage market (Yeoh, 2011).[5] When Lehman Brothers filed for bankruptcy in September 2008, the situation deteriorated markedly (Gorton et al., 2012a) and an increasing number of financial institutions were at the risk of defaulting. More specifically, there was a run on money market mutual funds after one large fund "broke the buck" (ie its net asset value fell below 1$). As a result the US Treasury

[3] See Ely, 1993 for a discussion on the public policies that could have contributed to the Savings and Loan crisis

[4] According to Flow of Funds Accounts data of the United States, shadow bank funding includes commercial paper and other short-term borrowing (bankers' acceptances), repos, net securities loaned, liabilities of asset backed securities issuers, and money-market mutual fund assets.

[5] See also Gorton et al., 2012a for an overview of the most relevant literature related to the 2008 financial crisis.

announced a temporary guarantee of such funds, and central banks engaged in unprecedented interventions to restore confidence in the stability of the system.

It has been argued that amongst other factors, the failure of supervision was a contributory cause of the financial crisis (Llewellyn, 2009) and the Financial Crisis Inquiry Commission report (Yeoh, 2011) itself argues that with the multi trillion-dollar repo lending market, off-balance-sheet entities and the use of over-the-counter derivatives, the US had a 21st -century financial system with 19th-century safeguards.

2.1.3 Shadow banking, market-based finance or non-bank financial intermediation?

Since the 2008 financial crisis, policy makers and academics have focussed more closely on non-bank financial intermediaries - including the role they play in the economy and how they can impact financial stability. Over time, different parts of the NBFI sector have been referred to by different names, including for example shadow banking and market-based finance.

The term "Shadow banking" was first used by Paul McCulley in 2007 in his speech at the annual financial symposium, describing non-bank financial institutions that engaged in maturity transformation similar to banks, but were not subject to traditional bank regulation – i.e., they operate in the "shadows" (McCulley, 2007). Since then, shadow banking became a popular term used in some cases in a broad manner to describe any non-bank institutions that undertake bank-like activities or in certain cases refer mainly to securitization (Pozsar, 2008), or non-bank activities that require a backstop to operate (Claessens and Ratnovski, 2014).

Following Paul McCulley's decription of shadow banking in 2007, Pozsar, 2008 mapped and described the assets of the shadow banking sector in the US and the funds that flow through it. Studies focussed on the US shadow banking system were focussed mainly on securitization - where *credit transformation* (transforming risky assets into safer assets), *maturity transformation* (transforming long-term assets into short-term assets) and *liquidity transformation* (transforming asset portfolios into at par on demand instruments) were being done through a chain of various intermediaries (Pozsar et al., 2010).

These functional activities of shadow banks were explored more broadly in the following years by various authors. Caballero, 2010 focussed on credit transformation by shadow banks and the shortage of "safe" assets. Bernanke et al., 2011 similarly argue that increased capital flows into the US from jurisdictions where savings were larger than investments, contributed to lower-than-expected US interest rates. These foreign investors exhibited a preference for perceived "safe" assets in the US, including US Treasuries and agency sponsored mortgage-backed securities. Bernanke et al., 2011 also notes that strong domestic and foreign demand for these "safe" assets not only decreased their yields, but also reinforced incentives of US financial intermediaries to develop products that transformed "risky" loans into "safe" assets.

Gorton et al., 2012b focussed on the maturity transformation that occurs in shadow banks and argue that the combination of securitization and repurchase finace were the nexus of the 2008 financial crisis, given the observed increase in margin which they document as a "run" on this short-term market that provides finance for securitization activities. While this study focussed on the bilateral repo market, Copeland et al., 2014 finds there was no system-wide run on the repo market.

McCabe, 2010 examines the liquidity transformation done by shadow banks - specifically money market funds (MMFs), focussing on two crises in the MMF industry (i.e the asset-backed commercial paper crisis in 2007 and the run on money funds in 2008) despite the widely-held belief that investments into MMFs are "safe".

This research, while broadening the focus to extend beyond securitization activities, was still micro-focussed and included mainly private credit, while a macro-perspective was lacking (Pozsar et al., 2010). Mehrling et al., 2012 proposed that shadow banking can be defined as *money market funding of capital market lending*. Pozsar et al., 2010 argues that this definition is too broad and should focus on non-banks that do not have reserve accounts at a central bank.

Over the past decade a voluminous literature on the topic emerged (see for example Kaufman, 2014 and Jokivuolle, 2018). *Market-based finance* has been used to describe more resilient non-bank financial intermediation than shadow banking- for example, collective investment schemes (IMF, 2017), and others used this term to measure assets held by NBFIs (BoE, 2017)).

A widely used definition for the NBFI-sector is one of the Financial Stability Board (FSB) (FSB, 2011). The FSB defines shadow banking as “the system of credit intermediation involving entities and activities (fully or partly) outside of the regular banking system” (FSB, 2011). This definition establishes that financial entities and activities that do not perform credit intermediation should not make up part of the shadow banking estimate. However, credit intermediation can occur in a complex chain of entities connected through markets and activities, and the focus should not only be on actual credit intermediation but also on its facilitation (e.g. the provision of guarantees and liquidity facilities). Furthermore, banks could also be involved in the complex credit intermediation chain, excluding traditional credit intermediation that is subject to prudential capital and liquidity regulation. Therefore, it is important to keep in mind that not all activities of non-bank financial intermediaries are viewed as shadow banking activities, whilst some activities of banks can be regarded as shadow banking activities. In 2018 the FSB moved away from the term "shadow banking" and now makes use of the "narrow measure of non-bank financial intermediation" instead (FSB, 2018).

In this thesis, we will use the term NBFI to refer to the activities of entities within the non-bank financial sector. Such entities include all financial institutions that are not central banks, banks, public financial institutions, or financial auxiliaries. We will adopt the FSB methodology (FSB, 2011), discussed in Section 2.2 below, to estimate the "narrow measure of NBFI" in South Africa.

2.1.4 Financial stability and non-bank financial entities

As already alluded to in the previous section, activities conducted in the NBFI sector can give rise to financial stability risks. In addition to maturity- liquidity- and credit transformation as well as leverage, these entities are linked amongst each other and to banks and as such could give rise to systemic risk. Given that they perform these activities that are similar to banks there is the potential for regulatory arbitrage. Moreover the non-banking space is an important channel for capital flows and given their role in the economy they can impact the monetary policy transmission channel. These are discussed in more detail below.

Systemic risk

The IMF, FSB and BIS (Board, 2009) defines systemic risk as the "risk of disruption to financial services that is caused by an impairment of all parts of the financial system and has the potential to have serious negative consequences for the real economy". As a result of interconnectedness with the operations of core regulated institutions such as banks or bank-holding companies as well as insurance corporations, the activities of non-bank financial intermediaries could become a source of systemic risk for the financial system (Adrian, Ashcraft, et al., 2013; FSB, 2018). It is important to take into consideration that even though the non-bank financial intermediaries are typically regulated or supervised from a micro perspective, these policies are not necessarily aimed at addressing systemic risk. For example negative externalities could result from large financial institutions (for example institutions could be 'too big to fail'), or if institutions are highly interconnected and the failure of one institution could result in the failure of others (too connected to fail). Moreover micro-prudential tools can be used as macroprudential tools to address systemic risk, such tools could also contribute to systemic risk. In fact, Acharya, 2009 finds that micro-prudential policy, such as capital adequacy requirements and other regulatory mechanisms like bank closure policy, can worsen systemic risk.

Macroprudential policy involves developing, overseeing and delivering the appropriate policy response to the financial system as a whole, in contrast to micro-prudential policy that focusses on individual institutions or certain measures in separately. Two goals of macroprudential policy are to (i) enhance the resilience of the financial system as a whole, and (ii) to limit systemic risk spreading through the system. The latter includes the tendency of financial institutions to act in a procyclical manner which would result in amplifying the financial cycle (Ferguson et al., 2010). In this context, bank and non-bank financial cycles are analysed in this thesis in Chapters 5 and 6.

In South Africa, the size and activities of certain non-bank financial intermediaries remain opaque and not fully understood due to data limitations. This could lead to systemic risks emerging unnoticed. Moreover, the financial system in South Africa is relatively highly interconnected, with banks facing high funding risk from non-bank financial intermediaries.[6] Furthermore, there is also high indirect interconnectedness or portfolio overlap, with MMFs' portfolios, for example, being very similar. Against this backdrop, it is important to map the non-bank financial system not only to measure it but also to understand its evolution and interconnectedness with other financial intermediaries in South Africa. This is key to properly assess and mitigate potential risks as well as make informed policy decisions, keeping in mind the possible unintended spillovers of policy changes.

Systemic risk is further discussed in Section 2.3, where we explore systemic risk measures and contagion analysis for banks and non-banks.

Regulatory arbitrage

Given that non-banking entities often conduct activities that are similar to those of banks, but are not subject to the same level of regulation, and banks themselves operate in the non-banking space, there is the potential for regulatory arbitrage to occur. While non-bank financial intermediaries and their activities are not necessarily unregulated, the regulations they adhere to often differ to those of banks. The increased cost of compliance for banks could provide opportunities for NBFIs to meet clients' needs at more economical rates (see for example Duca et al., 2014; Acharya and Steffen, 2012; Buchak et al., 2018). In turn, increased activity in the non-banking system would transfer credit risk to the shadow banking industry. Furthermore, given that shadow banking activities are not regulated to the same extent as banks, if at all, there could be limitations on consumer protection. It is

[6] See for example FSB, 2018 showing that bank funding from non-bank, non-insurance, and non-pension funds in South Africa is the third largest of the 29 participating jurisdictions.

important for regulators to measure and be aware of such occurrences, as was the case in the great financial crisis.

Monetary policy transmission and decisions

It is possible that as financing moves to the non-banking sector, the monetary policy transmission mechanism could become less effective, given that shadow banks do not have access to the loan facilities of the South African Reserve Bank (SARB) at the repo rate. However, according to the International Monetary Fund, 2016, an increase in non-bank financial intermediation actually strengthens the monetary policy transmission. A partial reason highlighted for this observation is the relationship between risk-taking and monetary policy – specifically for asset managers. Changes in the interest rate result in movements in bond yields and risk premiums, and thus affect the cost of borrowing and real activity. This implies that monetary policy might need to adapt to changes in the transmission mechanism as the non-bank financial sector becomes relatively larger. Therefore, if credit intermediation outside of the regular banking sector is not measured properly, the Monetary Policy Committee is unable to make well-informed policy decisions.

Channel for capital flows

Capital flows matter for EMEs - Ghosh et al., 2016 finds that a fifth of periods of exceptionally large net capital inflows ends in financial crises for emerging markets. Raddatz et al., 2012 finds that capital flows through mutual funds exposed countries to foreign shocks.

Several non-banking entities, specifically collective investment schemes (CISs) invest offshore or attract and accommodate foreign investors, making these non-bank entities an important channel for capital flows. These channels should be well understood and measured in order to evaluate the impact that the implementation of available policy tools could have.

Improve financial inclusion and competition for financial services

Non-banks can bring lenders and borrowers together outside of traditional banking channels, as these products and services play an important role in increasing financial inclusion. In South Africa, the sources of non-bank credit can contribute toward this goal seeing that 11% of adults in South Africa are financially excluded (Abrahams, 2017). By increasing the number of credit providers, shadow banks could also lower the lending rates due to higher competition, thereby benefitting borrowers. A larger number of financial intermediaries would also imply that financial system risk would be split between a larger number of parties. Therefore, the beneficial role that shadow banking entities can play and are playing in increasing financial inclusion should not be ignored.

2.2 Measuring NBFI following the FSB methodology

At the November 2010 Seoul Summit, the Group of Twenty (G-20) leaders identified certain unresolved issues of financial sector regulation. Following the global financial crisis, new regulatory capital standards for banks were determined (Basel III); however, these were not applicable to non-banks. G-20 leaders realised there was a potential threat that regulatory gaps might emerge from non-banking activities. The FSB, in collaboration with other international standard-setting bodies, developed recommendations to strengthen the regulation and oversight of the shadow banking system (FSB, 2011). The objective of the FSB's initiative was to ensure that "shadow banking" is subject to appropriate oversight and regulation to address bank-like risks to financial stability that could emerge outside of the regular banking system, while at the same time not preventing sustainable non-bank financing models that do not pose such risks.

The FSB formed a task force to draft a scoping paper on shadow banking systems, with particular emphasis on (i) what is meant by 'the shadow banking system'; (ii) potential approaches for a monitoring framework around shadow banking; and (iii) to develop options to discuss possible regulatory measures to address the issues posed by shadow banking, including the possibility for both the regulation of shadow banking directly and the regulation of banks' interactions with the shadow banking system. The FSB also coordinated the development of policies to mitigate the possible systemic risks associated with shadow banking and to help to transform shadow banking into resilient market-based finance (FSB, 2011). Since 2011, the FSB has coordinated an annual global shadow banking monitoring exercise and formed several working groups in order to develop recommendations to strengthen the regulation and oversight of the shadow banking system.

The FSB's global monitoring exercise consists of two steps: the first step entails 'casting the net wide', to observe all financial intermediaries. The monitoring universe of non-bank financial intermediaries (MUNFI) is the measure used to 'cast the net wide'. This broad measure for shadow banking activities comprises all entities that are not the central bank, banks, financial auxiliaries, or public financial institutions.

The second step of the exercise consists of narrowing down MUNFI activities based on a risk-based activities approach. The approach involves the classification of non-bank entities into five economic functions (EFs), each of which involves non-bank credit intermediation and may pose risks, including maturity/liquidity transformation and leverage (FSB, 2018). This classification framework allows the detection and assessment of the sources of financial stability risks from shadow banking in the non-bank financial space. The EFs are as follows: activities that are susceptible to runs (EF1), lending-dependent on short-term funding (EF2), market intermediation that depend on short-term funding or the secured funding of client assets (EF3), facilitating credit creation (EF4), and securitisation-based intermediation (EF5). Classification is done without taking potential policy measures into account.

2.3 Systemic risk and contagion in the financial sector

Systemic risk in financial markets can be the result of synchronised behaviour of agents (as a result of similar behaviours or herding or fire sales of assets) or as a result of direct interconnectedness amongst agents. The importance of

Figure 2.1 Classification of NBFI-activities into Economic Functions

Economic Function	Definition	Key shadow banking risks	Typical entity types*
EF1	Management of collective investment vehicles with features that make them susceptible to runs	Public funds: Liquidity and maturity transformation Private funds: Leverage and maturity transformation	Fixed income funds, mixed funds, credit hedge funds, real-estate funds
EF2	Loan provision that is dependent on short-term funding	Liquidity and maturity transformation, leverage	Finance companies, leasing companies, factoring companies, consumer credit companies
EF3	Intermediation of market activities that is dependent on short-term funding or on secured funding of client assets	Liquidity and maturity transformation, leverage	Broker-dealers
EF4	Facilitation of credit creation	Credit risk transfer	Credit insurance corporations, financial guarantors, monolines
EF5	Securitisation-based credit intermediation and funding of financial entities	Liquidity and maturity transformation, leverage	Securitisation vehicles

* The FSB's Policy Framework acknowledges that the narrow measure may take different forms across jurisdictions due to different legal and regulatory settings as well as the constant innovation and dynamic nature of the non-bank financial sector. It also enables authorities to capture new structures or innovations that may create financial stability risks from NBFI, by looking through to their underlying economic functions and risks. Thus, the entity types listed should be taken as typical examples. For details, see FSB, 2013).
Source: Financial Stability Board, Global monitoring report on NBFI

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understanding links amongst financial intermediaries and ultimately the systemic risk that entities could pose to the financial system has been an area of interest for academics for many years. While linkages in financial systems can be positive or negative, from a systemic risk perspective negative spillovers that occur as a result of high interconnectedness have been an area of significant focus (see for example Acemoglu et al., 2015 and more recently Akhtaruzzaman et al., 2021 analysing the increase in conditional correlations between the stock returns of firms during the COVID-19 period).

The global financial crisis demonstrated the importance of interconnectedness as a dimension of systemic risk. More specifically, non-bank financial entities share many commonalities from a systemic risk perspective, and that their behaviour can contribute to procyclicality in the financial system (Bengtsson, 2016). As such, it became even clearer during the 2008 financial crisis that the stability of the financial system does not only depend on the resilience of individual institutions, but also on how distress spreads amongst institutions (i.e. contagion - see Section 2.1. Since then, academics, central bankers and regulators alike have focussed on better understanding and measuring interconnectedness and contagion and developed a number of new systemic risk measures. Such measures include those that are based on market data, macro data, or micro data (see Rodríguez-Moreno et al., 2013).

Borio, 2003 outlines two views of systemic risks. The first commonly held view argues that widespread financial distress arises predominantly from the failure of individual institutions, that spread to the financial system via contagion as a result of balance sheet linkages, with structurally illiquid portfolios playing a key role as a source of vulnerability and amplification. Such a view falls in line with that described by Diamond et al., 1983, and several studies of systemic risk has focussed on domino effects (see for example Kaufman and Mote, 1994). Another view argues that systemic risk is the result of common exposures of financial institutions to macroeconomic risk factors. In contrast to the first view, the focus here is not the contagion as a result of individual failures but instead as a result of common exposures.

The seminal paper of F. Allen and Gale, 2000 the authors introduce an interbank liquidity market and show that when each bank is connected to all other banks, the system overall becomes more resilient. In contrast, incomplete networks (not all banks are connected) are more fragile as banks are not able to diversify their portfolios against idiosyncratic shocks. Cai et al., 2018 also finds that the risk reduction as a result of diversification (i.e., a higher number of linkages) of a single entity ignores the negative externalities of a more interconnected financial system. Acemoglu et al., 2015 finds that contagion depends on the size of the shock - if a shock is small, financial stability is enhanced by more densely connected networks (or fully diversified portfolios). However if the shock is large, densely connected networks will amplify shocks. While the majority of studies have focussed on interconnectedness amongst banks- for example links that arise as a result of interbank funding (Brunetti et al., 2019; Liu et al., 2015; F. Allen, Hryckiewicz, et al., 2014), Lux, 2016 uses a credit network between banks and non-bank corporate sector and finds that contagion via common exposures due to loans to firms is more important for a contagious spread of defaults than the interbank credit network is.

2.3.1 Multilayer financial networks

Financial systems are interconnected as a result of various types of balance sheet contracts that result in both direct and indirect exposures. Until recently, researchers focussed on aggregate exposures because contract-level specific data were not readily available. However, as more disaggregated data became available, modelling techniques were developed to take advantage of such data.[7] Multilayer financial networks is one example of a modelling technique to take advantage of increased data. Such networks can be used to model different types of contracts (and thus contagion mechanisms) in a single model, where different layers represent different contract types. Several studies have taken the multilayered aspects of a financial system into account (see for example Battiston, Caldarelli, et al., 2016, Lux, 2016, Aldasoro, Gatti, et al., 2017).

The most commonly studied interconnections are direct exposures; equity shares, credit exposures, and other contracts with a counterparty, which are directly written down/off as the counterparty, becomes insolvent. Aldasoro and Alves, 2018 for example, uses multi-layer network to show importance of bilateral exposure data. More recently, indirect exposures have garnered attention (Cont and Schaanning, 2019). Indirect exposures arise when two or more institutions' portfolios of tradable assets overlap; when one of these institutions decides to liquidate (part of) its

[7] To overcome data limitations, methods were also developed to to reconstruct financial networks based on available aggregate data, see Anand et al., 2018.

portfolio of tradable assets, the market price of these assets is depressed, causing mark-to-market losses to the other(s).

Contagion mechanisms that act on the layers of the network

The multilayer approach not only requires modelling the layers (or contracts) of the financial network, but also the contagion mechanisms that act on these layers. The literature typically distinguishes between three contagion mechanisms, namely funding contagion, overlapping portfolio contagion and counterparty risk contagion (Aymanns, Farmer, et al., 2018).

Funding contagion refers to the transfer of liquidity shocks from a financial intermediary to their debtors. In a scenario where an intermediary - like a bank - experiences liquidity shortages, the bank can raise liquidity by not rolling over loans that it has extended. This forces borrowers to repay their loans, thereby transferring the liquidity shortage. Liquidity hoarding can exacerbate funding contagion and if an institutions' liquidity hoarding is substantial, a liquidity spiral can ensue (Cespa et al., 2014).

Overlapping portfolio contagion occurs when market participants are exposed to the same assets (i.e. have a portfolio overlap). In the scenario where a financial institution rapidly sells off securities, the security's price could be depressed and all institutions that have a position in the specific security could face mark-to-market losses. Brunnermeier et al., 2009 shows that an asset's market liquidity and a trader's funding liquidity can be mutually reinforcing in certain circumstances, leading to liquidity spirals and that market liquidity has commonality across assets. Cont and Wagalath, 2013 focuses on investment funds specifically and finds that in stressed periods investor sales and short selling of the fund's assets could lead to positive correlations between fundamentally uncorrelated assets, while Cont and Wagalath, 2016 quantifies the impact of fire-sales on portfolio risk. In a stressed scenario the mark-to-market losses can push institutions beyond their leverage constraints, and force them to delever through selling securities - resulting in a positive feedback loop to overlapping portfolio contagion. This would put additional pressure on market prices (Cont and Schaanning, 2017). The increased price volatility can also cause institutions with Value-at-Risk constraints to liquidate assets, as the perceived risk of an asset increased. Such a liquidation of assets further exacerbates the positive feedback loop (Aymanns, Caccioli, et al., 2016).

Counterparty risk contagion is the result of direct exposures amongst market participants. It refers to an institution's losses when their counterparties, or borrowers, default. Counterparty risk contagion was first studied in a network-setting in Eisenberg et al., 2001. For example, creditors suffer a Loss Given Default (LGD) on their loans to the defaulted institution, and counterparties to derivative contracts of the defaulted institutions may face previously hedged positions opening-up to market risk. Counterparty risk contagion can also materialise prior to a default: Accounting standards might require institutions to risk-adjust their assets' value (Bardoscia et al., 2017). As such, when an institution's Probability of Default (PD) increases, its creditors suffer risk-adjustment losses on their exposures to the institution. When institutions are highly leveraged, this can lead to the "risk-adjustment" spirals studied in Bardoscia et al., 2017. The counterparty risk exposure of an entire portfolio can be highly challenging to estimate when containing complex instruments. The efficient computation of portfolio-level counterparty risk exposure is studied in Graaf et al., 2018.

Measuring contagion

To understand financial stability, both the contract layers of the financial network and the contagion mechanisms that act upon them must be taken into consideration. Measures of institutions' interconnectedness through the contract-layers of a financial network, such as Molina-Borboa et al., 2015, Bravo-Benitez et al., 2016, and Bargigli et al., 2015, provide a valuable overview of the channels through which contagion can spread across the network, but do not describe the resulting contagion itself. Stylised models of contagion that abstract away the network's topology, such as Diamond et al., 1983, F. Allen and Gale, 2000 and Brunnermeier et al., 2009, yield valuable qualitative insights, but make deriving quantitative results challenging.

Network-approaches to modelling financial stability can be separated into two categories, stress tests that study the resilience of the financial system to a specific adverse scenario, and scenario-independent approaches. Simulation-based stress tests, such as Montagna and Kok, 2016 and M. Bluhm et al., 2014, study the financial system as a dynamic network by embedding an agent-based model (ABM) on top of it. The advantage of these scenario-based stress tests is that the interactions between layers can be included in the ABM, allowing for a holistic analysis of the resilience of the financial network to the stress scenario. The disadvantage of scenario-based stress tests is that they only study the system's stability with respect to the specific stress scenario and cannot evaluate the entire universe of potential stress scenarios.

Scenario-independent measures of stability find an upper bound to instability or study asymptotic (in)stability. Such measures include the clearing vector introduced by Eisenberg et al., 2001 and its extensions (Elsinger et al., 2009, Rogers et al., 2013), or bankruptcy costs and claims of different seniority Gouriéroux et al., 2013, DebtRank (Battiston, D'Errico, et al., 2016, Battiston, Puliga, et al., 2012, Battiston, D'Errico, et al., 2016, Bardoscia et al., 2015), and the Contagion Index and Contagious Links measures (Cont, Moussa, et al., 2010, Amini et al., 2013, Amini et al., 2016). These measures focus on counterparty risk in interbank liabilities networks; scenario-independent measures of overlapping portfolio contagion include Gai and Kapadia, 2010 and Caccioli, Shrestha, et al., 2014. To date, no scenario-independent stability measure exists that captures funding contagion, overlapping portfolio contagion and (pre-default) counterparty risk contagion in a single model.

2.3.2 Beyond direct and indirect links: Higher-Order exposures

An institution's exposure to another is not limited to direct and indirect exposures. The financial distress caused by the default of an institution may be propagated by the system, causing further losses down the line through write-downs/offs of assets that do not generate direct or indirect exposures to the defaulted institution. We refer to these as Higher-Order Exposures.

We contribute to the literature on financial exposures. A large body of work, dating back many years, exists that measures direct exposures between counterparties (see e.g. Altman et al., 1997; Crouhy et al., 2000; Jorion et al., 2009; Duffie et al., 2012; C. Bluhm et al., 2016). Since the Great Financial Crisis (2007-2008), the importance of measuring additionally indirect exposures has been emphasized and measures thereof have been introduced (see e.g. Cont and Wagalath, 2013; Caballero and Simsek, 2013; Greenwood et al., 2015; Clerc et al., 2016; Cont and Schaanning, 2017; Calimani et al., 2017; Aymanns, Farmer, et al., 2018; Cont and Schaanning, 2019; Aldasoro, Hüser, et al., 2020). The idea that higher-order interconnections between one institution i and another j could pose a financial risk to institution i – through the process of financial contagion – if institution j defaults is well-understood and has often been modeled (see e.g. F. Allen and Gale, 2000; Gai and Kapadia, 2010; Elliott et al., 2014; Glasserman et al., 2015; Wiersema et al., 2019; Farmer et al., 2020).

Yet 'higher-order exposures' have neither been conceptually introduced nor measured before. We propose that an institution's exposure to another is not just its direct exposures, or even its direct plus indirect exposures. Instead, the total loss that institution i is exposed to if j fails – i.e. its exposure – is correctly given by the sum of its direct, indirect and higher-order exposures. Failing to capture higher-order exposures may lead to an underestimation of loss institution i is exposed to upon j's failure, resulting in a potential underestimation of the true exposure of i to j. We are also the first to point out that the evaluation of large exposure limits may be misguided if it is based solely on direct exposures – as is common so far – which is only a part of the exposure. Our case study of the South-African financial system shows that higher-order exposure can be material, resulting in large exposures even if direct exposures are minimal, or even absent, reinforcing the importance of taking all components of exposure into account when calculating an institution's exposure to another for prudential regulatory purposes.

2.4 Financial cycles

2.4.1 The importance of measuring financial cycles

Macroprudential policy involves developing, overseeing and delivering the appropriate policy response to the financial system as a whole, in contrast to microprudential policy that focusses on individual institutions or certain measures in separately. Two goals of macroprudential policy are to (i) enhance the resilience of the financial system as a whole, and (ii) to limit systemic risk spreading through the system. The latter includes the tendency of financial institutions to act in a procyclical manner which would result in amplifying the financial cycle (Ferguson et al., 2010).

Therefore, understanding financial cycles is viewed as critical for informing the use of countercyclical macroprudential policy. An important question for policymakers is whether macroprudential policy should be aimed at controlling the 'financial cycle' or not. See Borio, 2014b and Constâncio, 2014 for differing views on this issue. Che et al., 2014, for example, find that attempting to improve the financial soundness of banks during a downturn of the financial cycle could amplify the cycle and that policymakers should therefore be careful about the timing of regulatory changes. However, despite their importance for policymakers, there is no consensus regarding the definition of financial cycles nor on the methodology that should be employed to measure them. Furthermore, even though there is a large and growing international literature,[8] we are not aware of published research that assesses the options available for measuring the South African financial cycle.

Moreover, several studies focus on bank-credit when considering the financial cycle. In Chapter 5 the financial cycle of South Africa is estimated. In line with literature and data availability, the credit measure used in this study is based mainly on credit provided by banks. The role of credit provided by non-bank financial intermediaries has not yet been analysed in detail in available literature, despite its role in the higher levels of global debt and its potential impact on

[8] Claessens and Kose, 2017 provide a recent review of studies that examine the features of business and financial cycles, and the linkages between them, for the credit, equity, and housing markets.

financial stability (Patalano et al., 2020).

2.4.2 Approaches to measuring the financial cycle

A working definition describes the financial cycle as reflecting self-reinforcing feedback within the financial system and between the financial system and the real economy (Borio, 2014a). Approaches to measuring financial cycles have therefore focussed on the co-movement of a broad set of financial variables (Bank for International Settlements, 2015). However, given macroprudential policy's focus on systemic risks and the challenges of measuring risk perceptions, it is not clear which set of financial variables or indicators best captures the financial cycle.

There are three main approaches to measuring the financial cycle in the literature namely turning-point analysis, frequency-based filters analysis, and other model-based approaches. These are discussed in turn.[9]

Turning-point analysis

Following Burns et al., 1946, traditional turning-point analysis defines the cycle as a pattern in the level of economic activity. In the financial cycle literature, Claessens, Kose, and Terrones, 2011 and Claessens, Kose, and Terrones, 2012, Drehmann et al., 2012, and Granville et al., 2017 provide turning point analyses. The approach has been employed in the South African context by Du Plessis, 2006 for the business cycle, and by Boshoff, 2005 for financial variables.

Frequency-based filters analysis

Frequency-based filters are used to extract the medium-term cyclical components of the indicators, which are then combined to provide an estimate of the financial cycle. Similar approaches have been adopted in the literature by Aikman et al., 2015 for the credit cycle, and by Schüler, Hiebert, et al., 2015b, Strohsal et al., 2015

[9] Other options include wavelet analysis, which attempts to simultaneously account for both the frequency and the time variations of a time series. See e.g.Verona, 2016, and Ardila et al., 2016.

, and Gonzalez et al., 2015 for the financial cycle. The frequently cited analysis of Drehmann et al., 2012 uses frequency-based filters, as well as turning point analysis. In the South African literature, Boshoff, 2005 has employed frequency-based filters to examine cycles in financial variables, and Boshoff, 2010 considers the properties of the South African business cycle, as measured by the deviation cycle.

Model-based approaches

Trends and cycles may be modelled as unobserved components within the framework provided by structural time series models (Harvey, 1990; Harvey and Jaeger, 1993). The statistical approach uses the state space form, with the components being obtained from the Kalman filter and smoother. Koopman and Lucas, 2005, Galati et al., 2016a, Rünstler et al., 2018, and Grinderslev et al., 2017 have used unobserved components time series models (UCTSMs) to measure financial cycles. We apply each approach to the South African data to estimate South Africa's financial cycle.

The indicators that have been found to give the most parsimonious description of the financial cycle are credit and property prices (Drehmann et al., 2012; Borio, 2014a). Credit aggregates (which can be used as a proxy for leverage) are often the sole focus (Aikman et al., 2015),[10] and together with property prices (a measure of collateral available) are jointly important for the financial cycle because of mutually-reinforcing feedback effects. Strong growth in credit extension, specifically mortgage credit, often results in higher property prices. In turn, higher house prices boost collateral values and the amount of credit the private sector can obtain. Such interactions have historically been associated with the most serious bouts of financial instability (Bank for International Settlements, 2014; Jordà et al., 2017; Schularick et al., 2012).

In addition to credit and housing market developments, a number of other variables have been proposed in the literature as proxies for the financial cycle. Equity

[10] A recent empirical literature finds that credit growth is a good predictor of financial crises. For example, Schularick et al., 2012 consider the experience of 14 developed economies and find that credit growth in the past five years has strongly predicted the probability of a financial crisis.

prices (see for example Claessens, Kose, and Terrones, 2011, Granville et al., 2017, bond prices Schüler, Hiebert, et al., 2015a, interest rates, non-performing loans, volatilities, risk premia, and the credit-to-GDP ratio (Borio, 2014a) have all been used.[11]

2.4.3 Non-bank credit cycles

While several studies have focussed on bank credit when estimating financial cycles, there is less consensus on the cyclicality of non-bank credit. Bond credit, in particular, has been found to be less procyclical than bank credit (Becker et al., 2014; S. Langfield et al., 2016). That is why the IMF, 2015 refers to market-based financing as a spare tyre for periods when bank credit is restrained. But this issue on the cyclicality of non-bank credit has not been fully settled, as non-bank credit can take many more different forms. For example, securitization markets, which typically transform bank credit into non-bank credit, showed a strong boom-bust pattern around the financial crisis. Similarly, collateralized short-term funding can result in procyclical leverage and investment behaviour as argued in Fostel et al., 2008, and shown to be the case for US broker dealers in Adrian and Shin, 2009. Moreover Herman et al., 2017 find that bank and non-bank credit exhibit different dynamics throughout the business cycle in the US.

With respect to financial instability, the literature has mainly focussed on credit provided by banks or total credit. Previous studies have already established a link between credit cycles and banking or currency crises (Borio and Lowe, 2002; Schularick et al., 2012; Mendoza et al., 2012). Several other studies have focussed on financial cycles more generally (e.g. Claessens, Kose, and Terrones, 2012; Drehmann et al., 2012; Schüler, Hiebert, et al., 2015b). However, less research has been conducted on the role of non-bank credit. One strand in the literature stresses that a stronger reliance on non-bank debt or market-based finance, relative to bank credit, should be beneficial for economic growth and financial stability (e.g. Gam-

[11] Even larger data sets are possible. Menden et al., 2017, e.g., propose constructing financial cycle measures for the US based on a data set of seven macroeconomic and 25 financial variables. They use a dynamic factor model to estimate three synthetic financial cycle components, which they find explain most of the variation in their data.

bacorta et al., 2014; Bats et al., 2017). But at the same time, several examples can be given of stress events in the non-bank sector, sometimes of a systemic nature (ESRB, 2016).[12]

[12] For example, in the early 1970s, in the UK, unregulated 'fringe institutions' funded themselves in the money markets and invested these funds largely in commercial property developments. Financial stress in this sector became known as the secondary banking crisis and led to legal reforms in the UK. On a similar tone, Kim et al., 2017 describe how non-bank mortgage companies in the US are vulnerable to liquidity pressures, and warn that they are vulnerable to a financial crisis. As a result, there may be additional information in non-bank credit developments for financial stability purposes.

Chapter Three

Measuring non-bank financial intermediation in South Africa

Non-banking financial entities, the activities they engage in, and their interconnectedness with financial intermediaries, have implications for financial stability. As such, it raises important policy concerns. However, research in this area in South Africa remains limited. While non-bank entities that could pose bank-like risks remain relatively small when compared to global peers, the NBFI-sector's assets under management is growing at a faster pace than those of banks. Furthermore, banks in South Africa obtain a relatively large portion of their funding from non-bank financial intermediaries and overall interconnectedness amongst financial intermediaries in South Africa.

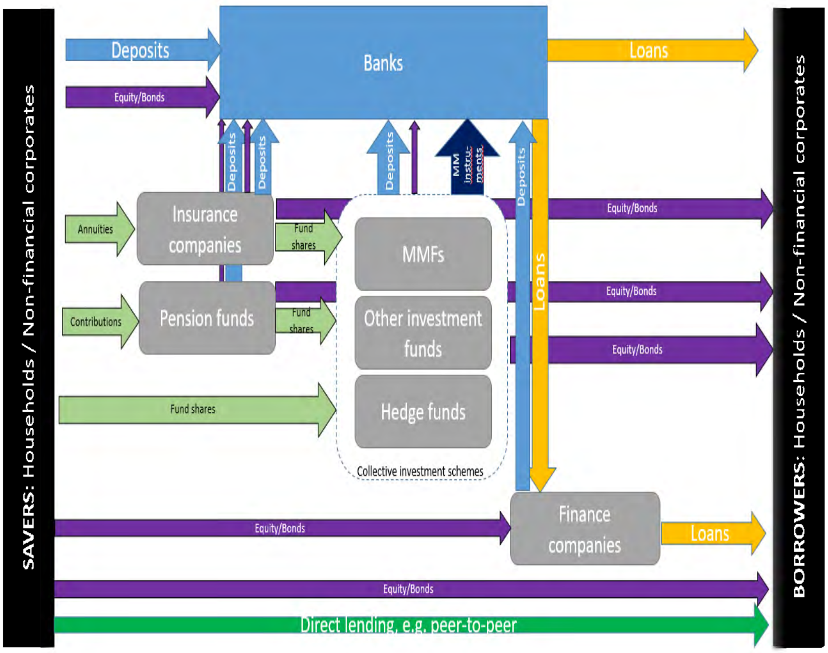
This chapter maps the financial landscape in South Africa, focusing on a broad set of non-bank financial intermediaries as well as the narrower measure of non-bank financial intermediation for South Africa that pose bank-like risks.[1] The measures are based on the Financial Stability Board's methodology. We also conduct some preliminary analysis to measure and visualise direct interconnectedness in South Africa's financial system and also propose a measurement for indirect interconnectedness, applied to money-market funds.

[1] This chapter is based on the South African Reserve Bank working paper Kemp, 2017.

3.1 Financial intermediation through banks and non-banks

Financial intermediaries channel funds between savers of funds and borrowers of funds. Figure 3.1 shows the simplified and stylised representation of the flow of money between savers and borrowers in South Africa, through banks and non-bank financial intermediaries.

Figure 3.1 Simplified stylised representation of financial intermediation in South Africa - flow of money and ownership of securities



Note: The direction of the arrow indicates flow of money. The type of instrument is shown inside the arrow. Banks and bank-like instruments are shown in blue boxes and blue arrows. Non-bank financial intermediaries are shown in gray boxes. For simplicity, the government and foreign sectors are not displayed. Given the relatively small size of known securitisation activities, special purpose vehicles are not shown.

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A saver, on one hand, can deposit money at a bank, invest in securities directly, or obtain more exposure and spread risk by investing in a collective investment scheme (CIS). Money can also be invested in insurance annuities or contributions to pension funds which, in turn, can be invested in CISs or directly in various securities. CISs invest in a portfolio of assets, including equities, bonds, and other more complicated security types. These securities are issued by banks, non-banks, or the government (not displayed). Recently, peer-to-peer (P2P) lending platforms, where savers can extend loans directly to borrowers by using a platform, also became available in South Africa.

A borrower, on the other hand, can obtain funding by means of a loan from a bank or a finance company, or by issuing various types of securities or debt instruments. Financial intermediaries can also securitize assets (including loans) by using special purpose vehicles (SPVs) to raise funds or increase liquidity (not displayed). Banks obtain funding from deposits, but also by issuing securities or using securitisation vehicles. In fact, several of the securities and debt instruments that individuals and CISs invest in are issued by banks. These securities include equities, bonds, and money-market instruments.

One could think of the basic function of a bank - to accept deposits from clients (savers) and transform these deposits into loans that are extended to borrowers. The bank engages in liquidity and maturity transformation and credit intermediation, by transforming deposits (cash) that can be withdrawn in a short time frame (daily or perhaps with a month's notice) into loans that are repayable over a number of years. Traditionally, this risk transformation occurs on a single balance sheet. The risk that banks face are well documented, and confidence in the bank is key. Diamond and Dybvig (Diamond et al., 1983) for example show how banks' liquidity liabilities (i.e. deposits) and illiquid assets (longer-term loans) can result in self-fulfilling panics, runs of banks and ultimately bank failures.

Similarly, non-bank financial intermediaries often engage in liquidity and maturity transformation. Using investment funds as an example, these funds accept investments in return for fund shares, and pools such investments to purchase debt instruments or invest in equity shares. These funds offer short-term redemption (often daily) to their investors while investing in longer-term assets, such as bonds. Non-bank financial intermediaries could also, similar to banks, be subject to run risk. For example money market mutual funds in the US - that have daily redemption and invest in assets with a short-term maturity - faced runs after the failure of an investment bank who was a major issuer of money market debt (Gordon et al., 2014). Moreover, non-banks engage in activities that are similar to those of banks; however, non-banks transform risks using several balance sheets or mechanisms and are not regulated to the same extent as banks given that they do not accept deposits.

3.2 The distribution of financial assets in South Africa

Following the FSB's methodology, the financial assets held by banks, the central bank (South African Reserve Bank), public financial intermediaries and non-bank financial intermediaries over time are shown in Figure 3.2.

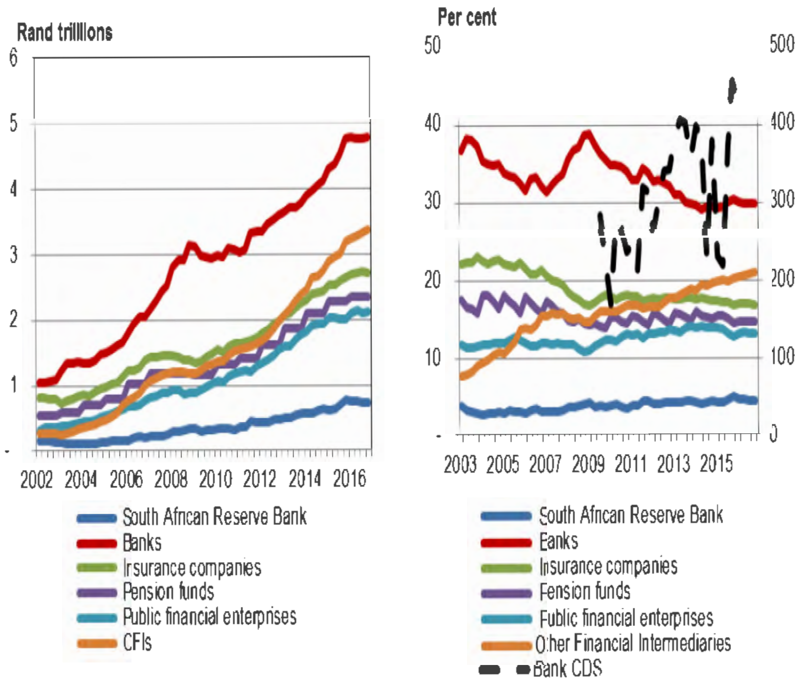
Banks hold the largest share of financial assets in South Africa; however, since the 2008 financial crisis, the share of assets held by banks has decreased – reflecting that the growth of assets held by the NBFI sector has outpaced that of banks. The NBFI sector is made up of heterogeneous entities, including insurance corporations, pension funds, collective investment schemes (CISs), finance companies, securitisation schemes, real-estate investment trusts (REITs), trust companies, stokvels, and certain activities of brokers. The portion of the NBFI sector that are not insurance corporations or pension funds are referred to as Other Financial Intermediaries or OFIs.[2]

In line with observations at a global level documented in annual exercises of the FSB, assets of OFIs specifically increased at a faster pace than those of banks, resulting in a decrease in the share of banks' assets as a percentage of total financial assets between 2008 and 2014. At the same time, the default risk for South African banks as a collective increased.[3] This trend reversed in 2013, and in 2014 and 2015

[2]Note that in the OFI measure, double-counting is involved and acknowledged because of attempting to measure the chain of credit intermediation. Following the approach of Pozsar et al., 2010, double counting of assets is the result of the same financial asset held by potentially more than one financial intermediary, i.e. intermediation chains, for example MMFs investing in instruments issued by banks, and investment funds investing in MMFs. The extent of double counting is not clear

[3]Data only available from from 2008.

Figure 3.2 Distribution of financial assets amongst intermediaries in South Africa

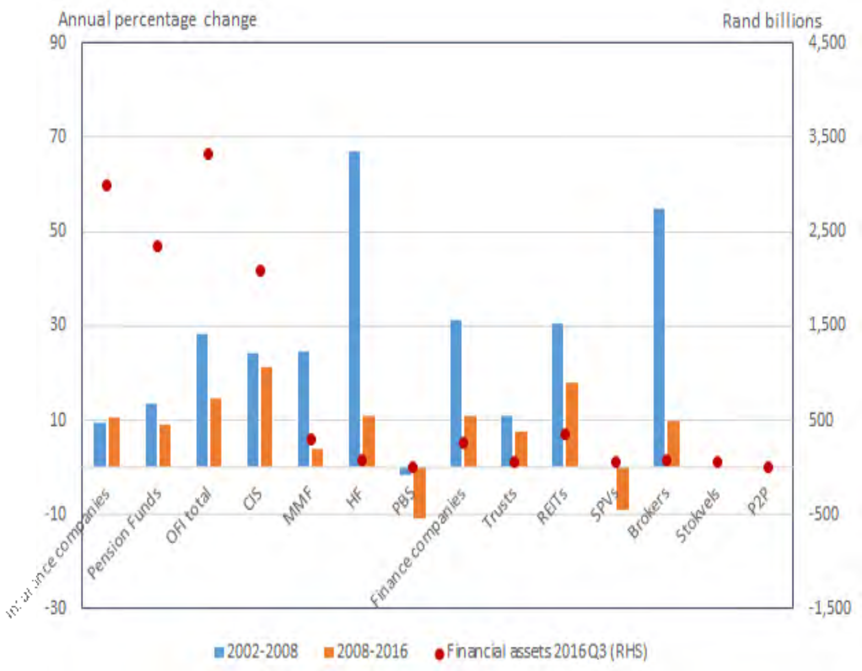


Note: OFIs = Other Financial Intermediaries which includes all financial intermediaries that are not central banks, banks, pension funds, insurance corporations or public financial enterprises; CDS = Credit Default Swaps
Sources: South African Reserve Bank, ASISA, Morningstar, Novare, SAREITS, Bloomberg, author calculations

banks' share of financial assets increased. Banks' Credit Default Swaps (CDS) have remained above 2008 levels. Based on FSB analysis, a notable difference to many other jurisdictions is the relatively larger share of financial assets held by pension funds and insurance corporations, adding to roughly 40% of total financial assets, whilst amounting to under 20% in Brazil, China, India, Mexico, Russia, and the euro area as a whole.

The steady increase of the NBFI sector over the past decade is attributable to several factors, including increased investment by pension funds and higher capital flows into South Africa against a global search-for-yield backdrop, in addition to valuation effects. Between 2008 and 2013, the relatively faster growth observed

Figure 3.3 Non-bank financial intermediaries: annual growth and size of assets under management



Note: OFI = Other Financial Intermediaries; CIS = Collective Investment Schemes; MMF = Money Market Funds; HF = Hedge Funds; PBS = Participation Bond Schemes; REITs = Real Estate Investment Trusts; SPVs = Special Purpose Vehicles; P2P = Peer to Peer platforms
Sources: South African Reserve Bank, ASISA, Morningstar, Novare, SAREITS, Bloomberg, author calculations

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in OFIs' assets under management compared to banks' assets corresponds to the period of quantitative easing in the US and relatively low interest rates in several advanced economies that could have contributed to higher capital inflows. Despite the search for yield, the annual growth rates of the assets of most categories of OFIs, whilst higher than those of banks, have decreased since the global financial crisis, apart from CISs (excluding MMFs, hedge funds, and participation bond schemes (PBSs)). The categories of OFIs are discussed in Section 3.2.1.

3.2.1 Non-bank financial intermediaries: OFIs in South Africa

Collective investment schemes

In South Africa, CISs were regulated by the Financial Services Board[4] under the Collective Investment Schemes Control Act 45 of 2002 (CISCA) up to 2018. Since then, the Financial Sector Conduct Authority (FSCA) has taken over the mandate to protect the interests of South African investors in the CIS industry and to promote a sound, transparent, efficient, and fair CIS industry. However, the regulations do not aim to guarantee an investment, and any investment is still subject to market losses. Instead, these regulations prescribe the asset holdings of a particular fund according to the type of fund it is registered as. According to CISCA, CISs can currently be categorised as MMFs, participation bond schemes (PBSs), hedge funds, and other collective investment schemes. Given that resources are pooled together by the CISs to purchase underlying assets with different maturities, while generally investments into the CIS are regarded as liquid, these funds could be subject to runs. The FSCA has the power to declare any tool to be used on an ad hoc basis and the conditions under which it may be used, including side pocketing, redemption gates, and imposition of redemption fees. In the case of distress, the application of these tools could limit a run on CISs.

It is worth noting that, apart from hedge funds, generally leverage is very low in South African investment funds domiciled in South Africa, and regulation allows borrowing only in two circumstances; namely to allow the fund to repurchase participatory interest where the loan period is shorter than 61 days, and to settle purchase and sale transactions (i.e. short-term bridge funding). Finally all asset managers are also required to maintain a certain minimum amount of capital, such requirements vary according to the type of CIS.

Money-market funds MMFs became available in South Africa in 1995 and are typically funds that invest in highly liquid assets with a shorter maturity – issued

[4]The Collective Investment Schemes Control Act 45 of 2002 (CISCA) regulates and controls the establishment and administration of CISs in South Africa. A list of approved schemes is available from the Financial Services Board at Approved Schemes.

by banks, other corporates, and government. The largest MMFs in South Africa are managed by companies owned by banks. CISCA Notice 90 of 2014 restricts the money-market instruments that a fund manager may invest in, in terms of maturity of the investments in addition to the exposure to a counterparty (inclusion limits). The weighted average legal maturity of the fund may not exceed 120 days, while the weighted average duration of the money-market instruments may not exceed 90 days. No single instrument that MMFs invest in may have a maturity exceeding 13 months. The regulations also limit the exposure in terms of the maximum percentage of the aggregate market value of the portfolio. These limitations include a 30% maximum exposure to MMF instruments issued by local or foreign banks (registered in South Africa) of which the holding company is listed on the exchange if the market capitalisation of the listed group holding company exceeds R20 billion, and to 20% if the market capitalisation of the listed group holding company is between R2 billion and R20 billion. Some MMFs are also compliant with Regulation 28 of the Pension Funds Act, which makes them eligible investments for South African pension funds.[5] MMFs can also invest in money market instruments issued by any local or foreign entity that is listed on an exchange. This exposure is limited to 10% per issuer.

Hedge funds Hedge funds in South Africa started in 1995 and, to date, have not become as popular as hedge funds internationally. Despite relatively high growth rates, these funds remain relatively small with R68,6 billion worth of assets under management in 2016.[6] Even though the hedge fund industry in South Africa is not large enough to present systemic risk to the local financial system, it has shown significant growth over time. A possible driver could be regulatory change, specifically the amendment to Regulation 28 of the Pension Funds Act 24 of 1956. Under the amendment, pension funds can invest up to 10% of their assets into hedge funds, whereas previously, hedge funds formed part of the

[5] Regulation 28 to the Pension Funds Act limits the investments of retirement funds with the aim of protecting funds against making imprudent investments once the requirement to invest in prescribed assets has fallen away. See Regulation 28.

[6] According to survey data published by Novare (2015), given that no other aggregated data for hedge funds are currently available.

‘other’ category with a limit of 2.5% on everything except equities, cash, bonds, property, and Krugerrands. Hedge funds can invest in a wider range of financial instruments than other CISs, and are also allowed to employ different investment strategies and use leverage and short selling. More than half of the assets under the management of hedge funds are equity long-short strategies.[7] Hedge funds are allowed to gear or use leverage, although a retail hedge fund may not have a potential loss of more than 20% of the net asset value of the portfolio, subject to a strict daily exposure risk measure of absolute Value at Risk (aVaR). It is estimated that over 60% of funds have gross exposure of between 150% and 300%, i.e. are leveraged up to between 1.5 and three times. In 2007, the Financial Services Board started regulating hedge fund managers (requiring that they hold a CAT II A license). After the proposed framework for regulating hedge funds in South Africa was released in 2014, National Treasury and the Financial Services Board released a regulation in 2015, which created a separate pillar for hedge funds under CISCA, and hedge funds became classified as CISs in South Africa. As such, the oversight and supervision of these funds are placed with the Financial Services Board. Since then, all hedge funds have been registering in terms of CISCA, and existing funds had to convert to CIS funds 12 months after registration. The regulation established two types of hedge funds, one for qualified investors and another for retail investors. The regulations that the two types of funds have to adhere to differ, with the Retail Investor Hedge Fund (RIHF) regulating more stringently than the Qualified Investor Hedge Fund (QIHF). Currently, most existing hedge funds have been registered at the Financial Services Board, but data reporting will only become due in approximately a year’s time. Therefore, for the time being, there are still potential data gaps when measuring hedge funds.

