

# A comprehensive stress testing model to evaluate systemic contagion and market illiquidity in banks

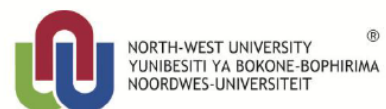
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## Abstract

This dissertation presents a liquidity stress-testing model for evaluating liquidity and systemic risk in banks from developed and emerging economies respectively. The model further relies on simulations to generate liquidity buffer losses for both a non-crisis and crisis period as well. The emerging economy is represented by South Africa (SA) and the developed economy by the United Kingdom (henceforth UK). The Liquidity Stress Tester model (LST) has been successfully applied to both the Dutch and UK markets in previous research.

The model's flexibility and adaptability allows it to assess different banking systems and different reactions (buffer restoration and leverage targeting) of participants within these milieus. The LST considers feedback effects arising from bank reactions and allows for the assessment of severely stressed haircuts and systemic risk increases caused by reputation degradation and increased contagion from other banks. Losses stemming from the second round effects of a liquidity event are explored through the reactions conducted by banks in the banking system.

The study conducts a review of liquidity risk models utilised in previous research. Characteristics of these models and the data they used are highlighted, shedding light on the advantages and shortcomings of these models. Possible restrictions in liquidity risk management are also explored. The study discusses the relevance of the South African/UK economies' comparison, as well as the selected periods chosen for investigation. To assist further research with the LST, the study illustrates and discusses how it is modelled and developed in Microsoft Office Excel.

The results obtained illustrate the potential severity of second round feedback effects of a liquidity event on liquidity positions in banks. The effects of mitigating actions conducted by banking institutions reacting to initial liquidity stress shocks are explored, as well as the way these actions could potentially affect second round effects on banks. The analysis and discussion of simulated results attempts to isolate and identify characteristics of economies and periods used that may have contributed to specific liquidity events. The study concludes with a summary of the research and suggestions for possible future work and development using the LST.

## Opsomming

Hierdie verhandeling bied 'n *Liquidity Stress Tester* (LST) model wat likiditeits- en sistemiese risiko in banksisteme evalueer. Die model evalueer likiditeit in 'n ontwikkelde ekonomie sowel as in 'n ontluikende ekonomie. Verder word likiditeitsposisies vir onderskeidelik banke en die banksisteem as 'n geheel gesimuleer vir 'n nie-krisis en krisis periode. Die ontluikende ekonomie word deur Suid Afrika verteenwoordig en die ontwikkelde ekonomie deur die Verenigde Koningryk. Die LST is in vorige navorsing suksesvol geïmplementeer met die gebruik van data uit die Verenigde Koningryk en Nederland.

Die LST se aanpasbaarheid en soepelheid laat toe dat dit amper enige ekonomie se banksisteem kan assesser in terme van likiditeit. Die model het die vermoë om verskillende tipes reaksies van banke op die gevolge van likiditeitskokke te assesser. Dit neem die tweede rondte gevolge wat deur die reputasie en sistemiese risiko van ander banke kan versprei en wat die hele banksisteem beïnvloed in ag. Die gevolge van strenger *haircuts* op balansstaatitems en 'n hoër vlak van mark spanning op die likiditeitsposisies van banke en die banksisteem word ook geanaliseer. Die verhandeling hersien vorige navorsing rakende likiditeits risiko modelle. Die eienskappe van modelle uit vorige navorsing word ondersoek om die moontlike voordele en tekortkominge van hierdie modelle te identifiseer. Die verhandeling bespreek verder hoekom dit relevant is om die Suid Afrikaanse en Verenigde Koningrykse ekonomieë te vergelyk en verduidelik met die behulp van illustrasies presies hoe om die LST in *Microsoft Office Excel* te modeleer.

Gesimuleerde resultate illustreer duidelik die beduidende moontlike effek van die tweede rondte van 'n likiditeitskok op die likiditeitsposisies van banke en die banksisteem as 'n geheel. Resultate illustreer die gevolge van banke se reaksies op die eerste rondte gevolge van die likiditeitskok en hoe hierdie reaksies kan bydra tot die tweede rondte gevolge. Die verhandeling poog om aan die hand van analise, vergelyking en bespreking van resultate wat gesimuleer is vir altwee ekonomieë vir beide periodes, die ekonomieë en periodes se eienskappe te identifiseer wat moontlik kon bydra daartoe om die gevolge van 'n likiditeitskok te verlig of te vererger. Die verhandeling sluit af met 'n opsomming van die studie en voorstelle vir moontlike toekomstige verwikkelinge en navorsing rakende die LST.

## **Key words**

Basel Committee on Banking Supervision (BCBS); buffer losses; contagion; financial stability; initial shock; liquidity; liquidity crisis; Liquidity Stress Tester (LST); mitigating actions; pre-crisis; stress test; systemic risk.