Participation bond schemes Participation bond schemes are currently the smallest of the available CISs in South Africa. These schemes are similar to a closed-end fund with these licensed schemes pooling money from investors and lending it to institutions/individuals in order to develop or purchase property. A mortgage bond is registered over the property, making the property the security

[7] According to the annual Hedge fund survey by Novare.

for the loan. This implies that if the property developer does not repay the loan according to the agreement with the scheme, the scheme can take over the property and sell it. The money from the sale can be used to pay back investors. There is no capital growth on the amount invested. Participation bond schemes, normally considered low-risk investments, are also governed by CISCA, with the investment into a participation bond scheme fixed for a minimum period of five years; thus, an investor cannot cancel an investment before five years have passed. In addition, even after five years, an investor can only recuperate an investment when the scheme finds a new investor in its place. However, where possible (mainly in terms of liquidity) and subject to the discretion of the manager, he may retain a basket of participatory interest that may be traded in the 5-year period.

Other collective investment schemes - including equity funds, fixed-income funds, multi-asset funds and real-estate funds and funds of funds The remaining CISs (excluding money-market funds, hedge funds, and participation bond schemes) hold the largest amount of assets, amounting over R1,7 trillion 2016. In order to facilitate analyses, these investment funds can be categorised, using their portfolio holdings as a basis, into equity funds, fixed-income funds, multi-asset funds and real-estate funds, and fund of funds.[8] The fastest growing CIS category is multi-asset funds, which holds 50% of the total CISs assets. Growth of multi-asset funds is supported by both valuation effects and increased inflows, especially since 2011. Multi-asset funds that are Regulation 28-compliant, in particular, have grown in popularity since compliant funds can be used for pension savings in vehicles such as retirement annuities. No leveraging is permitted in MMFs; however, other investment funds may use standard listed futures and options for hedging purposes, efficient portfolio management, and enhanced returns but without leveraging the portfolio (subject to regulations).

Exchange traded funds Exchange traded funds (ETFs) is a generic term that is often incorrectly used as parallel to exchange traded notes (ETNs). ETFs are a

[8]According to the ASISA classification. Note that ETFs are included in ASISA data but categorised according to thfe securities that the ETF is related to.

basket of shares, listed on the JSE, which gives the investor more exposure than investing in a single equity share. Therefore, ETFs can be seen as similar to CISs (a portfolio of underlying shares); however, ETFs are listed on the stock exchange.

Certain ETFs in South Africa are also registered CISs, other than the commodity ETFs. ETFs generally track an index (passive investment) of shares, or commodity value, whereas CISs are typically active investments. The index is a basket of shares that represent the performance (capital growth and dividends) of a sector of the market or the market as a whole, or types of assets. ETFs are not grouped into a separate category in the Association for Savings and Investment South Africa (ASISA) data and, depending on the underlying investment, these funds are included in the equity funds, real-estate funds, multi-asset funds, or interest bearing funds (Non-CIS commodity funds are excluded). Synthetic ETFs are available in South Africa to track commodities or currencies; however, there are currently no synthetic ETFs that track equity shares. The potential role of ETFs and other passive funds in amplifying herding behaviour is not clearly monitored or understood currently, and should be investigated.

The six commodity ETFs in South Africa physically hold bullion in custody to cover 100% of their liabilities, but are not recognised under the CISs as they only track a single asset. In addition, commodities are not recognised as an asset class by CISCA. Similarly, listed ETNs may only be permissible depending on the counterparty quality of the issuer and if the underlying physical assets are those permitted under CISCA. ETNs are not recognised as an asset class by CISCA. Synthetic ETNs would not be permissible.

Foreign domiciled CISs Foreign-based CISs have to be approved by the FSCA before they are allowed to solicit business from South Africans. Once approved, these foreign funds may be marketed, promoted, and advertised in South Africa subject to South African regulations pertaining to disclosure, marketing, and advertising. However, South Africans are free to invest in any CIS domiciled abroad of their own volition and provided that their investment has not been solicited by an unapproved fund. South Africans' investments into foreign-based CISs are not included in this study.

Finance companies

Finance companies are non-bank financial intermediaries established in terms of the Companies Act 71 of 2008 with the specific purpose of obtaining funds in various forms and the sole objective of lending or investing these funds again. Microlenders (if incorporated) are also included in this category. This is a diverse group of companies with the maturities of loans extended ranging from a few months (credit extended for retail purchases) to several years (vehicle finance and mortgages).

The assets of finance companies have increased over the past decade and at June 2016 the assets amounted to R261 billion. These data were also obtained using surveys, and thus there is a potential data gap when measuring assets of finance companies. Given that finance companies extend credit, they are regulated by the National Credit Regulator (NCR) from a market conduct perspective. However, finance companies do not accept deposits and therefore are not regulated from a macroprudential perspective like banks are, even though the business they conduct possibly involves maturity and liquidity transformation. This creates the opportunity for regulatory arbitrage given that these finance companies do not have to hold capital or adhere to any other of the regulations that banks have to adhere to, apart from being registered as a credit provider.

Securitisation

Securitisation is used by various bank and non-bank financial intermediaries (including finance companies) in South Africa to increase liquidity and/or reduce the capital requirement. Banks use securitisation to obtain additional funding by selling certain loans to a special purpose vehicle (SPV). Different securitisation structures exist, but generally a basket of loans is sold to an SPV at the purchase price of the loan, and the SPV becomes the registered credit provider under the credit agreement. Payments made by the borrowers are owned by the SPV. Currently, the issuance of commercial paper is seen as taking deposits for the general public, and therefore all securitisation schemes have to be approved by the South African Reserve Bank (SARB)[9] and if the scheme is to be listed, it has to adhere to the listing requirements of the JSE Limited (JSE). The FSB guides the JSE on what listing requirements should be included in terms of the Financial Markets Act No 19 of 2012 (section 6). In order to obtain funding, an SPV issues notes, for example, commercial paper. Generally, these notes are tradable in the capital markets. Securitisation activities in South Africa have decreased over time, with the assets of securitisation instruments traded on the JSE decreasing from R125.7 billion in 2008 to R59 billion in the third quarter of 2016. Banks also invest in securitisation schemes, often in the assets that the bank themselves have securitised. The amount that banks invested in their own securitisation has increased over time, possibly indicating that there is a limited demand in the market for these schemes. In 2008, banks invested in R38 billion worth of securitisation securities, R7.8 billion of which were issued by the same respective bank. In 2015, banks invested R25 billion in securitisation assets, R17 billion of which were their own assets.

Real-estate investment trusts

A real-estate investment trust (REIT) is a term used globally for real-estate investment vehicles. In South Africa, REITs comprise both company REITs (formerly known as property loans stocks) and trust REITs (formerly known as property unit trusts). These trusts use funds, which are raised by issuing investment securities to the public, to purchase real-estate properties and/or real-estate mortgages. South African REITs also invest in offshore commercial properties and are listed on the JSE. Depending on the activities of a REIT, it can be classified as either an equity REIT or a mortgage REIT. An equity REIT invests in and owns mostly commercial real-estate properties, while a mortgage REIT invests in mortgages or mortgage-backed securities, thus either extending credit directly to real-estate owners or indirectly through the acquisition of loans or mortgage-backed securities.[10] In South Africa, currently all REITs are equity REITs – effectively companies

[9] Exemption Notice on Securitisation Schemes, Government Gazette No. 30628 dated 1 January 2008, available here.

[10] See SA REITs for more information.

that own a portfolio of properties, including office buildings, shopping centres, and industrial parks. These properties are rented out, and expenses such as maintenance, repairs, rates, and taxes are paid from the rental income. If another debt was incurred (e.g. bonds issued) to fund the properties, interest payments are also subtracted from the rental income, which is then distributed amongst investors. Notwithstanding the JSE Listing Authority, REITs are subject to the REIT legislation particular to the country in which the company is incorporated, the Companies Act, as well as their own Articles of Association or the Collective Investment Schemes Control Act. The price of these securities is determined by the forces of demand and supply. Thus, investors are exposed to market risk as well as other risk factors specific to immovable property.

Trust companies

Trust companies are corporations whose main function is that of trustee administration of trust assets; however, these companies may also extend credit. These loans are mainly in the form of investments in participation mortgage bond schemes and loans extended to, or taken by, beneficiaries of the trusts. Assets under management increased from roughly R18 billion in 2002 to over R63 billion in 2016. The credit extended is only a small percentage of total assets, amounting to R1.4 billion in 2016. These loans are mainly in the form of investment in participation mortgage bond schemes or loans extended to trust beneficiaries.

Stokvels

A stokvel is a savings club or an association of individuals who make regular contributions to a common pool of savings. This pool of savings is generally then given (fully or partially) to each contributor on a rotational basis. The aim of these savings clubs can vary from buying groceries in bulk at reduced prices or assistance with funeral costs. Generally, stokvels are formed between people with a social connection. Even though stokvels accept monetary investments in a manner similar to banks, stokvels are excluded from the shadow banking measure because they are seen as a savings vehicle (there is an agreement to repay an amount in future). Stokvels are not defined as institutions that grant credit; hence, they are not credit intermediaries, and therefore this industry does not form part of the shadow banking industry. Furthermore, according to the industry, stokvels often invest in ETFs or interest-bearing CISs, and these funds are already included in the shadow banking measure. Granular data, including the activities and size of stokvels in South Africa over time, are currently not available.

3.2.2 Risks in the non-banking sector: the narrow measure of NBFI

To identify risks in the non-banking sector, the narrowing down approach of the FSB is followed. To achieve consistency across jurisdictions, regulatory frameworks or policy tools are not taken into consideration to estimate the part of the NBFI sector that could pose bank-like financial stability risks. Thus, the measure is estimated on a pre-mitigant basis.

The OFI measure is used as a basis for narrowing down, while activities by pension funds and insurance corporations that are related to credit intermediation or the facilitation thereof is added. This narrowing down, according to economic functions, is done in order to identify risks in the non-banking sector.

The approach involves the classification of non-bank financial intermediaries and their activities into five economic functions (EFs), each of which involves non-bank credit intermediation and may pose financial stability risks, including maturity/liquidity transformation and leverage (FSB, 2015). The five EFs are summarised in Figure 3.4.

Activities that are excluded from the narrow measure comprise activities that do not participate in or facilitate credit intermediation and do not exhibit bank-like risks. Specifically, if non-bank entities are prudentially consolidated into a banking group and subject to Basel-like regulatory requirements, they are also excluded from the narrow measure. In South Africa, equity funds, REITs, real-estate funds, trust companies, PBSs, stokvels, peer-to-peer lending platforms, and banks' investment in their own securitisation schemes are excluded from the

Figure 3.4 The FSB's five Economic Functions to classify non-bank financial entities or activities

Economic Function	Definition	Key shadow banking risks	Typical entity types*
EF1	Management of collective investment vehicles with features that make them susceptible to runs	Public funds: Liquidity and maturity transformation Private funds: Leverage and maturity transformation	Fixed income funds, mixed funds, credit hedge funds, real-estate funds
EF2	Loan provision that is dependent on short-term funding	Liquidity and maturity transformation, leverage	Finance companies, leasing companies, factoring companies, consumer credit companies
EF3	Intermediation of market activities that is dependent on short-term funding or on secured funding of client assets	Liquidity and maturity transformation, leverage	Broker-dealers
EF4	Facilitation of credit creation	Credit risk transfer	Credit insurance corporations, financial guarantors, monolines
EF5	Securitisation-based credit intermediation and funding of financial entities	Liquidity and maturity transformation, leverage	Securitisation vehicles

Source: Financial Stability Board, Global monitoring report on NBFI

.

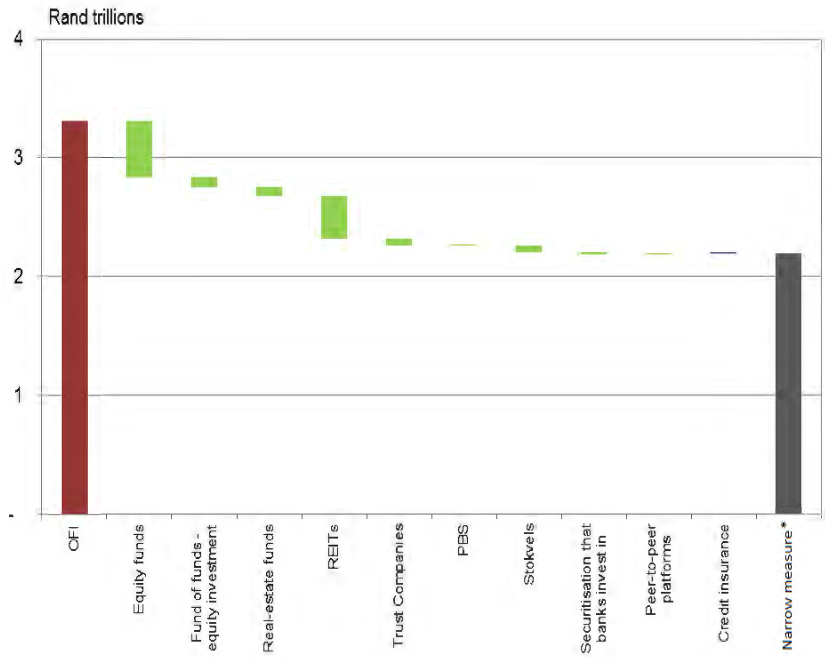
narrow measure.[11] More details on reasoning for not including these entities or activities in the narrow measure of NBFI are discussed in Appendix A.

As a result, the the narrow measure of NBFI in South Africa comprise MMFs, multi-asset funds, fixed-income funds, hedge funds, fund of funds (entities that are susceptible to runs), finance companies (credit intermediation dependent on short-term funding), activities of brokers, securitisation schemes (excluding securitisation that banks invest in), and credit insurance. The narrow measure of NBFI amounted to R2 208 billion in 2016.

Collective investment schemes, of the types indicated in blue in Figure 3.6, have experienced the highest growth rate since the global financial crisis and make up

[11] Note that there is a case to be made to exclude a portion of the brokers' activities given that most of these are banks; however, due to a lack of data and the conservative approach of the exercise, the entire estimate is classified.

Figure 3.5 From OFI to the narrow measure of NBFI - i.e. removing those activities that do not pose bank-like risk to financial stability



Note: OFI = Other Financial Intermediaries; REITs = Real Estate Investment Trusts; PBS = Participation Bond Schemes;
* Narrow measure = Narrow measure of Non-Bank Financial Intermediation
Sources: South African Reserve Bank, ASISA, Morningstar, Novare, SAREITS, Bloomberg, author calculations

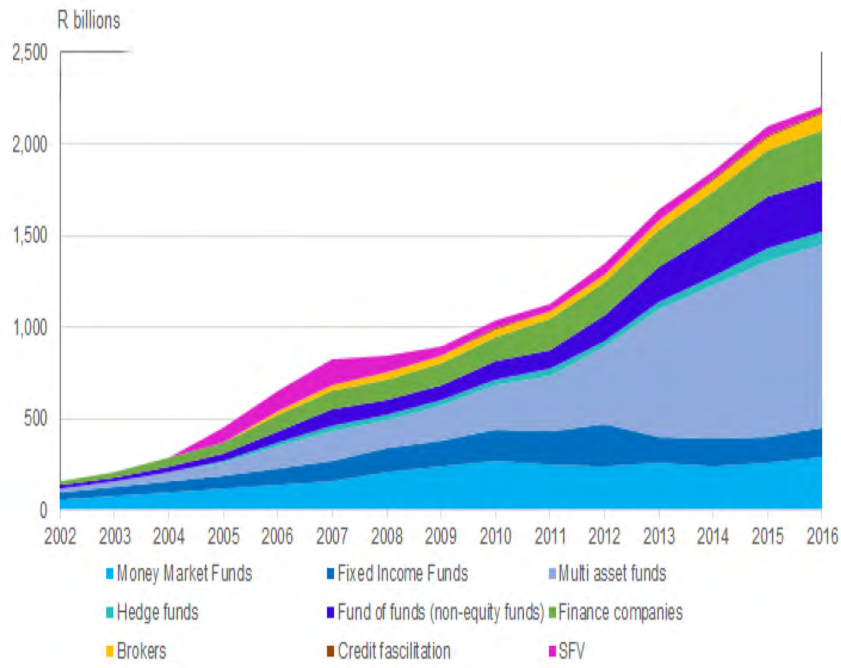
the largest portion of this measure, amounting to just over 80% of the narrow measure of NBFI. These activities are classified into Economic Function 1 – collective investment schemes that are susceptible to runs.

Risks in investment funds other than MMFs and hedge funds

In South Africa, these funds are regulated by the Financial Sector Conduct Authority (FSCA),[12] and suspensions and a form of gating is accommodated in the regulations. Furthermore, in the current regulatory framework, the regulator

[12] Previously known as the Financial Services Board.

Figure 3.6 Composition of the narrow measure of NBFI over time



Note: SPVs = Special Purpose Vehicles. The narrow measure of non-bank financial intermediation (NBFI) are those entities and activities that were categorised into the five economic functions of the FSB.
Sources: South African Reserve Bank, ASISA, Morningstar, Novare, SAREITS, Bloomberg, author calculations

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essentially has the authority to declare any tool to be used on an ad hoc basis, and also the conditions under which it may/must be used. Therefore, it can be argued that the tools exist to mitigate potential risks. Risks could also be described as less severe than in several other jurisdictions given that the majority of CISs in South Africa are not leveraged. However, these funds generally offer daily redemption while investing in less liquid assets. This liquidity transformation could result in the fund becoming unable to meet redemption requests in times of stress. Finally, it should be emphasized that whilst these funds are regulated from a micro perspective, currently there is no regulation mandating a regulator to conduct macroprudential supervision. While the introduction of the Twin Peaks regulatory framework[13] starts to address this, there is limited oversight of the interlinkages of these funds with the rest of the system, specifically on their investors.

Risks in MMFs

MMFs are regulated by the Financial Sector Conduct Authority (FSCA). The instruments that MMFs in South Africa invest in tend to be more vanilla-type than those used in more advanced economies like the US. In addition, the focus of MMFs, and their managers, is not on funding but rather on providing a competitive interest-earning vehicle – the managers have a fiduciary duty to seek the best rates. Even though some investors could be under the impression that the associated bank will stand behind the fund in times of distress, the bank is not legally required to do so. The aftermath of African Bank Limited being placed under curatorship in 2014 is an example where investors in MMFs that had exposure to money-market instruments issued by African Bank made 'unexpected' losses because the MMFs were marketed by banks and also perceived to be safe.[14] Several MMFs in South Africa 'broke the buck' for a day, which means the income for the day was negative — only one fund experienced negative income against the previous twelve days accumulated income – and, following redemptions, the Registrar of CISs intervened and authorized the creation of new funds, called 'side pockets' in which to keep African Bank Limited's debt instruments.[15] These interventions by the Financial Services Board avoided a possible run on MMFs.

Risks in Hedge Funds

While hedge fund managers are required to hold a license and according to available data the size of these entities in South Africa remain small with limited leverage, oversight of the activities are limited. According to the Novare survey,

[13]The Financial Sector Regulation Bill was signed into law in August 2017.

[14]Since several MMFs had been marketed by a commercial bank, they were seen to be 'safe' for deposits and hence not subject to losses.

[15]This segregated the less-liquid African Bank instruments from the remaining assets in the respective MMF portfolios, and ensured that new investors were not exposed to African Bank debt.

there is an average gearing of 167 percent amongst hedge funds, which amounts to R82,6 billion. This is an area where data gaps exist.

Risks in Finance companies

Finance companies are regulated from a market conduct perspective by the National Credit Regulator. In South Africa, financial assets of these entities make up 12% of the narrow measure. Generally these companies extend credit, and an argument can be made that they thus compete with banks, without being regulated to the same extent. This situation could result in regulatory arbitrage in addition to encouraging banks to start operating in the non-banking space themselves. Moreover, there is no data available on where finance companies obtain their funding from – whether its from parent companies or capital markets. Therefore it is not possible to assess the extent of maturity transformation that these entities engage in.

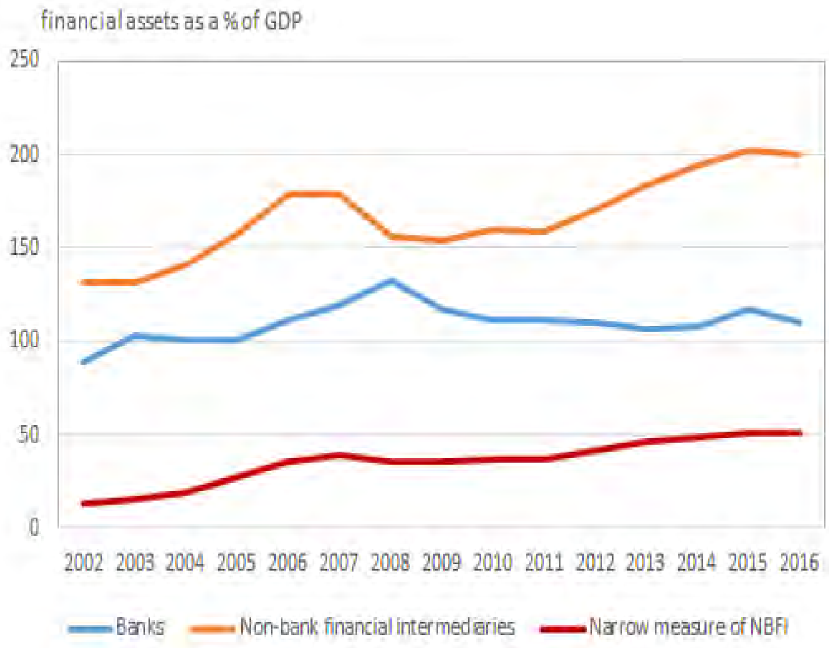
Risks in Insurers

The insurance of credit extension amounts to less than 1% of the narrow measure. This includes companies supervised by the Financial Services Board that are involved in the facilitation of credit, and thus classified as EF4. Thus, according to available data, the transfer of credit risk in South Africa to insurers is limited. However, data limitations prevent a complete assessment. Moreover, beyond credit risk transfer, while more data has become available on the investment activities of insurers in general, it is not clear to which extent these insurers are exposed to the same assets as investment funds. Given the relative size of the insurance sector in South Africa, it can be argued that changes in their investment decisions could have systemic implications.

Risks in Securitisation activities

Securitisation activities, amounting to 2% of the narrow measure assets, are classified as EF5 (securitisation-based credit intermediation). These activities are generally unregulated given that there are currently no tools in place to limit financial stability risks apart from the listing requirements from the JSE Limited. For example, there is no limit or prescriptions on the types of assets that may be securitised. The JSE is currently working on proposals for risk retention by the issuers for inclusion on the exchange.

Figure 3.7 Size of banks, the NBFI sector and the narrow measure of NBFI relative to GDP



Sources: South African Reserve Bank, ASISA, Morningstar, Novare, SAREITS, Bloomberg, author calculations

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When measured as a percentage of GDP, the increase in assets under the management of OFIs and the narrow measure of NBFI entities since the global financial crisis can be observed in Figure 3.7. Even though the narrow measure of NBFI is currently less than half the size of the banking sector in South Africa, financial assets amount to 50% of gross domestic product (GDP) and therefore turmoil in this sector could impact the financial stability in South Africa.

3.2.3 Other approaches to measuring non-bank financial intermediation

The FSB estimates the narrow measure of NBFI according to risks that these entities and the activities they conduct pose. There are several other approaches, not covered in this thesis, to measure non-bank financial intermediation broadly or to assess risks in the system in a more focussed manner. A brief overview of selected other approaches taken are highlighted below. The decision to follow the FSB approach was made taking into consideration the size of various NBFI activities in South Africa - i.e. relatively large investment fund sector, limited size of securitisation etc; and also data constraints such as limited data availability on repo activities. While this is a good starting point for measuring the size of the sub-sector of non-banks that could pose risks to financial stability, it is worthwhile to consider other approaches on an ongoing basis - not least because of changes taking place in the non-banking space. Adrian, Ashcraft, et al., 2013 for example flag that the type of non-bank activities that could be of concern changes over time. Moreover, as highlighted by Claessens and Ratnovski, 2014 the FSB measure has certain shortcomings - including that it potentially includes entities that are not traditionally regarded as risky non-banks such as leasing and finance companies, while also regarding shadow banking activities primarily taking place outside of the banking sector. Nevertheless, as noted previously the FSB approach is a generally accepted approach globally, and as such provides a useful starting point.

Measuring credit extension Another approach to measuring financial assets would be to determine how much credit extension is occurring outside of the regular banking system irrespective of what kind of risk exists. As a simple approach, credit extended by different non-banks (e.g. pension funds, stokvels and PBSs) could be compared to credit extended by banks. This approach would thus include any non-bank credit extension for example PBSs, trust companies, P2P platforms, and credit extension by pension funds and insurance corporations in the narrow measure. However, in the case of pension funds and insurance corporations where lending takes place against contributions and policies respectively, it remains questionable whether this can really be considered as lending as it boils down to clients borrowing against their own contributions.

Measuring all non-bank financial activities that require a public backstop
Other approaches include viewing all non-bank financial activities that require a public of a private backstop to operate, as non-bank financial intermediation (Claessens and Ratnovski, 2014). Focusing mainly on the US financial system, the authors argue that this approach is somewhat more forward looking in the sense that it is likely to capture both those activities that are currently considered shadow banking and also those that could become shadow banking in the future. Private backstops are obtained by using the existing franchise value of financial institutions - i.e. shadow banking activities taking place within existing large banks. Public backstops are those using explicit or implicit government guarantees - such as the too-big-to-fail banks that are engaging in shadow banking activities and implicit guarantees for tri-party repo clearing offered by banks to other dealer banks. Using this approach Claessens and Ratnovski, 2014 argues that the regular capital market activities (including traditional banking and insurance) involve no risk transformation while other traditional activities (including traditional intermediation by hedge funds, investment companies and leasing and finance companies) have high margins and do not attempt to avoid specific risk. Thus only activities that involve risk transformation and low margins (including securitisation, collateral services, bank wholesale funding agreements including the use of collateral repo, and deposit-taking and or lending by non-banks) are seen as systemically important shadow banks. This approach has been applied to the Chinese financial system (Gupta et al., 2018) focusing on entrusted loans.

Focusing on non-core liabilities of banks and non-bank financial institutions
Harutyunyan et al., 2015 propose measuring the shadow banking system as all non-core liabilities of banks and non-bank financial institutions, viewing shadow banking as all credit intermediation that is non-traditional when seen from the funding source - thus dividing non-equity funding into traditional (core, mainly

bank deposits) and non-traditional (non-core i.e. all other funding sources for financial intermediaries, in particular market funding) liabilities. The authors apply this approach to 26 jurisdictions using monetary statistics data reported to the International Monetary Fund in addition to alternative data sources. This approach differs to the approach of the FSB in two ways. Frist, the FSB approach includes investment fund shares, while such shares are excluded from non-core liabilities. Second, the FSB approach excludes bank liabilities, while these liabilities are included in non-core liabilities. Using this approach the authors find that the shadow banking system in South Africa reached roughly 50% of GDP in 2008 and declined to less than 50% by 2013. In comparison to the FSB approach as outlined in the rest of this paper, the non-core liabilities approach finds similar trends and magnitude between 2002 and 2010. Between 2010 and 2013, the broad measure of the FSB (OFIs) results in a slightly larger measure in US dollar terms.

3.2.4 Interconnectedness in the system

A financial system becomes more interconnected when a small number of financial institutions have large direct exposures to each other (direct interconnectedness) or when there is a high level of common exposures to the same counterparties (indirect interconnectedness). While there are various investment options available to South Africans, the financial system remains relatively small, and the role of non-bank financial intermediaries has increased over time both by being an important source of funding for the South African economy and also for banks. In total, the funding that banks obtain from OFIs in South Africa amounts to just under 15% of banks' assets. When comparing South Africa to other jurisdictions that participated in the monitoring exercise (FSB, 2016), globally this is the third-highest percentage of banks' funding obtained from OFIs.

With a limited number of investment options and a relatively small number of banks, it is not surprising that interconnectedness in the system is high. It is, however, not only banks and OFIs that are interconnected. As alluded to earlier, pension funds, and insurance corporations also share high interconnectedness in the South African financial system, which is not surprising given their relatively large size. Data available on the asset allocation of pension funds registered with the Financial Sector Conduct Authority show that assets invested in CISs increased from 7% in 2008 to 12% in 2014. OFIs and pension funds are also indirectly connected because of common exposures – pension funds invest in the same equities, bonds, other securities, and other OFIs that OFIs invest in.

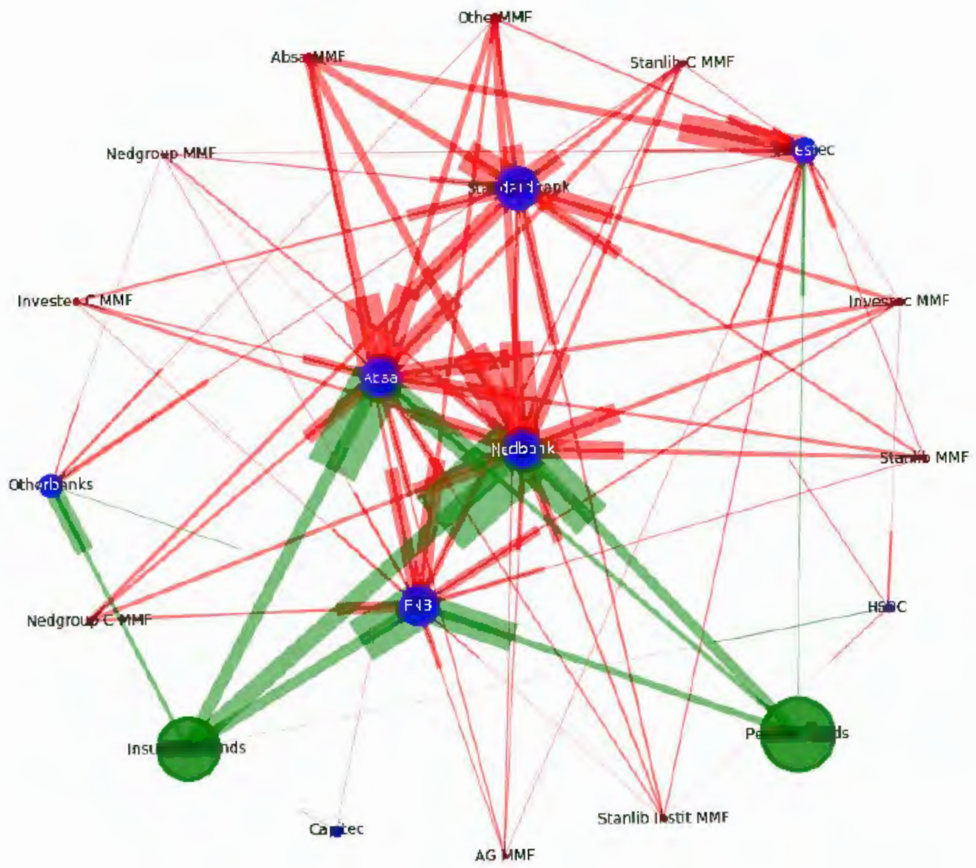
In the section that follows, specific exposures of various financial intermediaries will be discussed in detail, focusing on the exposures of MMFs (12% of shadow banking assets), CISs excluding hedge funds and PBSs (70% of the narrow measure of NBFI) and finance companies (12% of the narrow measure of NBFI).

The interconnectedness amongst individual banks, the largest individual MMFs, pensions fund, and insurance corporations is shown in Figure 3.8. Nodes are sized according to assets under management, whilst the lines represent the relative size of the exposure, with the thick-end of the line indicating the direction of the net-exposure. Blue nodes represent banks (split between selected individual banks and "other banks", red nodes represent MMFs (split between selected individual MMFs, and "other MMFs", while the green nodes represent the insurance corporations and pension funds respectively, as indicated. MMFs marketed by a specific bank generally have exposure to that specific bank. However, these exposures are subject to the same limitations as with other investments (see Annexure B for more information). Given that CISs in South Africa are trusts and not companies, a bank cannot own a CIS as part of its group of companies, but only be the administrative manager.

Non-MMF collective investment schemes Roughly 37% of CIS assets - excluding MMFs, hedge funds and PBSs - are invested in domestic equities, 13% in domestic bonds and 18% of the assets under management are invested in domestic funds (invested in another fund). The largest portion of domestic equities that CISs invest in is issued by non-bank entities and banks. Furthermore, the largest portion of bonds that CISs invest in is issued by banks and the government. Money-market instruments that CISs invest in are also mostly issued by banks. In aggregate, 18% of CIS assets are invested in instruments underwritten by banks and, as of September 2016, this amounted to R376 billion (8% of bank assets). These figures exclude

Figure 3.8 Direct interconnectedness amongst MMFs, banks, insurance corporations, and pension funds

Data as of 2016.



Note: Only on-balance sheet exposures and investments are taken into account. Size of the nodes show the relative size of intermediaries' balance sheets, lines show the relative size of the balance sheet exposures amongst intermediaries. Pension Funds and Insurers shown by green nodes; Banks by blue nodes and Money Market Funds by red nodes.

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investments made into the funds that are managed/marketed by banks.

Figure 3.9 Holdings of other CISs, excluding MMFs, hedge funds, and PBSs

Data as of 2016.

	Percentage of total	R millions	Bank	Non-bank	Government	SOE	REIT	Other
Another fund domestic	18	374 669	-	-	-	-	-	-
Another fund foreign	16	344 306	-	-	-	-	-	-
Bond - domestic	13	268 265	110 572	36 861	96 222	12 923	10 912	775
Bond - foreign	0	160	-	-	-	-	-	160
Cash and interest	3	58 774	28 688	-	-	-	-	30 086
Cash-foreign (foreign cash)	0	7 711	-	-	-	-	-	7 711
Equity - domestic (including equity options)	37	771 145	103 733	577 619	-	3 969	85 563	260
Equity - foreign (foreign equity)	4	79 248	-	-	-	-	-	79 248
MMF instrument - ZAR and other	8	157 020	128 266	15 448	1 007	5 608	2 415	4 276
Other	1	30 582	4 824	-	-	-	-	-
TOTAL		2 091 880						
Percentage of total			18%	30%	5%	1%	5%	6%

Note: Column headers show the counterparty by sector. SOE = State Owned Enterprises; REIT = Real Estate Investment Trusts.
In order to analyze the holdings of CISs in South Africa, data from Morningstar were used. Similar to the ASISA data, hedge funds and Participation Bond Schemes are not included in the data, while certain Exchange Traded Funds were included, but Exchange Traded Notes are excluded
Source: Morningstar

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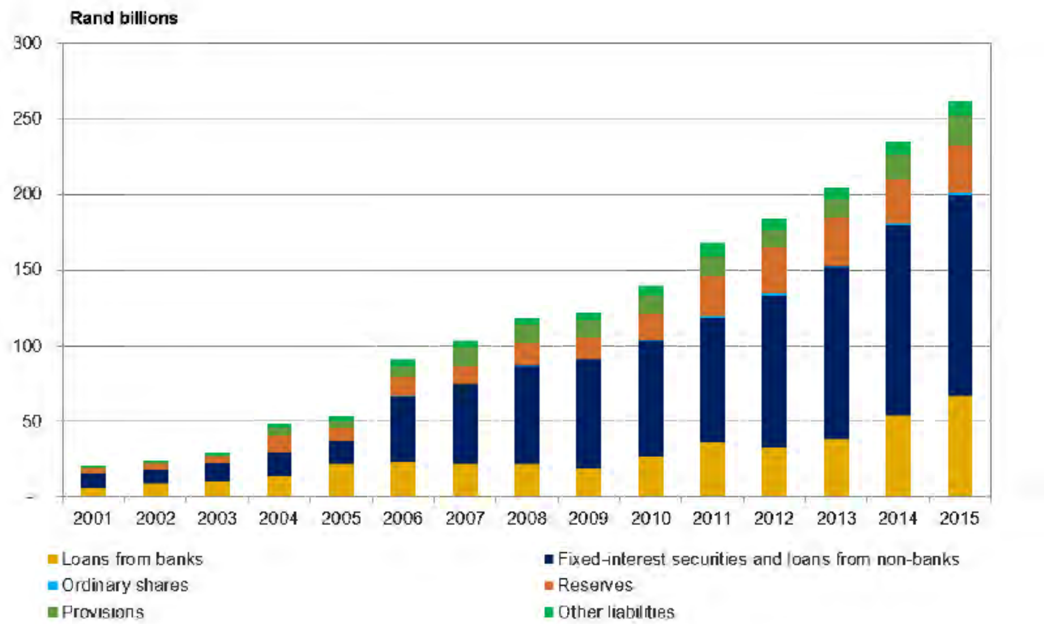
Finance companies Finance companies are also interconnected with the rest of the financial system as a result of their assets and liabilities. While disaggregated data are not available on the sectors to which finance companies extend loans, some data – collected by the South African Reserve Bank, are available on funding sources. Certain finance companies are fully or partially owned by banks or banking conglomerates, which implies that capital could be held by banks against these exposures. Finance companies are also connected to the rest of the financial system due to their funding sources, which include borrowing from banks or parent companies; issuing equity, bonds, debentures, or notes (hence funding from capital markets); or by establishing special purpose vehicles (SPVs) to facilitate the securitisation of loans (Banks can also be the arranger of securitisation schemes that finance companies use to raise funds). Finance companies in South Africa obtain the majority of their funding from loans originated by non-bank financial institutions or from market-based financing by, for example, issuing commercial paper (See Figure 3.10).

Figure 3.10 Liabilities of finance companies



Source: South African Reserve bank

3.2.5 Indirect interconnectedness

An important channel for contagion is holding the same assets, or portfolio overlap (Cai et al., 2018) given common losses in the event of a counterparty default. Following the methodology of Cai et al., 2018, we develop a simple measure of portfolio overlap in MMFs in South Africa.

Let $W_{i,j}$ be the share of MMF_i to $counterparty_j$ relative to the total MMF exposure to $counterparty_j$, thus

$$\sum_{j=1}^{J} W_{i,j} = 1 \tag{3.1}$$

where J is the number of counterparties.

We then compute the distance between two MMF portfolios as the Euclidean distance between them in this J-dimensional space.

$$Distance_{i,k} = \frac{1}{\sqrt{2}} \times \sqrt{\sum_{j=1}^{J} (W_{i,j} - W_{k,j})^2} \quad (3.2)$$

where $\text{Distance}_{i,k}$ is the distance between MMF_i and MMF_k ($i \neq k$).

The distance measure varies from 0 to 1, where a smaller Euclidean measure indicates a more similar portfolio, and a higher measure indicates a smaller overlap.

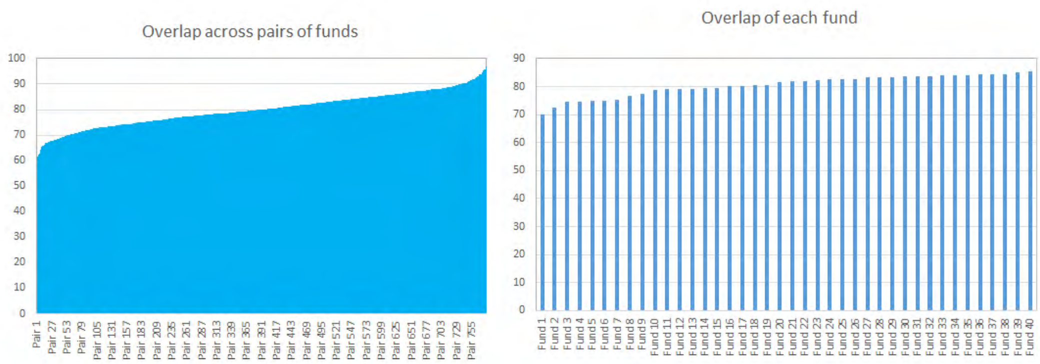
The overlap of each money market fund is then calculated by taking the simple average of the funds' distance to other funds. Given that a smaller Euclidean distance means higher interconnectedness, the simple average of distance is transformed into an overlap measure for each fund. This measure is normalized to a scale of 0–100 with 0 being least interconnected and 100 showing the highest overlap.

$$Overlap_i = (1 - \sum_{k \neq i}^{J} (\frac{1}{N} \times Distance_{i,k})) \times 100 \quad (3.3)$$

Where N is equal to the number of MMFs.

Figure 3.11 Portfolio overlap in Money Market Funds

Data as of 2016.



Sources: Morningstar, author calculations

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The interconnectedness measure ranges from 0, showing no overlap, to 100, showing identical portfolios.

Using data sourced from Morningstar as at December 2016, we include 40 MMFs in our analysis, resulting in 780 pairs of funds. We identify 78 unique counterparties comprising mainly a number of banks, SOEs, finance companies, and securitisation schemes. On the left-hand side of Figure 3.11, the overlap for each pair of MMFs is shown, and on the right-hand side, the average overlap calculation for each fund. The analysis confirms significant indirect interconnectedness amongst MMFs in South Africa as a result of portfolio overlap or exposures to the same counterparties. This shows that in a scenario where a large bank defaults, it is likely that several MMFs will face losses and potentially 'break the buck'. This confirms observations during the African Bank curatorship - see Havemann, 2019. Moreover, in a scenario where MMFs have to sell assets, shocks can propagate through fire-sales (see Cai et al., 2018 for a study on fire sales as a result of banks' portfolio overlap).

Given the findings of high direct interconnectedness amongst financial intermediaries in South Africa, and high levels of portfolio overlap among MMFs - more extensive analysis of interconnectedness and the vulnerability of the system is undertaken in Chapter 4 which subjects the South African financial system to the shock of a bank failure. This chapter merely takes a small step in the direction of better understanding and visualising interconnections in the financial system. It would also be useful as part of further research work to conduct additional interconnectedness analysis to determine how shocks could propagate through the financial system. Such analysis could include network-based analysis (see for example Elliott et al., 2014 and Gai and Kapadia, 2010) as well as non-network based studies using econometric analyses to determine interconnectedness between sectors or entities.

3.3 Data and policy gaps in South Africa

While significant progress has been made to measure and better understand the NBFI sector in South Africa, several pertinent data gaps remain that are important to address to get a clearer view of systemic risk in South Africa. Some of these data gaps and suggested developments are discussed below.

Develop risk indicators for the non-bank financial sector

Measuring the size of non-bank financial sector is an important first step; however, to inform policy decisions, a monitoring framework comprising various risk indicators should be developed. Following the FSB's monitoring exercise, this could include indicators or credit intermediation, liquidity, and maturity transformation and credit risk transfer. In addition, indicators on direct and indirect interconnectedness could be further developed an monitored. Of crucial importance here is to better understand how stress in the NBFI sector can spill over into the banking sector.

Identify investors and analyse procyclicality of investor behaviour

Using Morningstar data, insights are gained into which sectors investment funds are exposed and what the direct links to other financial intermediaries and non-financial corporates are based on funds' investments. However, limited data are available on who the investors in these funds are. Identifying the investors and their behaviour especially in stressed times would shed light on how these funds would be impacted in crisis times. For example, Timmer, 2018 finds that insurance corporations and pension funds act countercylically while banks can act procyclically as a result of differences in the structure of their balance sheets. We also do not measure where finance companies obtain their funding from and in what currency these funds are obtained.

Use credit data to develop a credit registry

Another important question to understand is the sources and terms of corporate and consumer credit, and how and if preferences for sources of credit change in periods of stress. Morevover, from a policy perspective, it would be insightful to better understand corporate and consumer behaviour in times of stress. While more detailed datasets are available for credit extended by banks, credit obtained by non-banks or via markets is more difficult to aggregate, and thus a complete overview remains elusive. Credit data in the form of a credit registry would lead to more insightful analysis.

Enhance national accounts data

In order to more enhance financial stability risk monitoring, the flow of funds dataset could be enhanced. This should include more comprehensive statistics on the institutions within the NBFI sector, or more specifically OFI sector, as well as availability of more disaggregated sectoral aggregate data. The further enhance interconnectedness analysis, assets and liabilities between counterparties should be matched in the who-to-whom data. In the absence of more detailed interconnectedness analysis, it is difficult if not impossible to anticipate how financial stress could propagate through South Africa's financial system. This chapter highlighted the large direct links between banks and non-banks, in addition to a high level of portfolio overlap amongst MMFs. Further analysis could focus on whether the current financial system is more prone to vulnerabilities than if the system was less connected. Analysis could also seek to estimate the amount of losses that would result from the failure of certain nodes.

Develop policy tools for the NBFI sector

Financial intermediaries in South Africa are generally supervised from a micro-policy perspective. In this chapter we highlighted several regulations that non-banks adhere to and covered the size of the industry based on various data sources, we have also highlighted several data gaps. However, the macroprudential toolkit currently available in South Africa does not include policy tools to address the build-up of systemic risk in the NBFI-sector specifically. While tools have been developed for the banking sector, for example the countercyclical capital buffer, tools are limited for the NBFI-sector. As a first step it is important to assess the systemic risk and thus address data gaps, but it is important that South Africa focusses on developing macroprudential tools to address systemic risk in the NBFI-sector as well.

3.4 Conclusion

This chapter aims to take the first step toward measuring first the NBFI sector broadly and second the narrow measure of NBFI that pose bank-like financial stability risks. It also highlights the interconnectedness between some CISs and the banking sector. It is shown that the assets under the management of the NBFI sector have been growing at a faster pace than those of banks over the past decade. Furthermore, the chapter measures direct interconnections (due to high net exposures) amongst financial intermediaries in South Africa and proposes a measure for indirect interconnections (as a result of common exposures); it also applies this measure to MMFs registered in South Africa. We find significant links between banks and collective investment vehicles – in particular, MMFs.

It should be noted that non-banking activities, vehicles and entities are constantly evolving (Jones, 2016), and the monitoring and measuring thereof will have to be done on a continuous basis. Several data gaps remain. The first gap can be addressed by casting the net wider, that is, by better measuring the NBFI sector. For example, measures of securities' financing transactions and repo-transactions, derivatives, as well as private equity that are not captured. These transactions can be a major source of linkages between banks and non-banks and by including them in the study our understanding of the system will be enhanced.[16] Furthermore, the activities of CCPs can be evaluated and included if applicable. The role of virtual currencies and fintech should also be explored, specifically when credit intermediation is present. A second gap can be addressed by further refining the narrow measure of NBFI. This would involve more granular data collection and analyses of individual entities. As a result there will be more clarity on which entities and activities are posing bank-like risks to financial stability. For example, more detailed data on finance companies that are consolidated into banking groups will result in fewer finance companies being included in the narrow measure. As explained above, depending on whether a risk-based approach is taken, certain activities will be included in the measure, while they will be excluded if an

[16] Securities lending was not included due to a lack of data. A 2015 survey shows that between R17 billion and R20 billion worth of South African equities are on loan at any given time (Analytics, 2015).

approach of pure credit intermediation fully or partially outside of the banking system is taken.

Finally, further research could focus on identifying and measuring the systemic risk that non-bank financial intermediaries' activities pose to the financial system.

This chapter does not advocate increasing regulation in the NBFI sector, but instead suggests that increased focus should be placed on measuring the activities and risks appropriately and ensuring that risk management practices are in place, especially from a macroprudential perspective. Furthermore, any policy decision should take the high interconnectedness amongst financial intermediaries into account.

Chapter Four

Higher Order Exposures in the South African Financial System

In this chapter we show that the exposures of financial institutions to one of the largest six banks in the South African financial system may be severely underestimated when only considering direct and indirect exposures. This is because such a default by a large bank causes distress to spread through the system and additional losses that accumulate over time would not be clear from only direct or indirect links. How the losses spread strongly depends on the network structure in addition to the robustness of individual institutions. This underlines the importance of access to granular data and network-based modelling approaches to take advantage of such granular data to estimate exposures.

In this chapter we show that an institution's exposures are not limited to only direct and indirect exposures. We introduce the concept of *higher-order share of exposure* (HSE), which expresses what percentage of an exposure is overlooked when only considering direct and indirect exposure. We apply this concept to South African data and find that the HSE is close to 100% for a substantial part of the financial system. We also show that in other parts of the financial system, the HSE increases significantly during times of financial distress - when exposures matter most.

4.1 Introduction

Traditional financial-risk models typically measure the *direct exposure* of one financial institution to another (L. S. Allen, 2003; Canabarro et al., 2014). Such direct exposures stem from counterparty risk; the risk that an institution's counterparties to its contracts do not meet their contractual obligations. However, a financial institution may also be exposed to institutions it does not have contracts with as a result of *indirect exposures.* For example, institutions are exposed to their counterparties' counterparties through "cascading defaults". Furthermore, if two institutions' trading books significantly overlap, they are exposed to the other institution initiating a firesale of those assets (which depresses the liquidity and market price of those assets).

In an unstable financial system, financial distress is amplified and spreads rapidly across the systems. In such systems, indirect exposures are high. However, if risk models neglect indirect exposures, an institution's exposure to another firm can be significantly underestimated.

Cont and Schaanning, 2019 propose indicators to quantifying *indirect exposures* (or indirect contagion, as they usually refer to it) via overlapping portfolios of bonds, and highlight its importance in properly estimating risk exposures. While this work provides a significant advancement in the conceptual understanding of an institution's true exposures, their method only captures the overlapping portfolios and does not include other relevant asset classes that may give rise to indirect exposures.

In this chapter, we introduce the concept of *higher-order exposures* and provide a *simple* and *robust* method to compute it across multiple asset classes – to properly account for risky financial exposures. The higher-order exposure of institution i to j is given by the losses that institution i accumulates over time as financial distress caused by the default of j spreads through the system.

Assuming discrete time dynamics, this spread of financial distress is modelled iteratively. As such, higher-order exposures are measured in reference to a specific iteration, or "round". This is important because no model is perfect and therefore higher-order exposures measured in earlier rounds are expected to be most accurate.

We apply this method to a novel and unique data set of the South-African financial system, used in Chapter 3. Other than in most data sets on the interconnections in the financial system, it not only includes banks but also Collective Investment Schemes like Money Market Funds, Fund-of-Funds and Other Investment Funds. The data include bilateral exposures through multiple asset classes, such as loans, deposits, bonds, money-market instruments (MMIs), stocks, and investment fund shares.

Studying indirect exposures in the South African financial system is especially relevant since its banks and non-banks have high levels of direct linkages as highlighted in Chapter 3 (Kemp, 2017, FSB, 2018). Academic studies have focussed on interbank linkages in South Africa and the network that these result in, but limited work has been done on measuring the linkages beyond the banking sector. While the direct links between banks and some non-bank financial intermediaries has been quantified in Chapter 3, knowledge is limited on the indirect linkages in the system and the impact of failures of large intermediaries on the financial sector has not yet been analysed.

Our main finding demonstrates that *total risk exposures can be significantly underestimated if indirect exposures are overlooked.* This finding gives impetus to *expand the traditional risk models used by regulators and in risk management departments to account for indirect risk* – to properly estimate the size of an institution's (in)direct exposures. Doing so remedies underestimating the requisite capital buffers to protect against risky exposures, and hence aids regulators to set an institution's capital requirements appropriately. In support of this main finding, we show the following. First, we show that the marginal increase in look-through exposures diminish in higher rounds. This shows that it is most important to take the higher-order exposures into account that are most proximate in order to adequately account for risk. Second, we show that higher-order exposures vary strongly across types of institutions, but also across institutions of the same type, depending on the institutions investment portfolios and specific bilateral exposures. This highlights the importance of granular bilateral exposure data to properly estimate systemic risk.

4.2 Higher-Order Exposures

An institution's exposure to a counterparty is typically understood to be the loss the institution stands to suffer when the counterparty defaults.

The most commonly studied exposures to a counterparty are *direct exposures*; loans, bonds, derivative contracts and other credit exposures to a counterparty that are directly written-down as the counterparty becomes insolvent (Jorion et al., 2009). More recently, *indirect exposures* have garnered attention (Cont and Wagalath, 2013; Cont and Schaanning, 2019). Indirect exposures arise when the portfolios of two or more institutions' tradable assets overlap. When one of these institutions decides to liquidate (part of) its portfolio of tradable assets, a downward pressure is exerted on the market price, causing mark-to-market losses to the other(s) (Coval et al., 2007; Shleifer et al., 2011; Caccioli, Shrestha, et al., 2014; Greenwood et al., 2015; Cont and Schaanning, 2017).

However, institutions' exposures to others are not limited to direct and indirect exposures. When institution i defaults, other institutions in the system may propagate the losses caused by the default. The propagation of losses by financial institutions is referred to as contagion (F. Allen and Gale, 2000; Gai and Kapadia, 2010; Elliott et al., 2014; Glasserman et al., 2015). Consequently, when j defaults, institution i may suffer losses on other assets than its contracts with j and its portfolio overlap with j. Hence, these losses are not captured by i's direct and indirect exposures to j. We refer to the losses that were caused by the default of j and propagated by at least one intermediate institution k before being suffered by institution i, as i's *higher-order exposure* to j. The exposure that institution i has to institution j (i.e. the total losses that it risks losing if j defaults) thus has a higher-order component:

$$Exposure_{ij} \stackrel{\text{def}}{=} Direct\ Exposure_{ij} + Indirect\ Exposure_{ij} + Higher\text{-}Order\ Exposure_{ij} \tag{4.1}$$

To the best of our knowledge, we are the first to introduce the concept of higher-order exposures and provide a measure of it. We further introduce the *higher-order share of exposure* (HSE), which expresses the share of an exposure made up by higher-order exposures. The HSE of the exposure of i to j is given by

$$HSE_{ij} \stackrel{\text{def}}{=} \frac{\textit{Higher-Order Exposure}_{ij}}{\textit{Exposure}_{ij}}. \tag{4.2}$$

Hence, the HSE expresses the fraction of an exposure that is overlooked when only considering direct and indirect exposures. When the HSE is high, conventional methods will dangerously underestimate exposures.

4.2.1 Stylised example

Consider three financial institutions, i, j and k, part of a larger economic system. Institution i has extended a loan l_{ij} to institution j. Furthermore, i has assets a_i in other parts of economic system and debt d_i to other parts of economic system (i.e. investments in and debt to institutions except i, j and k). We assume for simplicity that the institutions' assets in and debt to the other parts of the economy do not generate exposures. i's equity is denoted as e_i. Institution j holds s_j shares in stock S and has assets a_j in other parts of economic system. Furthermore, j has debt $d_{ji} = l_{ij}$ to i and d_j to other parts of economic system. j has equity e_j. Lastly, institution k holds s_k shares in stock s, has assets a_k in other parts of economic system and debt d_k to other parts of economic system, and equity e_k. The balance sheets are shown in panel 4.1.

Figure 4.1 Balance sheets of institutions i, j and k.

Assets	**Liabilities**
Loan l_{ij}	Other Debt d_i
Other Assets a_i	**Equity** e_i

(a) Balance sheet institution i

Assets	**Liabilities**
Shares s_j	Debt d_{ij}
Other Assets a_j	Other Debt d_j
	Equity e_j

(b) Balance sheet institution j

Assets	**Liabilities**
Shares s_k	Other Debt d_k
Other Assets a_k	**Equity** e_k

(c) Balance sheet institution k

Let us consider the direct exposures in this system first. The loan from institution i to j gives rise to a direct exposure E_{ij}; the value of the loan l_{ij} is written-down to its recovery value when j defaults. This write-down of contracts with a counterparty when a financial shock causes the counterparty to default is typically referred to as *counterparty default contagion* and the corresponding direct exposure is equal to the write-down. We assume throughout this paper that the Loss Given Default (*LGD*) is 100% (although this assumption can be easily modified without changing the overall message of the paper).[1] The time taken to resolve a default is much longer than the typical timescales over which contagion materializes so short-term recovery may be realistically assumed to be zero (Elsinger et al., 2006; Cont, Moussa, et al., 2010). The loan l_{ij} is written-off when j defaults, so i's corresponding direct exposure to j is given by

$$E_{ij} = l_{ij}. \tag{4.3}$$

[1]Assuming zero recoveries leads a conservative estimate of maximum exposures and losses, and thus could impact the contagion channels included in this model.This is not expected to alter our findings concerning higher order exposures outline in 4.4.3.

The assumption of zero recoveries on defaulted loans is justified by the short-time scales considered in this paper, since in the short-run the recovery on loans is typically zero. [2] This direct exposure is visualized by the blue arrow in Figure 4.2.

We now consider the indirect exposures in this system. The portfolio overlap between institutions j and k generates an indirect exposure; when j defaults, its assets are liquidated as part of the default resolution, which includes the sale $\Delta s = s_j$ of j's shares in stock S. Such a sale typically depresses the market price of stock S, which is referred to as the sale's *price impact.* Let P_s denote the price of a share in stock s and assume a linear price-impact function of the form

$$\Delta P_s = \frac{\Delta s}{D_s}, \tag{4.4}$$

where Δs is the number of shares in stock S sold, and the market depth D_s expressed as the number of shares sold per unit change in price P_s. The market depth D_s captures the elasticity of the price P_s to changes in the supply of shares in stock S and depends, among other things, on the average daily trading volume and daily volatility of the asset (Bouchaud, 2010; Cont, Kukanov, et al., 2014; Cont and Schaanning, 2017).

Modern accounting practices require mark-to-market accounting, such that the accounting value of a tradeable asset is affected by it market price. Hence, when a financial shock forces an institution to liquidate its tradeable assets, other institutions that hold the same assets suffer mark-to-market losses, which is typically referred to as *overlapping portfolio contagion.*

Institution k's indirect exposure E_{kj} to the default of j is given by k's mark-to-market loss on its shares s_k, resulting from the price-impact of the liquidation of j's shares:

$$E_{kj} = \Delta P^s s_k = \frac{s_j s_k}{D^s}. \tag{4.5}$$

[2] We assume throughout this paper that the Loss Given Default (*LGD*) is 100% (although this assumption can be easily modified without changing the overall message of the paper). The time taken to resolve a default is much longer than the typical timescales over which contagion materializes so short-term recovery may be realistically assumed to be zero (Elsinger et al., 2006; Cont, Moussa, et al., 2010).

As a consequence of the linear price-impact function we use, j's indirect exposure E_{jk} to the default of k is also, symmetrically, given by

$$E_{jk} = \frac{s_j s_k}{D^s}. \tag{4.6}$$

The right-hand side of equation 4.6 is referred to as the *liquidity-weighted portfolio overlap* of j and k in stock S (Cont and Schaanning, 2017; Cont and Schaanning, 2019). The indirect exposure from j to k is thus given by j's liquidity-weighted portfolio overlap with k. This indirect exposure is visualized by the red arrows in Figure 4.2.

Finally, we are ready to discuss the higher-exposures in this system. Assume that j's indirect exposure to k exceeds its equity buffer, i.e.

$$E_{jk} > e_j. \tag{4.7}$$

Hence, when k defaults and its shares in stock s are liquidated, j's mark-to-market loss from the price-impact causes j to default too, resulting in a write-off of i's loan to j. Hence, i has a higher-order exposure to the default of k equal to the size of i's loan to j in turn;

$$E_{ik} = l_{ij} \tag{4.8}$$

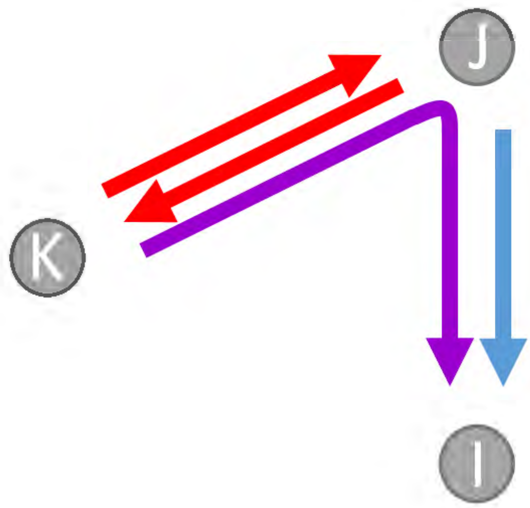
This higher-order exposure is visualized by the purple arrow in Figure 4.2. Because i has no direct or indirect exposures to k, its higher-order share of exposure to k is given by

$$HSE_{ik} = \frac{l_{ij}}{0 + 0 + l_{ij}} = 100\%. \tag{4.9}$$

In other words, without considering higher-order exposures, i completely overlooks its exposure to k. It is worth emphasising that higher-order exposures to i could have also arisen if an institution j would not have failed through exhausting its equity buffer. For instance, if i would have invested in a fund j who experienced a drop in NAV due to the failure of k.)

This example illustrates that a central bank needs granular data in order to understand the exposure of a regulated institution will, as well as models that use these data to simulate how financial distress propagates resulting in higher-order exposures; without understanding that j defaults when k defaults, a regulator cannot quantify i's exposure to k. Furthermore, the example also highlights the importance of capturing all relevant contagion channels and their interactions in the same model; studying either the counterparty default contagion channel or overlapping portfolio contagion channel individually would result in overlooking completely the higher-order exposure of i to k.

Figure 4.2 Stylised example of a higher-order exposure



.

Note: Bank i lends to bank j. This *direct exposure* is depicted by the blue arrow. Banks j and k have a large portfolio overlap through their position in security S. When either defaults, it liquidates its position in s, which results in mark-to-market losses to the other bank, causing it to default too. This *indirect exposure* is depicted by the red arrows. Bank i has neither a direct nor an indirect exposure to bank k. Yet, when k defaults, j defaults as a consequence, causing y's debt to i to be written-off. Hence, bank i has a *higher-order exposure* to bank k, which is depicted by the purple arrow. The magnitude of i's higher-order exposure to k is equal to the loss i stands to suffer when k defaults, i.e. the value of i's loan to j.

4.3 Higher-order exposures in the SA financial system

We apply the concept of higher-order exposures to the South African financial system. South Africa is a small open economy with a relatively well developed financial market compared to other African or other emerging-market economies. The South African debt market is liquid and well developed in terms of the number of participants and their daily activity, and its equity market dominates the region in terms of capitalisation (Andrianaivo et al., 2010). Banking sector assets exceed GDP in aggregate terms, but are smaller than the assets held by non-bank financial intermediation sector (including entities such as insurers, pension funds and collective investment schemes (henceforth referred to as "funds"). Since the 2008 financial crisis, the share of assets held by banks has decreased – as the growth of assets held by the non-bank financial sector – in particular funds - has outpaced that of banks (see Section 3.2). Non-bank financial intermediaries are an important source of funding for banks – and direct linkages among banks and non-bank financial intermediaries other than pension funds and insurers are relatively high – amounting to 15% of bank assets (FSB, 2018).

4.3.1 Data

The study makes use of two publically available datasets as of Q4 2016. Aggregate balance sheet data (aggregate assets, liabilities and equity) on individual banks are sourced from the BA900 data published by the South African Reserve Bank (SARB, 2016a). Balance sheet entries are aggregated by asset type and counterparty type (e.g. "loans and deposits to domestic banks"). Data on funds' assets were sourced from Morningstar Inc and are highly granular. These data report funds' investments per instrument type in individual counterparties (e.g. "bonds in Absa"). The data do not explicitly report funds' shareholders. However, we observe that banks do not invest funds based on the banks' balance sheet data, and from the funds' asset data we know funds' holdings of shares in other funds. Hence, all of a fund's shareholders that are included in the model are given by the data at the level of individual counterparties. We assume that the remainder is held by external parties.

The largest players on the South African financial market are banks, Collective Investment Schemes (or "funds"), pension funds, insurance companies, non-financial corporates, and the South African government. In this study, we focus on banks and funds domiciled in South Africa. The data used are sourced from two publicly available datasets as at the end of 2016: Aggregate balance sheet data on the individual banks, and granular data on funds' assets, disaggregated to include investments' individual instruments in individual counterparties.[3] Pension funds and insurers are not included due to data limitations, but we do not expect this to affect our results substantially as pension funds and insurers typically do not generate substantial contagion (see for example Schich, 2010). Non-financial corporates, henceforth referred to as the corporate sector, and the South African government are not modeled. However, through our data of banks' and funds' investments in these institutions, we include the tradable securities corporates and the government issue.

Banks

The South African banking sector comprises 34 registered banks, local branches of foreign banks, and mutual banks at the end of 2016. The sector is concentrated, with the five largest banks by assets holding more than 90% of the banking sectors' assets (South African Reserve Bank, 2017) as illustrated in Figure 4.3. We calculate higher-order exposures to the six largest banks by total assets, as they form the core of South Africa's financial system and generate the largest exposures. These are the Standard Bank of South Africa Ltd (Standard Bank), FirstRand Bank Ltd (Firstrand), Absa Bank Ltd (Absa), Nedbank Ltd (Nedbank), Investec Bank Ltd (Investec), and Capitec Bank Ltd (Capitec). While the assets held by Capitec are significantly smaller than the assets held by the top 5 banks, it is included in our analysis given that it is the second largest retail bank based on the number of customers.

[3] Banking sector data were sourced from the BA900 data published by the South African Reserve Bank. Collective Investment Scheme data were sourced from Morningstar.

Overall, the banking sector is largely funded by deposits, but banks also issue debt instruments (bonds and money market instruments) and equity. The banking sector hold the largest share of financial assets in South Africa, although its share of assets has decreased from almost 40% of total financial assets in 2008 to 30% in 2016.

Investment Funds

Investment funds provide investors with an alternative opportunity to earn a higher return on their funds than deposits, in return for taking on greater risk. However, instead of purchasing and trading securities directly, investment funds pool investors' money together and purchase a portfolio of assets, thereby offering investors the opportunity to obtain exposure to a wider set of underlying assets by investing in fund shares. Each share represents a portion of the underlying portfolio.

We divide funds into three categories: Money Market Funds (MMFs), Fund of Funds (FoFs), and Other Funds (OFs).

MMFs MMFs are formally designated according to legal requirements (Financial Sector Conduct Authority, 2014): Board Notice 90 of 2014 (Financial Sector Conduct Authority, 2014) restricts the money-market instruments that a fund manager may invest in, in terms of maturity of the investments in addition to the exposure to a counterparty (inclusion limits).[4] The weighted average legal maturity of the fund may not exceed 120 days, while the weighted average duration of the money-market instruments may not exceed 90 days. No single instrument that MMFs invest in may have a maturity exceeding 13 months.

The MMF industry in South Africa is relatively small, amounting to 2% of total financial assets in 2016. The sector is concentrated – of the 49 MMFs in South Africa, 82% of assets are held by the 10 largest MMFs, as illustrated in Figure 4.3.

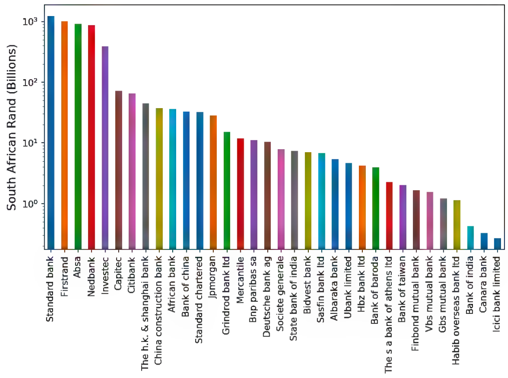
[4] For example, there are limits on the maximum percentage of the aggregate market value of the portfolio of 20% and 30% respectively for instruments issued by a holding company with a market capitalization for the listed group holding company of between R 2 billion and R 20 billion, and over R20 billion respectively.

Money-market instruments issued by banks and deposits made to banks make up 90% of the overall portfolio of MMFs, with the remainder of the holdings made up of instruments issued by non-banks (South African Reserve Bank, 2017).

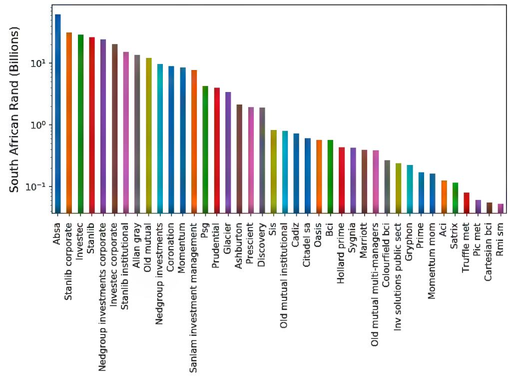
FoFs Although there is no formal distinction amongst types of non-MMF funds, subsets of these funds is typically singled-out because of their particular investment strategy or mandates – for example, equity funds invest predominantly in equity shares and bond funds predominantly in fixed-term assets. In this study, we make a distinction between Fund of Funds – that invest heavily in other investment funds, making them highly susceptible to instabilities in the fund sector, as we will see below. We classify funds that invest more than 80% of their portfolio in the shares of other funds as FoFs.The data include over 400 FoFs, and the distrubtion of their total asset sizes resembles a power law, as shown in Figure 4.3.

OFs The remaining funds (Other Funds or OFs) include multi-asset funds, equity funds, non-MMF fixed income funds and real-estate investment trusts. These funds invest in a mixture of equity shares, bonds, and other instruments (issued both domestically and off-shore). Hence, their portfolios are highly variable. The data include over 800 OFs and the distribution of their total asset sizes resembles a power law, as show in Figure 4.3.

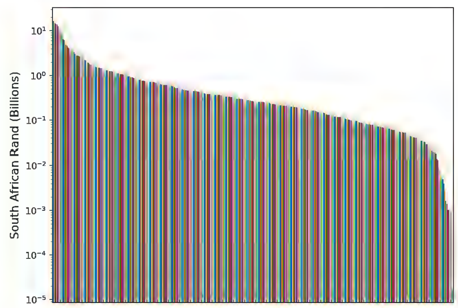
Figure 4.3 Distribution of South African financial institutions by asset size.



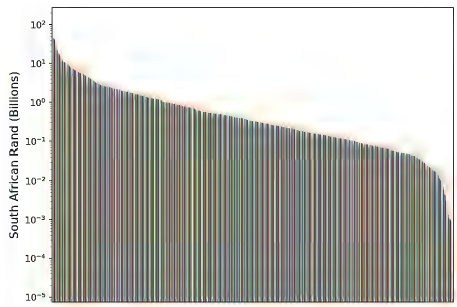
(a) Banks ranked by total assets



(b) MMFs ranked by total assets



(c) FoFs ranked by total assets



(d) OFs ranked by total assets

Note: The institutions are listed on the x-axis in decreasing order of total assets size and their total assets in billions of South African Rand are on the y-axis (log-scale). Note that the FoFs' and OFs' names are not listed because they are too numerous. The banking sector consist of a core of six large banks – the Standard Bank of South Africa Ltd (Standard Bank), FirstRand Bank Ltd (Firstrand), Absa Bank Ltd (Absa), Nedbank Ltd (Nedbank), Investec Bank Ltd (Investec) and Capitec Bank Ltd (Capitec) – and a periphery of 28 smaller banks. The FoF and OF sectors also show a strong concentration in terms of asset size, whereas the concentration in the MMF sector is less pronounced.

Assets

The data include five types of assets: Loans and Deposits, Bonds, Money Market Instruments (MMIs), Stocks (i.e. equity shares), and fund shares. Figure 4.4 shows where these assets appear on institutions' balance sheets. The characteristics of these assets are as follows:

Loans and Deposits Only banks receive loans and deposits, because funds do not have debt. The bank data do not distinguish between deposits and loans (of any maturity), so they are all treated as one and the same and we only distinguish between deposits/loans to different counterparties.

Bonds Bonds are issued by banks, the corporate sector, and the South African Government. These assets are tradable; therefore, their value depends on the nominal value, creditworthiness of issuer, and liquidity of the market for this asset.

MMIs Money market instruments are defined in line with Board Notice 90 of the Financial Sector Conduct Authority (Financial Sector Conduct Authority, 2014), and include commercial paper, negotiable certificates of deposits, bankers acceptances, and promissory notes. The majority of these instruments are traded and therefore, their value depends on the nominal value, creditworthiness of issuer, and market liquidity.

Stocks Stocks/equity shares are issued by banks and the corporate sector. These assets are traded and therefore their value depends on the performance and creditworthiness of issuer, and liquidity of the market for this asset.

Fund Shares When individuals or corporates invest in investment funds, they in effect purchase a share of the funds' underlying assets. This investment is referred to as a fund share. Fund Shares are issued by funds and represent a fraction of the asset value of the fund, which determines the fund share's value. These are withdrawable and therefore not tradable.

Figure 4.4 Stylised balance sheets of the types of modelled financial institutions in the South-African Financial System

<table>
<tr><th colspan="2">Assets (A)</th><th>Liabilities</th></tr>
<tr><td colspan="2">Loans + Deposits (l)</td><td>Loans + Deposits (l)</td></tr>
<tr><td rowspan="3">Tradable assets</td><td>Bonds (b)</td><td>Bonds (b)</td></tr>
<tr><td>MMIs (m)</td><td>MMIs (m)</td></tr>
<tr><td>Equity Shares (e)</td><td>Other liabilities</td></tr>
<tr><td colspan="2">Other assets</td><td>Equity (e)</td></tr>
</table>

(a) Stylised balance sheet of a bank.

<table>
<tr><th colspan="2">Assets (A)</th><th>Liabilities</th></tr>
<tr><td colspan="2">Deposits (l)</td><td rowspan="4">Fund shares (f)</td></tr>
<tr><td>Tradable assets</td><td>MMIs (m)</td></tr>
<tr><td colspan="2">Fund shares (f)</td></tr>
<tr><td colspan="2">Other assets</td></tr>
</table>

(b) Stylised balance sheet of a MMF.

<table>
<tr><th colspan="2">Assets (A)</th><th>Liabilities</th></tr>
<tr><td colspan="2">Deposits (l)</td><td rowspan="6">Fund shares (f)</td></tr>
<tr><td rowspan="3">Tradable assets</td><td>Bonds (b)</td></tr>
<tr><td>MMIs (m)</td></tr>
<tr><td>Equity shares (e)</td></tr>
<tr><td colspan="2">Fund shares (f)</td></tr>
<tr><td colspan="2">Other assets</td></tr>
</table>

(c) Stylised balance sheet of FoFs and OFs.

Note: We consider: (a) banks; (b) MMFs; and (c) FoFs and OFs. FoFs have the same balance sheet structure as OFs, but FoFs invest more than 80% of their assets in fund shares. Pension funds are insurers are not modeled, because of a lack of granular data (but we do not expect them to significantly contribute to higher-order exposures).

Initialization Values

For simplicity, we normalize the (initial) NAV of each fund share and the (initial) market price of each tradable security to one, such the (initial) value of a position in a security is equal to number of securities that make up the position. We follow this approach given that we do not have data on the market prices or NAVs of financial securities that institutions hold, nor the number of securities they hold, but only on the value of an institution's positions in a security (i.e. the market value of a position in a tradable security and the NAV times the number of shares of a position in shares issued by a fund). This normalization has no effect on our results and is only for simplicity.

Network construction

The data can be represented as a directed network, with the nodes representing the institutions and the edges their assets (a node's out-edges are given by its assets and its in-edges by its liabilities and/or issued shares). We refer to this as the "asset network". The network is multiplex, consisting of five layers, which each layer representing one of the asset types $\alpha \in \{l, b, m, e, f\}$. Each layer includes the same set of nodes, made up by the (individual) banks and funds, the node $\mathscr{G}$ representing the government, and a single "corporate" node $\mathscr{C}$ representing the domestic non-financial corporate sector.[5] As noted before, we do not model the government and corporate sector.[6]

The edges corresponding to to funds' investments are given directly by our (disaggregate) data on the funds' investments in individual SA banks and other funds. As we only have aggregate data on banks' investments, the edges corresponding

[5] We do not have disaggregate data on investments in the corporate sector, but do not expect this to affect our results substantially as this only affects the granularity of the overlapping portfolio contagion channel. Thus while we do not know which specific corporates banks and funds are exposed to, given that only the overlapping portfolio is at play here we do not expect that not included data that shows the specific corporate that banks or investment funds are exposed to, will significantly change our findings outlined in 4.4.3.

[6] The government node and corporate node are only included in the asset network to capture the indirect exposures generated by financial instruments these nodes issue. As we focus on exposures between financial institutions, the government node and corporate node are not included in the exposure networks introduced below.

to banks' investments in individual counterparties are reconstructed based on our balance sheet information on aggregate positions of institution per asset and liability type.

Reconstructing interbank asset-liability linkages

South African banks do not invest in funds as the banks' aggregate balance sheet data do not show fund shares among their assets. Furthermore, the government and domestic non-financial corporate sector are each represented by a single representative node, and the banks' balance sheets already give the aggregate investment in each. Hence, we only reconstruct the interbank assets.

We know banks' liabilities to funds from the fund data. Therefore, for asset type $\hat{a} \in \{l, b, m, e\}$ in which banks invest, we first subtract each bank's liabilities of type $\hat{a}$ to funds from that bank's aggregate liabilities of type $\hat{a}$ and then perform the following procedure:

1. We subtract from each bank's aggregate liabilities (or equity) of type β the funds' investments of type β in that bank.
2. We pick a random pair of banks y and z, where bank y is the investor and bank z is the investee. Bank y is picked from the banks with nonzero aggregate assets of type β and z is picked from the banks with nonzero aggregate liabilities (or equity) of type β.
3. We pick a random number $x \in U(0,1)$ and generate an investment of type β of bank y in bank z equal in size to the product of x and the minimum of y's aggregate assets of type β and z's aggregate liabilities (or equity) of type β.
4. The investment is added to the network layer of investments of type β (i.e. added to w^{β}_{yz}) and subtracted from y's aggregate assets of type β and z's aggregate liabilities (or equity) of type β.
5. Steps 2-4 are repeated until all banks' assets of type β are allocated.[7]

[7] The last 500 Rand are invested in a single chunk so the algorithm terminates: we set $x = 1$

After step 5, the asset network is complete and all of its edges w_{ir}^{α} are defined. Edges corresponding to banks' assets are randomly generated, based on banks' aggregate assets and liabilities (and funds' investments in banks). Edges are randomly constructed using a simple algorithm, which is explained in Appendix B, that produces a power-law distribution similar to Montagna and Lux, 2017.

Direct Exposure Network Construction

The above procedure creates a direct exposure network among banks. Each generated investment of type $a \in \{l, b, m, e\}$ of one institution in another creates an edge of weight $\hat{w}_{ij}^{a}$ in layer a that points from node i to node j. We also know from data the weight $\hat{w}_{ij}^{a}$ of each edge from each fund to other banks/funds, for $a \in \{l, b, m, e, f\}$. The hat highlights that the weight represents a direct exposure. The direct weight is equal to the notional amount in case of loans l and is equal to the market value (i.e. price times unit holdings) in case of tradable assets and fund shares (i.e. $a \in \{b, m, e, f\}$). The direct exposure network is obtained by summing together all layers of the investment network (and omitting the government and corporate nodes, as were only interested in exposures between financial institutions). The edges in this network are given by $\hat{w}_{ij} = \sum_{\{a \in \{l,b,m,e,f\}\}} \hat{w}_{ij}^{a}$. The resulting direct exposures network is visualized in figure 4.5.

Indirect Exposure Network Construction

Indirect exposures are generated by tradeable assets. All tradeable assets held by nodes in our network are issued by other nodes in the network and are of types $a \in \{b, m, e\}$. When two institutions both invest in the same tradable asset issued by a third institution, the first two institutions share a portfolio overlap. From the multiplex investment network, we calculate a multiplex network of liquidity-weighted (or "market-depth weighted") portfolios. The nodes are again given by the institutions.

when the minimum of y's aggregate assets of type β and z's aggregate liabilities (or equity) of type β is less than or equal to 500 Rand).

Let $\mathcal{I}$ denote the set of institutions in the network and let $\tilde{w}_{ij}^a$ denote the weight of the edge between node i and j corresponding to their indirect exposure (i.e. their liquidity-weighted overlap), in the layer corresponding to asset type $a \in \{b, m, e\}$. The tilde highlights that the edge corresponds to an indirect exposure. The weight of the corresponding edge in the corresponding asset layer of indirect exposure network is given by

$$\tilde{w}_{ij}^a = \sum_{k \in \mathcal{I}} \frac{\hat{w}_{ik}^a \hat{w}_{jk}^a}{D_k^a}, \tag{4.10}$$

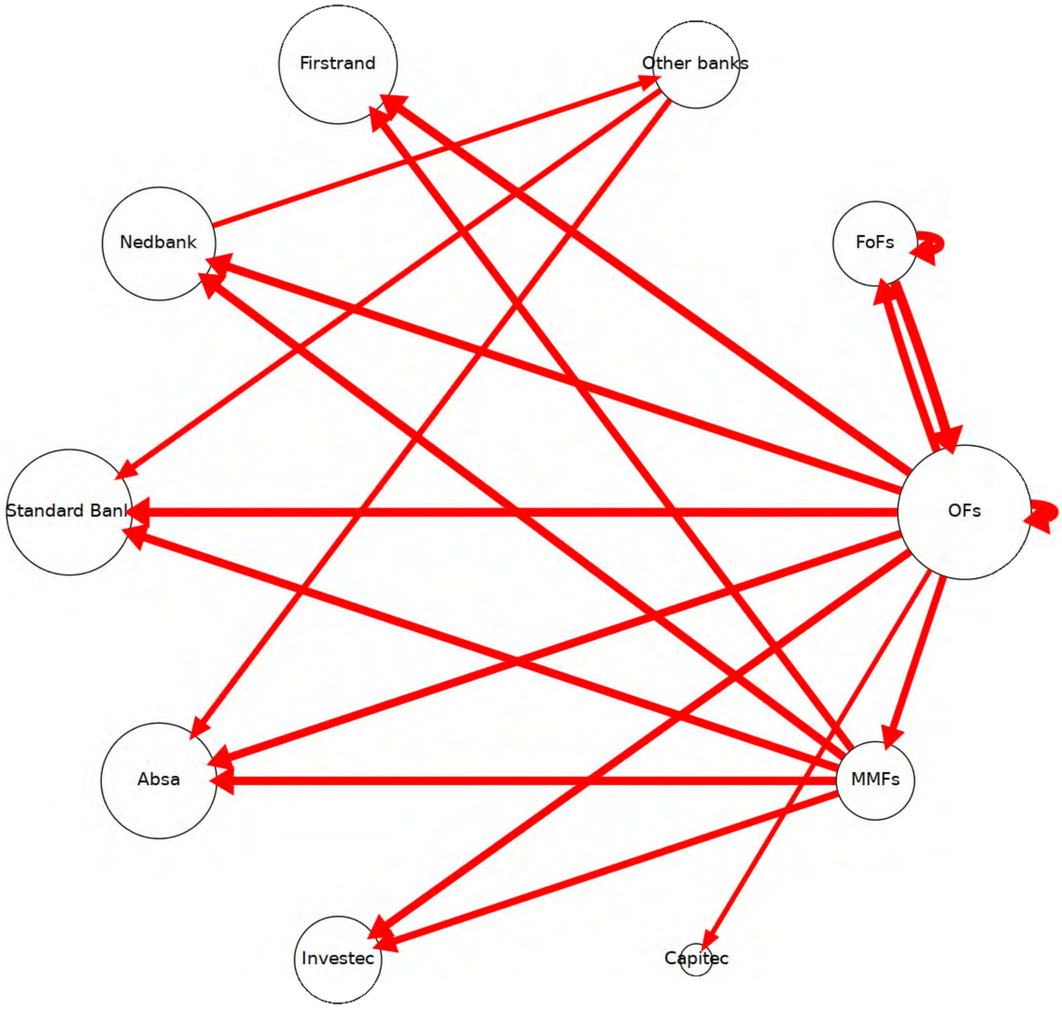
where the choice of the market depth D_k^a is explained in section 4.3.2. Note that the edges in the portfolio overlap network are symmetric (i.e. $\tilde{w}_{ij}^a = \tilde{w}_{ji}^a$), so it can be represented as an undirected network. A liquidity-weighted portfolio overlap between two institutions represents an indirect exposure between them, so the indirect exposure network is obtained by summing together all layers of the liquidity-weighted portfolio overlap network. The edges in this network are given by $\tilde{w}_{ij} = \sum_{\{a \in \{b,m,e\}\}} \tilde{w}_{ij}^a$. Figure 4.6 visualizes the indirect exposures network.

Notably, in the tradable asset layers $a \in \{b, m, e\}$ of the multiplex network, we thus have both direct and indirect linkages. If both institution i and j hold an asset issued by institution k in common, then i will have a direct link to k ($\hat{w}_{ik}^a$), and so will j ($\hat{w}_{jk}^a$). Furthermore, i and j have an indirect link between themselves ($\tilde{w}_{ij}^a$). We thus model both the counterparty exposure that i and j have towards an issuer k as well as the mark-to-market exposure that institution i and j have towards each other because they hold an asset in common. The literature that studies contagion via tradable assets typically models the indirect linkages only, while the direct linkages are ignored. In our model we newly capture that holding tradable assets also carries counterparty risk.

First Order Exposure Network Construction

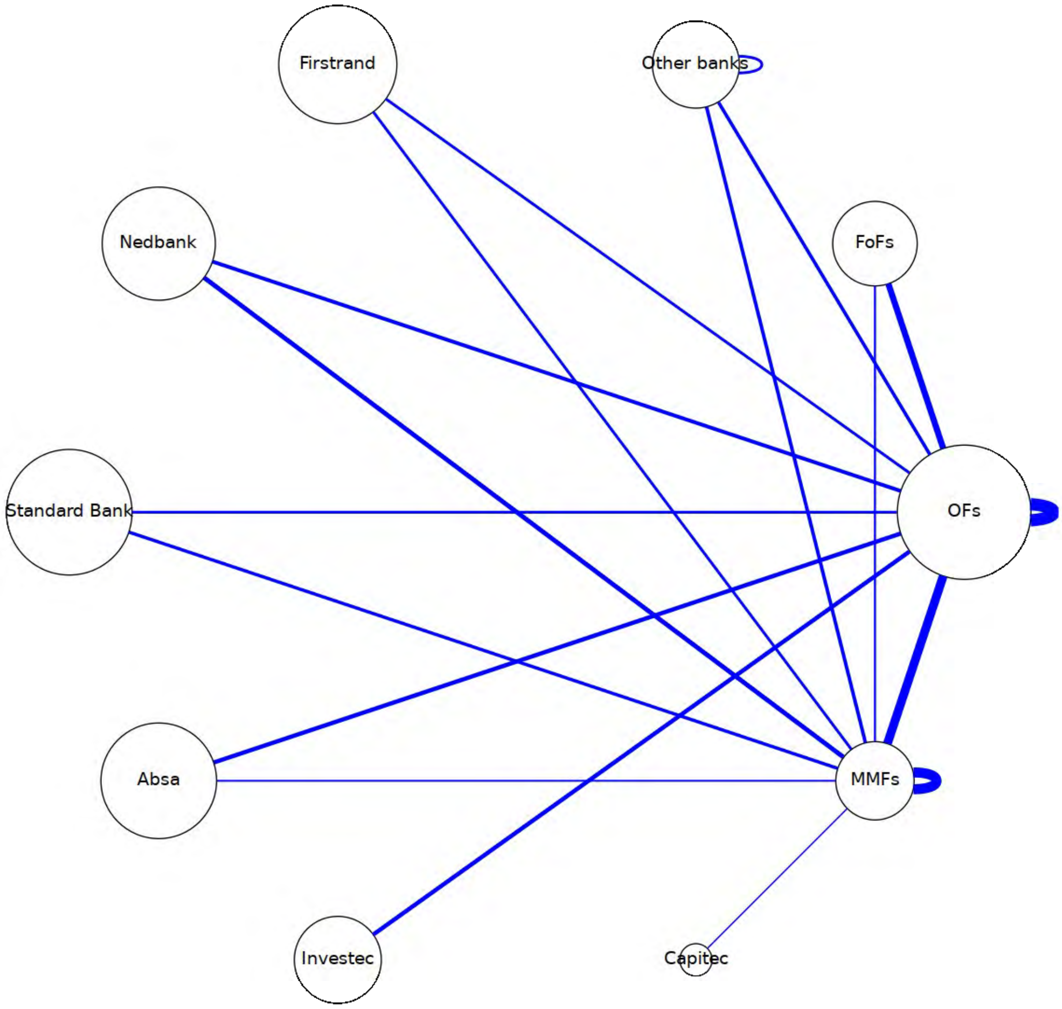
The first-order exposure network is obtained by summing together the direct and indirect exposure networks. The edges in this network are given by $w_{ij} = \hat{w}_{ij} + \tilde{w}_{ij}$. The first-order exposure network is visualized in Figure 4.7.

Figure 4.5 Network of largest direct exposures in the South African financial system



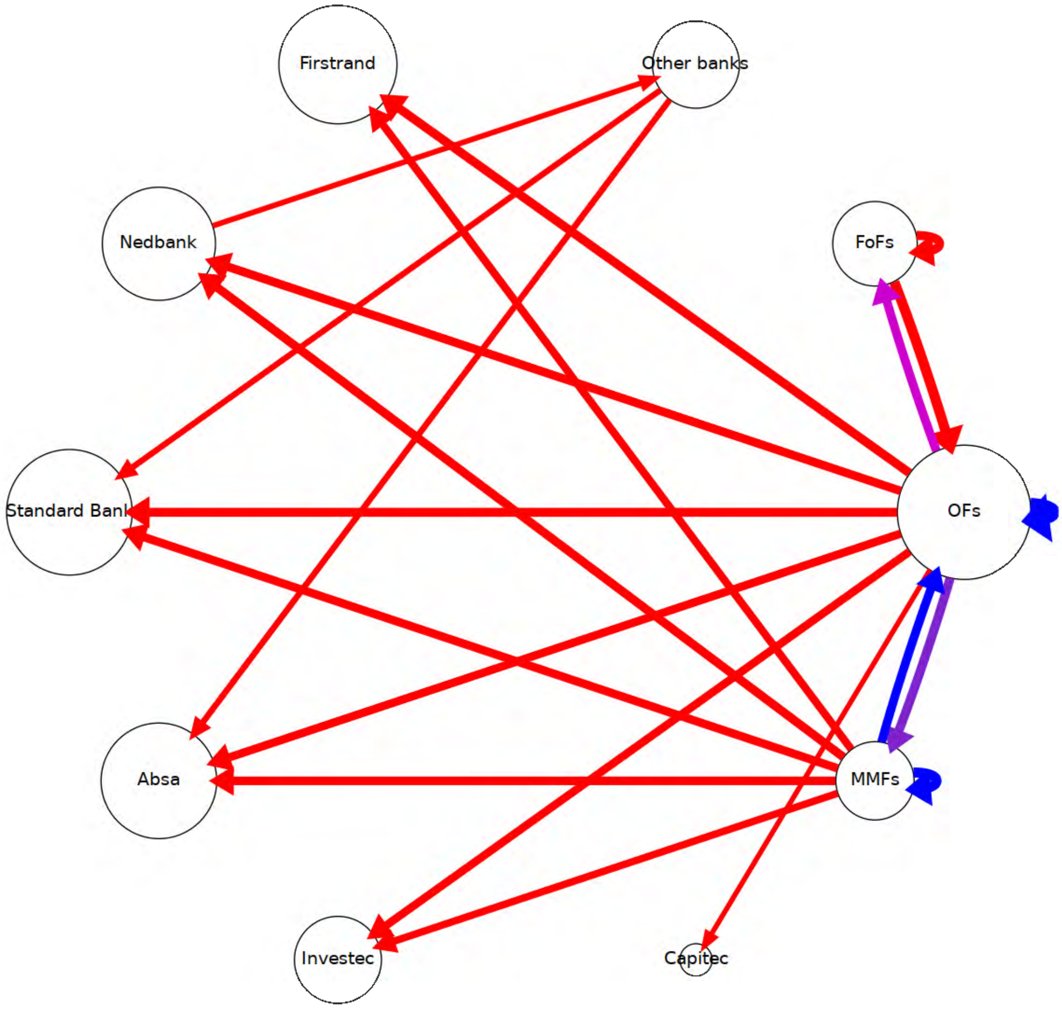
Note: We plot the largest direct exposures between the six largest banks, the rest of the banking sector, and the three fund sectors. Edge widths visualize the size of the exposure, varying between 5 billion to 196 billion South African Rand, and node sizes visualize the total asset size of the node, ranging from 717 billion to 1.6 trillion. South African Rand. The scaling is logarithmic for both edge widths and node sizes. Other than the six largest banks, all institutions of the same type are aggregated into a single node. Edges point in the direction of the exposures. For example, the edge from the MMFs to Absa denotes the sum of all MMFs' direct exposures to Absa. The OF and FoF sectors' self-loops denote the sums of all direct exposures between OFs or FoFs. The figure shows that the largest exposures are those of the MMF and OF sectors to the six large banks, and the OF and FoF sectors' exposures to itself.

Figure 4.6 Network of largest indirect exposures in the South African financial system.



Note: We plot the largest indirect exposures (i.e. institutions' liquidity-weighted portfolio overlaps) between the six largest banks, the rest of the banking sector, and the tree fund sectors. Edge widths visualize the size of the exposure, varying between 2 billion and 887 billion. South African Rand, and node sizes visualize the total asset size of the node, ranging from 717 billion to 1.6 trillion. South African Rand. The scaling is logarithmic for both edge widths and node sizes. Other than the six largest banks, all institutions of the same type are aggregated into a single node. Indirect exposures are symmetric, so they are drawn as an undirected network. The MMF and OF sectors' self-loops denote the sums of all indirect exposures between MMFs or OFs. These self-loops make up the system's largest indirect exposures. Note that the MMF sector is much smaller than the OF sector in total asset size. Hence, the large indirect exposures between MMFs highlight their exceptionally similar portfolios.

Figure 4.7 Network of the largest First-Order (direct + indirect) exposures in the South African financial system

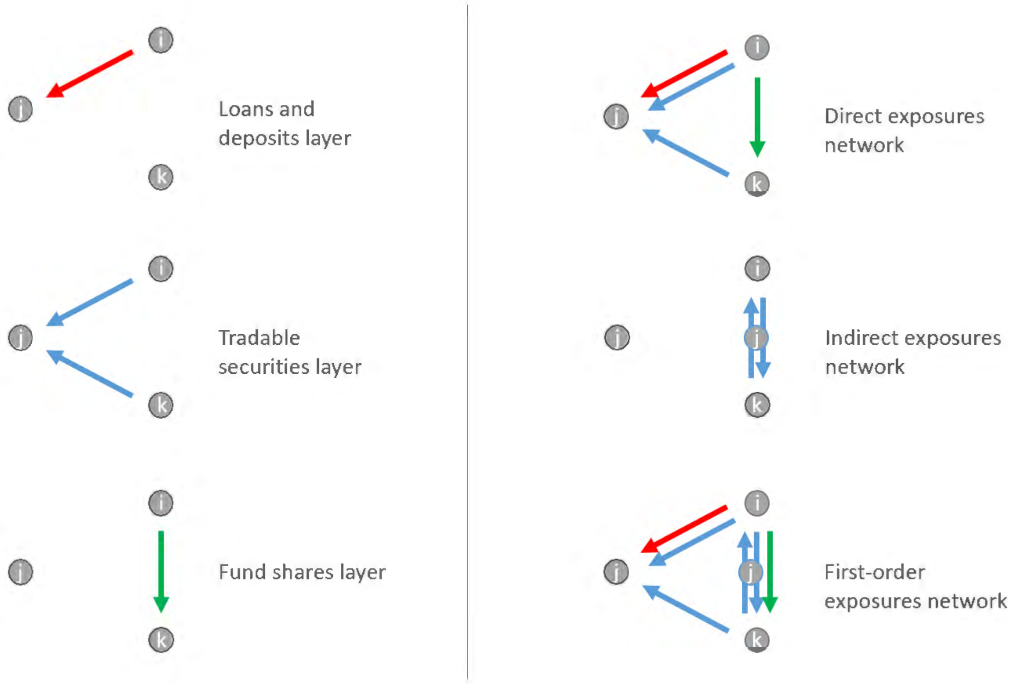


Note: We plot the largest first-order exposures (i.e. direct + indirect exposures) between the six largest banks, the rest of the banking sector, and the tree fund sectors. Edge widths visualize the size of the exposure, varying between 5.7 billion and 1 trillion. South African Rand, and node sizes visualize the total asset size of the node, ranging from 717 billion to 1.6 trillion. South African Rand. The scaling is logarithmic for both edge widths and node sizes. Other than the six largest banks, all institutions of the same type are aggregated into a single node. Edges point in the direction of the exposures. For example, the edge from the MMFs to Absa denotes the sum of all MMFs' first-order exposures to Absa. The color of an arrow indicates the composition of that first-order exposure: A red edge indicates an exposure that is predominantly direct and a blue edge indicates an exposure that is predominantly indirect. Shades of purple, a mix between red and blue, indicate exposures with both a substantial direct and indirect component (the more red the shade is, the larger is the direct component and the more blue, the larger the indirect component). The figure shows that all large exposures to banks are direct and that OFs and MMFs have very large indirect exposures between them.

As illustrated in Figure 4.8, the multilayer network made up by institutions' asset holdings generates a multilayer exposure network; the direct network is made up of the direct exposures generated by the assets, the indirect network of the indirect exposures, and the first order network of the direct and indirect exposure networks. Note that edges in the exposure network point in the direction of the flow of losses, which is opposite to the direction of the flow of investments depicted by the edges in the asset networks.

The largest exposures in the direct, indirect, and first- order networks generated by the South African financial system are illustrated in Figures 4.5-4.7 (where exposures are calculated as explained in Section 4.3.2). Note that funds' exposures to the six largest banks make up the majority of the largest direct exposures. On the other hand, the largest indirect exposures are between funds. Given that we simulate exposures by letting one of the big six banks default, first-order exposures are predominantly caused by direct exposures, whereas indirect exposures play an important role for higher-order exposures.

Figure 4.8 Stylised multilayer network: correspondence between the asset network and exposure networks.



Note: The figure summarizes our explanation of the network construction by illustrating the correspondence between the exposure networks and layers of the asset network. The left column shows the layers of the asset network and the right column the corresponding exposure networks. Because each of the three tradable securities layers $\tau \in \{b, m, e\}$ (as well as the corresponding exposures) can be visualized identically, we only plot one of the tradable securities layers for simplicity. Arrows in the left column point in the direction of the (principal) cashflow: FoF i deposits at bank j and buys fund shares in MMF k, so i suffers a write-off when either j or k defaults. The deposits are visualized by the red arrow and the fund shares by the green arrow. Both i and k buy MMIs in j, so either suffers a mark-to-market loss when the other liquidates their MMIs, and both suffer a write-off on the MMIs when j defaults. The MMIs are visualized by the blue arrows. Arrows in the right column point in the direction of the exposure and their color reflects the asset that generates the exposure. For example, an arrow from i to k represents an exposure of i to k and the color of the arrow is equal to that of the asset that generates the exposure. Exposures in the direct network are made-up of the write-offs that an institution would suffer on investments in a counterparty when that counterparty defaults. Exposures in the indirect network are made-up of institutions' liquidity-weighted portfolio overlaps, i.e. the mark-to-market losses suffered by an institution that has a portfolio overlap with another institution, when that other institution liquidates its portfolio. The first-order network is the sum of the direct and indirect networks. Note that the same MMIs generate both direct and an indirect exposures, causing exposures to multiple counterparties for both i and k in the first-order exposures network.

4.3.2 Measuring Higher-Order Exposures

Having set-up the asset and exposure networks, we are ready to compute the higher-order exposures. In the Stylised example, we calculated the exposure to an institution by recording all losses that would follow from the default of that institution. We did so by simulating how losses would propagate upon the default of the institution, where the propagation was dictated by the contagion mechanisms we formulated.

Here, we list the general steps for computing exposures, comprised of first-order and higher-order exposures:

1. Formulate a model of how contagion channels propagate losses across assets α present in the financial network.

2. Start the simulation by assuming the (idiosyncratic) default of one institution, to calculate the exposures to that institution. We use j to denote the institution that defaults at the start of the simulation.

3. Assume discrete time dynamics and use n to denote the n^{th} round following j's default.

4. Tally the losses $L_{ij,1}$, $i \in \mathscr{I}$, in the first round following j's default. These constitute the first-order exposures $E_{ij,1}$ (i.e. the sum of direct and indirect exposures) and are given by the first-order exposure network (eq. **??**):

$$E_{ij,1} = L_{ij,1} = \hat{w}_{ij} \tag{4.11}$$

5. Tally the losses $L_{ij,n}$ in round $n > 1$. These constitute the higher-order exposures and are given by the contagion channels' propagation of the losses in the $(n-1)^{th}$ round. We specify the round in which losses were incurred as the order of the exposure, so i's n^{th}-order exposure is given by

$$E_{ij,n} = L_{ij,n}, \tag{4.12}$$

where the losses are found by summing losses across all asset types:

$$L_{ij,n} = \sum_{\alpha} L^{\alpha}_{ij,n}. \tag{4.13}$$

We refer to i's losses incurred up to and including the n^{th} round as i's exposure up to n^{th} order to j. All losses incurred over the course of the simulation are recorded as exposures to failed institution.

6. Define the Higher-Order Share of Exposure (HSE) up to n^{th} order as the fraction of an exposure up to n^{th} order made up by higher-order exposures, i.e.

$$HSE_{ij,n} \stackrel{\text{def}}{=} \frac{\sum_{k=2}^{n} E_{ij,k}}{\sum_{k=1}^{n} E_{ij,k}}. \tag{4.14}$$

Table 4.1 summarizes our terminology.

Table 4.1 Terminology

<table>
<tr><td colspan="6">Exposure</td></tr>
<tr><td colspan="2">First order exposure</td><td colspan="4">Higher-order exposure</td></tr>
<tr><td>Direct exposure</td><td>Indirect exposure</td><td>Second order exposure</td><td>$\cdots$</td><td>n^{th} order exposure</td><td>$\cdots$</td></tr>
<tr><td colspan="5">Exposure up to n^{th} order</td><td>$\cdots$</td></tr>
</table>

For our case study of the South-African financial system, we implement this general recipe for computing exposures as follows. As noted, we will study the exposure of the South-African financial system, and the institutions therein, to the default of one of the "big six" South-African banks. We will study how exposures arise from interconnections in the financial system via the prevailing asset types in the South-African financial system. Since we do not know the interlinkages between banks, we first reconstruct this, in the manner explained before, before we run our model. We use the contagion model, as we will discuss below, to simulate how losses propagate throughout the network upon the (idiosyncratic) default of one of the six large banks. We repeat the network reconstruction and loss recording following a failure a thousand times for each of the big six banks to average institutions' exposures to these banks over the random realizations of the reconstructed interbank network.

In what follows, we will describe how we decided to formulate the contagion model underlying the computation of higher-order exposures, as well as the simulation variables we use for this. Our modelling choice has been motivated by the contagion mechanisms that could prevail in the South-African financial system, and should by no means be seen as the gold standard. Others should feel free to choose a different contagion model to compute exposures. It would be expected, for instance, that a different contagion model would be chosen depending on the financial institutions, assets, contagion mechanisms in the jurisdiction that is being modelled. The modeling choice might also be motivated by the degree to which granular contractual data and market data is available. Finally, it would also be expected that the results could change depending on which contagion channels are included in the simulation, and also under which assumptions the simulation is conducted. However, we choose a set up assumptions and contagion channels to demonstrate and quantify higher-order exposures, and while the actual exposure measurements would change when assumptions are altered, the conceptual contribution of how to measure such exposures will remain unchanged.