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# Chapter 1: Introduction and Background

## 1.1 Background

The 21<sup>st</sup> century has so far (2013) produced both highly attractive and adverse global market conditions. The previous period, known as the pre-crisis period spanning from approximately 2003 to the end of 2007, has been labelled as one of the greatest economic booms in post-war history (Kirkland, 2007). During this period several industries, including housing markets and construction sectors, experienced significant positive growth (Financial Crisis Inquiry Commission (FCIC), 2011). The latter was caused by the worst financial crisis since the Great Depression (Nastase *et al.*, 2009:691). This crisis, commencing in 2008, is still ongoing. In 2009 the liquidity crisis gave rise to a severe *credit* crisis, with no clear end in sight. Several countries, including Cyprus and Greece, remain in severe financial distress. Cyprus has received a bailout of €10 billion, provided by the European Union (EU), European Central Bank (ECB) and the International Monetary Fund (IMF), albeit attached to severe austerity measures (Inman, 2013). Greece continues to suffer the effects of a 5-year-old recession and an economic contraction of 4.2% forecast for 2013 (Avent, 2012). The financial crisis of 2008 witnessed the rapid evaporation of liquidity in financial markets (van Vuuren, 2011:37). Figure 1.1 clearly illustrates the domain of the two periods using the Chicago Board Options Exchange (CBOE) global volatility index, the VIX.



**Figure 2.1:** CBOE Volatility Index (VIX), showing the pre-crisis and severe crisis periods.

Source: Chicago Board Options Exchange (2013)

The CBOE volatility index in Figure 1.1 indicates the non-volatile period labelled as the non-crisis period that lasted up until the approximately the end of 2007 after starting in 2003. The figure also shows the volatile period that characterises the crisis commencing in mid-2008.

The International Monetary Fund (IMF) in 2009 estimated losses stemming from the financial crisis to exceed US\$4 trillion (Dattels & Kodres, 2009). However, speculation regarding losses from the crisis is far and wide apart. Many economies experienced negative GDP growth rates in 2009 due to suffering the severe effects of the financial crisis, with a decline of 7.4% and 9.8% in GDP in the UK and the Euro area respectively (Nastase *et al.*, 2009:695).

Prior to the crisis, liquidity risk was underestimated and was rarely assessed in stress testing frameworks. This may have been due to the probability of liquidity shortages being extremely low, but the many dimensions of liquidity risk may also have complicated quantification (van den End, 2010:39). The need for further quantification of liquidity risk has increased as banks have begun to acknowledge the tendency of liquidity risk to spread from one bank to another contagiously, possibly resulting in a system-wide financial crisis (Alessandri *et al.*, 2008). Traditionally, liquidity risk is known to cause market wide stress through interbank markets and bank runs on financial institutions. However, liquidity risk can also spread through markets when there are changes in the market prices of a bank's assets (Adrian & Shin, 2008).

## **1.2 Problem Statement and Objectives**

The problem statement addressed in this dissertation is that reduced liquidity in the banking sector can cripple an individual bank's ability to operate optimally, resulting in knock-on systemic contagion in the broader economy. The effect of reduced liquidity on banks stemming from asset fire sales, systemic contagion or a combination of both is little understood.

Several objectives are set out in this study to resolve the problem statement put forward above. The first is to use simulations to introduce liquidity shocks or reductions to both the South African and the UK banking systems (i.e. stress test the South African and UK banking systems with regard to a lack of liquidity). The aim is to use a mathematical model to evaluate and quantify the effect of these induced liquidity reductions on banks within the South

African and UK banking systems. Through this mathematical model, the most effective way of dealing with a dearth of liquidity is also explored.

The relevant calibrations to the mathematical model attempts to investigate several factors that may affect the liquidity positions of banks within both banking systems investigated. These factors include mitigating actions in the form of buffer restoration and leverage targeting conducted by banks to mitigate the effects of induced liquidity shortages. The final stage of the model estimates and attempts to shed light on the second round feedback contagion effects stemming from mitigating actions conducted by banks. Furthermore, the effects of severely stressed haircuts and systemic risk increases are investigated by means of the model to assess their possible effects on liquidity within the banking system.

Applying the model to different periods (non-crisis and crisis) for both economies allows the comparison of how different banks in different banking systems would be affected by liquidity shortages in different market conditions.

### 1.3 Overview

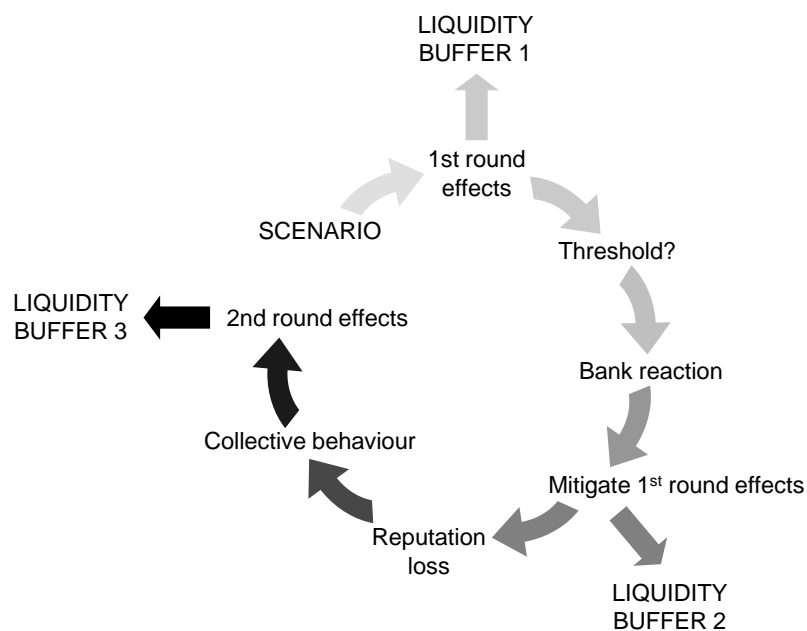
The field of risk management is broad and deep, with several forms of risk contributing to the practice. Liquidity risk, which has previously been underestimated, showed its destructive ability in the crisis of 2008 (van den End, 2010:38-39). The crisis saw both market and funding liquidity vanishing from financial markets, ultimately leading to the paralysis of certain financial markets (van Vuuren, 2011:37). These markets include short-term funding markets banks relied on to fund activities (Brunnermeier, 2009:78).

Liquidity risk spreading through financial markets via interbank exposures, deposit withdrawals (which may be caused by reputation risk) and changing asset prices has the ability to severely affect financial markets and its participants (Adrian & Shin, 2008).

The interbank market can act as a source of liquidity risk for all banks within the system even though it improves the resilience of a banking sector. Any defaults by counterparties in the interbank market can lead to banks becoming insolvent and this can cause market wide stress (Upper, 2006). Banks may also experience liquidity shortages when deposit withdrawals are excessively high, which may lead to bank runs. These bank runs may be due to reputation risk (i.e. if news in the financial system spreads that an institution might be experiencing financial difficulties) (Upper, 2006).

Liquidity risks' ability to spread through financial markets in the form systemic risks caused by asset price changes contradicts the assumptions of the domino model of financial contagion, suggesting that assets are fixed to their books values and only defaults can cause contagion (Adrian & Shin, 2008). Liquidity risk as a result of asset price changes occurs when a bank attempts to sell some of its assets to fund its liquidity needs and avoid a liquidity shortage. If demand is not perfectly elastic, prices in the market are affected and this ultimately affects the balance sheets of all of banks owning these assets in the system. Market risk may thus affect liquidity positions of banks in a banking system (Estrada & Osorio, 2006). Liquidity risk, in contrast to other forms of risk, is not institution-specific risk as it may spread from one institution into markets, affecting all institutions involved (Borio, 2003).

The Liquidity Stress Tester model (LST) developed by van den End (2010:41) is based on a practical algorithm that makes it operational for simulations with real data. This model accounts for first and higher order effects of liquidity shocks on the liquidity positions of banks. These effects range from asset market price changes to idiosyncratic reputation effects, thus the model takes into account several different liquidity risk dimensions (van den End, 2010:39). Figure 1.2 illustrates the process of a liquidity event and the positions at which liquidity buffers are estimated in the LST.



**Figure 1.2:** Flow chart showing the assumed cycle that follows from a liquidity 'event' and the stages at which buffers should be initiated.

The LST was applied to Dutch banking system by van den End (2010:38) and illustrates that in specific scenarios, second round liquidity shock effects caused more damage to banks' liquidity positions than first round effects. This effect is explained by Nikolaou (2009). This was due to the behavioural reactions of banks on first round effects, leading to higher reputation risk and ultimately the withdrawal of liquid liabilities from banks. Furthermore, the similarity of reactions by banks across the banking sector may have led to crowded trades that accelerated the drying up of market liquidity. The reactions of banks mitigating first round effects or restoring their liquidity buffer during liquidity events increased reputation risk, which then led to greater second round effects (van den End, 2010:43).

The LST is a highly flexible and adaptable model. Van Vuuren (2011) successfully applied it to the UK banking sector data. Different dimensions of liquidity risk (including the collective reactions by banks in a liquidity event and idiosyncratic reputation effects) were effectively modelled using the LST. The model gives clarification on the effect of collective reactions by banks on liquidity risk, as well as its contribution to market stress (van Vuuren, 2011:51). The LST can be applied not only by central banks to stress test the liquidity risk of a financial system, but also by any banking system as long as data for liquid assets and liabilities are available on an individual bank level (Van den End, 2010:61).

## **1.4 Dissertation outline**

Work on market and funding liquidity crises has significantly increased since the beginning of the 21<sup>st</sup> century. Since the onset of the credit financial crisis, detailed work regarding this form of risk has proliferated (van Vuuren, 2011:38). Some of this work include Brunnermeier and Pederson (2009), Chordia *et al.* (2001), Crockett (2008) and Yeyati *et al.* (2007). Chapter 2 reviews the literature and attempts to identify the characteristics of models used in previous research. These characteristics include the advantages and shortcomings of previous models concerning the data they employ and the effects they capture. Chapter 2 further reviews liquidity risk management proposals put forward by the Basel Committee on Banking Supervision (BCBS) to promote the effective management of liquidity risk (BCBS, 2010).