Contagion Channels

We include three contagion channels, *counterparty (default) risk contagion*, *overlapping portfolio contagion* and what we refer to as "*shareholder contagion*", which are explained below. These contagion channels are driven purely by the mechanics of asset valuation.

Strategic decisions and/or behavioral actions institutions might optimize their balance sheets during times of stress, which could lead to additional channels of contagion. In particular, institutions may start liquidating assets which are perceived as risky, leading to liquidity spirals (Hoerova et al., 2009; Acharya and Skeie, 2011; Gai, Haldane, et al., 2011). However, strategies and behaviors, in particular those during times of stress, are inherently uncertain and difficult to predict and will vary across institutional types. To avoid these sources of uncertainty, we restrict the model to the aforementioned set of contagion channels by assuming that (a) the composition of an institution's balance sheet is fixed as long as the institution does not default (although the value of the assets on the balance sheet may fall as part of the simulation). Furthermore, we assume that (b) at default, the institution's tradable assets are firesold as the institution is liquidated.[8] Specifically, as institutions are assumed not to withdraw their deposits from banks, banks cannot default through illiquidity in our model. Under assumptions (a) and (b), any contagion that occurs is driven purely by market mechanics of asset valuation and covered by the three contagion channels in the model. Thus, the subjectivity and uncertainty inherent to modelling strategies and behaviors is avoided, allowing us to measure higher-order exposures accurately and objectively.

We assume that an institution does not liquidate any of its assets before it defaults, and that only upon its default are all of its tradable securities liquidated as part of the resolution process. Assuming liquidation of tradable securities upon default is in line with contagion literature such as Burrows et al., 2012; Caccioli, Farmer, et al., 2015; Kleinnijenhuis et al., 2021.

The propagation of losses is dictated by the contagion channels we include in the simulation. The Stylised example illustrated two types of contagion: *direct contagion*, which spreads from counterparty to counterparty through the contracts between them, and *indirect contagion*, which can spread even between institutions that do not have mutual contracts, through overlapping portfolios. Here, we include the two most relevant direct contagion channels, counterparty risk contagion and shareholder contagion. Counterparty risk contagion occurs when the risk of default of a counterparty rises, which depresses the risk-adjusted

[8]It should be noted that the assumption of no strategic decisions or behavioral actions is a strong assumption that does not reflect reality. Moreover it likely that including reactive behavior would result in different levels of our higher-order exposure measure. However, it is not clear whether this assumption renders the measure more conservative or more overstated. On one hand it can be argued that this assumption is more conservative in nature as it does not take into consideration that action could limit contagion, thus this assumption could result in a higher outcome of higher order exposures. On the other hand, it is also possible that in a stress scenario the reaction of financial intermediaries result in systemic stress, thus increasing the systemic risk. In such a stress scenario fire sales and liquidity spirals (see for example Brunnermeier et al., 2009), and likely result in a higher measure of higher-order exposure.

value of any contracts with this counterparty. Hence, counterparty risk contagion expands the counterparty default contagion channel introduced in the example by including write-downs/offs in the lead-up to the default. Shareholder contagion describes how any losses an institution makes are passed on to (equity or fund) shareholders, as they share ownership of the institution. Indirect contagion is caused by the overlapping portfolio contagion channel from example, which is expanded here but conceptually analogous.

We first demonstrate how each contagion channel acts between two institutions in isolation from other contagion channels and counterparties. Depending on the asset type, multiple contagion channels may interact. We show below for each of the individual asset types how they are affected by interacting contagion channels.

Shareholder Contagion

Shares in an institution represent part ownership of the institution's balance sheet. As such, any losses an institution incurs are propagated to its equity or fund shareholders, via shareholder contagion. In our model equities and fund shares are subject to shareholder contagion, we discuss losses to these asset types in turn.

In our model of the South African financial system, banks are the only institutions that have issued equity (recall Figure 4.4). Let $e_{k,0}$ denote bank k's equity at the start of the simulation and $e_{k,n}$ its equity at the end of the n^{th} round following j's default, such that the equity lost in round n is given by

$$\Delta e_{k,n} = e_{k,n} - e_{k,n-1}. \tag{4.15}$$

Henceforth, we will for any variable x define $\Delta x_{k,n} \stackrel{\text{def}}{=} x_{k,n} - x_{k,n-1}$. Using $e_{ik,0}$ to denote the value of bank i's equity shares in k at the start of the simulation, i's equity loss from shareholder contagion in round $n+1$ resulting from k's losses in round n is equal to

$$L^{jes}_{ik,n+1} = \frac{\Delta e_{k,n}}{e_{k,0}} e_{ik,0}, \tag{4.16}$$

where the superscript j denotes that the loss arises from the exposure to the default of counterparty j, the superscript e denotes that the loss affects equity shares and the superscript s denotes the shareholder contagion channel through which the loss materializes.

Similarly, for fund h with initial total assets as $A_{h,0}$, the fund share value losses from shareholder contagion suffered by institution i, which has fund shares (f) initially worth $f_{ih,0}$ in h, are equal to

$$L_{ih,n+1}^{jfs} = \frac{\Delta A_{h,k}}{A_{h,0}} f_{jh,0}, \tag{4.17}$$

For investment funds changes in the value of the underlying asset will impact the value of the total assets under management of the fund. For funds with a variable net asset value (VNAV - i.e. fund of funds and other investment funds), changes in the value of the assets that the fund invests in, impacts the price per share of the fund. In the case of a constant NAV (CNAV) fund – i.e. MMFs – the number of shares will be impacted while the price per share remains constant. Therefore we can model changes in the value of fund shares based on the changes in asset value.

Hence, both equity and fund shareholder contagion distribute an institution's losses proportionally across its owners.

Counterparty risk contagion

When an institution defaults, the value of its liabilities (or fund shares) is written-down to the recovery value, which we assume to be zero.

Modern accounting standards require assets to be risk-adjusted, which reflects that the expected value of the liabilities of any institution with non-zero default risk is below their face value; the higher the risk of default, the lower the risk-adjusted value.

Banks default through insolvency when their equity is reduced to zero, as was illustrated in the Stylised example for bank y. Funds cannot become insolvent as they do not have debt, but are subject to runs that could render them unable to meet redemptions if they have trouble liquidating assets to increase cash to pay redeeming investors. The threshold at which such illiquidity is encoutered would depend both on the liquidity of the assets held within the fund, as well as the relative size of the fund's holdings compared to the rest of the market. For simplicity, we assume that when a run on a fund is initiated, and the fund becomes unable to meet redemptions when its portfolio loses 45% of the value it had at the start of the simulation. This threshold is in line with Cont and Wagalath, 2013 and we explore how this assumption affects exposures in the results section. Our model capturing redemption risk following NAV losses aligns with the empirical literature on fund inflows and outflows, which has shown that funds tend to experience outflows following declines in their NAV (see e.g. Coval et al., 2007; Goldstein et al., 2017).

We refer to the amount of losses an institution can absorb before it defaults as its *buffer* B. Hence, a bank's buffer is given by its equity and a fund's buffer is equal to 45% of its total asset value at the start of the simulation. When an institution's buffer is decreased, the probability that a shock of random size exceeds the buffer and causes default rises. Hence, the risk-adjusted value of each asset of another institution towards this institution falls when its buffer is decreased.

Assume for simplicity that assets' risk-adjusted values are equal to their face values at the start of the simulation, and are written-down/off proportionally to the counterparty's buffer losses as the simulation evolves. Let $B_{k,n}$ denote institution k's buffer at the end of the n^{th} round following the default of institution j and let a_{ik}, $a \in \{l, b, m, f\}$ denote the face value of i's investments of type a in k. Hence, the counterparty risk contagion loss i suffers in round $n+1$ on its investment in k is given by

$$L^{jac}_{ik,n+1} = \frac{\Delta B_{k,n}}{B_{k,0}} a_{ik}, \tag{4.18}$$

where the superscript c denotes the counterparty risk contagion channel through which the loss materializes. We test the sensitivity of our results to the rate at which exposures are written-down through counterparty risk contagion in Figure 4.18.

Overlapping Portfolio Contagion

Let institution k default in the n^{th} round following j's default, i.e. $B_{k,n} = 0$ and $B_{k,n-1} > 0$, and let k hold a number r_k^{ah}, $a \in \{b, m, e\}$ of tradeable assets of type a issued by h. From the Stylised example, we know that when institution k defaults and its tradeable assets r_k^{ah} issued by k of type a are sold, institution i, with overlapping portfolio holdings r_i^{ah}, suffers a loss equal to

$$L_{ik,n+1}^{jaho} = \frac{r_k^{ah} r_i^{ah}}{D_{ah}}. \tag{4.19}$$

where the superscript o denotes that the loss materializes through the overlapping portfolio contagion channel and D_{ah} denotes the market depth of tradeable assets of type a issued by h. Using $P_{ah,0}$ and $C_{ah,0}$ to denote the price and market capitalization of tradeable assets of type a issued by h at the start of the simulation, the total number of R^{ah} tradeable assets of type a issued by h in circulation is given by

$$R^{ah} = \frac{C_{ah,0}}{P_{ah,0}}. \tag{4.20}$$

We set the market depth

$$D_{ah} \stackrel{\text{def}}{=} \frac{R^{ah}}{P_{ah,0}}, \tag{4.21}$$

which implies that the price of the stock falls to zero when the entire market cap C_{ah} is (fire)sold. We test the sensitivity of our results to the market depth in Figure B.3 of appendix B.

In general, k's portfolio of tradeable assets of type a may include asset issued by multiple institutions, all of which can generate portfolio overlaps with i. Hence, to cover all losses that i suffers on its assets of type a when k's assets are liquidated, we sum over all nodes h.

Contagion by asset

We are now ready to discuss how assets are devalued through multiple interacting contagion channels and calculate the terms $L_{i,n}^{ja}$ from equation 4.13 for each asset type $a \in \{l, b, m, e, f\}$.

Loans and Deposits

Loans and deposit are subject only to counterparty risk contagion. As only banks take deposits and receive loans, let l_{ik} denote all loans and deposits made to bank k by institution i and $\mathscr{B}$ the set of all banks. In the $n+1^{th}$ round after j's default, i suffers a loss on its loans and deposits portfolio given by the sum of its loan exposures to its counterparties k weighted by their relative change in equity value between round n and $n-1$

$$L^{jl}_{i,n+1} = L^{jlc}_{i,n+1} = \sum_{k\in\mathscr{B}} \frac{\Delta b_{k,n}}{b_{k,0}} l_{ik}, \tag{4.22}$$

where $B_{k,n} = e_{k,n}$ for banks.

Fund shares

Fund shares are subject to counterparty risk contagion and shareholder contagion; when a fund suffers a loss, the nominal value of its shares is reduced through shareholder contagion. However, this does not cover the fund's increased default risk, so the risk-adjustment caused by the counterparty risk contagion channel further reduces the (book) value of the fund's shares.

However, when applying both contagion channels, we need to take into account that when a fraction of the value of a fund share is already written-off by one contagion channel, that fraction cannot be written off by the other as well. Therefore, we add an interaction term to each contagion channel that captures the fraction of the asset's value not yet written-off by the other contagion channel. Using $\mathscr{F}$ to denote the set of all funds, the counterparty (c) risk contagious losses suffered by i on its fund shares (f) following the default of j is given by

$$L^{jfc}_{i,n+1} = \sum_{k\in\mathscr{F}} \frac{\Delta B_{k,n}}{B_{k,0}} \frac{A_{k,n-1}}{A_{k,0}} f_{ik,0}, \tag{4.23}$$

where the interaction term $A_{k,n-1}/A_{k,0}$ captures the fund share value left after any (fund) shareholder contagion that may have occurred in previous rounds.

The shareholder contagion suffered by i on its fund shares (f) is given by

$$L_{i,n+1}^{jfs} = \sum_{k \in \mathscr{F}} \frac{\Delta A_{k,n}}{A_{k,0}} \frac{B_{k,n}}{B_{k,0}} f_{ik,0}, \tag{4.24}$$

where the interaction term $B_{k,n}/B_{k,0}$ expresses the fraction of the share's value not yet written-off through counterparty risk contagion. For simplicity, we apply the counterparty risk contagion first and the shareholder contagion after, which is why the interaction term $B_{k,n}/B_{k,0}$ already includes the counterparty risk contagion that materialized in round k, but applying the two contagion channels in reverse order would yield the exact same result. Summing equations (4.23) and (4.24), we find that the loss suffered by i on its fund shares in the $n+1^{th}$ round after j's default is equal to

$$L_{i,n+1}^{jf} = L_{i,n+1}^{jfc} + L_{i,n+1}^{jfs}. \tag{4.25}$$

Tradable assets: bonds, MMIs & equities

The tradable assets include bonds, MMIs and equity shares. Bonds, MMIs and equities are subject to not only overlapping portfolio contagion but also counterparty credit risk contagion. For these assets, losses as a result of counterparty default is taken into account first, and losses as a result of overlapping portfolio is subsequently taken into account.

An institution needs to mark down the value its tradable asset if it decreased in price due to overlapping portfolio contagion. Furthermore, if the issuer of the tradable asset fails, the price of the tradable asset becomes zero. Even if the issuer does not fail but becomes more credit risky, the price of the tradable asset will reflect this (in informationally efficient markets), as discussed before we model this price effect as a separate price loss, and thus asset value loss, due to increased counterparty risk.

Comparison of equations (4.16) and (4.18) and using that $e_i = b_i$ when i is a bank reveals that we model the shareholder contagion channel for equity shares identically to the counterparty risk contagion channel for other assets. We choose to also model the interaction of both contagion channels with the overlapping portfolio contagion channel identically, such that we can model equity shares identically to bonds and MMIs.[9]

To keep the explanation here simple, we assume that the market price of a tradeable asset does not reflect the performance of the issuer and is only affected by the overlapping portfolio contagion channel. The counterparty risk contagion channel (or shareholder contagion channel in case of equity shares) is applied as an adjustment to the book value of the tradeable asset. However, one can assume equivalently that the market price reflects the risk-adjusted value of the tradable asset, and not apply the risk-adjustment separately, and arrive at the exact same result.

Let

$$P_{ak,n} = P_{ak,0} - \sum_{t=1}^{n} \Delta P_{ak,t} \tag{4.26}$$

denote the price at the end of round n of the asset of type $a \in \{b, m, e\}$ issued by h. The losses from counterparty risk contagion suffered by i on its tradeable assets of type a is then given by the sum of the asset value $P_{ak,n} r_i^{ak}$ of each asset k it holds weighted by the relative change in the creditworthiness of each issuer k (as expressed by k's relative change in buffer value $\Delta B_{k,n}/B_{k,0}$)

$$L_{i,n+1}^{jac} = \sum_{k \in \mathscr{I}} \frac{\Delta B_{k,n}}{B_{k,0}} P_{ak,n} r_i^{ak}, \tag{4.27}$$

where the interaction term $P_{ak,n}$ captures what is left of the bond's initial price after any overlapping portfolio contagion that may have occurred leading up to round $n+1$.

Using $\mathscr{D}_n = \{h \in \mathscr{I} : b_{h,n} = 0 \text{ and } b_{h,n-1} > 0\}$ to denote the set of institutions that default in round n, the overlapping portfolio contagion suffered by i on its tradeable assets of type $a \in \{b, m, e\}$, is given by its liquidity-weighted overlap summed across its defaulted counterparties h (i.e. $\sum_{k \in \mathscr{I}} \sum_{h \in \mathscr{D}_n} \frac{r_h^{ak} r_i^{ak}}{D^{ak}}$) adjusted by the fraction of the bond's value not yet written-off through counterparty risk

[9] Note that we do not record losses suffered by non-financial corporates and the SA government. Therefore, $\Delta b_{i,n} = 0$ when i is non-financial corporate representative node or the SA government.

contagion (i.e. $B_{k,b}/B_{k,0}$):

$$L_{i,n+1}^{jao} = \sum_{k\in\mathscr{I}} \sum_{h\in\mathscr{D}_n} \frac{r_h^{ak} r_i^{ak}}{D^{ak}} \frac{B_{k,n}}{B_{k,0}}. \tag{4.28}$$

Summing equations (4.27) and (4.28), we find that the loss suffered by i on its tradeable assets of type $a \in \{b, m, e\}$ in the $n+1^{th}$ round after j's default is given by

$$L_{i,n+1}^{ja} = L_{i,n+1}^{jac} + L_{i,n+1}^{jao}. \tag{4.29}$$

From contagion by asset to HSE

Summing the losses institution i will suffer in round n as a result of its exposure to a default of institution j across its loan and deposit $L_{i,n}^{jl}$ (equation 4.22), fund share $L_{i,n}^{jf}$(equation 4.25) and tradable asset portfolio $\sum_{\{a\in\{b,m,e\}\}} L_{i,n}^{ja}$ (equation 4.29) gives the loss in round n, $L_{i,n}^{j}$, as defined earlier in equation 4.13. Since the loss in round n is the exposure generated in round n, as per equation 4.12, we obtain the HSE by plugging $L_{i,n}^{j}$ for each round n into equation 4.14 defined earlier.

4.4 Results

We measure the exposures to six largest banks in the South African financial system (i.e. ABSA, Standard Bank, Fistrand, Nedbank, Investec and Capitec), so every simulation starts with the default of one of these six banks. As losses in subsequent rounds are determined from those in previous rounds, inaccuracies compound and losses in higher rounds become increasingly inaccurate. Therefore, we focus on exposures up to fifth order.

In this Section, we first study whether higher-order exposures matter in the South African financial system (Section 4.4.1). We also study here whether higher-order exposures can be proxied as a function of simpler exposure measures, such as direct exposures multiplied with some constant. One might think that higher-order exposures scale with direct and/or indirect exposures. Next, we study whether higher-order exposures of institutions in one sector (e.g. MMFs) to an institution in another sector are homogeneous and heterogenous (Section 4.4.2). If higher-order exposures are homogenous within a sector then exposures can be modeled at the sectoral level and details of inter-sectoral exposures can be omitted for simplicity. Finally, we study whether higher-order exposures are relatively constant through time or whether they become smaller or larger in, for instance, times of financial crises (Section 4.4.3). If higher-order exposures become more pronounced in times of crisis, then this has profound implications for prudential regulation and risk management.

4.4.1 Higher-Order Exposures are Substantial & cannot be Extrapolated from Classic Exposure Measures

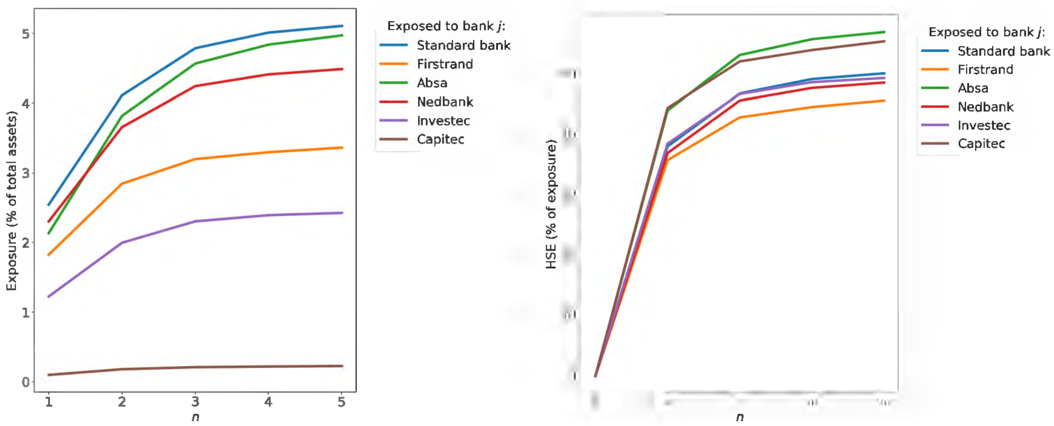
Figure 4.9 provides the baseline results of our experiments. In Figure 4.9a, we plot the exposure up to order N of the entire South African financial system to South Africa's six largest banks (Absa, Capitec, Firstrand, Investec, Nedbank, Standard Bank), where $N = 1, \ldots, 5$. Exposure is plotted on the vertical axis as a percentage of the system's total assets, and N is presented on the horizontal axis. As outlined in section 4.3.2, the first-order exposure, i.e., the exposure up to order $N = 1$, comprises the combination of all direct and indirect exposures. The difference between first-order exposure and exposure up to order $N > 1$ is driven by higher-order exposures. The figure shows that the exposure up to order N increases substantially as N is increased, especially from $N = 1$ to $N = 2$. Hence, second-order exposures in particular are substantial.

The six banks appear in the legend in descending order of total asset size. As this ordering is not reflected in the exposures, exposures cannot be inferred from total asset size alone. However, the vertical ordering of exposure to these six banks also changes as N is increased. This shows that higher-order exposures are qualitatively different from first order exposures, and hence higher-order exposures cannot be simply "extrapolated" from first- order exposures.

Figure 4.9b plots the HSE (the share of exposure made up by higher-order exposure) as a percentage of exposure up to order N. By definition, the HSE is zero for $N = 1$; however, for exposure up to order $N > 1$, the figure shows that the HSE is substantial, exceeding 50% for $N = 5$ in Absa's case, highlighting the importance of capturing higher-order exposures to accurately measure exposure.

Both figures are limited to $N \leq 5$. The reason for this is twofold. First, as noted in section 4.3.2, any model has finite accuracy, and because inaccuracies compound, the accuracy of the higher-order exposures is smaller for larger N. Second, the vast majority of higher order exposures materialize as second and third-order exposure. This is shown by both figures, as increases in exposure or HSE up to order N taper off for large N. This also suggests that the vast majority of look-through exposures accumulate when our confidence in the accuracy of the model is greatest.

Figure 4.9 Exposure and higher-order share of exposure (HSE) up to n^{th} order of the South African financial system to the six largest banks]



(a) Exposure up to n^{th} order

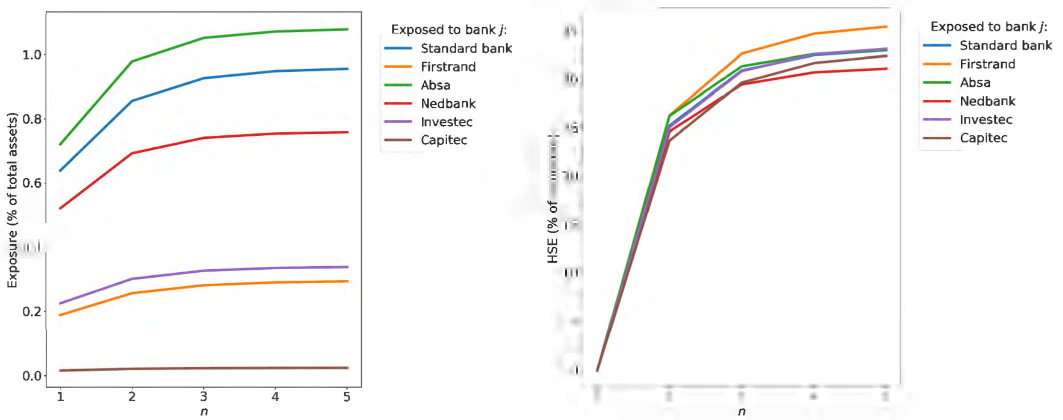
(b) HSE up to order N

Note: Plot (a) shows the exposure (as % of the system's total assets) up to n^{th} order of the South African financial system to the default of bank j, where j is one of the six large banks and the system's exposure is calculated as the sum of all banks' and funds' exposures. (Note that the six banks appear in the legend in descending order of total asset size.) The exposure increases substantially from $n = 1$ (direct and indirect losses caused by the bank failure) to $n = 2$, which corresponds to the second-order exposures. Further increases in exposure level out as n approaches 5. Plot (b) shows HSEs up to n^{th} order, which are substantial for all $n > 1$. (Note that the HSE up to order $n = 1$ is zero by definition.) In particular, the HSEs indicate that exposures to Absa and Capitec are underestimated by more than 50% when ignoring higher-order exposures.

While Figure 4.9 show the exposure of the South African financial system as a whole to one of South Africa's six largest banks, Figures 4.10-4.13 break down the exposures to South Africa's six largest banks by sector. Figure 4.10 shows the exposure of the banking sector to the six largest banks, 4.11 the exposure of the MMF sector, 4.12 of the OF sector, and 4.13.

Figure 4.10 shows that exposure of the banking sector to the six largest banks is small, but that the HSE is substantial (above 25 percent) in all cases. This shows that banks in South Africa have significant higher-order exposures to one another. Furthermore, note that Figure 4.10 looks qualitatively different from Figure 4.9, as the vertical ordering of exposures to the six banks is different across figures. This is also reflected in Figures 4.11-4.13. Hence, the exposures vary qualitatively across sectors.

Figure 4.10 Exposure and HSE up to n^{th} order of the banking sector to the six largest banks.



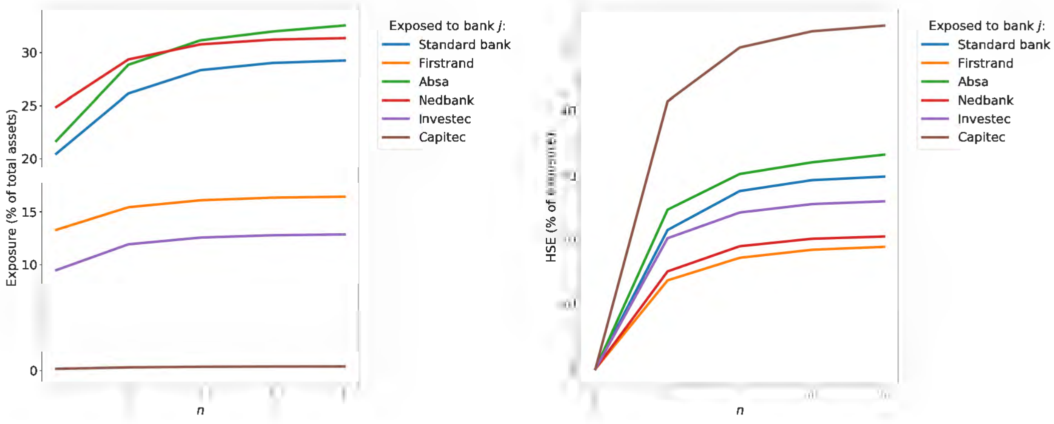
(a) Exposure up to to n^{th} order

(b) HSE up to n^{th} order

Note: Plot (a) shows the exposure (as % of the sector's total assets) up to n^{th} order of the South African banking sector to the default of bank j, where j is one of the six large banks and the sector's exposure is the sum of the banks' exposures. Plot (b) shows the corresponding HSE up to n^{th} order. Exposures of the banking sector to the largest six banks are small, yet the HSE of the exposures is substantial.

Figure 4.11 shows that the MMF sector has large exposures to South Africa's six largest banks through its investments in them. As a result, first-order exposure makes up a comparatively large component of exposure, and HSEs are — with the notable exception of exposures to Capitec (which highlight that network structure matters in the context of MMFs too) -– consequently smaller for MMFs than they are for banks. Nevertheless, look-through exposures do push the MMFs exposures to several individual counterparties above the regulatory limit of 25 percent.

Figure 4.11 Exposure and HSE up to n^{th} order of the MMF sector to the six largest banks

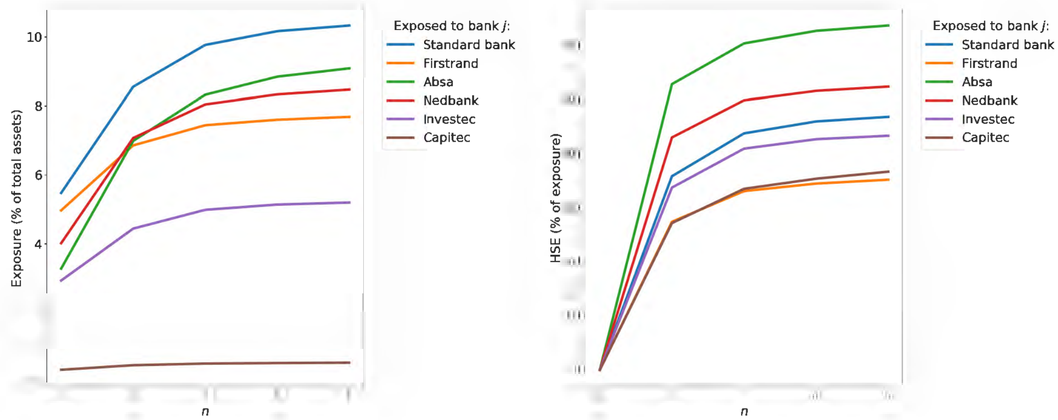


(a) Exposure up to order N **(b)** HSE up to order N

Note: Plot (a) shows the exposure (as % of the sector's total assets) up to n^{th} order of the South African MMF sector to the default of bank j, where j is one of the six large banks and the sector's exposure is the sum of the MMFs' exposures. Plot (b) shows the corresponding HSE up to n^{th} order. The MMF sector has substantial first-order exposures to the largest six banks, as banks are the main recipients of MMFs' investments. Moreover, the higher-order exposures push the MMF sector's exposures to Absa and Nedbank beyond the regulatory limit of 30%.

Figure 4.12 shows that exposure of the OF sector to the six largest South African banks is smaller than that of the MMF sector, but a smaller proportion of exposures is made up of first-order exposure, and consequently the HSE tends to be very large. Ignoring the OF sector's higher-order exposures to Absa would be particularly problematic and underestimate exposure by more than half.

Figure 4.12 Exposure and HSE up to n^{th} order of the OF sector to the six largest banks

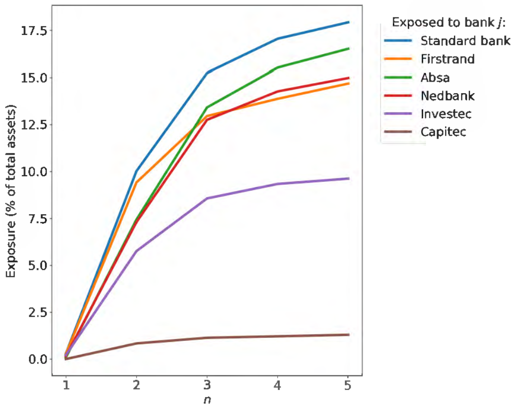


(a) Exposure up to order N **(b)** HSE up to order N

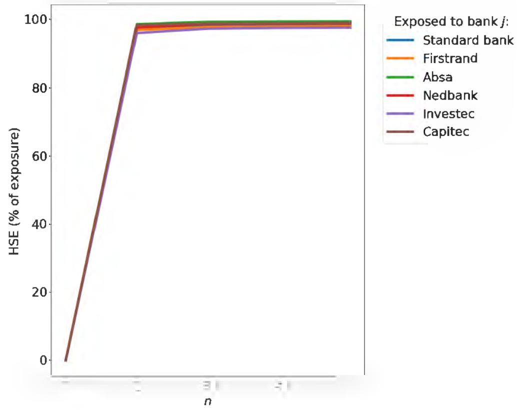
Note: Plot (a) shows the exposure (as % of the sector's total assets) up to n^{th} order of the OF sector to the default of bank j, where j is one of the six large banks and the sector's exposure is the sum of the OFs' exposures. (b) shows the corresponding HSE up to n^{th} order. Exposures of the OF sector to the six largest banks are smaller than those of the MMFs but HSEs are vast, reaching up to 60% in the case of Absa. Hence, OFs are expected to underestimate their exposure to Absa by more than half when only taking first-order exposures into account.

Because funds of funds typically invest in other funds, it is unsurprising that first-order exposures to South Africa's six largest banks are modest in this sector. As a result, conventional exposure metrics (capturing direct and indirect exposure) would find modest or no exposure at all (HSE is over 90 percent for each bank). However, Figure 4.13 suggests that such a finding would be mistaken: even though higher-order exposures of Funds of Funds tend to be modest, they can still make up well over 10 percent of the sector's total assets.

Figure 4.13 Exposure and HSE up to n^{th} order of the FoF sector to the six largest banks



(a) Exposure up to order N



(b) HSE up to order N

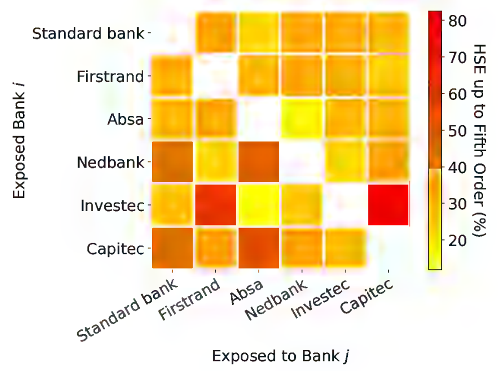
Note: Plot (a) shows the exposure (as % of the sector's total assets) up to n^{th} order of the FoF sector to the default of bank j, where j is one of the six large banks and the sector's exposure is the sum of the FoFs' exposures. (b) shows the corresponding HSE up to n^{th} order. FoFs' first-order exposures to the six largest banks are small, as FoFs typically invest in other funds. The FoF sector's higher-order exposures are substantial; exposures to the four largest banks are around 15% of the sector's total assets. Nevertheless, because first-order exposures to the largest six banks are close to zero, the FoF sector's HSEs are close to 100%. Hence, FoFs completely overlook their exposure to these banks when not taking higher-order exposures into account.

4.4.2 Heterogeneity of Intersectoral Higher-Order Exposures

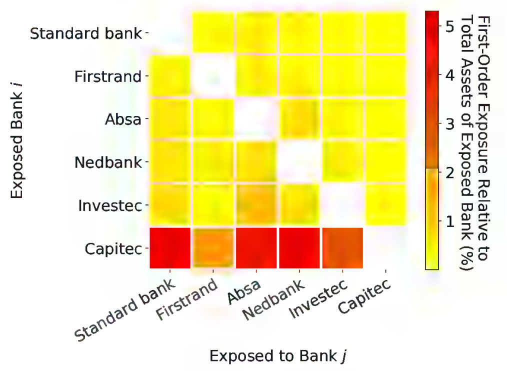
Figures 4.14-4.17 show that exposures to each of the six largest banks, do not only vary strongly across these six banks, but also across the exposed institutions, even within the same sector. Figure 4.14 shows the HSE and first, second and fifth-order exposure of the largest six banks to each other. We show the first-order (direct+indirect) exposure because this is the exposure that is traditionally considered by risk models, the second-order exposure because it is typically the higher-order exposure that matters most and the fifth-order exposure to show how ever higher-order exposures tend to reduce in size as well as to show that higher-order exposures in round $k = 5$ and another round $k = 2$ are not necessarily proportional/qualitatively similar.

The Figures use a color gradient to indicate the exposure of an institution on the vertical axis to another institution on the horizontal axis. (Note that across plots the color gradients are not necessarily consistent, in order to accommodate the heterogeneity of exposure sizes). The banks are ordered by total asset size (descending from top to bottom and left to right). In general, exposures of the six largest banks to each other are very moderate and HSEs do not vary much in either along the rows or the columns. The only exception is Capitec, which has substantial exposure to all five other banks.

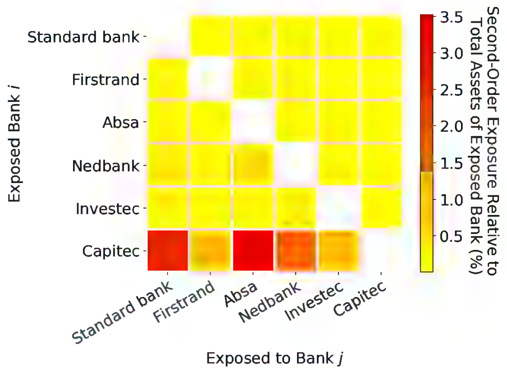
Figure 4.14 Heatmaps showing the HSE and exposure of the six largest banks to each other relative to each bank's total assets



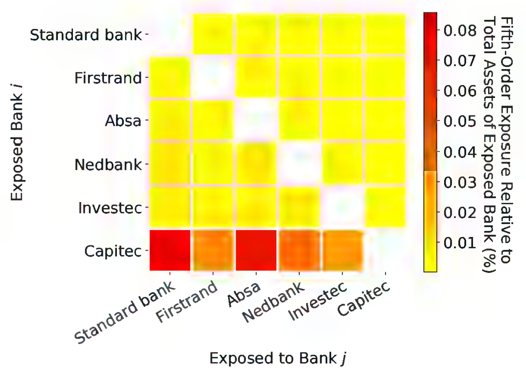
(a) HSE up to Fifth Order



(b) First Order Exposure



(c) Second Order Exposure

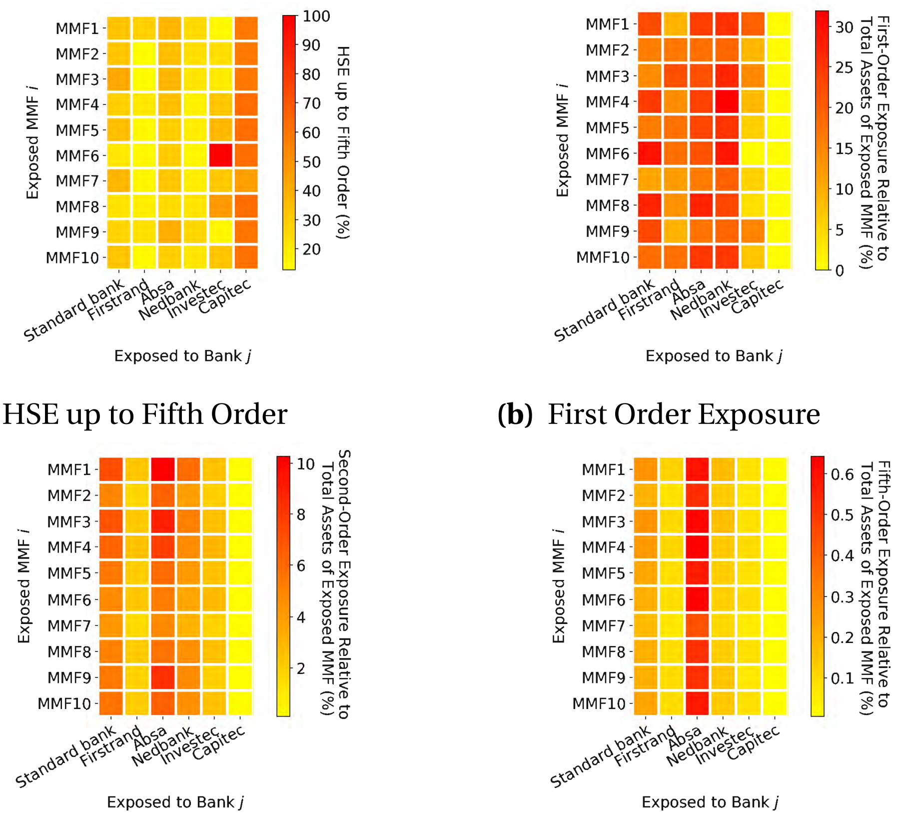


(d) Fifth Order Exposure

Note: The figure shows the exposures (as % of each bank's total assets) and HSEs between the six large banks. The banks are ordered by total asset size (descending from top to bottom) and the plots use a color gradient to indicate the HSE or exposure of one bank on the vertical axis to another bank on the horizontal axis. The scales for figures differ in order to optimise the relative differences within each order of exposures. Note that the banks on the horizontal axis are ordered from left to right by descending total asset size. In general, figures (b)-(d) show that the banks have very modest exposures between them. Other than Capitec, the banks have both low first-order and low higher-order exposures. Yet, figure (a) highlights a few cases where the exposures' HSEs are substantially smaller or larger than the average. Hence, the higher-order exposures cannot be proxied by "scaled" first-order exposures in general.

Figure 4.15 shows the HSE and first, second, and fifth-order exposure of the ten largest MMFs to the six largest banks. The MMFs are ordered by total asset size (descending from left to right). The exposures show very little variation in the horizontal direction, highlighting how similar the MMFs' investment porfolios are. Consequently, HSEs do not show substantial variation in the horizontal direction either. Both the exposures and HSEs do vary substantially in the vertical direction, reflecting the result from Figure 4.11 that the MMFs' exposures to the six largest banks vary strongly across the banks. A notable exception is that all ten MMFs' first-order exposure to Capitec and MMF 6's first-order exposure to Investec is close to zero, resulting in high corresponding HSEs.

Figure 4.15 Heatmap showing the exposures to the six largest banks of the ten largest MMFs as % of each MMF's total assets



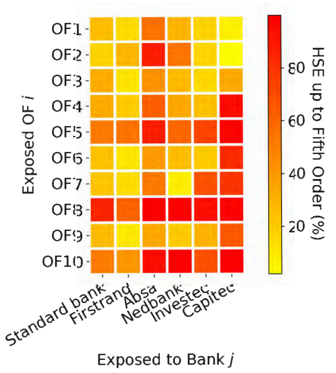
(a) HSE up to Fifth Order **(b)** First Order Exposure

(c) Second Order Exposure **(d)** Fifth Order Exposure

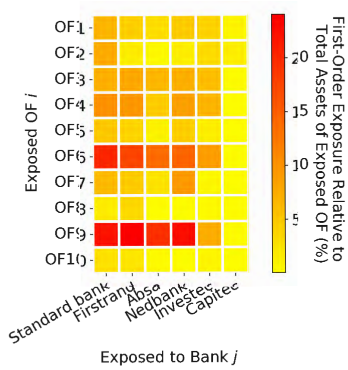
Note: The figure shows the exposures (as % of each MMF's total assets) and HSEs of the ten largest MMFs. The MMFs are ordered by total asset size (descending from top to bottom) and the plots use a color gradient to indicate the HSE or exposure of an MMF on the vertical axis to a bank on the horizontal axis. (Note that the banks are ordered from left to right by descending total asset size.) The scales for the figures differ in order to optimise the relative differences within each order of exposures. The plots show little variation in HSEs and exposures across the MMFs, which is due to the MMFs' exceptionally similar portfolios. The first-order exposures (which are predominantly driven by direct exposures) in (b) show that all MMFs' investments in the four largest banks are close to the 30% limit, with Investec receiving the remainder of the investments and Capitec virtually nothing. Plots (c) and, in particular, (d) show that the higher the order of the exposure, the more the variation across the MMFs is damped out and gets dominated by the variation across the banks to which the MMFs are exposed.

Figure 4.16 shows the HSE and first, second, and fifth-order exposure of the ten largest OFs to the six largest banks. The OFs are ordered by total asset size (descending from left to right). The exposures show substantial variation in the horizontal direction, and, consequently, the HSEs as well, showing that exposures can vary strongly across exposed institutions even within the same sector. Furthermore, the OFs' first-order exposure looks qualitatively different from the higher-order exposures. Hence, (the distribution of) higher- order exposure cannot be simply extrapolated from first-order exposure, but must be evaluated individually for each institution.

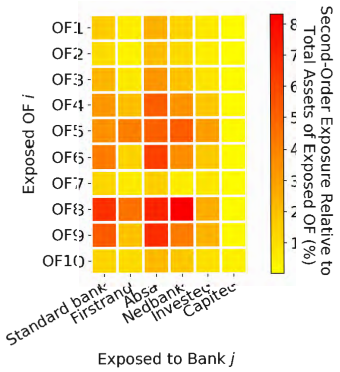
Figure 4.16 Heatmaps of individual OFs' exposures to the six largest banks



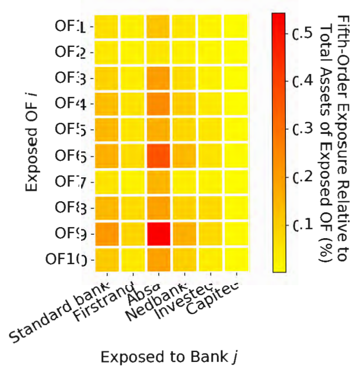
(a) HSE up to Fifth Order



(b) First Order Exposure



(c) Second Order Exposure

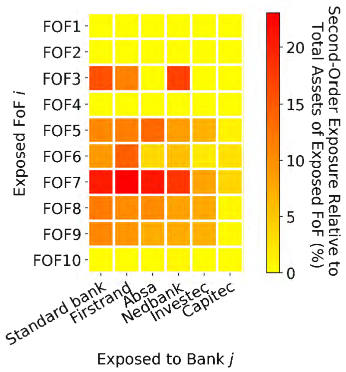


(d) Fifth Order Exposure

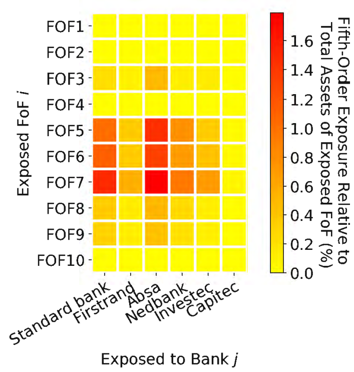
Note: The figure shows the exposures (as % of each OF's total assets) and HSEs of the ten largest OFs. The OFs are ordered by total asset size (descending from top to bottom) and the plots use a color gradient to indicate the HSE or exposure of an OF on the vertical axis to a bank on the horizontal axis. The scales for the figures differ in order to optimise the relative differences within each order of exposures. Plot (a) shows that HSEs vary strongly across OFs, and comparison of the first-order exposures in (b) to the second-order and fifth-order exposures in (c) and (d) clearly shows that the second-order and fifth-order exposures are qualitatively different from the first-order exposures. Hence, the higher-order exposures cannot be extrapolated from first-order exposures. Furthermore, similar to the MMFs, (d) shows that in the fifth order exposures, most of the variation across the OFs is damped out and gets dominated by the variation across the banks to which the OFs are exposed. However, this is not the case for the second-order exposures, which show substantial variation across the OFs.

Figure 4.17 shows the second and fifth-order exposure of the ten largest FoFs to the six largest banks. As the FoFs typically do not invest directly into banks, the ten largest FoFs' first-order exposures to the six largest banks is zero, and consequently the HSE is 100% in all cases. Therefore, the first-order exposures and HSEs are not shown. The FoFs are ordered by total asset size (descending from left to right). The exposures show substantial variation in the horizontal direction, and, consequently, the HSEs as well, showing (like for the OFs) that exposures can vary strongly across exposed institutions even within the same sector. Furthermore, as the FoFs have no first-order exposure to the banks, we again find (same as the OFs) that higher order exposures must be evaluated individually for each institution and cannot be inferred from first-order exposures.

Figure 4.17 Heatmaps showing individual FoFs' exposures to the six largest banks



(a) Heatmap Second order higher-order exposures of FoFs



(b) Fifth Order Exposure

Note: The figure shows the second-order exposures in (a) and fifth-order exposures in (b) of the ten largest FoFs, as % of each FoF's total assets. The FoFs are ordered by total asset size (descending from top to bottom) and the plots use a color gradient to indicate the exposure of a FoF on the vertical axis to a bank on the horizontal axis. (Note that the banks are ordered from left to right by descending total asset size.) We do not show the FoFs' HSEs or first-order exposures, as the first-order exposures are all zero and, consequently, the HSEs are all equal to one hundred percent. The second and fifth-order exposures show strong variation across the funds. Hence, the FoFs' exposures cannot be modelled at the sectoral level but must be modelled explicitly for individual FoFs.

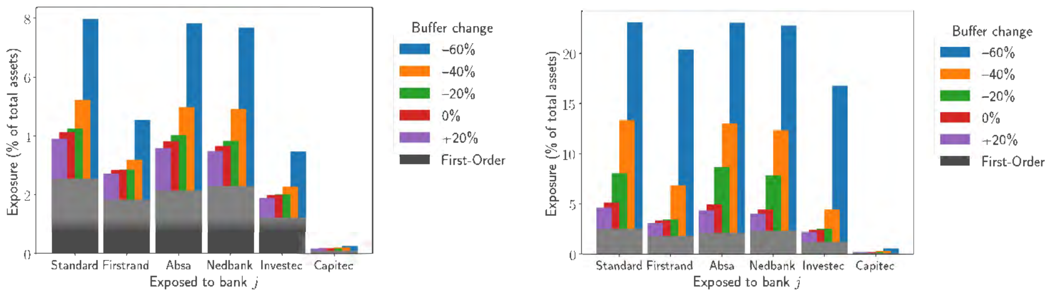
4.4.3 Higher-Order Exposures Matter Most in Times of Crises

Figures 4.18 and 4.19 show that during times of financial distress, higher-order exposures become particularly pronounced. Put differently, higher-order exposures are largest exactly when they matter most, i.e. in times of crisis when defaults are most likely to occur and, consequently, exposures are most likely to materialize into losses.

Due to adverse macroeconomic conditions (i.e. crisis scenarios), institutions may incur unexpected losses, reducing their buffers. For illustrative purposes, figure 4.18 shows the exposure up to second-order and up to fifth-order when all banks' and funds' (initial) buffers are reduced by 20%, 40% or 60%. For comparison's sake, the exposures are also shown for the case the institutions' buffers are not changed ("0%"), or increased by 20%. Banks increase their equity buffer by raising capital, whereas funds raise their effective equity buffer by increasing liquidity. The more "usable" (i.e. the opposite of required) liquid assets a fund has the more losses it can suffer before investors would initiate a destabilising run on the fund that causes it to fail through illiquidity. Having more liquid asset holdings means the fund can repay any redeeming investors without having to fire sell assets resulting, thereby preventing asset price declines that can iteratively prompt next rounds of redemptions. The figure shows that when buffers are reduced, higher-order exposures increase substantially and start to dominate exposure. (Note that first-order exposures are not affected by the buffers.) Furthermore, (a) shows that exposures up to second order to Standard Bank, Absa and Nedbank become particularly pronounced when buffers are reduced by 60%. (b) shows that exposures up to fifth order to Standard Bank, Absa and Nedbank increase substantially when buffers are reduced by 20% or 40% and that fifth-order exposures to all but Capitec are substantially increased when buffers are reduced by 60%.

Reduced buffers are not the only reason why higher-order exposures increase in times of financial distress. During crises, market liquidity for tradable securities $t \in \{b, m, e\}$ typically falls. In more illiquid markets, i.e. when the market depth is reduced, the price impact of the liquidation of a defaulted institution's portfolio increases. Figure B.3 in the appendix shows that when buffers are at their baseline, the market depth has only a modest impact on the higher-order exposures. However, when buffers are reduced, the market depth has a pronounced effect on the higher-order exposures. The reason is that, when buffers are at their baseline, only few defaults follow from the initial default of one of the six large banks. On the other hand, when buffers are reduced, many defaults follow and hence many portfolios are liquidated.

Figure 4.18 Exposure of the South-African financial system to the six largest banks for various values of institutions' initial buffers

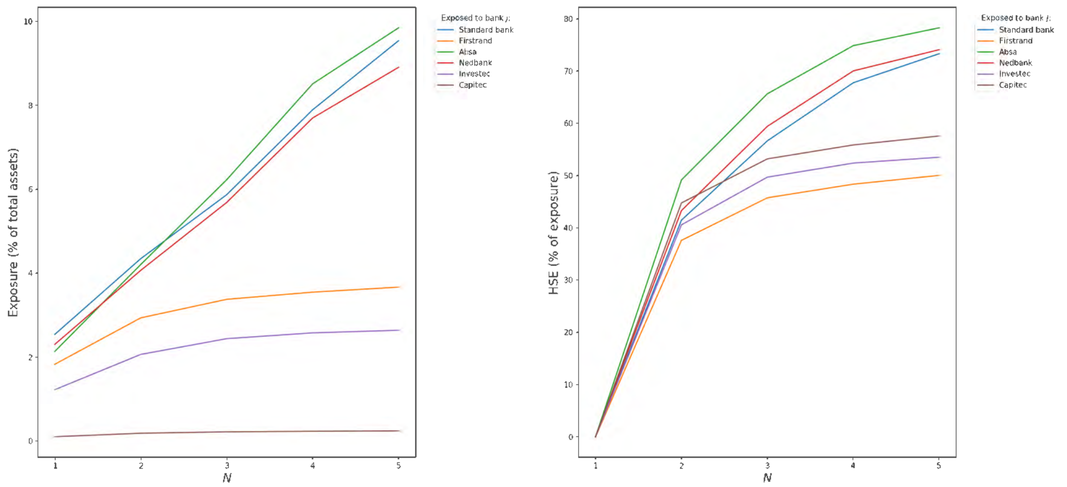


(a) Exposure up to second order **(b)** Exposure up to fifth order

Note: (a) shows the exposure up to second order and (b) the exposure up to fifth order (as a % of total system assets) of the South-African financial system to the default of bank j, where j is one of the six large banks and the system's exposure is the sum of the banks' and funds' exposures. The colors indicate the percentage change applied to all banks' and funds' initial buffers. The figures show that higher-order exposures become particularly pronounced when institutions' buffers are reduced (first-order exposures are not affected by the buffers), with exposures to Standard bank, Absa and Nedband increasing most strongly. (Note that exposures are capped to less than 30% of total system assets, as about 70% of total system assets, consisting predominantly of banks' real-economy lending, is not affected by the contagion channels included in our model.) More specifically, (b) shows for exposures up to fifth order, that the exposures to Standard bank, Absa and Nedband are almost doubled even when initial buffers are reduced by just 20%.