Chapter 3 proceeds with the methodology of the LST as developed by Van den End (2010:46-52). This methodology includes descriptions of how the haircuts and market stress variables are calibrated to deliver results. Furthermore, the chapter describes and illustrates



the difference between the possible mitigating actions banks may conduct. Chapter 3 also provides a description of the data used in the study and why the data used are relevant. This description highlights characteristics of the two banking systems and how they differ, as well as the differences between the non-crisis and crisis periods used in this study. Chapter 3 concludes with a detailed description of how to model the LST in Microsoft Office Excel, with the aim of assisting future researchers attempting to use the LST.

The first of the result chapters, Chapter 4, illustrates possible loss distributions for the South African banking system in both the non-crisis and crisis periods. Results are compared between the two periods and reasons for the differences in possible liquidity buffer losses are discussed. Chapter 5 is similar to Chapter 4, with the exception that it illustrates possible liquidity buffer loss distributions for the UK banking system. The comparison of results across the non-crisis and crisis periods in Chapters 4 and 5 sheds light on how market conditions changed and how these conditions affected banks and their liquidity positions throughout these two periods. Chapter 6 compares the results of the economies for both periods with one another. This comparison attempts to identify possible positive and negative characteristics of both economies that may have caused or prevented further possible liquidity buffer losses. This comparison of results also aims to confirm the flexibility of the LST and that it can be applied to almost any banking system as long as data at individual bank level are available.

Chapter 7 concludes the study by summarising the work conducted and the results obtained. The chapter also suggests further future research possibilities and developments with the LST that may yield interesting results.

## **1.5 Research Procedure**

The research procedure in this dissertation is initiated by posing relevant objectives to be achieved throughout the study. These objectives ultimately contribute to resolving the problem statement put forward. A review of the relevant literature regarding liquidity risk models is conducted to identify characteristics of models, as well as their advantages and possible shortcomings. Further, the proposals suggested to promote effective liquidity risk management in banking institutions forms an important part of the literature review.

Reconstruction of the LST is done in Microsoft Office Excel and it is recalibrated using the relevant data for both economies investigated. Data used in the study are gleaned directly from the balance sheets of the relevant banks. The data also includes relevant weights (haircuts on assets and run-off rates on liabilities) for balance sheet items and market stress levels. Stress testing has to be conducted with the LST to produce distributions of possible liquidity buffer losses for both economies assessed. A comparison of results attempts to identify causes or severities of possible liquidity buffer losses for both economies across both periods. The procedure concludes with a summary of the entire study and suggestions of possible future research regarding the LST.

Chapter 2 reviews the literature concerning liquidity risk models used in previous studies.

## Chapter 2: Literature Study

This chapter conducts a literature study highlighting liquidity risk and reviewing relevant topics regarding the concept. These topics include, amongst others, ways to manage the risk and how it has been measured via liquidity risk models in the past.

The BCBS recognised the urgent need for coherent liquidity risk measurements, standards and monitoring and consequently expressed their concern regarding the lack of attention and low priority assigned to liquidity risk in the years preceding the crisis. They further acknowledged the lack of efficient and accurate liquidity risk management as one of the main characteristics of the 2008 crisis (BCBS, 2010). This chapter reviews liquidity risk in terms of the different themes constituting it. The evolution of liquidity risk in the international banking sector is assessed in order to comprehend how banks have become more susceptible to this phenomenon over recent years. The best practices to measure and manage liquidity risk are also reviewed in this chapter, which concludes with an exploration and evaluation of other models to clarify how the LST contributes to the field of liquidity risk management.

### 2.1 Major themes of liquidity risk

Liquidity within financial systems can be divided into market liquidity and funding liquidity and although both affect market participants uniquely, they are caused by similar underlying factors. Van Vuuren (2011:38) defines market liquidity as the trading of assets and financial instruments at short notice with such ease that there is little or no impact on the prices of these assets and instruments. Funding liquidity is the ability to raise cash or cash equivalents through the process of selling or borrowing additional assets. Although these two types of liquidity affect banks differently, there are clear links between them. Investigating traders as their main focus of market participants, Brunnermeier and Pederson (2009) constructed a model that shows how funding of traders affects (and is affected by) market liquidity. They argue that if funding liquidity is tight market liquidity would also be pressured as traders who provide liquidity to markets become reluctant to take on positions. In addition, if lower market liquidity is expected, risks relating to financing trades increase, thereby increasing margins (Brunnermeier & Pederson, 2009:2202).

Caused by problems regarding funding and market liquidity, a liquidity crisis or stress event is also defined as the sudden evaporation of both market and funding liquidity for an extended period. The 1987 stock market crash and the instability in fixed income markets in 1998 were characterised by the sudden evaporation of market liquidity (Borio, 2003). The crisis of 2007 was a cut above these events being the worst financial crisis since the Great Depression (Nastase *et al.*, 2009:691). It witnessed a surge of uncertainty that caused evaporation of market and funding liquidity respectively (Brunnermeier & Pederson, 2009). The disappearance of liquidity caused a system-wide scramble for it, forcing central banks to intervene and provide crucial liquidity lines in order to avoid solvency issues for several financial institutions (Drehman & Nikolaou, 2009). This was only effective to a certain extent and was followed by restructuring and resolution schemes allowing governments to nationalise financial institutions branded as too big to fail (Cihak & Nier, 2010). Setting liquidity risk apart from other forms of risk is its ability to affect other market participants through contagion, whereas other forms of risk, like credit risk, are often institution-specific (Borio, 2003).

The crisis revealed the significant role contagion plays when it comes to liquidity risk. Contagion may thus also be regarded as one of its major characteristics. The ability of contagion to spread through the financial system in the form of systemic risk was underestimated and the effect of falling asset prices via fire sales was unprecedented in the financial crisis of 2008 (Adrian and Shin, 2008). The BCBS does not discuss systemic risk in their paper of proposals on sound practices regarding the management of liquidity in banking organisations in 2000 prior to the crisis (BCBS, 2000). Contagion in a financial system traditionally spreads through defaults in the interbank market and major deposit withdrawals, also known as bank runs (van den End, 2010:39). However, Adrian and Shin (2008) argue that defaults are not always necessary to initiate contagion and that the effect of price changes alone may be enough. These price changes emerge from asset fire sales disturbing prices within markets, increasing systemic risk in financial systems. To comprehend how susceptible financial institutions are to systemic risk, the evolution of the global financial system must be assessed.

## **2.2 Evolution of liquidity risk**

The worldwide banking sector has gone through significant changes in the last couple of decades (Allenspach & Monnin, 2006). The demand for funding liquidity has increased over

time as financial systems have developed and expanded (Borio, 2003). Furthermore, the demand is significantly increased due to market based financial systems being funding-liquidity thirsty (Borio, 2009). According to Allenspach and Monnin (2006) one of the leading contributors to these developments of the global financial system is integration.<sup>1</sup> Integration does not necessarily indicate that liquidity risk has increased over time, but rather that the exposure to possible liquidity risk has increased. It is important to recognise that this increased exposure to liquidity risk is accompanied by increased possibilities to mitigate it. These possibilities refer to the vast number of markets and securities financial institutions have access to in order to mitigate liquidity risk (Allenspach & Monnin, 2006). These possibilities give banks the ability to diversify their portfolios and actively manage their balance sheets in such a way as to control their liquidity risk exposure amongst others as effectively as possible.

However, with a greater selection of markets and instruments available to banks for diversification purposes, the banking sector as a whole may become more homogeneous due to the possibility of banks being exposed to the same risks. If banks in a financial system are all exposed to the same risks the possibility of systemic risk increases become more likely. Over-diversification of balance sheets would increasingly expose banks and other financial institutions to similar risks, which would be difficult to avoid as diversification will have already taken place. Furthermore, the synchronisation of financial systems and markets around the world also reduces the ability to diversify in the first place, since it will be difficult to find markets in a boom when most others are in a bust, for instance (Allenspach and Monnin, 2006). The integration of the global financial system forces business cycles around the world to converge, which means that they become more exposed to each other. This ultimately suggests that events in one system will certainly affect other business cycles for several forms of risk (Allenspach and Monnin, 2006).

The introduction of the euro in Europe promoted the integration of the financial systems. However, this integration was severely hampered by the crisis of 2008 (ECB, 2012). As a result of the Maastricht Treaty in 1992, the euro was established in 1999 and adopted by several European countries. The euro acts as core currency for 17 of the 27 member states

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<sup>1</sup>Financial markets can be considered to be integrated when the law of one price holds, in other words if securities with identical cash flows demand similar prices in different regions (Jappelli & Pagano, 2008).

obliging to the regulations of the European Union (EU) (ECB, 2011). The introduction of the euro has significantly impacted the European financial system, encouraging integration especially within securities markets (Lane & Wälti, 2006 and Lane, 2006). Furthermore, Lane & Wälti (2006) conclude that amongst other global factors the establishment of the euro contributed significantly to the integration of the European financial system. The euro has also eased the access of other economies to euro member economies (ECB, 2012).

The integration of the financial systems globally has thus had a significant effect on how financial system and participants operate and how they can be affected by events in global finance. Banks have increased their ability to acquire liquidity at short notice, reducing overall liquidity risk due to the vast number market and instruments at their exposure (Allenspach and Monnin, 2006). However, this has also increased their systemic risk exposure, amongst other things (Allenspach and Monnin, 2006). The developments and events in the global financial system up until the present have led to further ways of managing liquidity risk in terms of monitoring and measurement. Proposals on liquidity risk measurement and monitoring are discussed in the following section.