Based on SARB, 2016b, we formulate a macroeconomic stress scenario, which consists of a 25% reduction in institutions' buffers and 50% reduction in the market depth for all tradable securities. Figure 4.19 shows that when all banks and funds are subjected to the stress scenario, higher-order exposures are substantially larger (compared to figure 4.9). Furthermore, exposures to Standard Bank, Absa and Nedbank no longer level out for large n. Hence, the practice adopted in this paper of only considering exposure up to order $n = 5$ may still underestimate exposure in times of financial distress. This is confirmed by figure B.1 in the Appendix, which shows that exposures up to at least $10th$ order are substantial when institutions are subjected to the stress scenario. Figures 4.18 and 4.19 illustrate the importance of measuring both normal-times and stressed exposures for prudential purposes. As in stressed time exposures matter most (as they are most likely to turn into losses then) and thus should be kept at prudent levels. Regulators can estimate stressed exposures by applying an adverse, plausible and coherent scenario, like they do for regulatory stress tests

Figure 4.19 Exposure and higher-order Share of Exposure (HSE) up to order N of the entire South African financial system to the six largest banks, where institutions' buffers are shocked by 25%



(a) Exposure up to order N **(b)** HSE up to order N

Note: All banks and funds are subjected to the macroeconomic stress scenario, which consists of a 25% reduction in the institutions' buffers and 50% reduction in the market depth of all tradable securities. (a) shows the exposure (as % of the system's total assets) up to n^{th} order of the South African financial system to the default of bank j, where j is one of the six large banks and the system's exposure is the sum of the banks' and funds' exposures. (b) shows the corresponding HSE up to order n.

Figure 4.18 shows the second and fifth order exposure for various reductions or increases of institutions' buffers. In particular, the figures show these higher order exposures when institutions' buffers are either reduced by 20%, 40%, or 60% or increased by 20%. For comparison, the exposures are also shown for the case where the institutions' buffers are not changed ("0%"). The figure shows that when buffers are reduced, higher order exposures increase substantially and dominate exposure. As exposures are most relevant during times of financial distress (when defaults are most likely), these results highlight the importance of higher-order exposures.

4.4.4 Summary observations: the application of HOE to the South African system

Our results can be summarized into the following general observations about higher-order exposure in the South African financial system:

1. *Higher-order exposures can make up a significant component of exposure. The exposure of an institution to another can be significantly underestimated if the higher-order exposures are not taken into account.* Where previous literature concluded that ignoring indirect exposure may lead to a significant underestimation of total exposure, our findings suggest that even focusing on both direct and indirect losses as traditionally understood (captured as first-order exposure here) may still not be enough. This finding is, for instance, shown in Figure 4.9a. It showed that exposure up to order N increases substantially with N, with Figure 4.9b highlighting that higher-order exposure makes up well over 30 percent of exposure towards the six largest South African banks. In the case of Absa, higher-order exposure exceeds 50% of total exposure.

2. *Higher-order exposures and HSEs to each of the six largest banks only in part be explained by an institution's first-order exposure, suggesting that higher-order exposures cannot be proxied satisfactorily by an institution's direct or indirect exposure to another institution.* If higher-order exposure were explained fully by traditional proxies for exposure like the total asset value on a bank's balance sheet, detailed network-analysis into higher-order exposure may be unnecessary. The results in Figure 4.9 show, however, that

higher-order exposures manifest in subtler ways that are not fully explained by asset size. Moreover, the first-order exposure does not get the ordering of higher-order exposures right (for exposure up to order $N = 5$, the exposure to Absa overtakes that of Nedbank), so an extrapolation from the combination of direct and indirect exposures may also lead to inaccurate results. This result suggests that models cannot accurately correct for the underestimation of total exposure using a multiplier (that is, without explicitly modeling higher-order exposure).

3. *Higher-order exposures and HSEs to an institution are not only highly heterogeneous across sectors, but also across institutions within a sector.* This shows the importance of granular firm-by-firm models to assess exposures rather than using models with representative sectors.

4. *An institution can have a significant and non-zero exposure to another institution even if its direct and indirect exposures to that institution are equal to zero.* If an institution that does not measure its higher-order exposures it would judge incorrectly that it is immune to losses arising from the failure of that institution.

5. *During times of financial distress, higher-order exposures become particularly pronounced and dominate first-order exposures in some cases.* As exposures are most relevant during times of financial distress (when defaults are most likely), capturing higher-order exposures is a vital component of understanding exposure.

4.5 Conclusion

Against a backdrop of a larger non-bank sector, oversight of the links within the financial system, in particular those between the banking sector and the non-banking sector is important to take into consideration for prudential policymaking.

A regulator may wish to know the exposures of its regulated institutions when evaluating large exposure limits, for instance. “Large exposures regulation limits the maximum loss that a bank could face in the event of a sudden counterparty failure to a level that does not endanger the bank’s solvency. This standard requires banks to measure their exposures to a single counterparty or a group of connected counterparties and limit the size of large exposures in relation to their capital” (Committee et al., 2014). Large exposure limits are enshrined in the Basel framework hence, these apply in many jurisdictions, including the US (Fed, 2018), the EU (Hannoun, 2013) and South-Africa (IMF, 2010). In South-Africa large exposure limits also apply the non-banks, in particular investment funds (Financial Sector Conduct Authority, 2014). Clearly, an institution will not be able to estimate either its indirect or higher-order exposures, since that requires knowing the network of financial contracts, which is the purview of the regulator only. It can only estimate its direct exposures in relation to the applicable large exposure limits. Higher-order exposures should thus be computed by the regulator.

These findings highlight the importance of granular data availability. The exposures of financial institutions in the South African financial system to the default of one one of its "big six" banks may be severely underestimated when only considering direct and indirect exposures. The contagion of stress depend strongly on the network structure of the SA financial system and the robustness of its institutions.

While this paper has provided a proof of principle for how the concept of higher-order exposures can be measured in practice using South-Africa as a case study, our method should by no means be seen as the gold standard. Regulators may want to consider various nuances, adjustments and extensions to the model, as well as to calibrate it more carefully to data. Depending on the financial system that is being studied, a different set of interconnections and associated contagion mechanisms might be relevant for higher-order exposures. Even if the same contagion mechanisms apply as in this study, they could be modeled differently. For example the counterparty risk contagion channel could be modeled with a different risk-adjustment rule and a different failure regime. Rather than assuming zero recovery in the short run on direct exposures to failed banks as we do (in line with Elsinger et al., 2006), a regulator could capture that SIBs will likely be resolved (e.g. via a bail-in) while non-SIBs will be liquidated. Making this distinction has implications for the LGD that will apply in the counterparty risk contagion mechanism. It also has implications for the overlapping portfolio contagion channel. Failed banks that are bailed-in do not have to liquidate their assets, potentially at discounted prices, while liquidated institutions do. Furthermore, overlapping portfolio contagion could be modeled using a more realistic price impact function. To be useful for regulatory purposes, our model could also be better calibrated to the prevailing and stressed market depths of tradable securities. It could also use more sophisticated stress test scenarios to determine stressed exposures.

Chapter Five

Measuring the Financial Cycle in South Africa

5.1 Introduction

In this chapter,[1] we estimate the financial cycle in South Africa. Financial cycles provide a broad perspective on the evolution of risks to financial stability, and therefore provide a useful monitoring tool for policymakers who are required to set macroprudential policies. A robust measure of the financial cycle is particularly important for South African policymakers at the present time, given the renewed emphasis on the financial stability regulatory and supervisory framework provided by the Financial Sector Regulation Act, which was enacted as a law in September 2017. A study of South Africa's financial cycle may also be of wider interest given the country's experience of not having suffered a systemic banking crisis since 1970.[2]

Understanding financial cycles is critical for informing the use of countercyclical macroprudential policy. More specifically, an important question for policymakers is whether macroprudential policy should be aimed at controlling the 'financial

[1]This chapter draws on paper published in the South African Journal of Economics (see Farrell et al., 2020).

[2]According to Laeven et al., 2018, a standard reference for information on banking crises. This has a number of interesting implications, including perhaps for studies of growth. Ranciere et al., 2008, for example, note that countries that have experienced occasional financial crises have, on average, grown faster than countries with stable financial conditions.

cycle' or not (See Borio, 2014b and Constâncio, 2014 for differing views on this issue). Che et al., 2014, for example, find that attempting to improve the financial soundness of banks during a downturn of the financial cycle could amplify the cycle, and that policymakers should therefore be careful about the timing of regulatory changes. However, despite their importance for policymakers, there is no consensus regarding the definition of financial cycles nor on the methodology that should be employed to measure them. Furthermore, even though there is a large and growing international literature,[3] we are also not aware of published research that assesses the options available for measuring the South African financial cycle.

To fill this gap, we identify the main characteristics of the financial cycle in South Africa using three different methodologies. This is motivated by the current lack of consensus on the best method to use to measure financial cycles,[4] and informed by the most popular approaches in the literature. First, we apply traditional turning point analysis to identify the financial cycle by detecting peaks and troughs in the individual component variables that make up the cycle. Second, we employ a frequency domain approach that uses band-pass filters to isolate the cycles that correspond to medium-term frequency intervals. Finally, we use a multivariate model-based approach to extract cycles using unobserved components time series models. We then provide a comparison of the results of the three approaches and compare the estimates of the financial cycle with those of the business cycle to determine whether the cycles are distinct from one another. We begin, however, by defining financial cycles and selecting a set of financial variables that can potentially capture the main characteristics of the South African financial cycle.

[3] Claessens and Kose, 2017 provide a recent review of studies that examine the features of business and financial cycles, and the linkages between them, for the credit, equity, and housing markets.

[4] The Bank for International Settlements, 2016 (Box III. A) draw an analogy with the business cycle here: it is often identified with movements in GDP but no consensus exists on the best method to use even after many years of research.

5.2 Definitions and data transformations

A working definition describes the financial cycle as reflecting self-reinforcing feedback within the financial system and between the financial system and the real economy (Borio, 2014a). Therefore approaches to measuring financial cycles have focussed on the co-movement of a broad set of financial variables (BIS, 2015). However, given macroprudential policy's focus on systemic risks and the challenges of measuring risk perceptions, it is not clear which set of financial variables or indicators best captures the financial cycle.

The indicators that have been found to give the most parsimonious description of the financial cycle are credit and property prices (Drehmann et al., 2012 and Borio, 2014a). Credit aggregates (which can be used as a proxy for leverage) are often the sole focus (Aikman et al., 2015),[5] and together with property prices (a measure of collateral available) are jointly important for the financial cycle because of mutually-reinforcing feedback effects. Strong growth in credit extension, specifically mortgage credit, often results in higher property prices. In turn, higher house prices boost collateral values and the amount of credit the private sector can obtain. Such interactions have historically been associated with the most serious bouts of financial instability (BIS, 2014; Jordà et al., 2014).

In addition to credit and housing market developments, a number of other variables have been proposed in the literature as proxies for the financial cycle. Equity prices (see for example, Claessens, Kose, and Terrones, 2012 and Granville et al., 2017), bond prices (Schüler, Hiebert, et al., 2015b), interest rates, non-performing loans, volatilities, risk premia, and the credit-to-GDP ratio (Borio, 2014a) have all been used.[6]

In this chapter we opt for a parsimonious specification that includes credit, property prices, and equity prices in this initial analysis of the South African financial

[5] A recent empirical literature finds that credit growth is a good predictor of financial crises. For example, Schularick et al., 2012 consider the experience of 14 developed economies and find that credit growth in the past five years strongly predicts the probability of a financial crisis.

[6] Even larger data sets are possible.Mendoza et al., 2012, e.g., propose constructing financial cycle measures for the US based on a data set of 7 macroeconomic and 25 financial variables. They use a dynamic factor model to estimate three synthetic financial cycle components, which they find explain most of the variation in their data.

cycle, although it is accepted that further research into this issue is warranted. The case for including credit and property prices as components of the financial cycle is generally well supported in the literature, although that for equity prices is perhaps less certain. For example, Drehmann et al., 2012 argue that equity prices can be a distraction, while Claessens, Kose, and Terrones, 2012 find that credit and equity cycles are the most synchronised across countries.

We analyse the behaviour of the three variables over the period 1966-2016 using quarterly data,[7] providing sufficiently long data samples to extract medium-term cycles. Credit data were sourced from the South African Reserve Bank (SARB), equity data from the JSE, and house price data from ABSA.[8] In line with Drehmann et al., 2012, the three data series are in logs and deflated by the headline CPI. Where necessary to facilitate comparability, the levels of the series were normalized by their respective values in 1985Q1. Real GDP data used to estimate the business cycle were sourced from the SARB (series KBP6006D).

The transformations applied to the data have implications for the types of cycles considered in the study, as is well known in the business cycle literature.[9] Classical cycles consider the data in (log) levels, while 'growth' or 'deviation' cycles focus on fluctuations around a trend and 'growth rate' cycles refer to fluctuations in the growth rate of the variable. Summary statistics of the four-quarter growth rates of the time series used in this study are shown in Table 5.1.

[7] South African data for these variables are generally available from the mid-1960s on a quarterly basis. A notable exception is the annual series on South African equities, bonds, and cash that dates back to 1900 (see, e.g. Firer et al., 2002 and the references cited therein).

[8] For credit data, total credit extended to the private sector (sourced from SARB: KPB1347) was used. This includes a consolidation of the balance sheets of institutions within the monetary sector, i.e. the SARB, the former National Finance Corporation, Corporation for Public Deposits (CPD) and the so-called 'pooled funds' of the former Public Debt Commissioners, the Land Bank, Postbank, private banking institutions (including the former banks, discount houses, equity building societies and mutual building societies). See South African Reserve Bank, 2018 for more information. House price data are smoothed by Absa in an attempt to exclude the distorting effect of seasonal factors and outliers. Note that the value for house prices in December 2016 was estimated.

[9] In the South African case, for example, see Du Plessis, 2006,Boshoff, 2010;Bosch and Ruch, 2013.

Table 5.1 Summary statistics of growth rates of variables considered for the financial cycle

	Credit	House prices	JSE returns	GDP
Mean	4.7	1.9	5.9	2.7
Standard deviation	5.9	9.4	23.5	2.5
Skewness	0.4	0.5	0.2	-0.3

At the indicator level, the amplitude of financial cycle variables are higher than those of the business cycle (GDP), with the volatility for equity returns the highest. The distributions of credit, house prices and JSE returns are positively skewed, whilst GDP is negatively skewed.

5.3 Approaches to measurement

There are three main approaches to measuring the financial cycle in the literature:[10]

5.3.1 Turning-point analysis

Following Burns et al., 1946, traditional turning-point analysis defines the cycle as a pattern in the level of economic activity. In the financial cycle literature, Claessens, Kose, and Terrones, 2012, Drehmann et al., 2012 and Granville et al., 2017 provide turning point analyses. The approach has been employed in the South African context by Du Plessis, 2006 for the business cycle, and by Boshoff, 2005 for financial variables.

5.3.2 Frequency-based filters analysis

Frequency-based filters are used to extract the medium-term cyclical components of the indicators, which are then combined to provide an estimate of the financial

[10] Other options include wavelet analysis, which attempts to simultaneously account for both the frequency and the time variations of a time series. See e.g. Verona, 2016, and Ardila et al., 2016.

cycle. Similar approaches have been adopted in the literature by Aikman et al., 2015 for the credit cycle, and by Schüler, Hiebert, et al., 2015c, Strohsal et al., 2015, and Gonzalez et al., 2015 for the financial cycle. The frequently cited analysis of Drehmann et al., 2012 uses frequency-based filters, as well as turning point analysis. In the South African literature, Boshoff, 2005 employed frequency-based filters to examine cycles in financial variables, and Boshoff, 2010 considers the properties of the South African business cycle, as measured by the deviation cycle.

5.3.3 Model-based approaches

Trends and cycles may be modeled as unobserved components within the framework provided by structural time series models (Harvey, 1990, Harvey and Jaeger, 1993). The statistical approach uses the state space form, with the components being obtained from the Kalman filter and smoother. Koopman and Lucas, 2005, Galati et al., 2016b, Rünstler et al., 2018 and Grinderslev et al., 2017 have used unobserved components time series models (UCTSMs) to measure financial cycles. We proceed by applying each approach to the South African data.

5.4 Turning-point analysis

Harding et al., 2002, Harding et al., 2006 and Harding et al., 2016 suggest using a dating algorithm introduced by Bry et al., 1971, adapted for quarterly data and termed the BBQ rule:[11] The steps for this analysis are as follows Harding et al., 2016:

1. Smooth the single time series y_t to eliminate outliers, high frequency variations and other uninteresting fluctuations.

2. Determine a potential set of turning points using a rule to locate the local maxima and minima. A local peak in y_t occurs at time t if $y_t > y_s$ for s in a window $t-k < s < t+k$, i.e., where $|y_s|$ is larger than $|k|$ values of $|y_t|$ (similarly, a trough is defined as $y_t < y_s$ for s in a window $t-k < s < t+k$).

[11] Bry et al., 1971 used monthly data (setting $k = 5$).

So, for $k = 2$:

Peak at t if $(y_{t-2}, y_{t-1}) < y_t > (y_{t+1}, y_{t+2})$
Trough at t if $(y_{t-2}, y_{t-1}) > y_t < (y_{t+1}, y_{t+2})$

3. Use some criteria, i.e., censoring rules, to ensure that peaks and troughs alternate and that the duration and the amplitude of the two phases are meaningful.

Changing the values of these parameters will result in different peak and trough dates. Given that we are interested in both short- and medium-term cycles, we used two different calibrations. Following Drehmann et al., 2012, for the shorter cycle used to extract the business cycle we specified censoring criteria for the BBQ algorithm such that the minimum duration of a phase of a cycle is 2 quarters, and that the minimum duration of a complete cycle is 5 quarters. The medium-term criteria used to extract financial cycles are that the minimum duration of the phase of a cycle is 9 quarters and the minimum duration of a complete cycle is 20 quarters.

The turning point information supplied by the BBQ algorithm can be captured by a binary random variable (S_t) that has a value of unity in expansions and zero in contractions (Harding et al., 2016).[12] Once the states have been constructed, we use the information in S_t to describe the characteristics of the cycle. More specifically, we produce measures of the duration of the expansions and contractions, which we use to examine the average features of phases and to compare these features across different variables (Harding et al., 2016).

An estimator which counts the number of peaks is:

$$\hat{K} = \sum_{t=1}^{T-1} (1 + S_{t+1}) S_t \tag{5.1}$$

since the series $(1 + S_{t+1})S_t$ equals 1 only when there is a peak at time t. Because the total time spent in expansions is $\sum_{t=1}^{T} S_t$, the average duration of an expansion

[12] The convention used by Harding et al., 2016 is that the peak is the last period of the expansion phase and the trough is the last period of the contraction phase.

is:

$$\bar{D}^E = \hat{K}^{-1} \sum_{t=1}^{T} S_t \tag{5.2}$$

The average amplitude of expansions is then:

$$\hat{A}^E = \hat{K}^{-1} \sum_{t=1}^{T} S_t \Delta y_t \tag{5.3}$$

Harding et al., 2016 also formulate a steepness index that is calculated as the ratio of the amplitude to the duration of a phase. The average degree of steepness over all expansion phases is:

$$STEEP = \frac{\hat{A}}{\hat{D}} = \frac{\sum_{t=1}^{T} S_t \Delta y_t}{\sum_{t=1}^{T} S_t} \tag{5.4}$$

This measure leads naturally to a comparison of the steepness of expansions versus contractions. Since the amplitudes of contractions have a negative sign, this is given by (Harding et al., 2016, 98):

$$\begin{aligned} COMP &= \frac{\sum_{t=1}^{T} S_t \Delta y_t}{\sum_{t=1}^{T} S_t} + \frac{\sum_{t=1}^{T} (1-S_t) \Delta y_t}{\sum_{t=1}^{T} (1-S_t)} \\ &= \hat{p}_e^{-1} T^{-1} \sum_{t=1}^{T} S_t \Delta y_t + (1-\hat{p}_e)^{-1} T^{-1} \sum_{t=1}^{T} (1+S_{t+1}) \Delta y_t \end{aligned} \tag{5.5}$$

where $\hat{p}_e = \sum_{t=1}^{T} S_t / T$ is the proportion of time spent in expansions. The test therefore compares the average steepness of expansions and contractions, weighted by $\hat{p}_e^{-1}$ and $(1-\hat{p}_e)^{-1}$ respectively, to assess the symmetry in Δy_t.

We also look at the degree of synchronization between different time series by considering the fraction of time the cycles are in the same phase. For two series x_t and y_t, Harding et al., 2002 and Harding et al., 2006 proposed a concordance index:

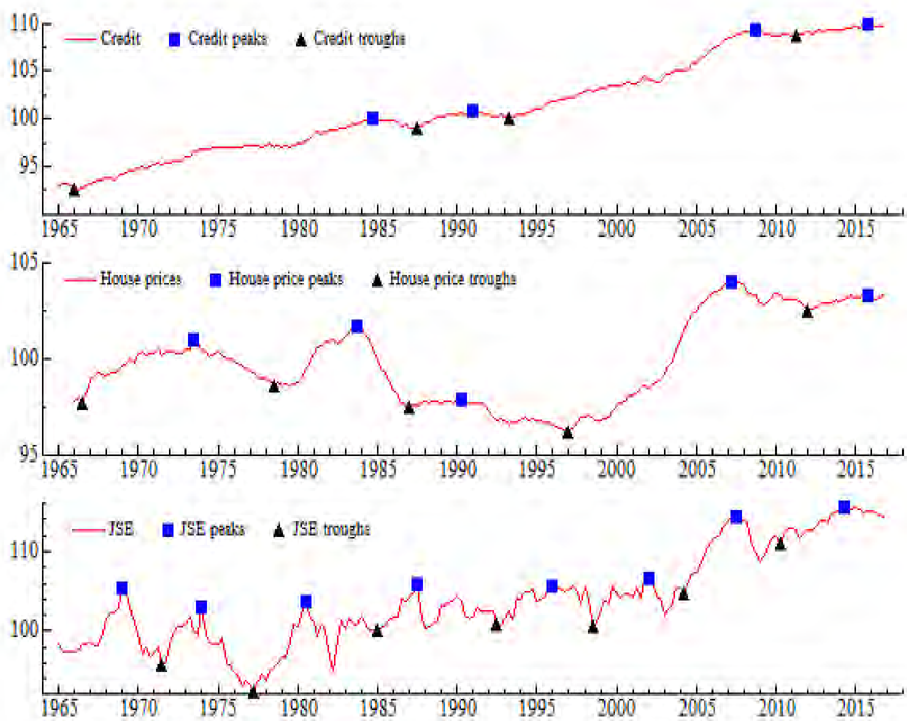
$$\hat{I} = \frac{1}{T} \left(\sum_{t=1}^{T} S_{xt} S_{yt} + \sum_{t=1}^{T} (1-S_{xt})(1-S_{yt}) \right) \tag{5.6}$$

Harding et al., 2016 point out that this measure considers the proportion of time the cycles of variables are in the same phase, but not the reasons for this.

5.4.1 Results

We describe cycles here in terms of amplitude, steepness, and duration, as well as their synchronization with other cycles. Figure 5.1 provides a graphical representation of the results for the medium-term criteria (the data are in log levels, indexed so 1985Q1 = 100).

Figure 5.1 BBQ dating of cycles
(Log levels, 1985Q1=100)



The BBQ rule was suggested by Harding et al., 2002, Harding et al., 2006 and Harding et al., 2016, using a dating algorithm introduced by Bry et al., 1971, adapted for quarterly data

Tables 5.2 and 5.3 show that in the short as well as medium term, credit and house price cycles have similar lengths (25 quarters or just over 6 years for the shorter cycle and around twice this for the medium-term cycle). In both cases, the average length of equity cycles is the shortest of the three variables. The equity, credit, and house price time series all have similar amplitude, with equity prices having the most symmetrical short-term cycles and house prices the most symmetrical medium-term cycles.

Table 5.2 Short cycles (cycle > 5 quarters and phase > 2 quarters)

	Average duration of contraction ($\bar{D}^C$)	Average duration of expansion ($\bar{D}^E$)	Average length of full cycle	Average amplitude of contraction ($\hat{A}^C$)	Average amplitude of expansion ($\hat{A}^E$)	Steepness contraction	Steepness expansion	Concordance with credit ($\hat{I}$)	Concordance with house prices ($\hat{I}$)
Credit	9.1	15.9	25	-11.4	2.1	-1.3	0.1	-	0.55
House Prices	16.5	8.5	25	-11.2	1.4	-0.68	0.16	0.55	-
Equity	7.6	7.1	14.7	-10.4	4.7	-1.4	0.65	0.51	0.47

Table 5.3 Medium cycles (cycle > 20 quarters and phase > 9 quarters)

	Average duration of contraction ($\bar{D}^C$)	Average duration of expansion ($\bar{D}^E$)	Average length of full cycle	Average amplitude of contraction ($\hat{A}^C$)	Average amplitude of expansion ($\hat{A}^E$)	Steepness contraction	Steepness expansion	Concordance with credit ($\hat{I}$)	Concordance with house prices ($\hat{I}$)
Credit	15.8	34.2	50.0	-22.5	3.91	-1.42	0.11	-	0.73
House prices	21.7	20.0	41.7	-18.86	2.57	-0.87	0.13	0.73	-
Equity	16.0	11.8	27.8	-17.35	6.4	-1.08	0.54	0.5	0.53

To measure the fraction of the time that two series are in the same phase we compute the concordance index $\hat{I}$. The statistic is equal to 1 if two series expand and contract together, and equal to zero if the two series are always in a different phase. When the concordance index is equal to 0.5, there is no systematic relationship in the dynamics of the two variables and the two series are independent. In the short term, the concordance indices between credit and both house prices and equity are low, measured as (0.55) and (0.51) respectively, suggesting that according to this measure, these variables are not synchronised in the short term. However, in the medium term, credit and house prices have a high concordance index (0.73) suggesting that the cycles are synchronised. The concordance index between equity and credit (0.5) indicates that the medium-term cycles for credit and equity are independent in the South African case. Similarly, the concordance index between equity and house prices is also close to 0.5, supporting the contention of Drehmann et al., 2012 that equity prices may be a distraction in analyses of the financial cycle.

5.5 Frequency domain analysis

We begin by using spectral methods to undertake an exploratory analysis of the component variables of the financial cycle. This analysis is intended to support the use of frequency-based filters to extract the medium-term cyclical components of these indicators, which are then combined to provide an estimate of the financial cycle. On their own, pure frequency-based filtering approaches that rely on pre-specified frequency bands run the general risk of spurious cycles[13] as well as a form of circularity in their methodology.[14]

[13]Schüler, 2018 finds that detrending financial variables across G7 countries with Hodrick-Prescott and bandpass filters leads to spurious cycles (especially when medium-term cycles are investigated). For more general discussions, see Cogley et al., 1995, Osborn et al., 1995) and Hamilton, 2018.

[14]As Rünstler et al., 2018 argue, "‘while Drehmann et al., 2012 regard financial and business cycles as “different phenomena”, such a finding emerges from their choice of frequency bands for the extraction of GDP (8 to 32 quarters) and financial cycles (32 to 120 quarters): once the filter bands do not overlap, estimates of the two cycles are uncorrelated by construction.

5.5.1 Nonparametric estimation of the spectral density

The spectral representation of a stationary time series y_t decomposes it into a combination of cosine (or sine) waves with differing frequencies. The spectral density is a frequency domain representation of a time series that is directly related to the autocovariance time domain representation.

If y_t is a zero-mean stationary time series with autocovariance function $\gamma(\cdot)$ such that $\sum_{h=-\infty}^{h=\infty} |\gamma(h)| < \infty$, the spectral density of y_t is the function $f(\cdot)$ (see e.g. Brockwell and Davis, 2002; Hamilton, 1994)

$$f(\lambda) = \frac{1}{2\pi} \sum_{h=-\infty}^{h=\infty} \gamma(h) e^{-ih\lambda} \tag{5.7}$$

where h is a time lag, λ is the frequency ($-\infty < \lambda < \infty$), $e^{i\lambda} = cos(\lambda) + i\, sin(\lambda)$ and $i = \sqrt{-1}$. Comprising cosine and sine functions, $f(\cdot)$ has period 2π so we can focus on the values of $f(\cdot)$ on the interval $(-\pi, \pi)$.

The spectral density and autocovariance are Fourier transform pairs, with the latter being given by:

$$\gamma(k) = \int_{-\pi}^{\pi} e^{ik\lambda} f(\lambda) d\lambda \tag{5.8}$$

For y_t with autocovariance function $\gamma(\cdot)$ and spectral density $f(\cdot)$, the periodogram $I_n(\cdot)$ of the observations can be viewed as a sample analog of $2\pi f(\cdot)$.[15] It provides information about the portions of the sample variance of y_t that can be explained by cycles of various frequencies. The periodogram $I_n(\lambda)$ is an asymptotically unbiased, but not consistent, estimator of $2\pi f(\lambda)$ (see e.g. Hamilton, 1994, p194).

The nonparametric approach to estimating the spectral density suggests averaging the periodogram estimates over a narrow frequency interval containing λ to construct a consistent estimator. Smoothing is applied here using the modified Daniell kernel.[16] The kernel determines how much weight each frequency is given.

[15] Due to the symmetry of the function and periodic repetition for frequencies outside the $-\frac{1}{2}$ to $+\frac{1}{2}$ range, analysis can be focussed on frequencies between 0 and $+\frac{1}{2}$, as in Figure 5.2.

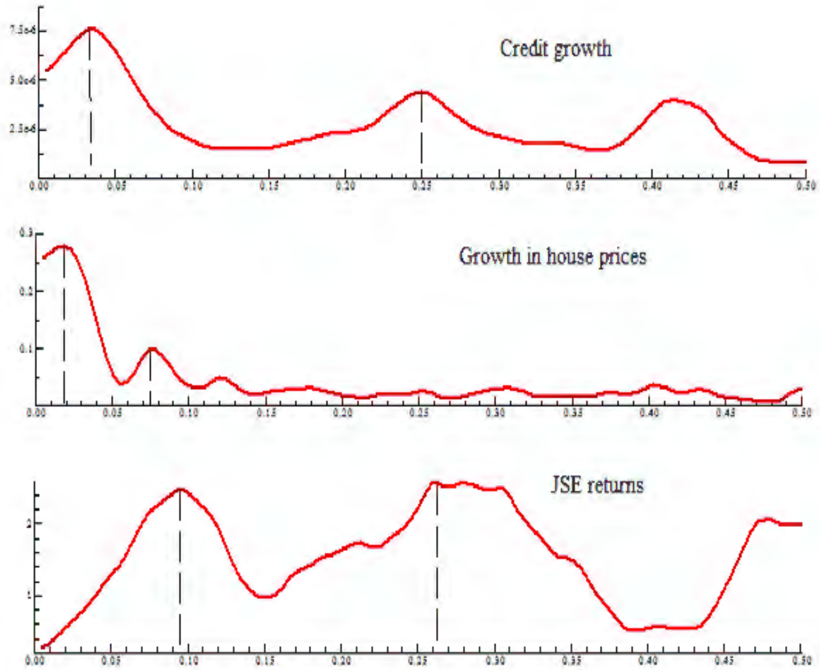
[16] The Daniell kernel with parameter m is a centered moving average of all values between $t-m$ and $t+m$ (inclusive). The smoothing formula for a Daniell kernel with $m=2$, e.g., is

For the modified Daniell kernel, the two endpoints in the averaging receive half the weight that the interior points do. Increasing m decreases the variance of the periodogram (more averaging), but introduces some bias.

5.5.2 Exploratory analysis

Figure 5.2 presents the periodograms of our component variables of the financial cycle:[17] credit, house prices, and equity prices. The data are constant price, demeaned log differences, over samples extending from the mid-1960s to 2016. [18]

Figure 5.2 Periodograms of the financial cycle component variables: Exploratory analysis



$$\hat{x}_t = \frac{x_{t-2} + x_{t-1} + x_t + x_{t+1} + x_{t+2}}{5}$$

[17]The R function spec.pgram was used to estimate the periodograms.

[18]The periodograms were smoothed using a modified Daniell kernel, which was used twice on each series. Both times, m = 2 was chosen for house prices and m = 4 for credit and equity prices. A split cosine bell taper was applied to the data at the beginning and end of the series to reduce leakage.

The periodograms of the credit, house price, and equity price series each have two peaks that are of interest to us. For the credit growth series, the periodogram has a peak at a frequency of 0.032, suggesting a cycle with a duration of 30.9 quarters or around 7.5 years, and a smaller peak at 0.25 suggesting a cycle of 4 quarters. The periodogram of the growth in house prices has a peak at a frequency of 0.019 suggesting a cycle with a duration of 13.5 years, and a smaller peak at 0.074 suggesting a cycle of around 3.5 years. Finally, the periodogram of the JSE returns has a peak at a frequency of 0.097 suggesting a cycle with a duration of 10.3 quarters, and a smaller peak at 0.26 suggesting a cycle of almost 4 quarters. The lower frequency cycles, particularly in the credit and house price series, we interpret as tentative evidence of a medium-term cycle in the South African data.[19]

5.5.3 Band-pass filters

We use band-pass filters to extract the medium-term cycles in the credit, equity price and house price series, then combine these to obtain an estimate of the financial cycle. Specifically, we apply the Christiano et al., 2003 filter to the data to isolate the cyclical component in the frequency range between 32 and 120 quarters. All data series were expressed as four-quarter changes, after having been deflated and logged.

The medium-term cycles obtained from Christiano-Fitzgerald band-pass filters for the component indicators are presented in Figure 5.3. These plots reveal evidence of common cyclical features, particularly in the upswings of the late 1970s and 2000s, and the downswings of the 1970s, 1980s, and late 2000s.

In Figure 5.4, we average the cycles obtained from the Christiano-Fitzgerald band-pass filters for credit, equity prices, and house prices to obtain an estimate of the financial cycle (the red line). Note that since these are growth rate cycles, a decline in the financial cycle that remains positive indicates that the financial cycle in levels is still increasing but at a decreasing rate. A turning point in the financial cycle would thus be reached when the growth cycle becomes zero, as occurred most recently in 2016Q4.

[19] To provide context here, Drehmann et al., 2012 find the average duration of financial cycles

Figure 5.3 Financial cycles: Christiano-Fitzgerald band-pass filters (Y-o-y % changes)

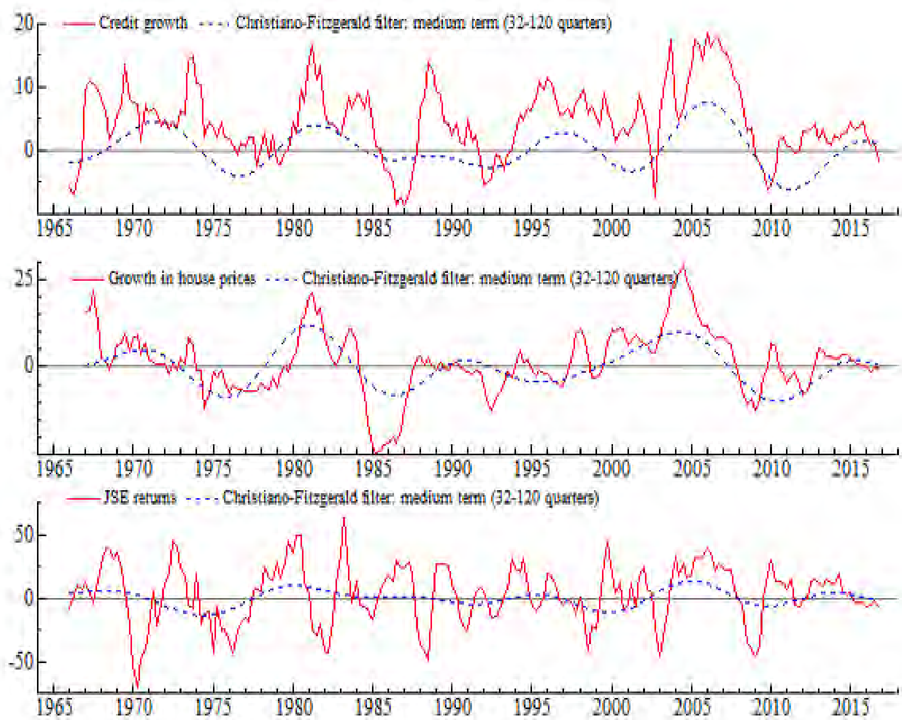
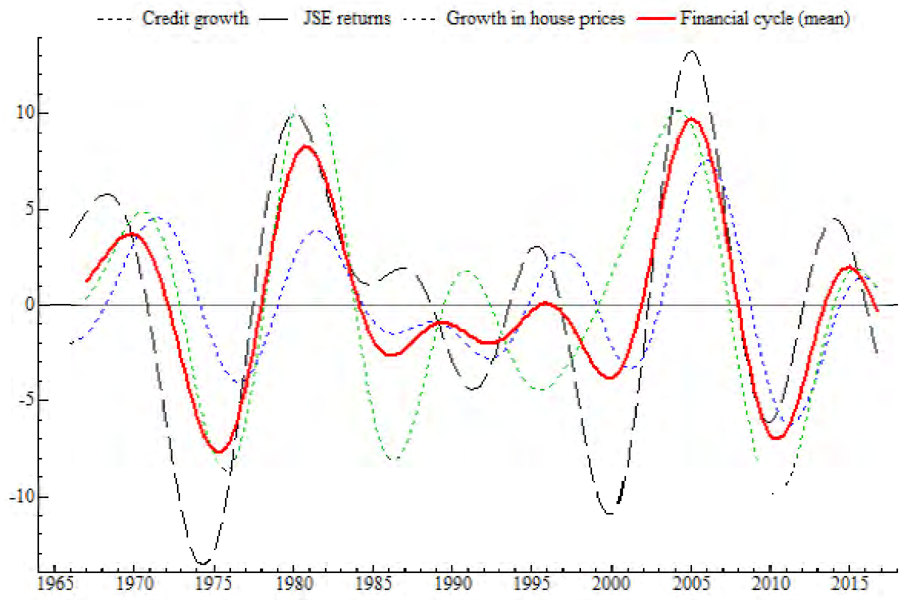


Figure 5.4 The financial cycle in South Africa: Frequency-based filters (Y-o-y % changes)



An alternative way of obtaining an aggregate financial cycle from the Christiano et al., 2003 estimates of the three variables is to use a principal components approach.[20] The first principal component is the loading vector (the rotation) that provides the linear combination of the three medium-term cycles that explains the largest proportion of the variability in the aggregate data. In the South African case, the results are essentially the same as those obtained by simply averaging the three cycles. Using the normalized loading of the first principal component for the three cycles, we find that the weights are approximately equal: Credit (0.332), House Prices (0.346), and JSE returns (0.322). This first principal component explains just over 70 percent of the variance in the data over the sample period.

across a number of countries to be around 16 years.

[20] See also Schüler, Hiebert, et al., 2015a.

5.6 Measuring financial cycles using unobserved components time series models

Our approach here is to first extract cycles from univariate UCTSMs for the credit, house price, and equity price series, and then extract the 'similar' cycles from a multivariate UCTSM consisting of the same three variables as the basis for our estimate of the financial cycle.[21]

A basic structural time series model, with a trend plus cycle plus irregular components specified as unobserved components, is fitted to each variable equation i ($i = 1, \ldots, N$):

$$y_{it} = \mu_{it} + \psi_{it} + \varepsilon_{it} \tag{5.9}$$

where y_{it} is the i^{th} component variable in y_t. For this component variable, μ_{it} is the trend, ψ_{it} the cyclical component, and ε_{it} the irregular ($\varepsilon_{it} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\varepsilon,i})$), and $t = 1, ..., T$.

The smoothness of the trend component μ_{it} - which determines how fluctuations in y_{it} are apportioned between the trend and the cycle – depends on the choice of m in the m-order trend model of Harvey and Trimbur, 2003. The m^{th} order stochastic trend $\mu_{i,t} = \mu^{m_i}_{i,t}$, for each component variable i and integer m, is given by

$$\begin{aligned} \mu^1_{i,t+1} &= \mu^1_{1,t} + \zeta_{i,t}, \;\; \zeta_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}) \\ \mu^k_{i,t+1} &= \mu^k_{i,t} + \mu^{k-1}_{i,t}, \;\; k = 2, \ldots, m_i \end{aligned} \tag{5.10}$$

The trend component is smoother for larger m. If $m = 0$, y_t is assumed to be stationary. For $m = 1$ the stochastic trend is a simple random walk, while for $m = 2$ the trend is an integrated random walk with a slope of $\mu_{i,t}$.[22]

[21] Besides the papers cited earlier that use UCTSMs to measure financial cycles, Creal et al., 2010 adopt a similar cycles approach to measuring the US business cycle, arguing that this is a reasonable approach to extracting a business cycle component that is common to a number of time series (assuming *a priori* that a business cycle exists).

[22] Valle e Azevedo et al., 2006 and Koopman and Lucas, 2005 select a value of $m = 2$ here.

$$
\begin{aligned}
\mu_{i,t+1} &= \mu_{i,t} + \zeta_{i,t}, \;\; \zeta_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\zeta,i}) \\
\beta_{i,t+1} &= \beta_{i,t} + \xi_{i,t}, \;\; \xi_{i,t} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\xi,i})
\end{aligned} \tag{5.11}
$$

The cycle component ψ_{it} is specified as an autoregressive model with polynomial coefficients that have complex roots. Specifically, the cycle is modeled as a trigonometric process that follows (Harvey, 1989):

$$
\begin{pmatrix} \psi_{i,t+1} \\ \psi^*_{i,t+1} \end{pmatrix} = \rho_i \begin{bmatrix} \cos\lambda_i & \sin\lambda_i \\ -\sin\lambda_i & \cos\lambda_i \end{bmatrix} \begin{pmatrix} \psi_{i,t} \\ \psi^*_{i,t} \end{pmatrix} + \begin{pmatrix} \omega_{it} \\ \omega^*_{it} \end{pmatrix}, \begin{pmatrix} \omega_{it} \\ \omega^*_{it} \end{pmatrix} \overset{iid}{\sim} \mathcal{N}(0, \sigma^2_{\omega,i}) \tag{5.12}
$$

where $\psi_{i,t}$ and $\psi^*_{i,t}$ are the states ($N \times 1$ vectors, $\psi^*_{i,t}$ is an auxiliary variable), ω_t and ω^*_t are mutually uncorrelated white noise disturbances with zero means and common variance $\sigma^2_{\omega,i}$, the frequency λ_i is measured in radians $(0 \leq \lambda_i \leq \pi)$ and the persistence ρ_i is the damping factor (restricted for stationarity so $0 < \rho_i < 1$). The period of ψ_{it} is $2\pi/\lambda_i$.

The trend, cycle, and irregular disturbances of component variables are unrelated with those of the other variables, but the covariance between the disturbances of specific components is generally non-zero.

This approach allows the restriction of similar cycles (Heij et al., 1997 to be imposed. Similar cycles have the same frequency and degree of dependence on the past, i.e., the same frequency and damping factor ($\rho_i = \rho$ and $\lambda_i = \lambda$). Since ρ and λ are the same in all series, the cycles have similar properties. Note that the scale of the cycle in a series depends on the variance and covariance of its disturbance, and can therefore differ despite the similarity restriction being imposed.

We place the univariate and multivariate UCTSMs in the general linear state space form, and apply the Kalman filter and related state space methods to estimate them.[23]

[23] Estimation was done using the STAMP 8.30 package, described in Koopman, Harvey, et al., 2000.

5.6.1 Results

In Table 5.4, we first report the parameter estimates from the univariate UCTSMs, obtained by maximum likelihood estimation. The estimates of persistence (ρ) are high and relatively similar for all three variables (0.93 for Credit, 0.99 for House prices, and 0.89 for JSE returns). Furthermore, the estimates of the period (measured by $2\pi/\lambda$) are 12.7 years for Credit, 15.5 years for House prices, and 9.3 years for JSE returns, longer than the typical business cycle duration and supportive of the existence of a distinct medium-term financial cycle.

Table 5.4 Unobserved components time series models: Model summary

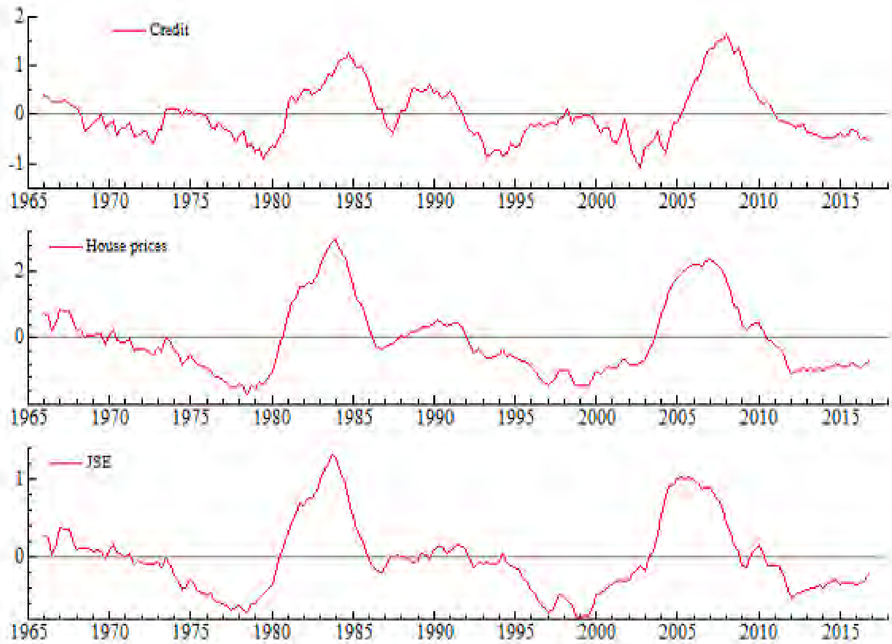
	Univariate			Multivariate
	Credit	House prices	JSE returns	Similar cycles
ρ_i	0.93	0.99	0.89	0.98
Period	12.66	15.50	9.28	14.74
Loglikelihood	356.16	306.08	-40.78	592.92
AIC	-3.54	-3.42	0.27	-3.66
BIC	-3.45	-3.32	0.34	-3.56
# observations	208	204	208	204

Note: The frequency of the cycle is λ (measured in radians, $0 \leq \lambda \leq \pi$) and the period is $p = 2\pi/\lambda$ (in years).

In Figure 5.5, based on the univariate results, we assume that the time- and frequency-domain properties of the three univariate financial cycles are similar, and estimate a joint multivariate UCTSM with the similar cycles restriction imposed. The cycles' damping factors and the frequencies are therefore constrained to be equal for each of the variables, i.e., the parameters $\rho_i = \rho$ and $\lambda_i = \lambda$). With this restriction, the estimate of persistence is $\rho = 0.98$ and the period of the financial cycle is 14.74 years.

Since aggregation of similar cycles leaves the properties unchanged (Heij et al., 1997), we combine the three cycles in Figure 5.5 in the same way as the Christiano-Fitzgerald band-pass filters to facilitate comparison. Figure 5.6 plots the average of the similar cycles obtained for credit, equity prices, and house prices to obtain an estimate of the financial cycle (the red line).

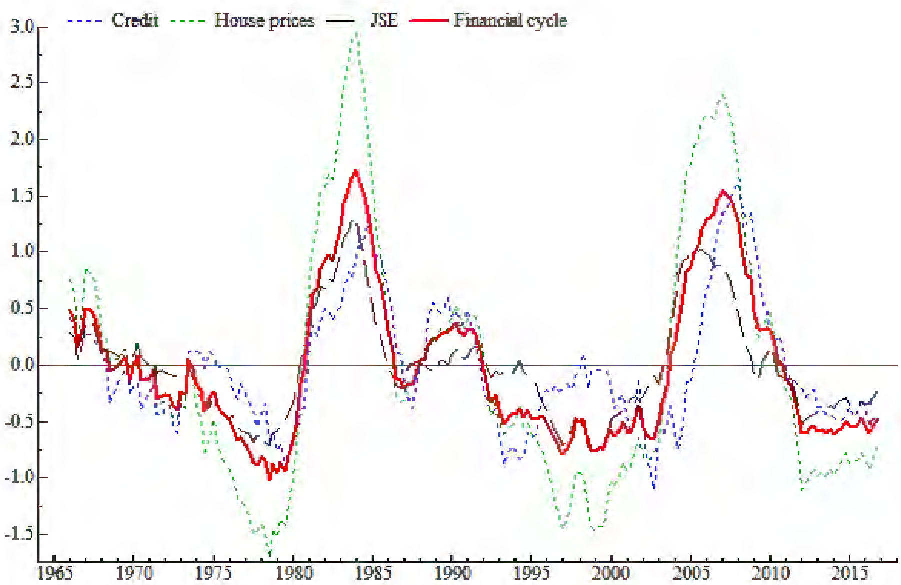
Figure 5.5 Similar cycles for credit, house prices and equity prices:
Unobserved components time series models
(Log levels)



5.7 Comparison of the results of the different approaches to measuring the financial cycle

In Figure 5.7, we compare the financial and component series cycles extracted using frequency-based filter analysis to the BBQ turning-point analysis and the cycles obtained from the unobserved components models. To facilitate this comparison, the frequency-based growth cycles were converted into levels by cumulating the growth rates, similar to Drehmann et al., 2012. The downswings obtained from the BBQ turning point analysis are shown as shaded areas.