### **2.3 Best practices of liquidity risk management**

The process of liquidity risk management is not a simple one-step procedure, but rather a combination of tools used to measure and monitor a bank's liquidity risk exposure. From the above it is evident that there are increasing numbers of factors to take into account that might affect a bank's liquidity positions through the evolution of liquidity risk and through the different themes constituting liquidity risk. The BCBS identifies several procedures and policies that can help banking institutions to manage their liquidity risk (BCBS, 2000, 2010). The procedures contribute to the timely flow of accurate information and the correct interpretation of the information within the organisation, as well as within certain markets. The relationships with bank clients, especially liability holders, and the construction of plans on how to deal with sudden liquidity shortfalls were also addressed (BCBS, 2010). Along with these suggestions, the measurement and frequent monitoring of liquidity risk exposure are equally important to ensure effective liquidity risk management.

### 2.3.1 Measurement of liquidity risk

The BCBS has proposed several sound practices and frameworks regarding the management of liquidity risk in terms of measurement, regulatory standards and monitoring (BCBS, 2000, 2010). These regulations stem from the liquidity crisis experienced in the global financial system, as well as the characteristics within the global financial sector that caused the crisis.

The regulation of liquidity and liquidity risk within any financial institution is of utmost importance. The BCBS (2010) developed two measures for liquidity risk, which serve separate but complimentary objectives. These two measures are formally known as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). The first measure (the LCR) was developed to promote the short-term resilience of banks by ensuring that the banks have enough high quality liquid assets to last them a month in a specific stress scenario. The horizon of 30 days is used because the committee assumes that banks would by then have taken appropriate action to orderly manage the scenario. The LCR measure is given by:

$$LCR = \frac{\text{Stock of high quality liquid assets}}{\text{Net cash outflows over a 30 – day time period}} \geq 100\%$$

The LCR measure estimates whether the bank has a sufficient level of unencumbered, high quality assets that may easily be converted into cash within a 30-day period. Since the original publication of the LCR the BCBS has revised the measure, changing the characteristics that high quality liquid assets and net cash outflows should comply with in January 2013 (BCBS, 2013). The standard of this ratio requires that the LCR never drops below 100%, in other words the stock of liquid assets should be no less than the estimated net cash outflows. The net cash outflows for the 30-day period should be calculated by supervisors according to the parameters they set for the scenario. The BCBS lists numerous characteristics for both the variables of the LCR to meet in order to qualify for the LCR measure. For high quality liquid assets, for instance, there are fundamental characteristics as well as market related characteristics that assets should have. These assets should have low market and credit risk and should be traded in active and sizeable markets to avoid significant price changes. Furthermore, the selection of assets to use should be cautiously undertaken since certain assets have a greater ability to trigger fire sales when traded in financial markets. These are only some of the standards put forward by the BCBS (2010) that assets should meet in order to qualify as high quality liquid assets. The net cash outflows are defined as

the expected cumulative cash outflows less the expected cumulative cash inflows. This is also known as the net cumulative liquidity mismatch position in a stress scenario. The cash outflows used in the LCR can be calculated by multiplying the outstanding balances of specified liabilities with the assumed percentages expected to roll-off and by adding the multiplication of certain off-balance sheet commitments with specific draw-down amounts. The BCBS also sets out several guidelines for which cash inflows should be considered in the LCR (BCBS, 2010).

The LCR ratio mainly stems from the fact that during the crisis, banks resorted to funding their operations with short-term instruments, including asset backed commercial papers amongst others, significantly increasing their risk exposures if markets were to experience trouble (Brunnermeier, 2009:78). The successful implementation of the LCR measure aims to protect financial institutions from the danger of relying on risky funding opportunities and the consequences if these risks should realise.

The NSFR measure was developed to promote medium and long-term funding of assets and activities of banks (BCBS, 2010). This measure ensures that there is a specified minimum acceptable amount of stable funding for a banking institution at any time for a one-year time horizon. The funding for each bank will differ according to the liquidity characteristics of each institution and their required stable funding. The specific objective of this measure is to promote structural changes in the liquidity profiles of banking institutions in order to get banks away from short-term funding mismatches and more towards longer-term stable funding of activities and assets. The NSFR is calculated using:

$$NSFR = \frac{\text{Available amount of stable funding}}{\text{Required amount of stable funding}} > 100\%$$

The NSFR consists of two components namely the *available* amount of stable funding (ASF) and the *required* amount of stable funding (RSF).

The ASF can be defined as or can include the institution's total amount of:

- capital
- preferred stock with maturity  $\geq 1$  year
- liabilities with maturity  $\geq 1$  year



- and the portion of deposits with no maturity or maturity less than one year expected to stay in the institution for an extended period during times of stress.

The RSF for the NSFR is calculated by multiplying the assets held and funded by the institution and the amount of off-balance sheet activity with its respected required stable funding factors. Assigning these RSF factors to assets and exposures arising from off-balance sheet activities indicates the amount of stable funding required to cover for each asset or off-balance sheet activity. The RSF factors assigned to assets will be low when assets are liquid and high for illiquid and not so readily available assets in times of stress, thus illiquid assets require more stable funding as they may be exposed to negative market conditions for longer. The BCBS (2010) further declares how categories for the assets used in the NSFR should be constructed in order to apply their relevant ASF and RSF factors respectively.