Figure 5.6 Financial cycles: Unobserved components time series models (Log levels)

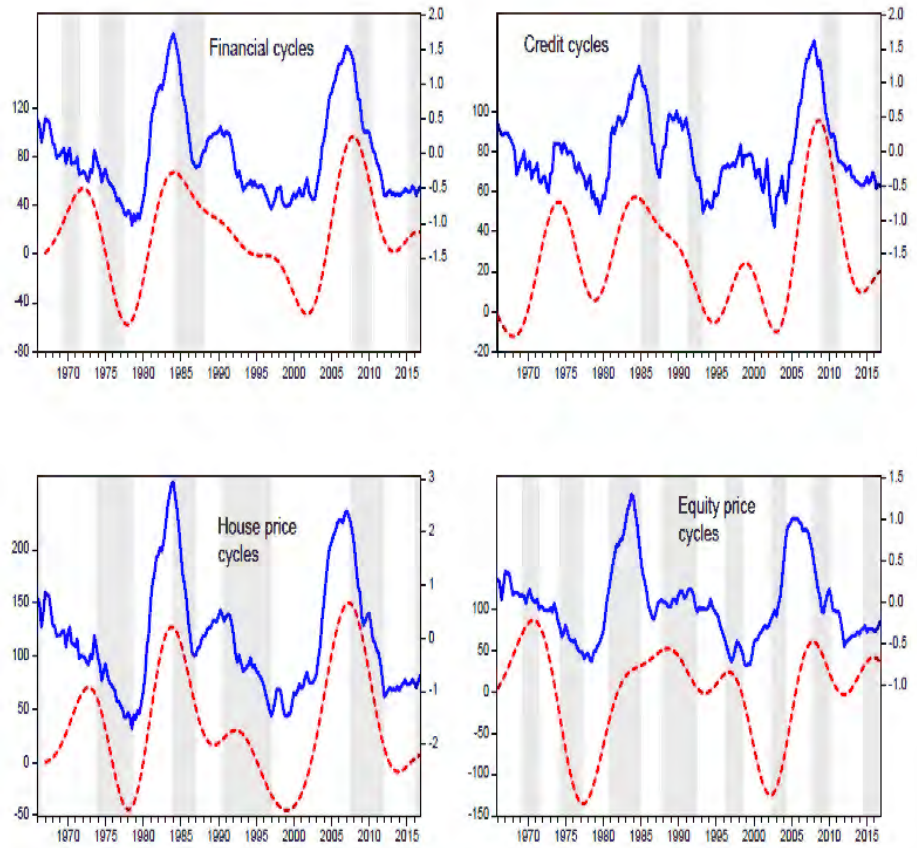


The results of the three methodologies are sufficiently similar to provide some confidence in the characteristics of financial cycles in South Africa that we report. The downswings obtained from the BBQ turning point analysis are generally closely aligned with the downswings in the cycles extracted from the unobserved components models (the blue solid lines). Our results from the frequency-based filters (the red dotted lines) provide somewhat smoother cycles, but these are generally also consistent with those of the other two methodologies.

Figure 5.7 also reveals that turning points preceding downturns, especially for credit and house price cycles, are generally consistent with international or domestic crisis periods: in the early 1970s – corresponding with the oil crisis; in the mid 1980s – corresponding with South Africa's external debt crisis; in 2008 – corresponding with the global financial crisis; and in 2015 – corresponding to South Africa's currency crisis. [24] This emphasis is that as a small open economy,

[24] It is interesting to note that two of these periods correspond with domestic crises identified by Laeven et al., 2018: the currency and the sovereign debt crisis in the mid-1980s and the currency crisis in 2015.

Figure 5.7 Comparison of financial cycles financial and component series cycles extracted using frequency-based filter analysis to the BBQ turning-point analysis and the cycles obtained from the unobserved components models



— Unobserved components model (right-hand axis, log levels)
--- CF filter (left-hand axis: cumulated percentage changes)
Shaded areas are BBQ turning point dated downswings

South Africa is heavily impacted by global developments. It may also provide some support for including JSE equity prices in the measure of the South African financial cycle. Even though we find shorter and more frequent cycles than those of the other components, the high levels of foreign ownership as well as dual-listed stocks may help to incorporate external factors in the calculation of the financial cycle.

The results for the overall financial cycle (the top left-hand graph in Figure 5.7) are less consistent at the end of the sample than elsewhere. The BBQ reports a downswing, the frequency-based filter financial cycle has just reached an upper turning point, and the unobserved components model financial cycle is relatively flat. These results are perhaps reflecting the end-of-sample problem common in the filter-based analysis of cycles, and this issue may benefit from further study.[25]

5.8 The South African financial cycle vs the business cycle?

The relationship between business cycles and financial cycles is important for policymakers. If financial and business cycles are closely correlated, they will seldom be in different phases, and policy conflicts will be rare. However, when they are not well correlated and the cycles are in different phases for extended periods of time, conflicts are more likely. The interactions between business cycles and financial cycles also play an important role in determining the characteristics of recessions and recoveries in the real economy, with recessions accompanied by financial disruptions tending to be longer and deeper (Claessens, Kose, and Terrones, 2012).

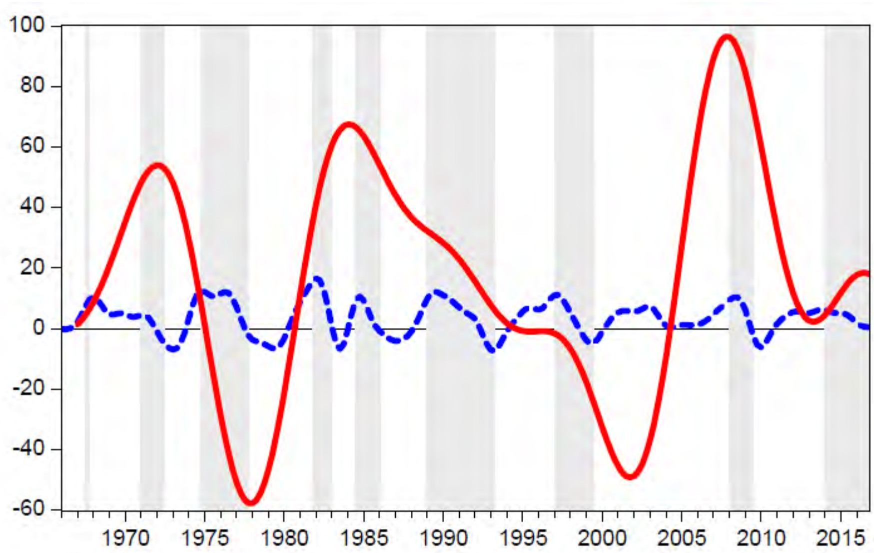
The international empirical evidence is mixed. Leamer, 2007 and Leamer, 2015 found that for the US, housing is the business cycle, and that the finance, housing and business cycles have correlated closely for several decades. Perhaps more generally, the financial cycles literature supports the existence of separate

[25]The end of sample problem is confirmed by Bosch and Koch, 2020, who finds a similar financial cycle, but without the last turning point.

financial and business cycles (Borio, 2014a, Claessens, Kose, and Terrones, 2012, Barrell et al., 2020).

In this section, we compare estimates of the South African business cycle with our estimate of the financial cycle. We use the results of the frequency-based filters approach to provide consistent estimates of both cycles and to facilitate the comparison.

Figure 5.8 The financial and business cycles in SA: Frequency-based approach



--- Business cycle (cum % changes, CF filter 5-32 quarters)
— Financial cycle (cum % changes, CF filter 32-120 quarters)
Shaded areas are SARB official BC downswings

The shaded areas showing downward phases of the business cycle in Figure 5.8, represent the official turning points for the South African business cycle taken from table S-151 of the SARB's Quarterly Bulletin. These shaded areas correlate closely with our estimate of the business cycle (the blue dotted line), which is the cumulated cycle extracted from real GDP growth data using the Christiano-Fitzgerald frequency-based filter (with a duration between 5 and 32 quarters). The financial cycle (the red solid line) is the cycle extracted using the frequency-based filter approach reported in Section 5.

Consistent with the results of other studies (e.g.Hiebert et al., 2018; David Aikman et al., 2018; Drehmann et al., 2012; Borio, 2014a; Claessens, Kose, and Terrones, 2011, we find in Figure 5.8 that the financial cycle has a lower frequency than the traditional business cycle, and that the amplitude of the financial cycle is larger than that of the business cycle. The medium-term business cycle that is extracted from real GDP growth data using the Christiano-Fitzgerald frequency-based filter with a duration between 32 and 120 quarters also confirmed these observations.

While it is not clear that a downward phase of the business cycle would last longer if the financial cycle is in a downturn, Figure 5.8 suggests that the business cycle downswing tends to be longer if it follows a downward phase in the financial cycle. On average, the downward phases of the business cycle last for 9 quarters. In the mid-1970s, corresponding with the oil crisis, the downturn lasted 13 quarters; in 1994, the downturn lasted 18 quarters; and from 2014 onward, the downward phase has so far lasted 12 quarters. These extended downward phases coincide with periods where the financial cycle had already been in a downward phase for at least 10 quarters prior to the turning of the business cycle.

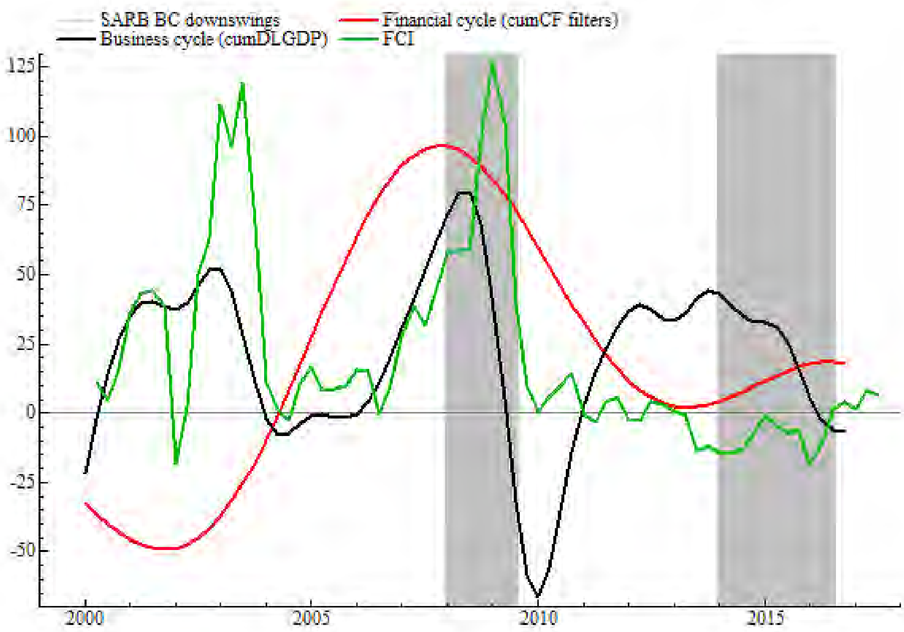
We also investigated the synchronicity between the business cycle and the financial cycle as well as its components using the concordance index.[26] We found that the business cycle is more synchronised with credit cycles for both the short and medium term business cycle (concordance indices of over 0.75) than with house price cycles or equity prices.

Finally, the financial cycle shown in 5.8 is closely associated with other measures of financial conditions in South Africa. Kabundi et al., 2021, for example, estimate a time-varying financial conditions index (FCI) for South Africa using 45 monthly financial series. The analysis includes indicators from five main sectors (the funding, credit, foreign exchange, real estate and equity markets), and uses different weights associated with different divisions within a financial market to facilitate the identification of sectors that are under stress. Figure 5.9 compares the FCI (converted from monthly to quarterly frequency using end-of-period

[26]See equation 5.6 in Section 5.4.

observations, available from 2000) to the financial and business cycles presented in Figure 5.8. The FCI and the financial cycle correlate closely from 2004 onwards, with the turning points in the financial cycle perhaps marginally leading those of the FCI (although there is as yet insufficient data to make this determination with any confidence). The peak in the FCI in 2003-4 is not reflected in the financial cycle estimate, although it does appear in our estimate of the business cycle.

Figure 5.9 Financial conditions index and the financial and business cycles in South Africa



Shaded areas are SARB official BC downswings

5.9 Conclusion

Financial cycles provide a broad indication of the changes in risks to financial stability and therefore provide an important monitoring tool for policymakers. Taking into account the phase of a country's financial cycle is also important when implementing macroprudential policy, given that the impact of policies may differ depending on the phase of the cycle. An understanding of financial cycles is therefore a key element informing macroprudential policy-making.

In this chapter we use credit, house prices, and equity prices as indicators to extract the financial cycle in South Africa using three different methodologies. We report the results obtained from traditional turning-point analysis, frequency-based filters, and unobserved components models, finding evidence of a financial cycle in South Africa that has a longer duration and a larger amplitude than the traditional business cycle. We also find that periods where financial conditions are stressed are associated with peaks in the financial cycle, suggesting that the estimated financial cycle may have similar leading indicator properties to financial conditions or stress indices.

We find that developments in credit and house price variables are important component indicators that serve to capture the financial cycle in South Africa. The case for including equity prices is less clear. Equity prices in South Africa are less consistent with these variables, but may be influenced by external variables such as international developments and foreign-exchange movements, and as a result provide important additional information.

Our finding that the financial cycle is distinct from the business cycle in South Africa differs, for example, from Leamer, 2007 and Leamer, 2015 finding for the US. In this regard, the existence of a separate South African financial cycle is more closely aligned with the findings of Borio, 2014a, Claessens, Kose, and Terrones, 2011 and Barrell et al., 2020.

An important implication of this finding is that the coordination of monetary and macroprudential policies could be more complicated. Distinct financial and business cycles that are not always well correlated and are in different phases for extended periods of time, mean that conflicts are more likely. The interactions between distinct business and financial cycles may also play an important role in determining the characteristics of recessions and recoveries in the real economy.

Critically important from a financial-stability perspective is that failure to take medium-term financial cycles into account and focusing only on the business cycle may allow vulnerabilities to build up unattended. Policymakers may contain recessions in the short run, but at the expense of larger crises down the road.

In terms of future analysis, it would be useful to consider the impact of global financial conditions and capital flows on South Africa's financial cycle.

Chapter Six

The Non-Bank Credit Cycle

Building on the work in the previous chapter, we investigate the cyclical properties of non-bank credit and its relevance for financial stability.[1] Moving beyond the bank-credit cycle, we construct a measure of non-bank credit for a large sample of countries and find that its cyclical properties differ from those of bank credit. We extend the analysis beyond South Africa to include several other emerging market- as well as advanced economies. We find that non-bank credit cycles are highly correlated with bank credit cycles in some countries but not in others. Moreover, non-bank credit cycles are less synchronised than bank credit cycles across countries. Finally, non-bank credit cycles can act as a leading indicator for currency, but not for systemic banking crises. The opposite is true for bank credit cycles. Overall, our findings highlight the added value of monitoring non-bank credit.

6.1 Introduction

While bank loans are generally seen as the main source of credit, credit can be obtained in many forms. In modern financial systems - more specifically those of advanced economies, the size of non-bank credit is often as large, or even larger, than bank credit (Patalano et al., 2020). The sources of non-bank credit are heterogeneous, as it can take the form of bond financing, or loans by a diverse group of lenders that include investment funds, non-bank mortgage providers,

[1] This chapter is based on the US Federal Reserve working paper Kemp et al., 2018.

foreign lenders or the government.

In this chapter, we construct a new measure of non-bank credit for a large international sample of advanced and emerging market economies and investigate the role of non-bank credit in the financial system. In particular, we compare cycles in non-bank credit to bank credit cycles and study their relevance for financial instability, separately exploring the effects on systemic banking, currency and sovereign debt crises.

Existing literature has mainly focussed on bank credit (see for example (Becker et al., 2014; S. Langfield et al., 2016) that found that the supply of bank credit is seen as procyclical). Banks are generally highly leveraged and subject to relatively large maturity and liquidity mismatches. When banks' buffers increase during bad times, or when banks are hit by adverse shocks, they need to rebuild their buffers and will curtail credit as a result (and vice versa in good times).

There is less consensus on the cyclicality of non-bank credit. Bond credit, in particular, is found to be less procyclical than bank credit (Becker et al., 2014; S. Langfield et al., 2016). That is why the IMF, 2015 refers to market-based financing as a spare tyre for periods when bank credit is restrained. However, this issue on the cyclicality of non-bank credit has not been fully settled, as non-bank credit can take many more different forms. For example, securitization markets, which typically transform bank credit into non-bank credit, showed a strong boom-bust pattern around the financial crisis. Similarly, collateralized short-term funding can result in procyclical leverage and investment behaviour as argued in Fostel et al., 2008, and shown to be the case for US broker dealers in Adrian and Shin, 2009.

We contribute to this academic debate by showing that the cyclical properties of non-bank credit are heterogeneous across countries and differ from those of bank credit. In some countries, non-bank credit cycles are highly synchronised with bank credit cycles, but not in others. Moreover, non-bank and bank credit cycles were less synchronised within countries in the period leading up to the global financial crisis, while non-bank credit is also less synchronised across countries than bank credit. [2]

[2] See also Herman et al., 2017, who find that bank and non-bank credit exhibit different dynam-

With respect to financial instability, the literature has mainly focussed on bank or total credit. Previous studies have already established a link between credit cycles and banking or currency crises (Borio and Lowe, 2002; Schularick et al., 2012; Mendoza et al., 2012). Several other studies have focussed on financial cycles more generally (e.g. Claessens, Kose, and Terrones, 2012; Drehmann et al., 2012; Schüler, Hiebert, et al., 2015b). However, less research has been conducted on the role of non-bank credit. One strand in the literature stresses that a stronger reliance on non-bank debt or market-based finance, relative to bank credit, should be beneficial for economic growth and financial stability (e.g. Gambacorta et al., 2014; Bats et al., 2017). But at the same time, several examples can be given of stress events in the non-bank sector, sometimes of a systemic nature (ESRB, 2016).[3]

We show that non-bank credit growth – or equivalently the non-bank credit cycle – can act as a leading indicator for currency crises and, perhaps, also for sovereign debt crises (although the latter result is more uncertain due to the low number of sovereign debt crises). This result is in sharp contrast to total or bank credit growth, which is not helpful in predicting the incidence of currency crises. On the contrary, bank credit growth is a useful leading indicator for systemic banking crises, while non-bank credit growth fails to predict such incidences. These findings highlight the value added of monitoring non-bank credit next to the traditional focus on bank credit.

The remainder of this chapter is organised as follows. Section 6.2 explains our definition of non-bank credit and takes a first look at our dataset of a global group of 36 countries. Section 6.3 investigates bank and non-bank cycle synchronicity within and across countries. Section 6.4 investigates the link to financial instability.

ics throughout the business cycle in the US. In comparison with their approach, we study the cyclical properties of non-bank credit for a much larger group of countries, and compare it not only to bank credit but also to investigate its link with periods of financial instability.

[3]For example, in the early 1970s, in the UK, unregulated 'fringe institutions' funded themselves in the money markets and invested these funds largely in commercial property developments. Financial stress in this sector became known as the secondary banking crisis and led to legal reforms in the UK. On a similar tone, Kim et al., 2017 describe how non-bank mortgage companies in the US are vulnerable to liquidity pressures, and warn that they are vulnerable to a financial crisis. As a result, there may be additional information in non-bank credit developments for financial stability purposes.

The main tables and figure are presented after the bibliography. Additional tables and figures are reported in Appendix C.

6.2 Data

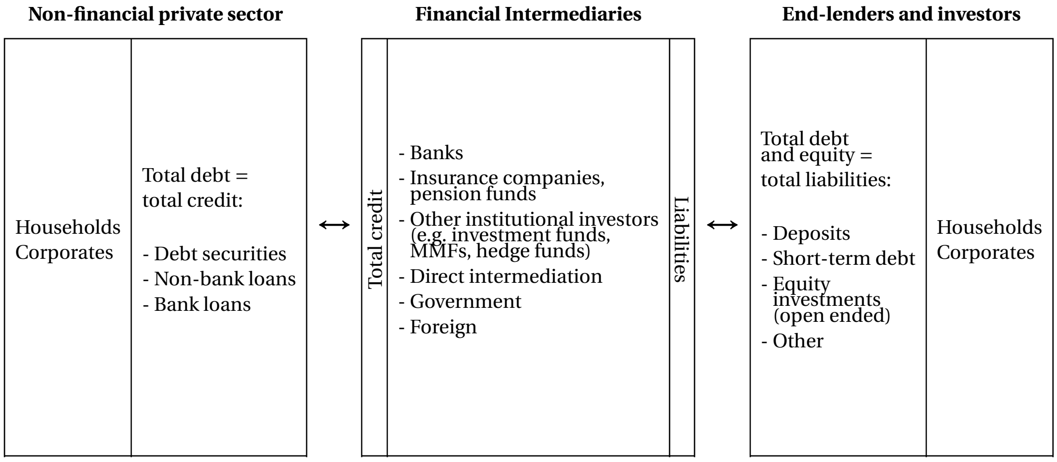
Credit to the non-financial private sector consists of the loans and debt securities on the liability side of the balance sheets of households and corporates (Figure 6.1). Most of the literature focuses on loans provided by banks (i.e. bank credit), or credit from all bank and non-bank sources. Non-bank credit is provided by a broad range of lenders, including insurance companies, pension funds, Other Financial Institutions (OFIs),[4] the government, and foreign non-bank credit providers. This makes it more complicated to study its properties, and to design supervisory approaches. We take a macro approach, as our interest is in the overall role of non-bank credit as a source of funding for the private sector and its link to financial stability. This latter perspective has been motivated by increasing attention for the growing role of non-bank financial intermediation and shadow banking (e.g. FSB, 2018). But non-bank credit is broader than shadow banking, as the latter term (only) includes non-bank entities with short-term funding and potential financial stability risks related to leverage, liquidity and maturity mismatches and interconnectedness (FSB, 2013).

The measures of non-bank and bank credit are computed using the BIS long series database on private non-financial sector credit (Dembiermont et al., 2013) and the BIS locational banking statistics. The former database contains quarterly series of private credit data for more than 40 economies for a period covering at least 30 years. The database's measure of total private credit covers all loans and debt securities to non-financial corporations, households, and non-profit institutions serving households. The first step for estimating non-bank credit is to subtract bank credit from total credit, with bank credit defined as all loans and debt securities held by domestic banks.[5] What remains encompasses loans

[4] OFIs include institutions such as Investment Funds, Money Market Funds, Finance Companies, Broker Dealers, ABS Issuers.

[5] See also Cizel et al., 2016.

Figure 6.1 Credit intermediation: a stylised representation.



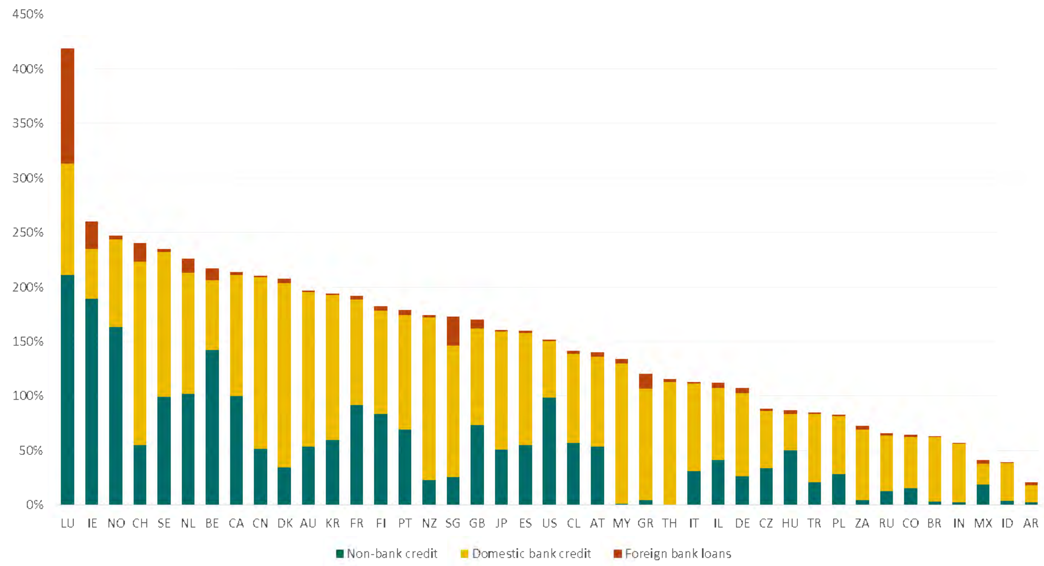
provided and debt securities held by all other sectors of the economy, both domestic and cross-border, (e.g., insurance companies, pension funds, investment funds, other firms, households), and cross-border lending by foreign banks. The inclusion of direct cross-border lending by foreign banks calls for a second step, i.e., to subtract cross-border loans by foreign banks (i.e., non-resident bank loans). What results is the measure of non-bank credit used in this chapter:

> ***Non-bank credit to private non-financial sector (PNF)*** ≈ *All sector credit to PNF − (Domestic) Bank credit to PNF − Non-resident bank loans to PNF.*

The data on non-resident bank loans are sourced from the BIS locational banking statistics, which are available as of end-2013. Although this correction is therefore not possible for the years preceding 2013, non-resident bank credit is generally relatively small, with a median of 3% of GDP across the averages of the countries. We therefore exclude countries that have an average large share of non-resident bank loans relative to non-bank credit and where the cross-border adjustments have a significant impact on the non-bank credit growth figures, i.e. Argentina, Greece, Hong Kong, Malaysia, and Saudi Arabia.[6] For the remaining

[6]We also excluded Colombia from the sample for not having CPI data, which is necessary for credit cycle calculations, and Thailand, since the level of non-bank credit is very close to zero for some observations, so that it is not possible to calculate meaningful growth rates.

Figure 6.2 Components of total credit, 2017Q3, % GDP

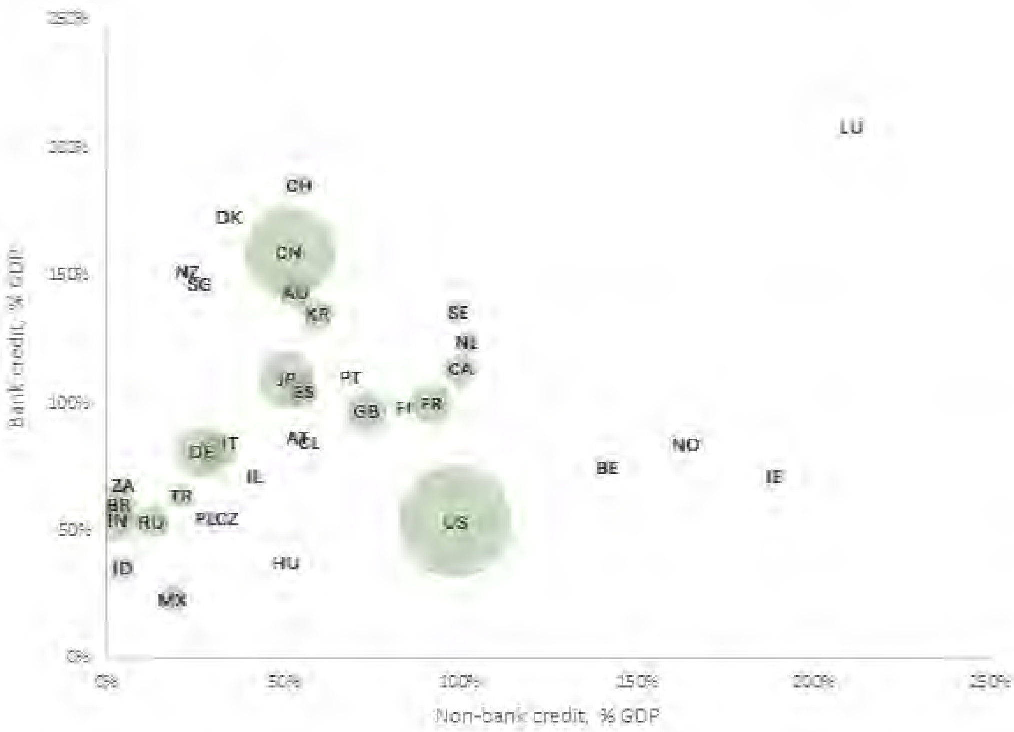


countries, we use two alternative methods for addressing the lack of non-resident bank loan data prior to 2013. First, we calculate non-resident bank credit backward by using the growth rate between 2013Q4 and 2015Q4 over the period for which data are available. This leads to a declining share of non-resident bank credit when we go back further in time, in line with an increasing international orientation of the financial sector over our sample period. Second, we also use an unadjusted series for a robustness check, leaving out the correction before 2013. This leads to a slight overestimation of non-bank credit before 2013. We compare the adjusted and unadjusted series directly, and find that differences are very small. Moreover, most of our analysis focuses on differences in growth changes in non-bank credit and those are negligible between the two datasets. Therefore, for the remainder of the chapter the adjusted non-bank cycle is used for analyses. Figure 6.2 shows the latest observation for total credit, split between domestic bank credit, non-bank credit, and non-resident bank loans for all countries in our sample.

Figure 6.3 shows the latest observation in our sample for the size of non-bank credit (horizontal axis), and bank credit (vertical axis), as % of GDP. Many

Figure 6.3 The size of bank and non-bank credit as a fraction of GDP

Data as of 2017Q3. Size of the bubbles denotes the country's GDP



Note: country codes are AT = Austria, AU = Australia, BE = Belgium, BR = Brazil, CA = Canada, CH = Switzerland, CL = Chile, CN = China, CZ = Czech Republic, DE = Germany, DK = Denmark, ES = Spain, FI = Finland, FR = France, GB = Great Britain, HU = Hungary, ID = Indonesia, IE = Ireland, IL = Israel, IN = India, IT = Italy, JP = Japan, KR = South Korea, LU = Luxembourg, MX = Mexico, NL = The Netherlands, NO = Norway, NZ = New Zealand, PL = Poland, PT = Portugal, RU = Russia, SE = Sweden, SG = Singapore, TR = Turkey, US = The United States of America, ZA = South Africa.

observations are above but relatively close to the 45-degree line, indicating that bank and non-bank credit generally are quite similar in size within countries. But some countries lean more toward bank credit (e.g. Denmark, China) and others more towards non-bank credit (e.g., the US, Ireland). Moreover, Advanced Economies (ADVs) show relatively larger sizes of non-bank credit than Emerging Market Economies (EMEs). In a few countries, the size of non-bank credit is very small, i.e., Indonesia, India, Brazil, and South Africa.

Ideally, a distinction should be made between non-bank credit from foreign and domestic sources. However, as a result of data limitations our measure includes non-bank credit both from domestic and foreign sources. Our finding on the role of non-bank credit as a leading indicator for currency crises only underlines the relevance of such a decomposition (see section 6.4). It turns out, however, that further decomposition that would allow us to calculate cycles for a large group of countries and a large enough sample period are not available for the long credit series. To get an indication, we therefore analysed more disaggregated data from the Euro Area Securities Holdings Statistics, which has only become available very recently. Looking at debt securities issued by non-financial corporations from the Euro Area, we found that in 2017Q3, approximately 28% of debt securities were held by non-banks domestically, and 72% by foreign investors.[7] Moreover, the relevance of non-bank credit from foreign sources also shows up in case studies about the experience of EMEs (see the discussion in section 6.3, Figure 6.5, where we show our results for the non-bank and bank credit cycles in different regions).

6.3 The non-bank credit cycle and its interaction with bank credit

6.3.1 Calculating the cycle

Various approaches can be used to empirically isolate credit cycles, including traditional turning point analyses, frequency-based filter analyses and model-based approaches (see for example Aikman et al., 2015; Claessens, Kose, and Terrones, 2012; Drehmann et al., 2012). In this chapter, we apply the Christiano et al., 2003 filter to non-bank and bank credit data. Turning-point analyses are also performed using a dating algorithm introduced by Bry et al., 1971 (see results

[7] The data show that 35% of debt securities issued by non-financial Euro Area corporations is held by non-banks domestically, and 65% by foreign non-banks from other Euro Area countries. This number, however, underestimates the total foreign portion, since 20% is held by investors form outside the Euro Area according to the quarterly sector accounts. Applying a correction for this gives the numbers mentioned in the main text.

in Table C.3). The aim is to isolate the cyclical component in the frequency range between 32 and 120 quarters (i.e. to identify the credit cycles with a duration of between 8 and 30 years). Similar approaches for the credit cycle have been taken by Aikman et al., 2015, and by Schüler, Hiebert, et al., 2015b, Strohsal et al., 2015 and Gonzalez et al., 2015 for the financial cycle.

Drehmann et al. (2012) apply frequency-based filters, as well as turning point analysis. Outstanding credit in domestic currency data is deflated by the Consumer Price Index (CPI) for each respective country and expressed in logs, with the filter applied to the 4-quarter log changes. The frequency-based growth cycles were calculated per country and can be converted into levels by cumulating the growth rates, similar to Drehmann et al., 2012.

6.3.2 Non-bank and bank credit cycles

The full set of results for the frequency-based non-bank and bank cycles in individual countries are shown in Figure 6.4. Note that since these are growth rate cycles, a negative value indicates a decrease in the level of outstanding credit in real terms, while increases are present when the growth cycles are positive. When the cycle is positive but declining, the cycle in levels is still increasing but at a decreasing rate. A turning point is therefore indicated when the growth rate cycle reaches zero.

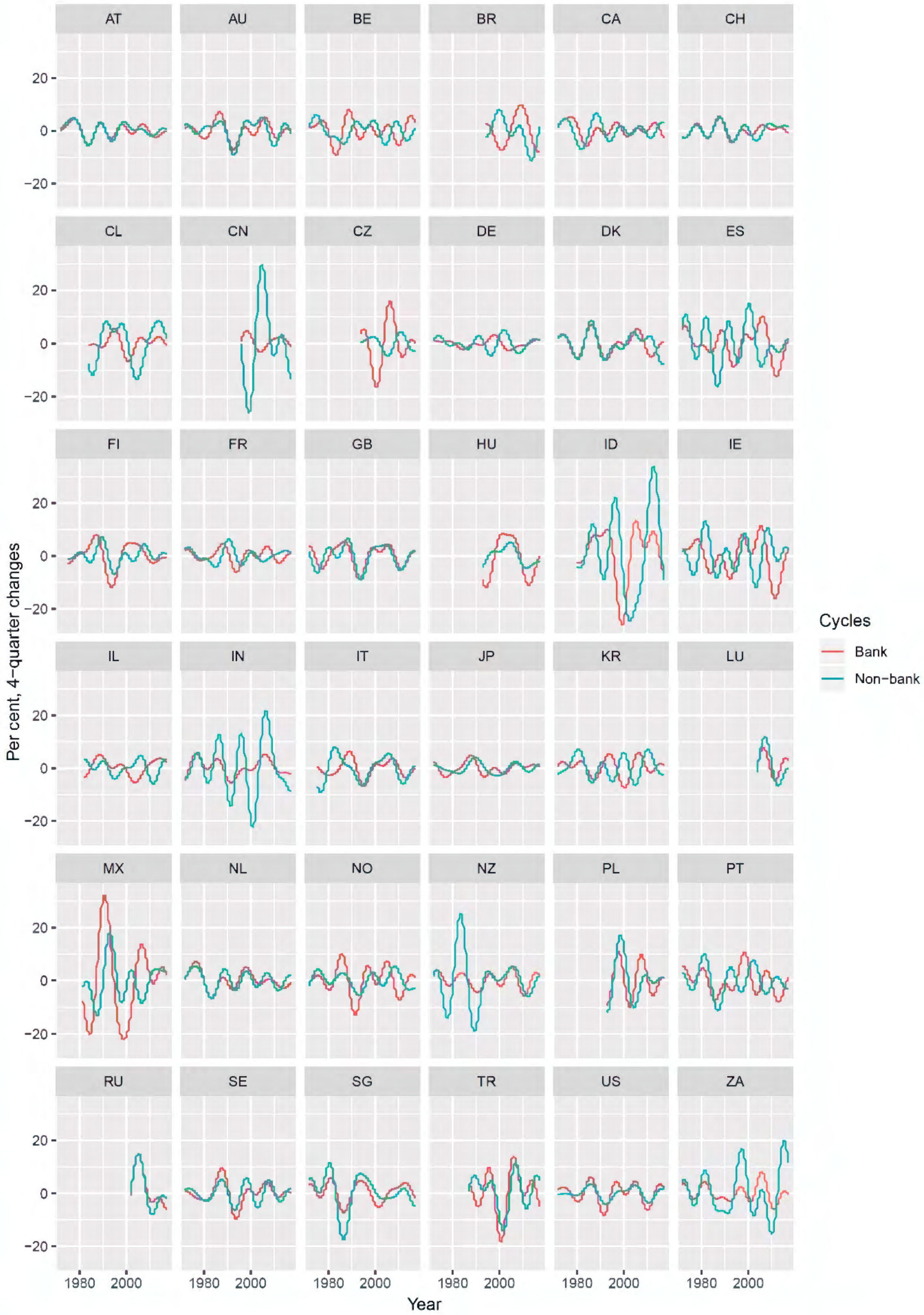
Given that this is the first study, to our knowledge, that attempts to identify non-bank credit cycles, and that we are estimating non-bank credit as a residual, we acknowledge that some of our findings should be approached with some caution.[8] Nevertheless, while there is limited research available for us to compare our cycle estimates against, any identified cycles would be dependent on the underlying data and what is deemed to be non-bank credit. Using Great Britain as an example, the increase in market-based finance is documented in various editions of the Bank of England's Financial Stability Report (Bank of England, 2018). While bank lending to non-financial corporates eased following the global

[8]For example in New Zealand we identify large swings in the non-bank cycle prior to 1990, however it is difficult to cross-reference our dataset given the credit data series available from the Reserve Bank of New Zealand is only available from 1990 onwards.

financial crisis, market-based finance, estimated as bonds, equities and commercial paper, increased. This is somewhat different from our finding that non-bank and bank credit cycles have followed a broadly positive correlation. We attribute this difference in the approach to measuring market-based finance - as in our approach we do not include equities as non-bank credit. In cases where other research on non-bank credit cycles have been conducted, we find our results compelling. For example, Durdu et al., 2019 also study the non-bank credit cycle in the US, using national data (i.e. a different source from ours), and find results that are broadly similar to those presented in this paper. More specifically, Durdu et al., 2019 find that bank and non-bank credit growth are positively correlated, similar to cycles shown in Figure 6.4, and note that bank credit tends to be more volatile than non-bank credit growth - witnessed in larger amplitude in our study. Finally, our cycles could be compared to the FSB's OFI estimate for each country.[9]

[9]See FSB, 2018. While data for Other Financial Intermediaries (OFIs) are available for a large number of jurisdictions, this data was not used in this study because it is available annually from 2002. Based on this dataset, however, we can verify that OFI financial asset growth exceeded that of banks in China from 2013, and in India relatively stronger OFI growth is evident in 2007

Figure 6.4 Bank and non-bank credit growth rate cycles



Note: Country codes are provided in Table C.1.A negative value indicates a decrease in the level of outstanding credit in real terms, while increases are present when the growth cycles are positive. A turning point is therefore indicated when the growth rate cycle reaches zero. Results based on available data from 1972 - 2017.

Overall, results show that the amplitudes of the bank and non-bank cycles vary significantly across countries, reflecting the differing growth rates in non-bank credit over time (Figure 6.4). This renders the calculation of an average global bank and non-bank cycle difficult. Against this backdrop, various groupings of data were considered, namely Emerging Market Economies (EME), advanced economies (ADV), EU (EU), and non-EU countries (NONEU). [10] As can be seen in Figure 6.5, the non-bank credit growth shows its highest peak in EMEs in the 1990s, before the Asian financial crisis of 1997, where it reaches a turning point. During the Asian financial crisis, foreign currency lending and risks related to (non-bank) bond market credit played a particularly important role (Black et al., 2010). Moreover, the turn up in the non-bank credit cycle in EMEs matches the description in Shin, 2013 and Chui et al., 2016. This period is referred to as the second phase of global liquidity, when easing of monetary conditions in AEs led to increased foreign currency borrowing by non-financial corporations in EMEs.

The period before the global financial crisis stands out as a period with a strong upturn in bank credit cycles in all groups of countries, while non-bank credit also shows a peak around that time, or slightly later. The downward cycle in bank credit is more severe in advanced and EU economies.

The robustness of these groupings is tested by using the correlation as well as concordance indices[11] between the unweighted and weighted-by-GDP cycles (see Table C.2 in the Appendix C). Concordance indices measure how synchronised cycles are by focusing on the fraction of time periods that the cycles are in the same phase. Both the concordance and correlation between the unweighted and weighted-by-GDP cycles for all the groupings of countries generally yield more robust results for the non-bank cycle than that for the global aggregate cycle, especially for EU and Advanced economies.[12] However, results also indicate a higher correlation and concordance for bank cycles than for non-bank cycles in all groupings considered, confirming that the calculation of a global non-bank cycle is difficult.

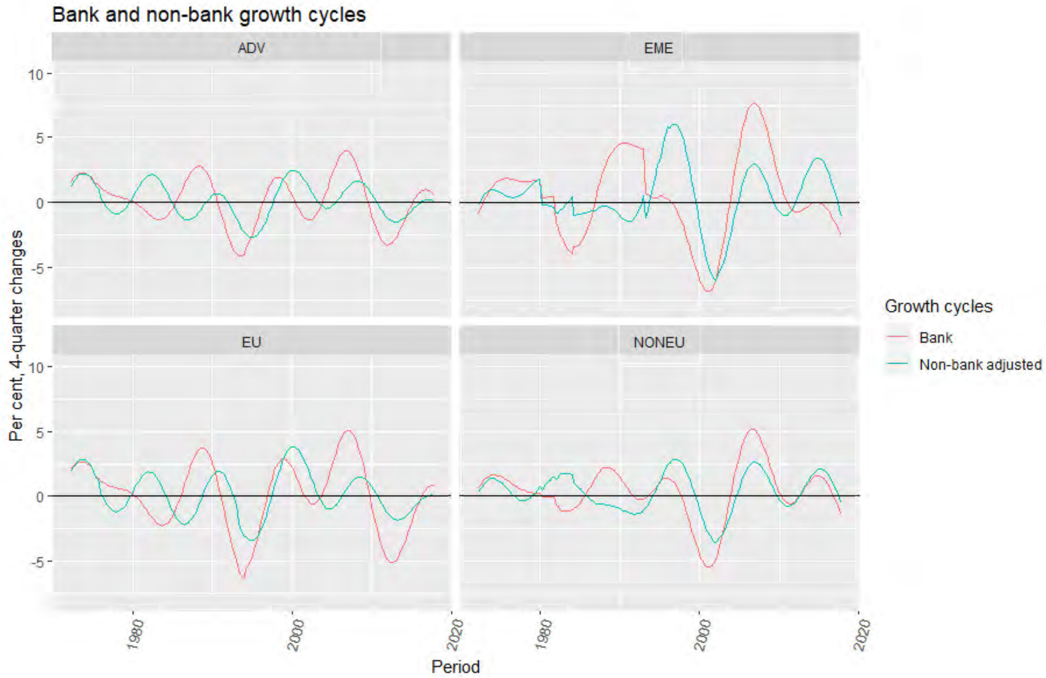
[10] Country groupings are shown in Appendix C.

[11] As proposed by Harding et al., 2002.

[12] Correlations within country groups were also calculated over time (Figures 6.4 and 6.6) and show that within groupings the correlation between cycles changes over time.

Figure 6.5 Country groupings: Bank and non-bank growth rate cycles

(Unweighted)

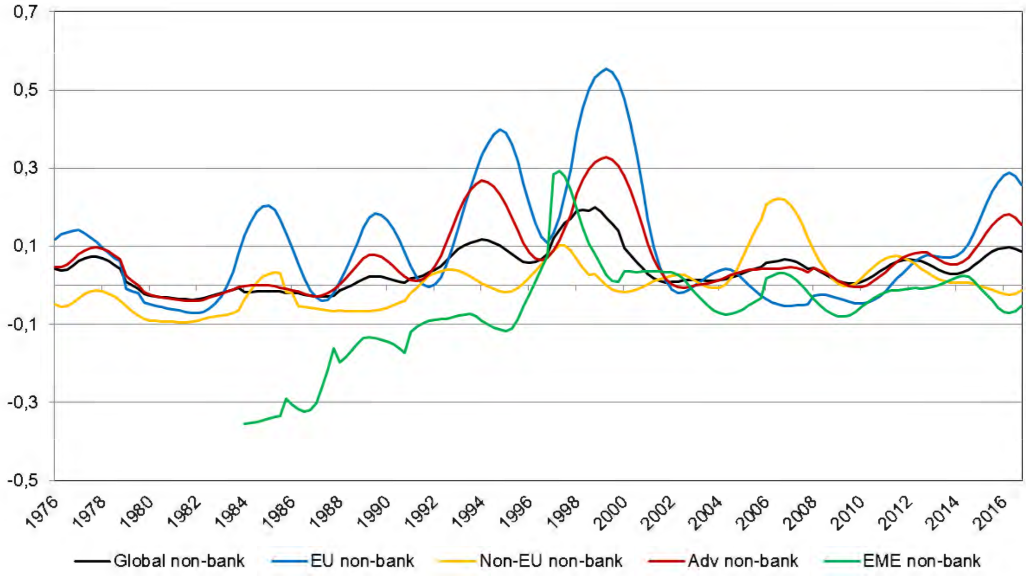


Note: ADV = Advanced economy jurisdictions; EME = Emerging Market Economy jurisdictions; EU = European Union jurisdictions; NONEU = Non-European Union jurisdictions. See Table C.1 for the list of jurisdictions. A negative value indicates a decrease in the level of outstanding credit in real terms, while increases are present when the growth cycles are positive. A turning point is therefore indicated when the growth rate cycle reaches zero. Results based on available data from 1972 - 2017.

These results are further confirmed with turning-point analyses. The approach followed is similar to that described in Section 5.4, and the results are shown in Table C.3 in A. In summary turning point analysis show that while on average the duration of bank and non-bank cycles is similar within countries, it is clear that there are large differences when examining results on a country-by-country basis. Furthermore, we find that on average the amplitude of the non-bank cycle is higher than the bank cycle. While this is related to the relative size of the non-bank sector (for example, the non-bank credit cycle amplitude is much larger than the bank credit cycle's amplitude in countries where non-bank credit is relatively small), even for countries where non-bank credit is roughly

Figure 6.6 Correlation across country groups, non-bank credit

(Average for country pairs, Spearman rank, 5-year rolling windows)



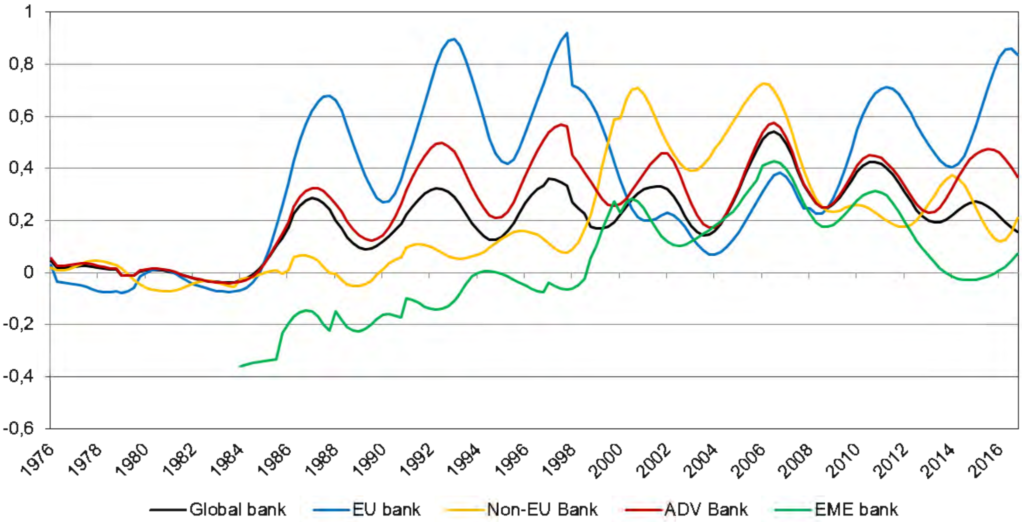
the same size as bank credit (i.e., Great Britain, France, The Netherlands) the amplitude of the non-bank cycle still exceeds that of the bank credit cycle. Even though the amplitude of bank cycles does not differ significantly from those of non-banks in the country groupings used in Figure 6.5, both turning point analyses and frequency-based filters indicate that the relationship between cycles is not constant over time.

Given that the amplitude and duration of cycles vary significantly across countries and over time, and the correlation of country-groupings change over time (Figures 6.6 and 6.7), insight into global non-bank credit cycles is gained by examining the number of countries in upward phases over time.

Figure 6.8 shows the percentage of countries in the sample in which the bank and non-bank credit cycle is in an upward phase. We observe that upward phases in several countries at the same time are more common for bank credit than for non-bank credit, and the number of countries experiencing an upward phase in the non-bank cycle at one point in time never falls below 30%, while for banks this falls to 19%.

Figure 6.7 Correlation across country groups, bank credit

(Average for country pairs, Spearman rank, 5-year rolling windows)



The peaks of the majority of countries in an upward phase of the bank credit cycle (i.e., 1973, 1987, 1997, 2007) coincide with global crisis periods: the OPEC oil price shock in 1973, Stock market crash in 1987, the Asian financial crisis in 1997, and the global financial crisis in 2007. Generally, during these periods the number of countries experiencing an upward phase in the non-bank credit cycles does not exceed the number of countries experiencing an upward phase in the bank credit cycle, except in 2000. The period leading up to the global financial crisis appears special: more than 90 per cent of the countries (i.e., 33 out of the 36 countries in the sample) were in an upward phase of the bank credit cycle – this is the highest number during the sample period (Figure 6.8, blue shaded area).

Upturns in non-bank credit within countries are somewhat less synchronised (Figure 6.8, green shaded area). This is confirmed by grouped-country analyses as shown in Figure 6.6. Correlations in non-bank credit were the highest in EMEs during the run-up to the Asian crisis, and in the EU during 1999-2001, at the time of the convergence plays in the run-up to monetary union. The highest number of countries experiencing an upward cycle in non-bank credit also occurred at this time (79% i.e. 27 out of 34 countries with available non-bank cycle data).

The higher percentage of countries in an upward phase at the same time

Figure 6.8 Percentage of countries in an upward phase in the same period for bank and non-bank cycles across countries

Note: We show the percentage of countries in the sample in which the bank and non-bank credit cycle is in an upward phase. Upward phases in several countries at the same time are more common for bank credit than for non-bank credit, and the number of countries experiencing an upward phase in the non-bank cycle at one point in time never falls below 30%, while for banks this falls to 19%.

for bank credit, on average, could be attributed to a number of reasons. Banks are more homogeneous as a group of lenders, and the large banks often operate across borders and generally not within only one country. Moreover, they are regulated as banks, i.e., they are a group of financial intermediaries recognized and regulated as banks across the globe. As discussed, non-bank credit is provided by a more diverse group of lenders, where the underlying financial intermediaries may not be as internationally connected as their banking counterparts. But at the same time, non-bank credit flows can be driven by international developments, especially when provided through the international bond market, which is highly integrated, while differences in interest rates can trigger large portfolio flows.

6.3.3 Cycles within countries: non-bank versus bank

To determine whether non-bank credit is a substitute for bank credit, i.e., acts as a spare tyre when bank credit contracts, the synchronization between the bank and non-bank growth cycles has to be determined. To do this, we investigate the relationship between non-bank and bank credit cycles within each individual country. Given that the relationships appear to be time-dependent, the synchronization of non-bank and bank cycles within countries is studied using various rolling-window Spearman rank correlation coefficients, following the Jordà et al., 2017 approach.[13] The Spearman rank correlation coefficient is calculated using credit cycles given that monotone, but not necessarily linear, relationships will be captured.[14] The windows are backward- looking, therefore the value for the 5-year rolling window at 1990Q1 will include the correlation between 1985Q1 and 1990Q1. If there is a high correlation between bank and non-bank credit cycles within a country, this would indicate that the spare tyre argument is not valid. A low correlation indicates a substitution between bank and non-bank credit, i.e., one cycle is expanding when the other is contracting in the most extreme case.

Individual level country results are shown in (Figures 6.9), and the same pattern is observed in several countries (Figures 6.7). The first general takeaway here is that generally, the relationship between bank and non-bank credit tends to change over time. Specifically in Mexico, Portugal, Norway, and Korea, the negative correlation between banks and non-bank credit cycles is noteworthy from the 1990s onward, showing that bank and non-bank credit cycles are not synchronized. However, in several countries, the correlation has increased over time, for example Chile and China, where bank and non-bank credit is moving

[13] Results reported in Figure 6.9. Pearson correlation coefficients were also calculated, yielding similar results.

[14] We denote the Spearman correlation coefficient between countries i and j calculated over the 5-year window ending at time t as $s_t^{i,j}$ for $i, j = 1, \ldots n$, where n is the cross-sectional sample size. A global measure of association between country-pairs for cycles can then be constructed as the average of these bilateral correlations as follows:

$$\bar{s}_t = \frac{\sum_i \sum_{j<i} s_t^{i,j}}{N}; \qquad N = \frac{n(n-1)}{2}$$

Figure 6.9 Spearman rank correlation: Bank and non-bank cycles within a country

(20 quarter rolling windows)

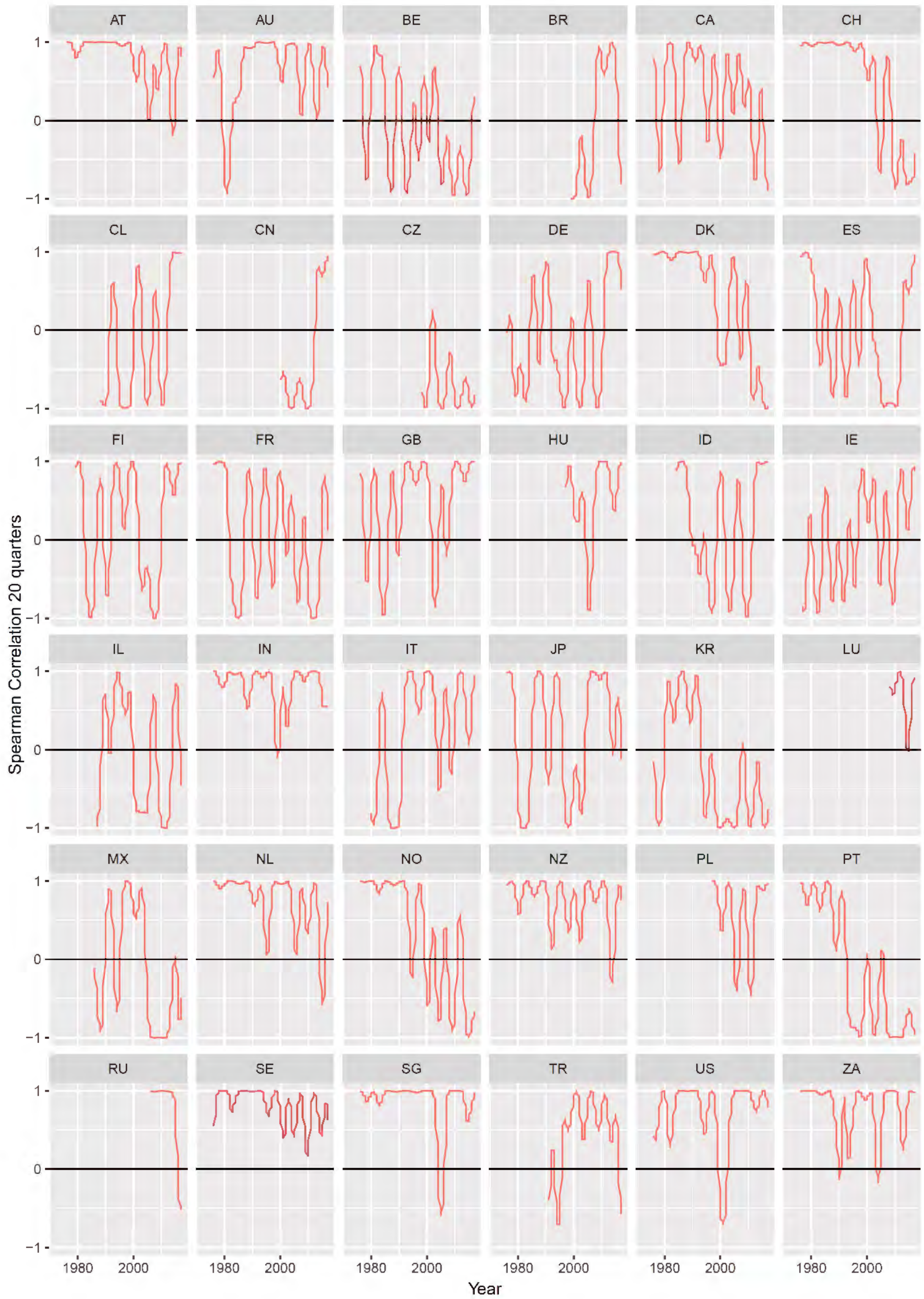
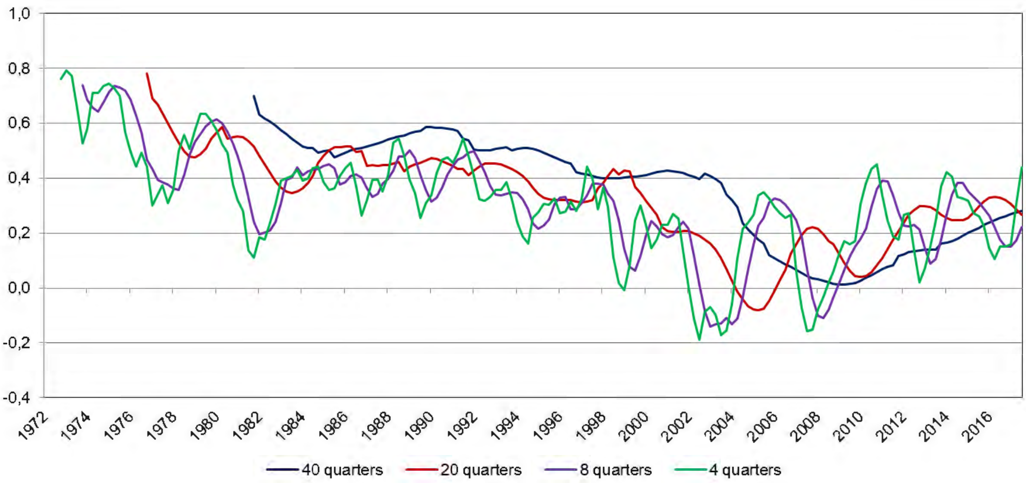


Figure 6.10 Correlation for non-bank and bank credit growth, within countries

(Spearman rank rolling window, average of all available countries over time)



in a more synchronized manner. It is also interesting to note that for a group of economies, the 5-year rolling window Spearman rank correlation is only briefly negative in the sampling period. This group consists of Hungary, the Netherlands, New Zealand, Poland, and South Africa. The US and Great Britain show a similar pattern - indicating that non-bank and bank credit typically do not act as substitutes in these countries. For Norway, the correlation seems to decrease over time, thus indicating that non-bank credit has been acting more like a spare tyre from early 2000, while the opposite seems to be observed in Germany. There are also a handful of countries where the case for high or low correlation is not evident - for example Canada, Finland and France. In these countries non-bank credit makes up a relatively large share of total credit (see Figures 6.2), but the relationship between bank and non-bank credit fluctuates over time.

At a global level on average, the correlation between bank and non-bank credit growth has decreased from the 1970s up to the early 2000s (Figure 6.10). It remained relatively low for several years and increased again during the past decade. During the period leading up to the global financial crisis, non-bank and bank credit were less synchronized on average within the 36 countries in our dataset. This confirms the results in Figure 6.8, showing that while the number of countries experiencing an upward phase in non-bank credit was high, the correlation of the non-bank cycles amongst country pairs was relatively low, and thus the upward phases were occurring at different growth rates amongst countries. For banks, however, the number of banks in an upward phase was high, and the correlation of the bank cycles was high amongst country-pairs, indicating similar growth rates in bank credit amongst country pairs.

Overall, it is clear that, while in certain countries there is an inverse relationship between bank and non-bank cycles, this relationship varies over time and differs amongst countries.

6.4 Non-bank Credit and Financial Crises

Given the apparent link between bank and non-bank credit growth cycle movements to financial crises periods, this section examines the implications of credit growth for the incidence of financial crises. Bank credit growth is an important indicator of crisis episodes as shown in Schularick et al., 2012 and international efforts to enhance the stability of the financial system have placed it at the center of macroprudential tools, such as the countercyclical capital buffer. However, the focus has been mainly on bank or total credit to nonfinancial private sector irrespective of the type of financial institution extending said credit. Our analysis suggests that bank and non-bank credit cycles are not synchronized and that the relationship between the credit cycles changes over time, therefore both may be useful in predicting the incidence of crises. Moreover, not all crises are similar and separately considering bank and non-bank credit may provide useful insights given their importance for systemic banking or currency crises that many countries have experienced. In order to stay close to the literature that has focussed on credit growth, our benchmark analysis examines the effects of credit growth on the probability of crises episodes. However, we complement our findings by studying the effect of credit cycles on the probability of crises as well, which we report in the Appendix. We use the credit cycles' measure computed and discussed in Section 6.3 above. The results are similar across the two specifications, which could also be interpreted as an indication that the cyclical component of credit matters mostly for crises prediction.

We base our analysis on the crises database of Laeven et al., 2012, which includes all systemic banking, currency, and sovereign debt crises during the period 1970–2011 and covers all countries for which we have computed non-bank credit. We have opted for this database versus the databases in Reinhart et al., 2009 or Jordà et al., 2017, because we are interested in the differential effects of bank and non-bank credit on distinct types of crisis episodes, and we have restricted our analysis to the period after 1971 because of the lower availability of computed non-bank credit before. The Laeven – Valencia database spans 162 countries, but we will restrict our analysis to the sample of 38 countries including Greece and Thailand such that we do not lose crisis observations (we obtain similar, but stronger, results if we exclude Greece and Thailand). Overall, our sample includes 79 crisis episodes out of which 42 are exclusively systemic banking crises, 28 exclusively currency crises, 6 exclusively sovereign crises, 2 jointly currency and sovereign crises, and 1 jointly systemic, currency and sovereign crisis. Detailed information about crises dates is shown in Table C.4.

We create a binary crisis indicator $C^{j}_{i,t}$, which takes value one if a crisis of type $j \in \{all, systemic, currency, sovereign\}$ occurred in county i in year t, and takes value zero otherwise. In particular, we estimate the following logit-panel regression:

$$\text{logit}\big(C^{j}_{i,t}\big) = \beta X_{i,t-1} + \gamma \Gamma_{i,t-1} + \theta_i + \varepsilon_{i,t},$$

where $\text{logit}(C_{i,t}) = \log\big(C_{i,t}/(1 - C_{i,t})\big)$ is the log of the odds ratio, $X_{i,t-1} = \Delta^4 \log(\textit{real credit}_{t-1}) = \log(\textit{real credit}_{t-1}) - \log(\textit{real credit}_{t-5})$ is the lagged four-year growth of real total credit, real bank credit or real non-bank credit, $\Gamma_{i,t-1}$ is the vector of lagged control variables, and θ_i are the cross-sectional (country) fixed effects. Since crises are rare events, the use of fixed effects creates identification issues. As a result, we choose to use country-level fixed effects, but no time-fixed effects. We include the lagged one-year real GDP growth ($\Delta^1 \log(\textit{real gdp}_{t-1})$) and lagged inflation, which are also used in other studies (Demirgüç–Kunt et al., 1998; Danielsson et al., 2018).[15] Other control variables could include the growth

[15]We have also considered four-year real GDP growth and four-year inflation as control variables, and we obtain the same results. We have opted for one-year lagged control because GDP and

in house prices and equity prices, the current account deficit, the government debt-to-GDP.[16]

Table 6.1 presents the results for total real credit to the non-financial business sector. The four-year lagged credit growth enters with a positive and statistically significant coefficient when all crises or systemic crises alone are considered; and the significance survives the inclusion of control variables. However, credit growth does not successfully predict currency crises in our sample. The results for sovereign crises alone should be taken with a grain of salt given the small number of observations. In addition to the real credit growth, lagged real GDP growth and lagged inflation enter with negative and positive signs, respectively, when all crises episodes are considered, but only inflation is statistically significant. Thus, countries that experience lower inflation are less likely to experience a crisis episode. In order to evaluate the ability of real credit growth to act as a leading indicator for crises, we compute the area under the receiving operating curve (AUROC) when all other controls are removed from the regression. AUROC has been suggested by Schularick et al., 2012 amongst others as a useful statistic to evaluate the ability of indicators to accurately signal the true incidence of a crisis.[17] We obtain an AUROC of 0.71 similar to Schularick and Taylor who find an AUROC of 0.72, providing some confidence in the ability of credit growth to predict crisis episodes in our sample. Finally, the estimated marginal effects show that a 1% increase in credit growth translates into about 0.1% increase in the probability of general crises and systemic crises episodes.

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inflation should respond to economic condition faster than credit aggregates and may capture the incidence of crises in a timelier manner.

[16]Kiley, 2018 reconsiders the role of asset prices and current account deficits as leading indicators of financial crises and finds that they are superior to credit growth. Danielsson et al., 2018 shows that abnormally low asset price volatility is a good indicator of crises through history for a large sample of countries.

S. J. Lee et al. (2020) show that a composite indicator of asset prices, lending standards, financial and non-financial leverage predicts international crises episodes. Catão et al., 2014 find that the ratio of net foreign liabilities to GDP is a good predictor of external crises. We do not include these indicators because the purpose of our analysis is not to find alternative indicators that perform better than credit growth in crisis prediction models, but rather to examine the differential effect of bank credit and non-bank credit on the incidence of different types of crises.

[17]AUROC equal to 0.5 suggests that the indicator is not informative, while AUROC of 1 suggests that the indicator can perfectly discriminate crisis episodes.

Table 6.1 Total credit: Prediction of financial crises

	All crises		Systemic crises		Currency crises		Sovereign crises	
Δ^4 *real t credit*$_{t-1}$	2.09**	2.66***	3.20***	3.29***	0.71	1.31	2.11	4.04**
	(0.92)	(0.79)	(0.94)	(1.01)	(1.23)	(1.13)	(2.54)	(2.05)
Δ^1 *real gdp*$_{t-1}$		-3.62		-0.31		1.44		-53.63**
		(3.72)		(3.47)		(7.40)		(27.00)
inflation$_{t-1}$		3.10**		0.72		3.61**		-5.01
		(1.53)		(2.38)		(1.68)		(10.31)
Num. of Obs.	972	972	883	883	459	459	103	103
Pseudo R^2	0.07	0.08	0.06	0.06	0.04	0.06	0.03	0.56
AUROC	0.71	0.72	0.68	0.68	0.64	0.71	0.66	0.95
Marginal effects								
Δ^4 *real t credit*$_{t-1}$	0.08	0.10	0.09	0.09				0.006

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All of the specifications include fixed effects. The standard errors, reported in parentheses, are robust and clustered at the country level. We report marginal effects only when the coefficients are statistically significant.

Tables 6.2 and 6.3 present the results for the same regressions when real bank and non-bank credit growth are considered as leading indicators, respectively.[18] As mentioned, our objective is to study the differential impact of bank and non-bank credit on the probability of different types of crises. Indeed, bank credit real growth can act as a leading indicator for all crises and especially systemic crises, as its coefficient is statistically significant even after the inclusion of control variables, and the AUROC is 0.70 when bank credit real growth is the only explanatory variable. The estimated marginal effects show that a 1% increase in bank credit growth translates into about 0.08% increase in the probability of general crises and systemic crises. Nevertheless, bank credit is not useful to discriminate currency (or sovereign) crises.

Turning to Table 6.3, real non-bank credit growth is also useful to predict crises episodes but its success concentrates on currency rather than on systemic crises. This is in contrast to bank or total credit which were mainly useful in predicting systemic crises episodes. The estimated marginal effects show that a 1% increase in credit growth translates into about 0.05% increase in the probability

[18]Tables C.5 and C.6 in the Appendix report the results when bank and non-bank credit cycles are considered as leading indicators. We exclude Greece and Thailand from the analysis, since we have not computed non-bank credit cycles for these two countries.

Table 6.2 Bank credit: Prediction of financial crises

	All crises		Systemic crises		Currency crises		Sovereign crises	
Δ^4 *real b credit*$_{t-1}$	1.41**	2.14***	3.10***	3.32***	-0.04	0.42	0.21	3.28
	(0.69)	(0.60)	(0.88)	(0.94)	(0.83)	(1.80)	(0.84)	(2.54)
Δ^1 *real gdp*$_{t-1}$		-4.68		-1.72		0.81		-54.05**
		(3.75)		(3.89)		(0.11)		(25.29)
inflation$_{t-1}$		3.58**		1.58		3.29		-4.45
		(1.58)		(3.00)		(1.86)		(10.50)
Num. of Obs.	962	962	873	873	453	453	103	103
Pseudo R^2	0.06	0.08	0.07	0.07	0.04	0.05	0.00	0.55
AUROC	0.70	0.71	0.70	0.70	0.62	0.67	0.54	0.94
Marginal effects								
Δ^4 *real b credit*$_{t-1}$	0.06	0.08	0.08	0.09				

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All of the specifications include fixed effects. The standard errors, reported in parentheses, are robust and clustered at the country level. We report marginal effects only when the coefficients are statistically significant.

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of general crises and currency crises episodes.

The differential ability of bank and non-bank credit to act as leading indicators for systemic and currency crises, respectively, is the main takeaway and contribution of our analysis with respect to crisis predictability. As mentioned, the literature has agreed that credit growth is an important indicator for crises, but we augment this argument by showing that not all types of credit to the nonfinancial business sector should be treated equally.[19]

Bank credit is useful to explain systemic banking crises, while non-bank credit could better explain currency crises due to the reversal of capital flows resulting in sudden stops.

Although additional analysis is needed to uncover the underlying mechanism, we conjecture that panics related to sudden stops around currency crises could be better tied to reversals in non-bank credit. One explanation is that non-bank credit provision – and in particular bond financing – is at times more closely related to movements in international capital flows compared to bank credit

[19]It should be noted that non-bank credit real growth—as well as total credit growth—appear to be useful in predicting sovereign crises when control variables are included in the regressions. Despite the statistically significant coefficient, the low marginal effects in combination with the few incidents of sovereign crises could cast some doubt on the robustness of this result.

Table 6.3 Non-bank credit: Prediction of financial crises

	All crises		Systemic crises		Currency crises		Sovereign crises	
Δ^4 *real nb credit*$_{t-1}$	1.24**	1.20**	0.45	0.43	1.51**	1.58**	3.56	3.69***
	(0.54)	(0.54)	(0.47)	(0.46)	(0.69)	(0.79)	(2.58)	(0.79)
Δ^1 *real gdp*$_{t-1}$		-2.59		0.96		3.37		-51.23**
		(3.68)		(4.17)		(7.76)		(27.39)
inflation$_{t-1}$		1.61		-1.41		3.12		-7.66
		(1.62)		(2.08)		(2.07)		(9.12)
Num. of Obs.	953	953	864	864	444	444	103	103
Pseudo R^2	0.06	0.07	0.03	0.03	0.07	0.08	0.19	0.58
AUROC	0.70	0.70	0.58	0.63	0.71	0.73	0.79	0.95
Marginal effects								
Δ^4 *real nb credit*$_{t-1}$	0.05	0.05			0.04	0.04		0.003

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All of the specifications include fixed effects. The standard errors, reported in parentheses, are robust and clustered at the country level. We report marginal effects only when the coefficients are statistically significant.

supported by deposits in domestic currency. Non-financial corporations tend to borrow in foreign currency – included in our non-bank credit measure – when interest rates abroad are relatively lower (Keloharju et al., 2001; Habib et al., 2008). A reversal in capital inflows worsens the ability of firms to rollover their debt, while, at the same time, domestic authorities may need to maintain higher interest rates to support the peg. The latter can be harmful for the domestic economy especially if corporations are highly indebted and cannot substitute external for more expensive internal credit. Overall, the ability to maintain the peg may be curtailed when non-bank credit from abroad is elevated amplifying the consequences of adverse shocks that can lead to currency crises. While total credit has been a leading indicator in several studies on early warning indicators for currency crises (based on the overview of the literature in Frankel et al., 2010), we are not aware of studies that have pointed specifically to the role of non-bank credit.

6.5 Conclusion

Our results show that the cyclical properties of bank non-bank credit differ from those of bank credit. First, the duration of non-bank credit cycles is, on average, similar to bank credit cycles, while the amplitude of non-bank cycles is larger generally for non-bank credit cycles than for bank credit cycles. Within countries the relationship between non-bank and bank credit cycles changes over time and generally has become less synchronised in the period up to the global financial crisis. Second, non-bank credit cycles are highly synchronised with bank credit cycles in some countries, but not in others. Third, we find that non-bank credit is less synchronised than bank credit across countries.

Moreover, we argue that monitoring non-bank credit can bring additional information as a leading indicator for periods of financial instability, in particular currency crises. We complement the existing literature on leading indicators for financial crises by showing that bank credit is a useful indicator for systemic banking crises, while non-bank credit is helpful to predict currency crises, but not vice versa. These findings highlight the value added of monitoring non-bank credit next to the traditional focus on bank credit. Hence, we believe that the large and growing literature on financial cycles and credit cycles could be complemented by research on cycles in non-bank credit.

A key difference of non-bank credit to bank credit, is that non-bank credit can be provided by a range of non-bank suppliers with different business models, both domestically and abroad. This more heterogeneous nature also explains why data availability is more comprehensive and available for bank credit than non-bank credit. Given data limitations for non-bank financial intermediaries, we based our analysis on a measure of non-bank credit that has been derived as a residual. Hence, one direction that further research could take is to complement our macro approach with a more disaggregated approach. Such analysis would have the advantage of being able to investigate the properties of non-bank credit from national and foreign sources, the different components of non-bank credit (i.e., debt securities and non-bank loans) and the different sources of non-bank credit, such as investment funds, insurance companies, pension funds, governments.

and foreign lenders. However, this would probably come at the expense of cross-country coverage and long sample periods.

Chapter Seven

Conclusion and policy implications

The growth of the NBFI sector has outpaced that of the banking sector over the past decade - at a global level and also in South Africa. This dissertation focused on measuring the NBFI sector and its interconnectedness with banks. It also estimated the traditional financial cycle in South Africa and analysed the non-bank cycle for several economies. The first part of this chapter summarizes our main findings. Section 7.2 presents recommendations for policymakers concerned with financial stability. Finally, Section 7.3 identifies areas for further research.

7.1 Summary of findings

The first aim of this study was to measure the portion of non-bank financial intermediaries that perform bank-like activities, but are not subject to bank-like regulation and are not, under normal circumstances, backed by the central bank in South Africa. We measure the size of individual non-bank financial intermediaries and note the regulations in place. We show that the growth of non-bank financial intermediaries – particularly investment funds – in South Africa has outpaced that of banks over the past several years. Based on available data we find high levels of direct interconnectedness, specifically between MMFs and banks. Moreover, we measure indirect interconnectedness – i.e. portfolio overlap – among MMFs in South Africa and find that the portfolios of the MMFs are very similar. We find that non-bank financial intermediaries in South Africa has increased in relative size over the past decade and that the interconnectedness of the financial sector could hide unexpected contagion channels.

The second aim of the study is to develop a model of the spread of contagion to quantify higher-order exposures more realistically taking into account the various assets included in the South African financial system. In the simulation our findings establish that a counterparty exposure can be underestimated if the chains of indirect exposures are not taken into account - emphasising the necessity to incorporate indirect exposures in exposure calculations. We show that even taking direct and indirect linkages into consideration still leaves a gap in our understanding of how stress might spread. More specifically, we show that the exposures of financial institutions in the South African financial system to the default of one one of its *big six* banks may be severely underestimated when only considering direct and indirect exposures, because additional losses accumulate to institutions over time that are not covered by such direct and indirect exposures.

We show that these higher-order losses depend strongly on the network structure of the SA financial system and the robustness of its institutions. This highlights the importance of granular data, and network-based modeling approaches that take advantage of these data to properly estimate exposures. We introduce the higher-order share of exposure (HSE), which expresses what percentage of an exposure is overlooked when only considering direct and indirect exposures. We show that the HSE is close to 100% to for a substantial part of the South African financial system, and that in other parts the HSE rises steeply during times of financial distress, when exposures matter most.

The third aim of the study is to determine the role of non-bank credit in the economy. To do this we identify the characteristics of the financial cycle in South Africa. Financial cycles provide a broad indication of the changes in risks to financial stability and therefore provide an important monitoring tool for policymakers. Taking into account the phase of a country's financial cycle is also important when implementing macroprudential policy, given that the impact of policies may differ depending on the phase of the cycle. An understanding of financial cycles is therefore a key element informing macroprudential policy-making. We use credit, house prices, and equity prices as indicators to extract the financial cycle in South Africa using three different methodologies. We report the results obtained from traditional turning-point analysis, frequency-based filters, and unobserved components models, finding evidence of a financial cycle in South Africa that has a longer duration and a larger amplitude than the traditional business cycle. We also find that periods where financial conditions are stressed, are associated with peaks in the financial cycle, suggesting that the estimated financial cycle may have similar leading indicator properties to financial conditions or stress indices.

We find that developments in credit and house price variables are important component indicators that serve to capture the financial cycle in South Africa. The case for including equity prices is less clear. Equity prices in South Africa are less correlated with these variables, but may be influenced by external variables such as international developments and foreign-exchange movements, and as a result provide important additional information.

Our finding that the financial cycle is distinct from the business cycle in South Africa differs, for example, from Leamer, 2007 and Leamer, 2015 finding for the US. In this regard, the existence of a separate South African financial cycle is more closely aligned with the findings of Borio, 2014b, Claessens, Kose, and Terrones, 2012 and Barrell et al., 2020.

To better understand credit in the economy we also focus on credit provided by non-banks and identify the cyclical properties of non-bank credit cycles. Our results show that the cyclical properties of bank non-bank credit differ from those of bank credit. First, the duration of non-bank credit cycles is, on average, similar to bank credit cycles, while the amplitude of non-bank cycles is generally larger for non-bank credit cycles than for bank credit cycles. Within countries, the relationship between non-bank and bank credit cycles changes over time and generally has become less synchronised in the period up to the global financial crisis. Second, non-bank credit cycles are highly synchronised with bank credit cycles in some countries, but not in others. Third, we find that non-bank credit is less synchronised than bank credit across countries. Moreover, we argue that monitoring non-bank credit can bring additional information as a leading indicator for periods of financial instability, in particular, currency crises. We complement the existing literature on leading indicators for financial crises by showing that bank credit is a useful indicator for systemic banking crises, while non-bank credit is helpful to predict currency crises, but not vice versa. These findings highlight the value added of monitoring non-bank credit next to the traditional focus on bank credit. Hence, we believe that the large and growing literature on financial cycles, and credit cycles could be complemented by research on cycles in non-bank credit.

7.2 Policy implications

The assets held by non-bank financial intermediaries amount to roughly 50 per cent of GDP in South Africa and could become a risk to the financial system if not properly measured and understood. Currently, one of the biggest concerns is data limitations. These gaps include the lack of comprehensive data to understand and measure the activities of finance companies, hedge funds, P2P lending platforms, limited data on securitisation schemes, and limited broker-dealer and securities financing data. There are also limited information and data available on the less formal sectors, for example stokvels. Moreover, the types of linkages that these intermediaries have amongst each other and to the banking sector are not well understood.

Furthermore, while this thesis is not aimed at exploring the question of whether NBFI activities should be regulated to the same extent as banks, it does highlight that there is currently room for regulatory arbitrage in South Africa and that it is possible that additional regulation in the banking sector could result in increased non-bank financial intermediation, possibly even by encouraging banks to operate in the NBFI space. Specifically, given the structural small retail deposit base and difficulty in obtaining long-term funding from the capital markets, challenges remain for South African banks to fully comply with the minimum net-stable funding ratio (NSFR), which became effective from 2018. Unintended consequences of this implementation could include lower economic growth due to banks having to curtail (long-term) credit extension, and an increase in the cost of funding, which translates to a higher cost of lending. This could also result in increased credit extension by non-bank financial intermediaries or more operations by banks in the NBFI space.

South Africa's financial system is unique in several important ways in comparison to other jurisdictions that participate in the FSB's annual monitoring exercise. Two differences are of particular importance (i) pension funds and insurance corporations hold a relatively large share of financial assets; and (ii) banks are more dependent on non-bank financial intermediaries for funding. These characteristics should be taken into account prior to introducing regulations designed for countries lacking these characteristics.

Despite having the potential to create and amplify risks to financial stability, the NBFI sector can provide useful and legitimate financial intermediation throughout economic fluctuations. In a relatively small open economy with a concentrated financial sector, such as South Africa, the NBFI sector has a role to play in improving liquidity and possibly even increasing competition between financial intermediaries. It is therefore worth noting that when considering regulatory responses to NBFI, the expected cost and benefits of potential policy interventions should be taken into account.

Our findings in Chapter 4 highlight the importance of granular data for systemic risk assessments. In addition to addressing data gaps in the non-banking space it is crucial to understand the linkages in the system to inform us on how stress might spread in crisis times. This is particularly relevant for South Africa – a small open economy with a high direct linkages among financial intermediaries.

Third, an important policy implication of our finding that the financial cycle is distinct from the business cycle in South Africa is that the coordination of monetary and macroprudential policies could be more complicated. Distinct financial and business cycles that are not always well correlated and are in different phases for extended periods of time, mean that conflicts are more likely. The interactions between distinct business and financial cycles may also play an important role in determining the characteristics of recessions and recoveries in the real economy.

Critically important from a financial-stability perspective is that failure to take medium-term financial cycles into account and focusing only on the business cycle may allow vulnerabilities to build up unattended. Policymakers may contain recessions in the short run, but at the expense of larger crises down the road. Finally, despite data challenges, we provide evidence to support the view that monitoring the non-bank credit cycle is important from a policy perspective – especially as a leading indicator for periods of financial instability.

7.3 Further research areas

This thesis scratches the surface of better understanding non-bank financial intermediation in South Africa. Additional work could be done to refine our measure of the *risky* portion of the NBFI sector or to develop alternative measures. Moreover, indicators to measure specific risks – including credit risk transfer, liquidity and maturity transformation, and leverage should be refined. Further analysis on systemic importance of entities – particularly non-bank financial entities – could be conducted to better understand the role of these intermediaries in providing liquidity during stressed times, and to better understand how stress can spread through the system.

While the measure for the financial cycle in South Africa is proposed in this thesis – more work could be done to include additional variables in this measure. It would be useful to consider the impact of global financial conditions and capital flows on South Africa's financial cycle. Finally, a key difference between credit provided by banks and that provided by non-banks is that non-bank credit can be provided by a range of suppliers, both domestically and abroad. This more heterogeneous nature also explains why data availability is much better for bank credit than non-bank credit. We therefore had to base our analysis in Chapter 6 on a measure of non-bank credit that has been derived as a residual. Hence, one direction that further research could take is to complement our macro approach with a more disaggregated approach. Given the data limitations, this would probably come at the expense of cross-country coverage and long sample periods. However, it would have the advantage of being able to investigate the properties of non-bank credit from national and foreign sources, the different components of non-bank credit (i.e., debt securities and non-bank loans) and different sources of non-bank credit, such as investment funds, insurance companies, pension funds, governments, and foreign lenders.

REFERENCES

Abrahams, R (2017). “Financial inclusion in South Africa: A review of the literature”. In: *Southern African Accounting Association*, pp. 632–661.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi (2015). “Systemic risk and stability in financial networks”. In: *American Economic Review* 105.2, pp. 564–608.

Acharya, Viral V (2009). “A theory of systemic risk and design of prudential bank regulation”. In: *Journal of financial stability* 5.3, pp. 224–255.

Acharya, Viral V and David Skeie (2011). “A model of liquidity hoarding and term premia in inter-bank markets”. In: *Journal of Monetary Economics* 58.5, pp. 436–447.

Acharya, Viral V and Sascha Steffen (2012). “Analyzing systemic risk of the European banking sector”. In: *Handbook on Systemic Risk, JP Fouque and J. Langsam, eds., Cambridge University Press, Forthcoming*.

Adrian, Tobias, Adam B Ashcraft, and Nicola Cetorelli (2013). *Shadow bank monitoring*. Vol. 1. September.

Adrian, Tobias and Hyun S. Shin (2009). “Money, liquidity, and monetary policy”. In: *American Economic Review: Papers & Proceedings* 99.2, pp. 600–605.

Adrian, Tobias (2017). *Shadow Banking and Market Based Finance Speech and SUERF*. Helsinki.

Aikman, D, A Haldane, and B. Nelson (2015). “Curbing the credit cycle”. In: *Economic Journal* 125.585, pp. 1072–1109.

Aikman, David, Jonathan Bridges, Stephen Burgess, Richard Galletly, Iren Levina, Cian O’Neill, and Alexandra Varadi (July 2018). *Measuring risks to UK financial stability*. Bank of England Working Papers 738. Bank of England.

Akhtaruzzaman, Md, Sabri Boubaker, and Ahmet Sensoy (2021). “Financial contagion during COVID–19 crisis”. In: *Finance Research Letters* 38, p. 101604.

Aldasoro, Iñaki and Ivan Alves (2018). “Multiplex interbank networks and systemic importance: An application to European data”. In: *Journal of Financial Stability* 35, pp. 17–37.

Aldasoro, Iñaki, Domenico Delli Gatti, and Ester Faia (2017). “Bank networks: Contagion, systemic risk and prudential policy”. In: *Journal of Economic Behavior & Organization* 142, pp. 164–188.

Aldasoro, Iñaki, Anne-Caroline Hüser, and Christoffer Kok (2020). “Contagion accounting”. In.

Allen, Franklin and Douglas Gale (2000). “Financial contagion”. In: *Journal of political economy* 108.1, pp. 1–33.

Allen, Franklin, Aneta Hryckiewicz, Oskar Kowalewski, and Günseli Tümer-Alkan (2014). “Transmission of financial shocks in loan and deposit markets: Role of interbank borrowing and market monitoring”. In: *Journal of Financial Stability* 15, pp. 112–126.

Allen, L. Steve (2003). *Financial Risk Management: A Practitioner's Guide to Managing Market and Credit Risk (with CD-ROM)*. Vol. 119. John Wiley & Sons.

Altman, Edward I and Anthony Saunders (1997). “Credit risk measurement: Developments over the last 20 years”. In: *Journal of banking & finance* 21.11-12, pp. 1721–1742.

Amini, Hamed, Rama Cont, and Andreea Minca (2013). “Resilience to contagion in financial networks”. In: *Mathematical finance*.

— (2016). “Resilience to contagion in financial networks”. In: *Mathematical finance* 26.2, pp. 329–365.

Analytics, Genesis (2015). *Securities Lending Guide for South Africa*.

Anand, Kartik, Iman van Lelyveld, Ádám Banai, Soeren Friedrich, Rodney Garratt, Grzegorz Hałaj, Jose Fique, Ib Hansen, Serafın Martınez Jaramillo, Hwayun Lee, et al. (2018). “The missing links: A global study on uncovering financial network structures from partial data”. In: *Journal of Financial Stability* 35, pp. 107–119.

Andrianaivo, Mihasonirina and Charles Amo Yartey (2010). "Understanding the growth of African financial markets". In: *African Development Review* 22.3, pp. 394–418.

Ardila, Diego and Didier Sornette (2016). "Dating the financial cycle with uncertainty estimates: a wavelet proposition". In: *Finance Research Letters* 19, pp. 298–304.

Aymanns, Christoph, Fabio Caccioli, J Doyne Farmer, and Vincent WC Tan (2016). "Taming the Basel leverage cycle". In: *Journal of financial stability* 27, pp. 263–277.

Aymanns, Christoph, J Doyne Farmer, Alissa M Kleinnijenhuis, and Thom Wetzer (2018). "Models of financial stability and their application in stress tests". In: *Handbook of Computational Economics*. Vol. 4. Elsevier, pp. 329–391.

Bank for International Settlements (2014). *84th Annual Report*.

— (2015). *85th Annual Report*.

— (2016). *86th Annual Report*.

Bank of England (2017). *Market-based finance: a macroprudential view*. Speech at Asset Management Derivatives Forum, Dana Point, California.

— (2018). *Financial Stability Report*.

Bardoscia, Marco, Stefano Battiston, Fabio Caccioli, and Guido Caldarelli (2015). "DebtRank: A microscopic foundation for shock propagation". In: *PloS one* 10.6, e0130406.

— (2017). "Pathways towards instability in financial networks". In: *Nature Communications* 8.1, pp. 1–7.

Bargigli, Leonardo, Giovanni Di Iasio, Luigi Infante, Fabrizio Lillo, and Federico Pierobon (2015). "The multiplex structure of interbank networks". In: *Quantitative Finance* 15.4, pp. 673–691.

Barrell, Ray, Dilruba Karim, and Corrado Macchiarelli (2020). "Towards an understanding of credit cycles: do all credit booms cause crises?" In: *The European Journal of Finance* 26.10, pp. 978–993.

Bats, J. V. and A. C. F. J. Houben (2017). *Bank-based versus market-based financing: implications for systemic risk*. DNB Working Paper 577.

Battiston, Stefano, Guido Caldarelli, and Marco D'Errico (2016). "The financial system as a nexus of interconnected networks". In: *Interconnected networks*. Springer, pp. 195–229.

Battiston, Stefano, Marco D'Errico, and Stefano Gurciullo (2016). "DebtRank and the network of leverage". In: *The Journal of Private Equity* 20.1, pp. 58–71.

Battiston, Stefano, Michelangelo Puliga, Rahul Kaushik, Paolo Tasca, and Guido Caldarelli (2012). "Debtrank: Too central to fail? financial networks, the fed and systemic risk". In: *Scientific reports* 2.1, pp. 1–6.

Becker, B and V. Ivashina (2014). "Cyclicality of credit supply: firm level evidence". In: *Journal of Monetary Economics* 62.C, pp. 76–93.

Bengtsson, E (2016). "Investment funds, shadow banking and systemic risk". In: *Journal of Financial Regulation and Compliance* 24.1.

Bernanke, Ben S (2013). *The Federal Reserve and the financial crisis*. Princeton University Press.

Bernanke, Ben S, Carol C Bertaut, Laurie Demarco, and Steven B Kamin (2011). "International capital flows and the return to safe assets in the united states, 2003-2007". In: *FRB International Finance Discussion Paper* 1014.

Black, S. and A. Munro (2010). *Why issue bonds offshore?* BIS Working Paper No. 334.

Bluhm, Christian, Ludger Overbeck, and Christoph Wagner (2016). *Introduction to credit risk modeling*. Chapman and Hall/CRC.

Bluhm, Marcel, Ester Faia, and Jan Pieter Krahnen (2014). "Endogenous banks' networks, cascades and systemic risk". In.

Board, Financial Stability (2009). "Guidance to assess the systemic importance of financial institutions, markets and instruments: initial considerations". In: *Report to G20 finance ministers and governors*.

Borio, Claudio (2003). "Towards a macroprudential framework for financial supervision and regulation?" In: *CESifo Economic Studies* 49.2, pp. 181–215.

— (2014a). "Macroprudential frameworks:(too) great expectations?" In: *Macroprudentialism*, pp. 29–45.

Borio, Claudio (2014b). “The financial cycle and macroeconomics: What have we learnt?” In: *Journal of Banking & Finance* 45, pp. 182–198.

Borio, Claudio and Philip Lowe (2002). “Assessing the risk of banking crises”. In: *BIS Quarterly Review* December, pp. 43–54.

Bosch, Adél and Steven F Koch (2020). “The South African Financial Cycle and its Relation to Household Deleveraging”. In: *South African Journal of Economics* 88.2, pp. 145–173.

Bosch, Adél and Franz Ruch (2013). “An Alternative Business Cycle Dating Procedure for S outh A frica”. In: *South African Journal of Economics* 81.4, pp. 491–516.

Boshoff, WH (2005). “The properties of cycles in South African financial variables and their relation to the business cycle”. In: *South African journal of economics* 73.4, pp. 694–709.

— (2010). “Band-pass filters and business cycle analysis: High frequency and medium-term deviation cycles in South Africa and what they measure”. In: *Universeteit Stellenbosch University, Working Paper* 200.

Bouchaud, Jean-Philippe (2010). *Price impact. Encyclopedia of quantitative finance.*

Boyd, John H, Mark Gertler, et al. (1994). “Are banks dead?” In: *The Region* 8.Sep, pp. 22–26.

Bravo-Benitez, Bernardo, Biliana Alexandrova-Kabadjova, and Serafin Martinez-Jaramillo (2016). “Centrality measurement of the Mexican large value payments system from the perspective of multiplex networks”. In: *Computational Economics* 47.1, pp. 19–47.

Brunetti, Celso, Jeffrey H Harris, Shawn Mankad, and George Michailidis (2019). “Interconnectedness in the interbank market”. In: *Journal of Financial Economics* 133.2, pp. 520–538.

Brunnermeier, Markus K and Lasse Heje Pedersen (2009). “Market liquidity and funding liquidity”. In: *The review of financial studies* 22.6, pp. 2201–2238.

Bry, Gerhard and Charlotte Boschan (1971). *Cyclical Analysis of Time Series: Selected Procedures and Computer Programs.* National Bureau of Economic Research, Inc.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2018). “Fintech, regulatory arbitrage, and the rise of shadow banks”. In: *Journal of Financial Economics* 130.3, pp. 453–483.

Burns, Arthur F and Wesley C Mitchell (1946). “Measuring Business Cycles. New York: National Bureau of Economic Research”. In: *BurnsMeasuring Business Cycles1946*.

Burrows, Oliver, David Learmonth, Jack McKeown, and Richard Williams (2012). “RAMSI: a top-down stress-testing model developed at the Bank of England”. In: *Bank of England Quarterly Bulletin*, Q3.

Caballero, Ricardo J (2010). *The" other" imbalance and the financial crisis*. Tech. rep. National Bureau of Economic Research.

Caballero, Ricardo J and Alp Simsek (2013). “Fire sales in a model of complexity”. In: *The Journal of Finance* 68.6, pp. 2549–2587.

Caccioli, Fabio, J Doyne Farmer, Nick Foti, and Daniel Rockmore (2015). “Overlapping portfolios, contagion, and financial stability”. In: *Journal of Economic Dynamics and Control* 51, pp. 50–63.

Caccioli, Fabio, Munik Shrestha, Cristopher 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, Jian, Frederik Eidam, Anthony Saunders, and Sascha Steffen (2018). “Syndication, interconnectedness, and systemic risk”. In: *Journal of Financial Stability* 34, pp. 105–120.

Calimani, Susanna, Grzegorz Hałaj, and Dawid Żochowski (2017). *Simulating fire-sales in a banking and shadow banking system*. Tech. rep. ESRB Working Paper Series.

Canabarro, Eduardo and Michael Pykhtin (2014). *Counterparty Risk Management: Measurement, Pricing and Regulation*. 15-146. Risk Books.

Catão, A. V. Luis and Gian Maria Milesi-Ferretti (2014). “External liabilities and crises”. In: *Journal of International Economics* 94.1, pp. 18–32.

Cespa, Giovanni and Thierry Foucault (2014). “Illiquidity contagion and liquidity crashes”. In: *The Review of Financial Studies* 27.6, pp. 1615–1660.

Che, Ms Natasha Xingyuan and Yoko Shinagawa (2014). *Financial Soundness indicators and the characteristics of financial cycles.* 14. International Monetary Fund.

Christiano, L. and T. Fitzgerald (2003). “The band-pass filter”. In: *International Economic Review* 44.2, pp. 435–465.

Chui, M., E. Kuruc, and P. Turner (2016). *A new dimension to currency mismatches in the emerging markets: non-financial companies.* BIS Working Papers No. 550.

Cizel, J., J. Frost, A. Houben, and P. Wierts (2016). “Effective macroprudential policy: cross-sector substitution from price and quantity Measures”. In: *Journal of Money, Credit and Banking* 51.5, pp. 1209–1235.

Claessens, Stijn and M Ayhan Kose (2017). “Macroeconomic implications of financial imperfections: a survey”. In.

Claessens, Stijn, M Ayhan Kose, and Marco E Terrones (2011). “Financial cycles: what? how? when?” In: *International seminar on macroeconomics.* Vol. 7. 1. JSTOR, pp. 303–344.

— (2012). “How do business and financial cycles interact?” In: *Journal of International economics* 87.1, pp. 178–190.

Claessens, Stijn and L. Ratnovski (2014). *What is Shadow Banking.* IMF working paper 25.

Clerc, Laurent, Sam Langfield, Alberto Giovannini, Richard Portes, Martin Scheicher, Tuomas A Peltonen, et al. (2016). “Indirect contagion The policy problem. No 9/January 2016”. In.

Cogley, Timothy and James M Nason (1995). “Effects of the Hodrick-Prescott filter on trend and difference stationary time series Implications for business cycle research”. In: *Journal of Economic Dynamics and control* 19.1-2, pp. 253–278.

Commission, Financial Crisis Inquiry et al. (2011). *The financial crisis inquiry report: The final report of the National Commission on the causes of the financial and economic crisis in the United States including dissenting views.* Cosimo, Inc.

Committee, Basel et al. (2014). “Supervisory framework for measuring and controlling large exposures”. In: *Bank for International Settlements.*

Constâncio, Vitor (2014). “The European crisis and the role of the financial system”. In: *Journal of Macroeconomics* 39, pp. 250–259.

Cont, Rama, Arseniy Kukanov, and Sasha Stoikov (2014). “The price impact of order book events”. In: *Journal of financial econometrics* 12.1, pp. 47–88.

Cont, Rama, Amal Moussa, et al. (2010). “Network structure and systemic risk in banking systems”. In: *Edson Bastos e, Network Structure and Systemic Risk in Banking Systems (December 1, 2010)*.

Cont, Rama and Eric Schaanning (2017). “Fire sales, indirect contagion and systemic stress testing”. In.

— (2019). “Monitoring indirect contagion”. In: *Journal of Banking & Finance* 104, pp. 85–102.

Cont, Rama and Lakshithe Wagalath (2013). “Running for the exit: distressed selling and endogenous correlation in financial markets”. In: *Mathematical Finance* 23.4, pp. 718–741.

— (2016). “Fire sales forensics: Measuring endogenous risk”. In: *Mathematical Finance* 26.4, pp. 835–866.

Copeland, Adam, Antoine Martin, and Michael Walker (2014). “Repo runs: Evidence from the tri-party repo market”. In: *The Journal of Finance* 69.6, pp. 2343–2380.

Coval, Joshua and Erik Stafford (2007). “Asset fire sales (and purchases) in equity markets”. In: *Journal of Financial Economics* 86.2, pp. 479–512.

Creal, Drew, Siem Jan Koopman, and Eric Zivot (2010). “Extracting a robust US business cycle using a time-varying multivariate model-based bandpass filter”. In: *Journal of applied econometrics* 25.4, pp. 695–719.

Crouhy, Michel, Dan Galai, and Robert Mark (2000). “A comparative analysis of current credit risk models”. In: *Journal of Banking & Finance* 24.1-2, pp. 59–117.

Danielsson, J., M. Valenzuela, and I. Zer (2018). “Learning from history: Volatility and financial crises”. In: *Review of Financial Studies* 31.7, pp. 2774–2805.

Dembiermont, C., M. Drehmann, and S. Muksakunratana (2013). “How much does the private sector really borrow? A new database for total credit to the private non-financial sector”. In: *BIS Quarterly Review* March, pp. 65–81.

Demirgüç–Kunt, A. and E. Detragiache (1998). “The determinants of banking crises in developing and developed countries”. In: *IMF Staff Papers* 45.1, pp. 81–109.

Diamond, Douglas W and Philip H Dybvig (1983). “Bank runs, deposit insurance, and liquidity”. In: *Journal of political economy* 91.3, pp. 401–419.

Drehmann, M., C. Borio, and K. Tsatsaronis (2012). *Characterising the financial cycle: don't lose sight of the medium term.* BIS Working Papers No 380.

Du Plessis, SA (2006). “Reconsidering the business cycle and stabilisation policies in South Africa”. In: *Economic Modelling* 23.5, pp. 761–774.

Duca, John V et al. (2014). “What drives the shadow banking system in the short and long run”. In: *Federal Reserve Bank of Dallas Research Department working paper* 1401.

Duffie, Darrell and Kenneth J Singleton (2012). *Credit risk: pricing, measurement, and management.* Princeton university press.

Durdu, B. C. and M. Zhong (2019). *Understanding bank and nonbank credit cycles: a structural exploration.* Federal Reserve Board Finance and Economics Discussion Series 031.

Edwards, Franklin R and Frederic S Mishkin (1995). *The decline of traditional banking: Implications for financial stabilityand regulatory policy.* Tech. rep. National Bureau of Economic Research.

Eisenberg, Larry and Thomas H Noe (2001). “Systemic risk in financial systems”. In: *Management Science* 47.2, pp. 236–249.

Elliott, Matthew, Benjamin Golub, and Matthew O Jackson (2014). “Financial networks and contagion”. In: *American Economic Review* 104.10, pp. 3115–53.

Elsinger, Helmut et al. (2009). *Financial networks, cross holdings, and limited liability.* Oesterreichische Nationalbank Austria.

Elsinger, Helmut, Alfred Lehar, and Martin Summer (2006). “Risk assessment for banking systems”. In: *Management science* 52.9, pp. 1301–1314.

Ely, Bert (1993). “Savings and loan crisis”. In: *Fortune Encyclopedia of Economics. New York: Time Warner.*

Eren, Egemen, Andreas Schrimpf, Vladyslav Sushko, et al. (2020). *US dollar funding markets during the Covid-19 crisis-the money market fund turmoil*. Tech. rep. Bank for International Settlements.

European Systemic Risk Board (2016). *Macroprudential policy beyond banking: an ESRB strategy paper*. Frankfurt.

Farmer, J Doyne, Alissa M Kleinnijenhuis, Paul Nahai-Williamson, and Thom Wetzer (2020). “Foundations of system-wide financial stress testing with heterogeneous institutions”. In.

Farrell, Greg and Esti Kemp (2020). “Measuring the financial cycle in South Africa”. In: *South African Journal of Economics* 88.2, pp. 123–144.

Fed, US (2018). *Single-Counterparty Credit Limits for Bank Holding Companies and Foreign Banking Organizations*. Tech. rep.

Ferguson, Roger W and Group of Thirty (Washington DC). Working Group on Macroprudential Policy (2010). *Enhancing financial stability and resilience: macroprudential policy, tools, and systems for the future*. Group of Thirty.

Financial Sector Conduct Authority (2014). *Board Notice 90 of 2014*.

Financial Stability Board (2013). *Policy framework for strengthening oversight and regulation of shadow banking entities*. Basel.

— (2018). *Global monitoring report on Non-bank financial intermediation*. Basel.

Fiordelisi, Franco, Maria-Gaia Soana, and Paola Schwizer (2013). “The determinants of reputational risk in the banking sector”. In: *Journal of Banking & Finance* 37.5, pp. 1359–1371.

Firer, Colin and Mike Staunton (2002). “102 Years of South African financial market history”. In: *Investment Analysts Journal* 31.56, pp. 57–65.

Fostel, A. and J. Geanakoplos (2008). “Leverage cycles and the anxious economy”. In: *American Economic Review* 98.4, pp. 1211–1244.

Frankel, J. A. and G. Saravelos (2010). *Are leading indicators of financial crises useful for assessing country vulnerability?* NBER Working Paper 16047.

FSB (2011). *Shadow Banking: Strengthening Oversight and Regulation*. Recommendations of the Financial Stability Board.

Gai, Prasanna, Andrew Haldane, and Sujit Kapadia (2011). "Complexity, concentration and contagion". In: *Journal of Monetary Economics* 58.5, pp. 453–470.

Gai, Prasanna and Sujit Kapadia (2010). "Contagion in financial networks". In: *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 466.2120, pp. 2401–2423.

Galati, Gabriele, Irma Hindrayanto, Siem Jan Koopman, and Marente Vlekke (2016a). "Measuring financial cycles in a model-based analysis: Empirical evidence for the United States and the euro area". In: *Economics Letters* 145.C, pp. 83–87.

— (2016b). "Measuring financial cycles in a model-based analysis: Empirical evidence for the United States and the euro area". In: *Economics Letters* 145, pp. 83–87.

Gambacorta, L., J. Yang, and K. Tsatsaronis (2014). "Financial structure and growth". In: *BIS Quarterly Review* March, pp. 21–35.