Similar to the LCR, the NSFR standard requires that the available stable funding should be more than the required stable funding at all times. Along with these measurement tools are several monitoring tools suggested by the BCBS to promote the capture and correct interpretation of information in order to identify and comprehend current or future liquidity problems (BCBS, 2010).

### **2.3.2 Monitoring of Liquidity risk**

Banks should not only be able to measure their liquidity risk, but should also monitor it constantly in the event of changes in liquidity risk exposure (BCBS, 2010). The BCBS proposed four different monitoring tools in addition to the measures discussed above with the objective of constantly monitoring the liquidity risk exposure of banks (BCBS, 2010). These monitoring metrics assess certain characteristics of banks where liquidity risk may arise, including cash flows, balance sheet structure, unencumbered collateral available and specific market indicators. The aim of these monitoring tools is to promote the correct flow and interpretation of information in order to ensure effective monitoring of liquidity risk.

The metrics proposed for monitoring of liquidity risk proposed by the BCBS (2010) are:

- Contractual maturity mismatch
- Concentration of funding
- Available unencumbered assets

- Market-related monitoring tools

A short discussion of these four monitoring tools follows in order to comprehend how they work and why they were created.

### **Contractual maturity mismatch**

This metric assesses all contractual cash and securities inflows and outflows stemming from on- and off-balance sheet items for specific time bands in order to identify liquidity mismatches (BCBS, 2010). By using this metric the bank gets an indication of how much liquidity to generate for the time bands in which maturities on instruments realise. However, when implementing it there are a few assumptions that the bank must acknowledge: the flow of assets should be reported according to its latest possible maturity date, it is assumed that rollovers of existing liabilities do not take place and the bank does not enter into any new contracts regarding assets. It is also assumed that penalty clauses for the withdrawal of funds do not discourage or deter creditors (BCBS, 2010). According to the BCBS, this metric will provide banks with insight into how much they rely on maturity transformation under its current contracts and it encourages banks to indicate how they plan to deal with possible maturity gaps once they have been identified. The contractual maturity mismatch can in practice assist financial institutions to avoid sudden liquidity shortages as maturities on assets and liabilities realise (BCBS, 2010).

### **Concentration of funding**

The BCBS (2000) recommend the diversification of funding sources and this is exactly what this metric encourages. The metric also identifies significant sources of wholesale funding which, if withdrawn, may trigger liquidity complications. According to the BCBS (2010), the application of this metric is relatively straightforward with the examination of funding concentrations by counterparties or by the type of instrument being all that is needed. Banks can thus monitor funding concentration by counterparties or instruments with constant monitoring, ensuring that they are aware of changes in the concentration of funding. This metric can indicate where additional diversification is needed. However, the metric also has its limitations. Although it can indicate that further diversification is needed, it does not indicate whether the replacement of certain funding instruments would be straightforward (BCBS, 2010). Furthermore, the fact that the counterparty for certain types of debt cannot

be immediately identified limits the examination of funding concentration by such a counterparty. Thus, according to the BCBS (2010), the actual concentration of funding may be higher than what this metric indicates. The committee also suggests that the concentration of funding metric can also be applied to estimate potential risks arising from instruments connected to foreign exchange. The BCBS further describes what constitutes significant counterparties, instruments and currencies that may pose potential threats in times of liquidity stress (BCBS, 2010).

The importance of this metric is significant, as it indicates to institutions where possible over-investment in certain instruments or with certain counterparties may have occurred (BCBS, 2010). Since we learned from the crisis where banks significantly invested in mortgage backed securities and relied on shorter-term wholesale funding markets, this metric can identify possible risks and show where further diversification might be needed.

#### **Available unencumbered assets**

Available unencumbered assets can be used as collateral by the bank to generate further secured funding in other secondary markets (BCBS, 2010). These assets might also be eligible at central banks, which may then ultimately be additional sources of liquidity for banks. In order to qualify, these assets have to be easily marketable in secondary markets. The BCBS states that in order for assets to be considered for this metric, operational procedures should be put in place in order to monetise the collateral (BCBS, 2010). These procedures would assist to speed up the process of monetising the collateral in order to create liquidity. This metric can provide the organisation with information regarding the characteristics, location and currency domination of available unencumbered assets. The BCBS states that it is important for banking supervisors to acknowledge that this metric does, however, not compare the available amount of unencumbered collateral to the outstanding secured funding and the metric should be accompanied with a maturity mismatch measure in order to get a clearer picture (BCBS, 2010). In practice this monitoring tool may ensure that institutions are prepared for liquidity stress at short notice. The crisis saw financial institutions scrambling to find liquidity in financial systems as markets froze up and market and funding liquidity evaporated (Van Vuuren, 2011:37). This metric may possibly ensure that institutions are aware of the types and location of marketable assets in order to address sudden liquidity needs up to a certain extent.