Ghosh, Atish R, Jonathan D Ostry, and Mahvash S Qureshi (2016). "When do capital inflow surges end in tears?" In: *American Economic Review* 106.5, pp. 581–85.

Glasserman, Paul and H Peyton Young (2015). "How likely is contagion in financial networks?" In: *Journal of Banking & Finance* 50, pp. 383–399.

Goldstein, Itay, Hao Jiang, and David T Ng (2017). "Investor flows and fragility in corporate bond funds". In: *Journal of Financial Economics* 126.3, pp. 592–613.

Gonzalez, R. B., J. Lima, and L. Marinho (2015). *Business and financial cycles: an estimation of cycles' length focusing on Macroprudential Policy*. Working Papers Series 385. Central Bank of Brazil, Research Department.

Gordon, Jeffrey N and Christopher M Gandia (2014). "Money market funds run risk: Will floating net asset value fix the problem". In: *Colum. Bus. L. Rev.*, p. 313.

Gorton, Gary and Andrew Metrick (2012a). "Getting up to speed on the financial crisis: a one-weekend-reader's guide". In: *Journal of Economic Literature* 50.1, pp. 128–50.

Gorton, Gary and Andrew Metrick (2012b). “Securitized banking and the run on repo”. In: *Journal of Financial Economics* 104.3. Market Institutions, Financial Market Risks and Financial Crisis, pp. 425–451. ISSN: 0304-405X. DOI: https://doi.org/10.1016/j.jfineco.2011.03.016. URL: http://www.sciencedirect.com/science/article/pii/S0304405X1100081X.

Gouriéroux, Christian, Jean-Cyprian Héam, and Alain Monfort (2013). “Liquidation equilibrium with seniority and hidden CDO”. In: *Journal of Banking & Finance* 37.12, pp. 5261–5274.

Graaf, Cornelis SL de, Drona Kandhai, and Christoph Reisinger (2018). “Efficient exposure computation by risk factor decomposition”. In: *Quantitative Finance* 18.10, pp. 1657–1678.

Granville, Brigitte and Sana Hussain (2017). “Eurozone cycles: An analysis of phase synchronization”. In: *International Journal of Finance & Economics* 22.2, pp. 83–114.

Greenwood, Robin, Augustin Landier, and David Thesmar (2015). “Vulnerable banks”. In: *Journal of Financial Economics* 115.3, pp. 471–485.

Grinderslev, Oliver Juhler, Paul Lassenius Kramp, Anders Farver Kronborg, and Jesper Pedersen (2017). *Financial cycles: What are they and what do they look like in Denmark?* Tech. rep. Danmarks Nationalbank Working Papers.

Gupta, Mayank and Massimiliano Caporin (2018). “The Evolution of Shadow Banking System in Emerging Economies: The Role of Entrusted Loans in China’s Capital Market”. In: *Available at SSRN 3179922*.

Habib, M. M. and M. Joy (2008). *Foreign-currency bonds,currency choice and the role of uncovered and covered interest parity.* ECB Working Paper No 947.

Hamilton, James D (2018). “Why you should never use the Hodrick-Prescott filter”. In: *Review of Economics and Statistics* 100.5, pp. 831–843.

Hannoun, Hervé (2013). “Sovereign risk in bank regulation and supervision: Where do we stand?” In: *BIS Paper* 72y.

Harding, Don and Adrian Pagan (2002). “Dissecting the cycle: a methodological investigation”. In: *Journal of Monetary Economics* 49.2, pp. 365–381.

— (2006). “Synchronization of cycles”. In: *Journal of econometrics* 132.1, pp. 59–79.

Harding, Don and Adrian Pagan (2016). *The econometric analysis of recurrent events in macroeconomics and finance*. Princeton University Press.

Harutyunyan, Artak, Mr Alexander Massara, Giovanni Ugazio, Goran Amidzic, and Richard Walton (2015). *Shedding light on shadow banking*. International Monetary Fund.

Harvey, Andrew C (1990). "Forecasting, structural time series models and the Kalman filter". In.

Harvey, Andrew C and Albert Jaeger (1993). "Detrending, stylized facts and the business cycle". In: *Journal of applied econometrics* 8.3, pp. 231–247.

Harvey, Andrew C and Thomas M Trimbur (2003). "General model-based filters for extracting cycles and trends in economic time series". In: *Review of Economics and Statistics* 85.2, pp. 244–255.

Havemann, Roy Charles (2019). "Lessons from South African bank failures 2002 to 2014". PhD thesis. Stellenbosch: Stellenbosch University.

Heij, Christiaan, JM Schumacher, Bernard Hanzon, and C Praagman (1997). "System dynamics in economic and financial models". In.

Herman, A., D. Igan, and J. Solé (2017). "The macroeconomic relevance of bank and nonbank credit: an exploration of U. S. data". In: *Journal of Financial Stability* 32, pp. 124–141.

Hiebert, Paul, Ivan Jaccard, and Yves Stephan Schüler (2018). "Contrasting financial and business cycles: Stylized facts and candidate explanations". In: *Journal of Financial Stability* 38.1, pp. 72–80.

Hoerova, Marie, Cornelia Holthausen, Florian Heider, et al. (2009). "Liquidity hoarding and interbank market spreads: the role of counterparty risk". In: *2009 Meeting Papers*. 929. Society for Economic Dynamics.

IMF (2010). *South Africa : Detailed Assessment of Compliance on Basel Core Principles for Effective Banking Supervision*. Tech. rep.

— (2015). *The asset management industry and financial stability*. Global Financial Stability Report, Chapter 3, Washington.

International Monetary Fund (2016). *GLobal Financial Stability Report, October*.

Jokivuolle, Esa (2018). *Shadow banking: Financial intermediation beyond banks.* SUERF Conference Proceedings No. 2018/1].

Jones, Garett (2016). *Banking Crises: Perspectives from the New Palgrave Dictionary of Economics.* Springer.

Jordà, Òscar, Moritz Schularick, Alan M Taylor, et al. (2014). "Private credit and public debt in financial crises". In: *FRBSF Economic Letter* 7.

Jordà, Òscar, Moritz Schularick, and Alan M Taylor (2017). "Macrofinancial History and the New Business Cycle Facts". In: *NBER Macroeconomics Annual 2016, volume 31.* Ed. by Martin Eichenbaum and Jonathan A. Parker. Chicago: University of Chicago Press.

Jorion, Philippe and Gaiyan Zhang (2009). "Credit contagion from counterparty risk". In: *The Journal of Finance* 64.5, pp. 2053–2087.

Kabundi, Alain and Asithandile Mbelu (2021). "Estimating a time-varying financial conditions index for South Africa". In: *Empirical Economics* 60.4, pp. 1817–1844.

Kaufman, George G (2014). "Shadow Banking Within and Across National Borders". In.

Kaufman, George G and Larry R Mote (1994). "Is banking a declining industry? A historical perspective". In: *Economic Perspectives* 18.May, pp. 2–21.

Keloharju, M. and M. Niskanen (2001). "Why do firms raise foreign currency denominated debt? Evidence from Finland". In: *European Financial Management* 7.4, pp. 481–496.

Kemp, Esti (2017). "Measuring shadow banking activities and exploring its interconnectedness with banks in South Africa". In: *SARB Occassional Papers.*

Kemp, Esti, René van Stralen, Alexandros Vardoulakis, and Peter Wierts (2018). "The Non-Bank Credit Cycle". In.

Kiley, M. T. (2018). *What macroeconomic conditions lead financial crises?* Finance and Economics Discussion Series 2018-038. Washington.

Kim, S., M. C. Plosser, and J. A. C. Santos (2017). *Macroprudential policy and the revolving door of risk: lessons from leveraged lending guidance.* Federal Reserve Bank of New York Staff Reports No. 815.

Kleinnijenhuis, Alissa M., Charles Goodhart, and J. Doyne Farmer (2021). *Systemic Implications of the Bail-In Design*. Tech. rep. Forthcoming Working Paper.

Koopman, Siem Jan, Andrew C Harvey, Jurgen A Doornik, and Neil Shephard (2000). "STAMP 6.0: Structural time series analyser, modeller and predictor". In: *London: Timberlake Consultants*.

Koopman, Siem Jan and André Lucas (2005). "Business and default cycles for credit risk". In: *Journal of Applied Econometrics* 20.2, pp. 311–323.

Laeven, Luc and Fabian Valencia (2012). *Systemic banking crises database: an update*. IMF Working Paper 12/163.

— (2018). *Systemic banking crises revisited*. International Monetary Fund.

Langfield, S. and M. Pagano (2016). "Bank bias in Europe: effects on systemic risk and growth". In: *Economic Policy* 31.85, pp. 51–106.

Leamer, Edward E (2007). *Housing is the business cycle*. Tech. rep. National Bureau of Economic Research.

— (2015). "Housing really is the business cycle: what survives the lessons of 2008–09?" In: *Journal of Money, Credit and Banking* 47.S1, pp. 43–50.

Lee, S. J., K. E. Posenau, and V. Stebunovs (2020). "The Anatomy of financial vulnerabilities and banking crises". In: *Journal of Banking and Finance* 112, p. 105334.

Li, Lei, Yi Li, Marco Macchiavelli, and Xing Alex Zhou (2020). "Runs and Interventions in the Time of COVID-19: Evidence from Money Funds". In: *Available at SSRN 3607593*.

Linsley, Philip M and Philip J Shrives (2005). "Transparency and the disclosure of risk information in the banking sector". In: *Journal of Financial regulation and Compliance* 13.3, pp. 205–214.

Liu, Zijun, Stephanie Quiet, and Benedict Roth (2015). "Banking sector interconnectedness: what is it, how can we measure it and why does it matter?" In: *Bank of England Quarterly Bulletin*, Q2.

Llewellyn, David T (2009). "Financial innovation and a new economics of banking: Lessons from the financial crisis". In: *Challenges for Monetary Policy-makers in Emerging Markets* 1.

Luttrell, D. Harvey Rosenblum and Jackson Thies (2012). *Understanding the risks inherent in shadow banking: A primer and practical lessons learned.* Staff paper 577.

Lux, Thomas (2016). “A model of the topology of the bank–firm credit network and its role as channel of contagion”. In: *Journal of Economic Dynamics and Control* 66, pp. 36–53.

McCabe, Patrick E (2010). *Cross Section of Money Market Fund Risks and Financial Crises.* DIANE Publishing.

McCulley, Paul (2007). “Teton reflections”. In: *PIMCO Global Central Bank Focus* 2.

Mehrling, Perry, Z Pozsar, J Sweeney, and D Neilson (2012). “Shadow banking, Central banking, and the Future of Global Finance”. In: *City University London, November.*

Menden, Christian and Christian R Proaño (2017). “Dissecting the financial cycle with dynamic factor models”. In: *Quantitative Finance* 17.12, pp. 1965–1994.

Mendoza, Enrique G. and Marco E Terrones (2012). *An anatomy of credit booms and their demise.* NBER Working Paper 18379.

Molina-Borboa, José Luis, Serafin Martınez-Jaramillo, Fabrizio López-Gallo, and Marco van der Leij (2015). “A multiplex network analysis of the mexican banking system: link persistence, overlap and waiting times”. In: *Journal of Network Theory in Finance* 1.1, pp. 99–138.

Montagna, Mattia and Christoffer Kok (2016). “Multi-layered interbank model for assessing systemic risk”. In.

Montagna, Mattia and Thomas Lux (2017). “Contagion risk in the interbank market: A probabilistic approach to cope with incomplete structural information”. In: *Quantitative Finance* 17.1, pp. 101–120.

Osborn, Denise R et al. (1995). “Moving average detrending and the analysis of business cycles”. In: *Oxford Bulletin of Economics and Statistics* 57.4, pp. 547–558.

Patalano, Robert and Caroline Roulet (2020). “Structural developments in global financial intermediation: The rise of debt and non-bank credit intermediation”. In.

Pozsar, Zoltan (2008). “The rise and fall of the shadow banking system”. In: *Regional Financial Review* 44, pp. 1–13.

Pozsar, Zoltan, Tobias Adrian, Adam Ashcraft, and Hayley Boesky (2010). “Shadow banking”. In: *New York* 458.458, pp. 3–9.

Raddatz, Claudio and Sergio L Schmukler (2012). *On the international transmission of shocks: Micro-evidence from mutual fund portfolios*. The World Bank.

Ranciere, Romain, Aaron Tornell, and Frank Westermann (2008). “Systemic crises and growth”. In: *The Quarterly Journal of Economics* 123.1, pp. 359–406.

Reinhart, C. M. and K. S. Rogoff (2009). *This time is different: Eight centuries of financial folly*. Princeton University Press.

Rodríguez-Moreno, María and Juan Ignacio Peña (2013). “Systemic risk measures: The simpler the better?” In: *Journal of Banking & Finance* 37.6, pp. 1817–1831.

Rogers, Leonard CG and Luitgard AM Veraart (2013). “Failure and rescue in an interbank network”. In: *Management Science* 59.4, pp. 882–898.

Rünstler, Gerhard and Marente Vlekke (2018). “Business, housing, and credit cycles”. In: *Journal of Applied Econometrics* 33.2, pp. 212–226.

SARB (2016a). *Banks BA900 Economic Returns*. Tech. rep. South African Reserve Bank.

— (2016b). *Financial Stability Review, Second Edition 2016*. Tech. rep. South African Reserve Bank.

Schich, Sebastian (2010). “Insurance companies and the financial crisis”. In: *OECD Journal: Financial market trends* 2009.2, pp. 123–151.

Schularick, Moritz and Alan M Taylor (2012). “Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008”. In: *American Economic Review* 102.2, pp. 1029–1061.

Schüler, Yves Stephan (Mar. 2018). *Detrending and financial cycle facts across G7 countries: mind a spurious medium term!* Working Paper Series. European Central Bank.

Schüler, Yves Stephan, Paul Hiebert, and Tuomas A Peltonen (2015a). “Characterising financial cycles across europe: One size does not fit all”. In: *Available at SSRN* 2539717.

Schüler, Yves Stephan, Paul Hiebert, and Tuomas A Peltonen (2015b). *Characterising the financial cycle: a multivariate and time-varying approach.* ECB Working Papers Series No 1846.

— (2015c). "Characterising the financial cycle: a multivariate and time-varying approach". In.

Shin, Hyun S. (2013). *The second phase of global liquidity and its impact on emerging economies.* Keynote address at Asia economic policy conference: prospects for Asia and the global economy.

Shleifer, Andrei and Robert Vishny (2011). "Fire sales in finance and macroeconomics". In: *Journal of Economic Perspectives* 25.1, pp. 29–48.

South African Reserve Bank (2017). *Financial Stability Review.*

— (2018). *Quarterly bulletin.*

Strohsal, T., C. R. Proaño, and J. Wolters (2015). *Characterizing the financial cycle: Evidence from a frequency domain analysis.* Discussion Papers 22/2015. Deutsche Bundesbank, Research Centre.

Timmer, Yannick (2018). "Cyclical investment behavior across financial institutions". In: *Journal of Financial Economics* 129.2, pp. 268–286.

Valle e Azevedo, Joao, Siem Jan Koopman, and Antonio Rua (2006). "Tracking the business cycle of the euro area: A multivariate model-based bandpass filter". In: *Journal of Business & Economic Statistics* 24.3, pp. 278–290.

Verona, Fabio (2016). "Time–frequency characterization of the US financial cycle". In: *Economics Letters* 144, pp. 75–79.

Vittas, D (2016). *The Role of Non-Bank Financial Intermediaries (with Particular Reference to Egypt.* World Bank Policy research working paper 1892.

Wiersema, Garbrand, Alissa M Kleinnijenhuis, Thom Wetzer, and J Doyne Farmer (2019). "Scenario-free analysis of financial stability with interacting contagion channels". In.

Yeoh, Peter (2011). "Financial Crisis Inquiry Commission Report: Anything New". In: *Bus. L. Rev.* 32, p. 150.

APPENDIX

Appendix A

In order to more accurately measure the narrow measure of NBFI, activities that do not adhere to the FSB definition of the narrow measure of NBFI and cannot be classified into an economic function (Table 1) is removed from the OFI measure, while activities by pension funds and insurance corporations that are related to credit intermediation or the facilitation thereof is added. This narrowing down, according to economic functions, is done in order to identify risks in the non-banking sector.

Activities that are excluded comprise mainly activities that do not participate in or facilitate credit intermediation and do not exhibit risks similar to those of bank; thus, they cannot be categorised into an economic function. If non-banks' activities are prudentially consolidated into a banking group and subject to Basel-like regulatory requirements, they are also excluded. In South Africa, this results in equity funds, REITs, real-estate funds, trust companies, PBSs, stokvels, peer-to-peer lending platforms and banks' investment in their own securitisation schemes being removed from the OFI measure in order to arrive at the narrow measure of NBFI. The fund of funds' investment into equity funds is also excluded. The reasons that these entities or activities are not included in the narrow measure of NBFI are discussed below. Note that there is a case to be made to exclude a portion of the brokers' activities given that most of these are banks; however, due to a lack of data and the conservative approach of the exercise the entire estimate is classified.

Equity funds

Equity funds is the largest OFI subcategory that is excluded from the narrow meausure of NBFI, given that investing in an equity fund involves no credit intermediation (i.e. there is no agreement to repay an investment into equities at a later date) and no maturity mismatch (these funds have a minimum of 80%

of their total portfolio invested in equity). This is an example of a more risky investment, where investors could lose their entire investment, while at the same time also being exposed to the possibility of higher returns than with a traditional bank deposit. For the same reason, funds that invest in equity funds are excluded from the narrow measure. In September 2016 equity funds held assets to the value of R479 billion under management, while funds that invested in equity funds amounted to R80 billion.

Real-estate funds

Real-estate funds in South Africa invest predominantly in both domestic and foreign REITs, other equities and other property funds. Furthermore, all REITs in South Africa are equity REITs. Since equity REITs do not involve any credit intermediation (as in the case of mortgage REITs), REITs and real-estate funds are excluded from the shadow banking measure. In September 2016, REITs and real-estate funds in South Africa had approximately R357 billion and R79 billion assets under management respectively.

Trust companies

The assets of trust companies are excluded from the shadow banking measure, since the primary goal of this type of company is the oversight of the administration of trust assets. Credit extended by trusts is made to trust beneficiaries. Therefore, this would be similar to borrowing against a pension fund investment. As the beneficiary is using his/her own assets, this is not seen as credit extension. Trust companies make up a much smaller part of OFIs, with assets amounting to R60 billion in September 2016.

Participation bond schemes (PBSs)

PBSs are involved in credit intermediation; however, there is no risk of a run on these funds given the regulations that are in place (see Annexure B for more details). Therefore, from the FSB's perspective, PBSs are not included in the narrow measure of shadow banking. Assets of PBSs have declined over time and at the end of the third quarter of 2016 amounted to R1.3 billion.

Banks' exposure to securitisation

Banks' investments into securitisation activities are also excluded from the narrow shadow banking measure, given that banks invest in their own securitisation products, and capital is then held against these investments. As at September 2016, this amounted to R22.7 billion (out of the R58.5 billion of total securitisation activities).

Stokvels

A stokvel, or a savings club, is an association of individuals who make regular contributions to a common pool of savings. This pool of savings is generally distributed (fully or partially) to each contributor on a rotational basis. Traditionally, stokvel contributions were collected physically and also distributed to members in the same manner. However, members have started to deposit their contributions into a bank account and other investment instruments. The aim of these savings clubs can vary from buying groceries in bulk at reduced prices or assistance with funeral costs. According to African Response (2014), there are different types of stokvels, with stokvels aimed at saving for funerals (i.e. burial societies) by far the most popular segment of the stokvel universe in South Africa (65%). Stokvels aimed at saving represents roughly 30% and groceries 21%, while stokvels formed for investment purposes represent only 4% of the stokvel industry.11 Stokvel segments with the aim of pooling together money to save are not regarded as shadow banking, given that there is no credit intermediation that takes place. An argument can be made to include stokvels in the narrow measure of NBFI, if there is credit extension to non-members, and loans of a longer maturity are based on short-term funding. However, currently stokvels are not included in South Africa's narrow measure, given the general lack of data indicating credit intermediation or maturity transformation. If the nature of these savings clubs changes, or if more disaggregated data becomes available, this stance should be reconsidered.

Peer-to-peer (P2P) lending

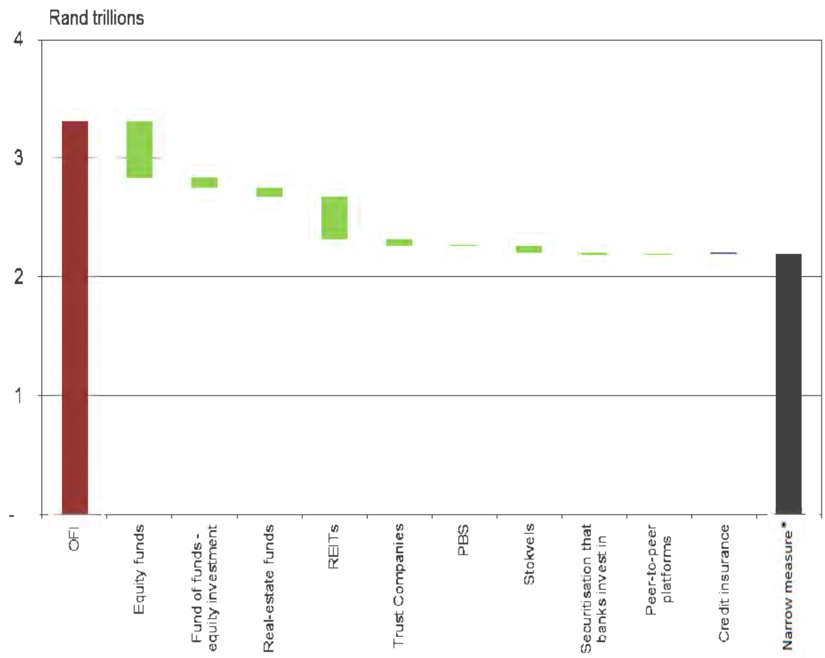
P2P lending platforms provide consumers with an alternative funding source to bank loans and at the same time provide net savers with additional investment opportunities. While in certain instances the shadow banking label is appropriate for P2P lending platforms, some of these entities do not have any maturity or liquidity mismatches or leverage (at least not for on-balance sheet activities). If, however, P2P vehicles obtain (part of) their funding through securitisation, these activities could be classified into EF5 (securitisation-based credit intermediation and funding of financial entities). In South Africa's case, P2P lending activities remain fairly small with an estimated R78 million worth of assets under management. However, its growth is recognised and the market conduct regulator might soon consider regulatory options. Currently P2P lending platforms are not included in South Africa's shadow banking measure when following the FSB approach. Detailed data on the operations of P2P lending platforms are limited.

Included in the narrow measure of NBFI - Insurance of credit

The assets of insurance corporations that are involved in the insurance of credit extension, thus making up part of the chain of credit facilitation, are added to the narrow measure of NBFI given that it facilitates credit. Pension funds also provide credit insurance, but the underlying loans are granted by banks, and therefore the credit guarantees do not form part of the shadow banking system. Credit insurance by registered insurance corporations amounted to an estimated R9,8 billion in September 2016.

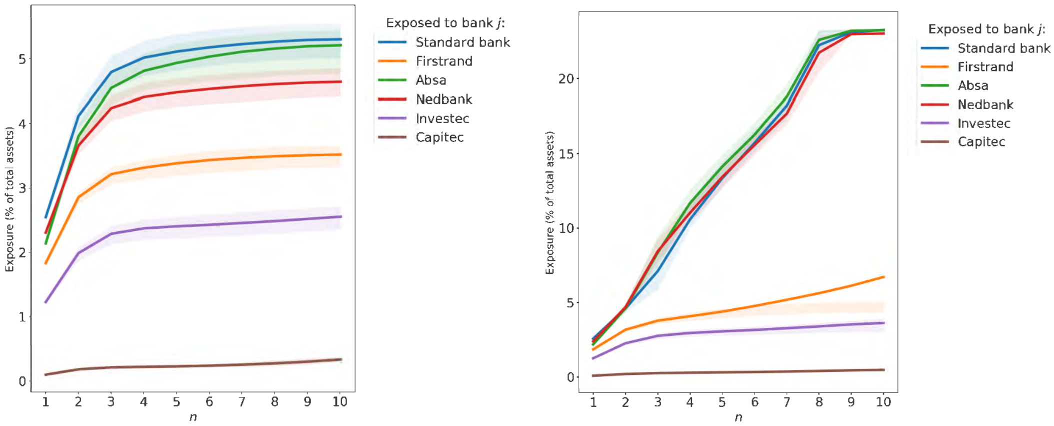
Thus, the narrow measure of NBFI in South Africa comprise MMFs, multi-asset funds, fixed-income funds, hedge funds, funds of funds that invest predominantly in fixed income of multi-asset funds, finance companies, activities of brokers, securitisation schemes (excluding securitisation that banks invest in) and credit insurance. This narrow measure amounted to R2 208 billion in the third quarter of 2016.

Figure A.1 From NBFI to the narrow measure of NBFI



Appendix B

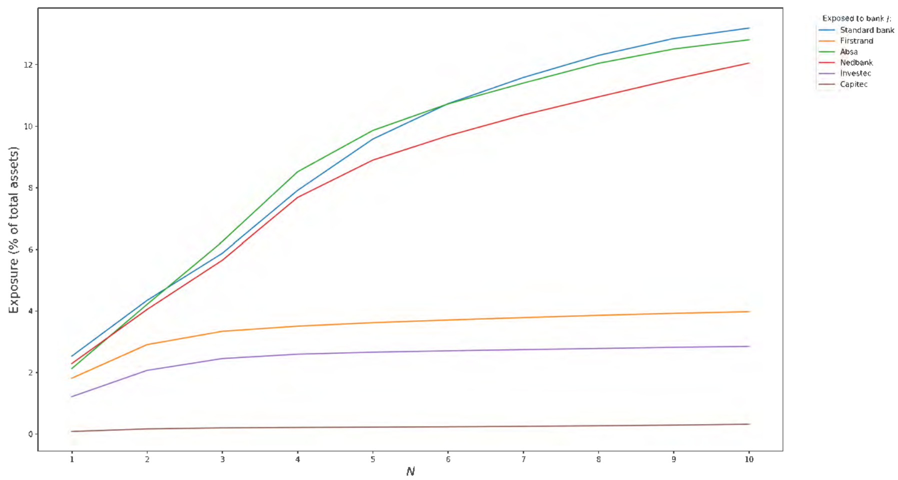
Figure B.1 25^{th} and 75^{th} percentiles of exposures of the South African financial system to the six largest banks



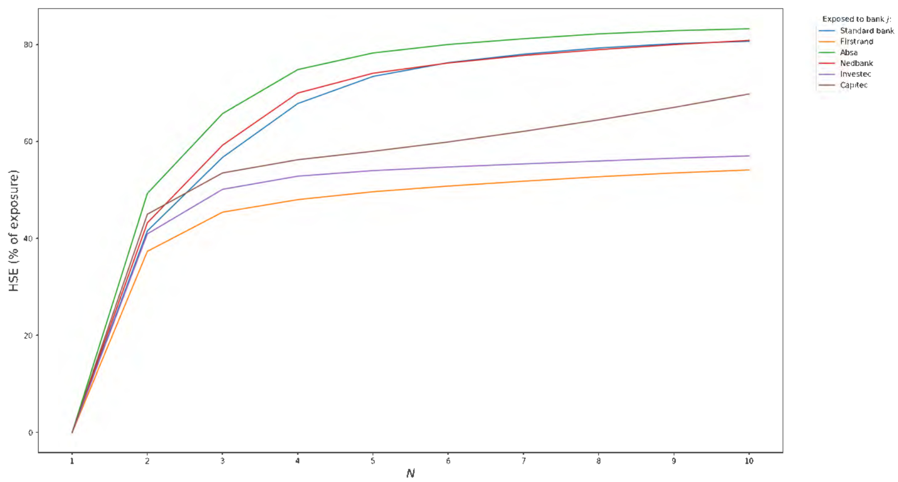
(a) Baseline exposure up to n^{th} order **(b)** Stressed exposure up to n^{th} order

Note:We plot exposure (as % of the system's total assets) up to n^{th} order of the South African financial system to the default of bank j, where $n \leq 10$, j is one of the six large banks and the system's exposure is the sum of the banks' and funds' exposures. (a) shows the baseline exposures and (b) the exposures when institutions are subjected to the stress scenario, which consists of a 25% reduction in all institutions' buffers and a 50% reduction in the liquidity of all tradable assets. We find a distribution of exposures over the 1000 realized samples of the reconstructed interbank network. As we do not know the true interbank network, the true exposures may lie anywhere within this distribution. We plot the mean of the distribution as a solid line and the area between the 25^{th} and 75^{th} percentiles of the distributions as a shaded region in the same color as the mean. Plot (a) shows that baseline exposures level out around $n = 5$ and that the distribution fans out as the order of the exposure increases, which is to be expected because inaccuracies compound. However, (b) shows that stressed exposures to Standard bank, Absa and Nedbank do not level out as n increases and that the distributions around the means do not fan out further for $n > 3$. Furthermore, because exposures are capped to a little under 30% of total system assets (about 70% of total system assets, consisting predominantly of banks' real-economy lending, is not affected by the contagion channels included in our model), and because this upper bound is not affected by the particular realization of the interbank network, the distribution actually narrows as this upper bound is approached. Note that mean exposures up to n^{th} order to Firstrand exceed the 75^{th} percentile for $n > 6$, which implies that the distribution has a heavy upper tail.

Figure B.2 Exposure and higher-order Share of Exposure (HSE) up to order N of the entire South African financial system to the six largest banks, where institutions' buffers are shocked by 25%.



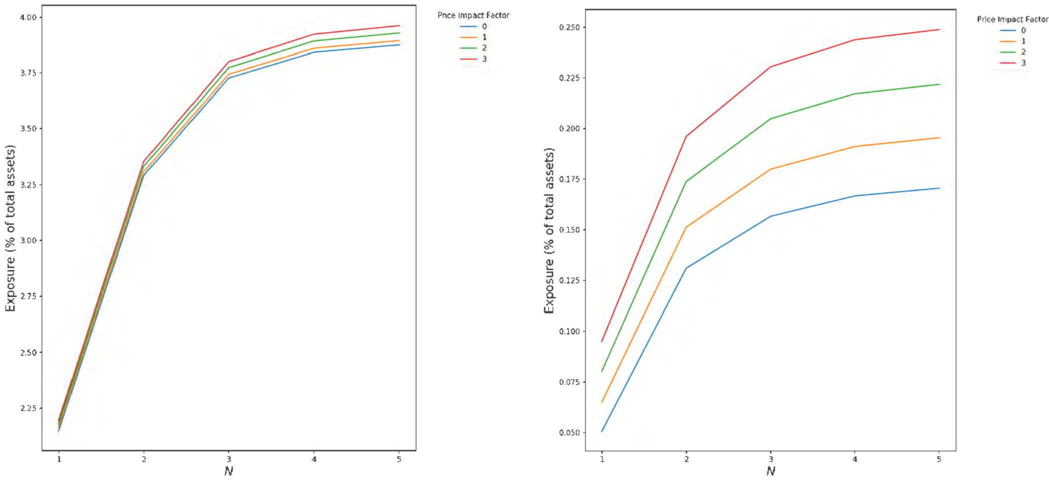
(a) Exposure up to order N



(b) HSE up to order N

Note: (a) shows the exposure (as % of the system's total assets) up to order N of the entire South African financial system (i.e. the summed across all institutions) to the default of bank j, where j is one of the big six banks, and (b) the corresponding HSE up to order N.

Figure B.3 Price-impact variations



(a) Total system exposure to Nedbank **(b)** MMF sector exposure to Capitec

Note: The figures show the exposure up to order N for various values of the price impact factor. A price impact factor of 3 implies that when 10% of the tradable asset's market capitalization is sold, the price falls by 30% when, whereas a price impact factor of zero implies no effect on price. The effect of the price impact factor on the exposures as generally quite moderate, as illustrated in figure (a), which shows the exposure of the entire South African financial system to Nedbank. The (relative) impact of the price impact factor is most pronounced for exposures to Capitec, as illustrated in figure (b), which shows the exposure of the MMF sector to Capitec.

Table B.1 Spearman rank correlation between the vectors of South African institutions' exposures (up to fifth order) and their exposures up to N^{th} order per exposed to bank i (where i is one of the big six banks).

N	1	2	3	4
Absa	0.478	0.945	0.992	0.999
Capitec	0.462	0.971	0.998	1.000
Firstrand	0.519	0.972	0.997	0.999
Investec	0.500	0.960	0.996	0.999
Nedbank	0.473	0.956	0.997	0.999
Standard Bank	0.527	0.968	0.996	0.999

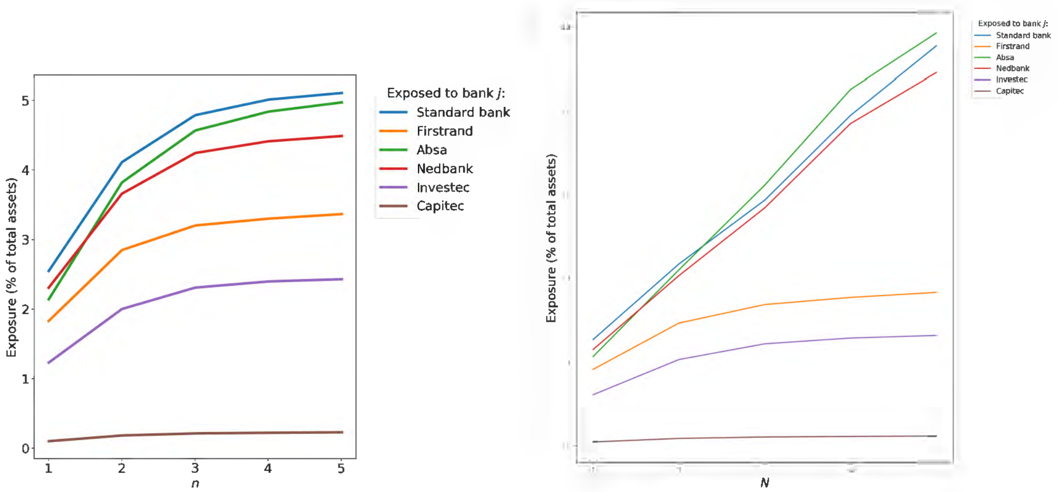
Note: The table shows that the rank-correlation between institutions' exposures and their first order exposures is generally quite low. Hence, to properly understand the ordering of institutions that are most exposed to the Big Six banks (e.g. to inform policy/regulation), higher-order exposures must be taken into account.

Table B.2 Spearman rank correlation between the vectors of South African institutions' exposures (up to fifth order) and their exposures up to N^{th} order separated by sector

N	1	2	3	4
Banks	0.956	0.999	0.999	1.000
FoFs	-0.005	0.935	0.991	0.998
MMFs	0.982	0.999	1.000	1.000
OFs	0.806	0.976	0.998	1.000

Note: Contrary to table B.1, we do not show the correlation per exposed to bank i (where i is one of the big six banks), but the average exposure over all six. The table gives additional insight into the results presented in table B.1: First order exposures are good predictors of the rank order of institutions that are most exposed for the Banks and MMF sectors. On the other hand, for the FoF sector, the rank order of first order exposures is meaningless when trying to understand the rank ordering of institutions by their exposures. This highlights the importance of higher-order exposures for understanding exposures of the FoF sector in particular, and the OF sector to a lesser extent.

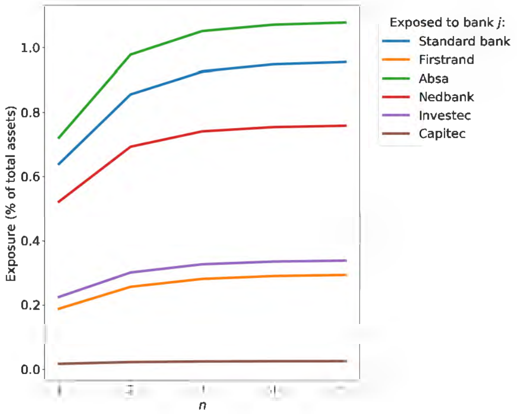
Figure B.4 Exposure up to order N of the entire South African financial system (i.e. the summed across all institutions) to the default of bank j, where j is one of the big six banks (as % of the system's total assets).



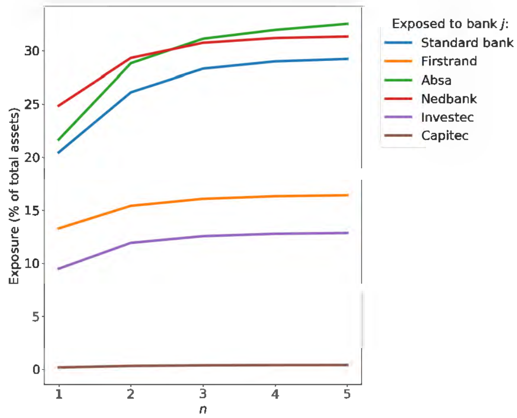
(a) Exposure for baseline buffers **(b)** Exposure for buffers shocked by 25%

Note: higher-order exposures are substantial, especially first order higher-order exposures. higher-order exposures taper off as the order approaches 4. Figure (b) shows the exposures after all institutions' buffers have first been reduced by 25% by a macroeconmic shock. The figure shows that this exacerbates higher-order exposures and, in fact, higher-order exposures to Nedbank, Standard Bank and Absa no longer taper-off. This is an important result: During times of financial distress, simulated here as a 25% reduction of all institutions' buffers, exposures are all the more relevant, as the default of counterparties becomes more likely. Hence, controlling exposure is most relevant during times of financial distress. Yet, these results show that exactly when financial distress occurs, exposures skyrocket. In fact, they may become arbitrarily large, as the exposures to Absa, Standard Bank and Nedbank, to not taper off and may potentially cause a write-off of most of the financial system. Furthermore, note that the three banks causing the largest exposures trade places across and within both graphs, and that Firstrand generally causes small exposures despite having a larger balance sheet than Nedbank and Absa.

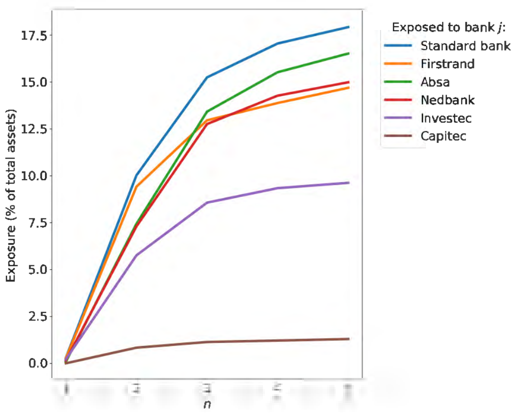
Figure B.5 Sector-specific exposure up to order N to the default of bank j (as % of the sector's total assets)



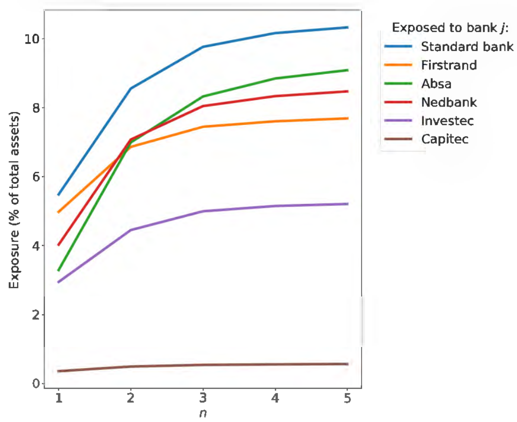
(a) Exposure up to order N of the banking sector (as % of the sector's total assets)



(b) Exposure up to order N of the MMF sector (as % of the sector's total assets)



(c) Exposure up to order N of the FoF sector (as % of the sector's total assets)



(d) Exposure up to order N of the OF sector (as % of the sector's total assets)

Note: The y-scale varies across subplots to highlight the relative differences between the banks. *Main point: The exposure curves vary strongly across sectors and FoFs in particular have much larger look-trough exposures than their direct + indirect exposure. The reason for the FoFs' small direct + indirect exposures is because the do not invest directly into banks, but only through investing in other funds (as shown in figure 4.5).*

Appendix C

Table C.1 Country groupings

Country	Country	EU countries	EMEs vs ADV
AT	Austria	EU	ADV
AU	Australia		ADV
BE	Belgium	EU	ADV
BR	Brazil		EME
CA	Canada		ADV
CH	Switzerland		ADV
CL	Chile		EME
CN	China		EME
CZ	Czech republic	EU	ADV
DE	Germany	EU	ADV
DK	Denmark	EU	ADV
ES	Spain	EU	ADV
FI	Finland	EU	ADV
FR	France	EU	ADV
GB	Great Britain	EU	ADV
HU	Hungary	EU	EME
ID	Indonesia		EME
IE	Ireland	EU	ADV
IL	Israel		ADV
IN	India		EME
IT	Italy	EU	ADV
JP	Japan		ADV
KR	Korea		ADV
LU	Luxembourg	EU	ADV
MX	Mexico		EME
NL	Netherlands	EU	ADV
NO	Norway		ADV
NZ	New Zealand		ADV
PL	Poland	EU	EME
PT	Portugal	EU	ADV
RU	Russia		EME
SE	Sweden	EU	ADV
SG	Singapore		ADV
TR	Turkey		EME
US	United States		ADV
ZA	South Africa		EME

Table C.2 Robustness test: The correlation and concordance* between weighted and unweighted cycles for all countries in the sample and for grouped countries

	Correlation	Concordence
All bank	0.81	0.79
All non-bank	0.23	0.56
EU bank	0.96	0.87
EU non-bank	0.81	0.76
ADV bank	0.87	0.84
ADV non-bank	0.55	0.72
EME bank	0.88	0.86
EME non-bank	0.36	0.67
Non_EU bank	0.58	0.70
Non_EU non-bank	0.26	0.52

*Correlation is measured as the correlation for the entire sample period between the unweighted and weighted-by-GDP series. Concordance, calculated as proposed by Harding et al. (2002), measures the percentage of total periods in which cycles are in the same phase. Numbers displayed were calculated over the entire sampling periods, subject to data availability.

Table C.3 Turning point analyses

Country	Phase	Amplitude			Duration			Total cycle duration		
		Non-bank	Bank	Difference between non-bank and bank	Non-bank	Bank	Difference between non-bank and bank	Non-bank	Bank	Difference between non-bank and bank
AT	Expansion	16.4	9.1	7.37	13.3	16.4	-3.15	41.0	32.4	8.60
	Contraction	18.0	10.0	7.97	27.8	16.0	11.75			
AU	Expansion	16.6	12.1	4.43	26.3	28.5	-2.25	41.3	42.5	-1.25
	Contraction	17.1	13.6	3.52	15.0	14.0	1.00			
BE	Expansion	35.3	16.5	18.85	27.7	20.5	7.17	47.3	41.5	5.83
	Contraction	30.1	16.0	14.03	19.7	21.0	-1.33			
CA	Expansion	20.0	19.6	0.48	21.0	12.5	8.50	37.7	62.0	-24.33
	Contraction	18.4	18.6	-0.16	16.7	49.5	-32.83			
CH	Expansion	19.7	9.6	10.15	24.0	21.0	3.00	68.0	36.5	31.50
	Contraction	17.2	9.8	7.39	44.0	15.5	28.50			
CL	Expansion	31.7	17.8	13.95	17.0	16.3	0.67	45.0	36.1	8.92
	Contraction	40.0	16.3	23.70	28.0	19.8	8.25			
CN	Expansion	75.3	15.8	59.47	13.0	25.5	-12.50	29.0	37.5	-8.50
	Contraction	52.3	18.7	33.67	16.0	12.0	4.00			
CZ	Expansion	22.9	30.1	-7.16	14.5	16.5	-2.00	30.2	36.5	-6.33
	Contraction	26.0	20.3	5.69	15.7	20.0	-4.33			
DE	Expansion	17.5	7.0	10.44	15.8	25.0	-9.25	30.8	46.0	-15.25
	Contraction	17.2	7.7	9.48	15.0	21.0	-6.00			
DK	Expansion	24.1	11.6	12.48	27.7	17.3	10.42	58.0	43.5	14.50
	Contraction	29.9	13.5	16.46	30.3	26.3	4.08			
ES	Expansion	41.1	15.0	26.10	24.3	24.0	0.25	43.3	43.3	-
	Contraction	47.2	19.1	28.06	19.0	19.3	-0.25			
FI	Expansion	25.9	26.7	-0.83	38.3	37.0	1.33	49.3	73.5	-24.17
	Contraction	30.2	24.8	5.46	11.0	36.5	-25.50			
FR	Expansion	15.9	9.0	6.97	16.3	19.3	-3.00	48.6	39.8	8.83
	Contraction	17.6	8.9	8.65	32.3	20.5	11.83			
GB	Expansion	28.4	16.3	12.06	29.5	28.3	1.17	44.0	58.3	-14.33
	Contraction	31.6	20.5	11.09	14.5	30.0	-15.50			
ID	Expansion	159.0	17.7	141.32	18.0	16.0	2.00	69.5	35.3	34.17
	Contraction	112.2	28.9	83.25	51.5	19.3	32.17			
IE	Expansion	44.7	27.6	17.12	22.0	24.8	-2.75	46.0	40.5	5.50
	Contraction	40.6	30.7	9.84	24.0	15.8	8.25			
IL	Expansion	25.7	10.1	15.55	34.5	16.0	18.50	55.2	44.0	11.17
	Contraction	29.3	25.1	4.20	20.7	28.0	-7.33			
IN	Expansion	77.7	22.3	55.44	27.0	33.3	-6.33	41.3	56.3	-15.00
	Contraction	91.4	18.5	72.87	14.3	23.0	-8.67			
IT	Expansion	43.1	12.0	31.06	46.5	25.7	20.83	79.0	62.2	16.83
	Contraction	31.5	15.4	16.09	32.5	36.5	-4.00			
JP	Expansion	15.1	10.6	4.41	25.7	30.3	-4.67	70.7	51.3	19.33
	Contraction	18.0	12.3	5.78	45.0	21.0	24.00			
KR	Expansion	33.3	17.1	16.21	22.3	20.6	1.73	55.3	34.2	21.13
	Contraction	31.3	20.3	10.95	33.0	13.6	19.40			
MX	Expansion	76.5	61.5	14.96	14.3	27.7	-13.42	36.6	52.7	-16.08
	Contraction	68.2	57.5	10.70	22.3	25.0	-2.67			
NL	Expansion	17.8	11.5	6.29	17.7	20.8	-3.08	55.7	38.8	16.92
	Contraction	18.2	13.1	5.14	38.0	18.0	20.00			
NO	Expansion	19.8	20.4	-0.63	19.3	19.3	0.08	47.3	39.6	7.75
	Contraction	15.8	24.8	-8.96	28.0	20.3	7.67			
NZ	Expansion	58.6	11.2	47.41	19.0	23.3	-4.33	40.5	57.0	-16.50
	Contraction	52.9	17.1	35.71	21.5	33.7	-12.17			
PT	Expansion	29.9	14.3	15.61	28.3	18.4	9.85	41.3	35.4	5.85
	Contraction	28.4	18.9	9.55	13.0	17.0	-4.00			
RU	Expansion	48.6	25.1	23.49	14.0	13.5	0.50	25.5	28.0	-2.50
	Contraction	60.3	35.5	24.82	11.5	14.5	-3.00			
SE	Expansion	23.8	11.9	11.86	21.5	38.5	-17.00	38.8	60.5	-21.67
	Contraction	26.9	17.2	9.72	17.3	22.0	-4.67			
SG	Expansion	60.7	19.1	41.64	19.7	35.5	-15.83	51.0	69.5	-18.50
	Contraction	63.6	22.0	41.56	31.3	34.0	-2.67			
TR	Expansion	68.3	78.4	-10.08	18.7	10.0	8.67	44.7	30.0	14.67
	Contraction	87.1	62.5	24.60	26.0	20.0	6.00			
US	Expansion	7.9	14.9	-7.04	16.8	19.6	-2.80	36.3	34.0	2.30
	Contraction	8.8	16.0	-7.25	19.5	14.4	5.10			
ZA	Expansion	86.4	18.0	68.33	59.0	20.8	38.25	74.0	39.3	34.75
	Contraction	130.9	17.9	113.00	15.0	18.5	-3.50			
AVERAGE	EXP	40.5	19.0	21.5	23.6	22.6	1.0	47.6	44.9	2.6
	CON	41.3	20.9	20.5	24.4	22.4	2.1			

Results shown were calculated using R.

Table C.4 Crisis periods

Country	Code	Systemic crises	Currency crises	Sovereign crises
Austria	AT	2008		
Belgium	BE	2008		
Brazil	BR	1990, 1994	1976, 1982, 1987 1992, 1999	1983
Chile	CL	1976, 1981	1972, 1982	1983
China, P.R.	CN	1998		
Czech Republic	CZ	1996		
Denmark	DK	2008		
Finland	FI	1991	1993	
France	FR	2008		
Germany	DE	2008		
Hungary	HU	1991, 2008		
India	IN	1993		
Indonesia	ID	1997	1979, 1998	1999
Ireland	IE	2008		
Israel	IL	1977	1975, 1980, 1985	
Italy	IT	2008	1981	
Japan	JP	1997		
Korea	KR	1997	1998	
Luxembourg	LU	2008		
Mexico	MX	1981, 1994	1977, 1982, 1995	1982
Netherlands	NL	2008		
New Zealand	NZ		1984	
Norway	NO	1991		
Poland	PL	1992		1981
Portugal	PT	2008	1983	
Russia	RU	1998, 2008	1998	1998
South Africa	ZA		1984	1985
Spain	ES	1977, 2008	1983	
Sweden	SE	1991, 2008	1993	
Switzerland	CH	2008		
Turkey	TR	1982, 2000	1978, 1984, 1991 1996, 2001	1978
United Kingdom	GB	2007		
United States	US	1988, 2007		

Source: Laeven et al., 2012

Table C.5 Bank credit cycle and financial crises

	All crises		Systemic crises		Currency crises		Sovereign crises	
Δ^4 *real b cycle*$_{t-1}$	-0.00	0.01	0.07*	0.08*	-0.05	-0.04	-0.06	-0.01
	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)	(0.05)
Δ^1 *real gdp*$_{t-1}$		-2.71		-3.56		2.07		-28.29***
		(3.84)		(4.41)		(8.61)		(9.16)
inflation$_{t-1}$		1.20		-1.44		1.69		-3.60
		(1.75)		(2.17)		(2.89)		(2.70)
Num. of Obs.	1038	1005	910	910	450	417	103	103
Pseudo R^2	0.04	0.08	0.04	0.04	0.05	0.06	0.05	0.27
AUROC	0.64	0.66	0.64	0.64	0.70	0.71	0.64	0.85

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All of the specifications include fixed. The standard errors, reported in parentheses, are robust and clustered at the country level.

Table C.6 Non-bank credit cycle and financial crises

	All crises		Systemic crises		Currency crises		Sovereign crises	
Δ^4 *real nb cycle*$_{t-1}$	0.07**	0.08**	0.03	0.03	0.13***	0.14***	0.06**	0.06**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Δ^1 *real gdp*$_{t-1}$		-2.84		-0.08		1.07		-25.96***
		(3.52)		(4.17)		(8.60)		(8.61)
inflation$_{t-1}$		1.42		-1.88		2.98		-2.39
		(1.66)		(2.15)		(2.26)		(2.86)
Num. of Obs.	1038	1005	910	910	450	417	103	103
Pseudo R^2	0.07	0.07	0.03	0.03	0.11	0.13	0.03	0.29
AUROC	0.69	0.69	0.61	0.63	0.76	0.78	0.70	0.87

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All of the specifications include fixed. The standard errors, reported in parentheses, are robust and clustered at the country level.