## **Market-related monitoring tools**

Market-related monitoring tools refer to several types of high frequency data with minimum time lag available in the market that may be used to indicate possible liquidity difficulties (BCBS, 2010). The BCBS (2010) suggests that banks categorise and monitor data according to market wide information, information on the financial sector and bank-specific information. According to the BCBS (2010) market information is essential when the assumptions behind a bank's funding plans are evaluated. Data contributing to market wide information include equity prices, debt markets and foreign exchange markets, amongst others. Information on the financial sector on the other hand can indicate whether the sector is mirroring the movements of other sectors or broader market movements. These types of data can also indicate problems or difficulties within the financial markets and includes similar types of data as market wide information (BCBS, 2010). Monitoring bank-specific information may indicate whether the market has lost confidence in a specific institution or identified certain risks that deter other market participants from that particular institution. Again, similar information and data are used for this monitoring tools, which ultimately amplifies the importance of how data are processed and information interpreted. The data for all three monitoring tools can be useful to banks as long as banks rely on data that are readily available and the information is interpreted correctly (BCBS, 2010). As market information may not imply similar risks for all institutions, it is crucial for each institution to correctly process data and interpret information in order to determine their exposure to risk and market conditions. Market information can in a financial system help institutions to identify possible current and future liquidity crises, which may give them the opportunity to act accordingly (BCBS, 2010). The crisis of 2008 affected most – if not all – financial institutions significantly, however, market information can still identify problematic sectors and institutions, allowing other market participants to avoid these situations even in non-crisis times.

The monitoring and measurement tools mentioned forms only one part of the concept of liquidity risk management. Several quantitative measures exist to monitor liquidity risk and those put forward in BCBS (2010) only offer the minimum institutions should consider. These measurement and monitoring tools should be used along with strategic planning and the management of market access in order to ensure on-going liquidity risk management (BCBS, 2010).

## 2.4 Liquidity risk models

Upper (2006) suggests that research (1996-2006) regarding liquidity risk and contagion in financial systems has significantly improved. However, he further suggests that there is still significant room for improvement within models. In the past, there have been several approaches to measuring liquidity and systemic risk, all of them with their advantages and shortcomings. Several of these approaches have been criticised for not focussing enough on the ability of contagion to spread to the entire financial system, ultimately effecting both market and funding liquidity. Furthermore, the data sets used in several modelling approaches have also received criticism, supporting the fact that liquidity and systemic risk models leave room for improvement.

Liquidity risk has the ability to spread through financial systems and to affect all participants within the financial system (BCBS, 2010). This is supported by the fact that liquidity risk is not institution specific, but can spread between financial institutions, affecting the entire financial system and all of its participants (Borio, 2003). The health of a financial system and its participants can thus contribute to determining the ability of liquidity risk to spread through systemic risk. The focus of future work should be on the ability of common shocks to affect the stability of a banking sector (Upper, 2006). The failure of a single institution has been the focus of most contagion studies, with the exception of a few studies, including El-singer, Lehar and Summer (2002) & (2004). Upper (2006) identifies several shortcomings of contagion models when used for conducting a survey of interbank contagion models. Data input into simulations do not fully take account of certain real world features (including collateralisation, credit risk transfer and differing seniorities) regarding interbank markets. He also states the specification of scenarios used in models leading to contagion can be improved.

Regardless of the shortcomings and advantages of financial models, Huang *et al.*, (2009) identify two necessities in order to assess the health of a financial system. The first is the ability to measure the systemic risk of the system and secondly the vulnerability of the system to downward risks (Huang *et al.*, 2009). The few financial models attempting to assess the health of financial systems in the past have resorted to using data and information gleaned directly from financial markets (Huang *et al.*, 2009). The reason for this is that traditional risk measures relying on balance information of financial institutions suffered two

setbacks. Firstly, there is a significant lag between market events and the balance sheet information, and secondly, balance sheet information has a low reporting frequency (Huang *et al.*, 2009). Studies suggesting other data for the measurement of systemic risk include Chan-Lau and Garvelle (2005), who propose the application of modern portfolio credit risk theory to the entire banking system. To measure systemic risk the authors implement the Expected Number of Defaults (END) indicator. The benefit of this indicator is that it uses forward-looking information entrenched in equity prices. The fact that equity prices are updated daily the END indicator allows for real-time monitor of markets for stress situations. Adapting a similar approach Avesani *et al.*, (2006) uses the  $n^{\text{th}}$ - to-default probability with Credit Default Swap (CDS) data. Concluding their study, Chan-Lau and Garvelle (2005) suggest that the END measure better captures systemic risk by using the best possible market information available. If Credit Default Swap (CDS) spread information is available in the market the probabilities of default can be directly extracted from the CDS information rather than from equity price data (Chan-Lau & Garvelle, 2005).

Other studies attempting to measure systemic risk with the use of equity return data include Lehar (2005:2578), as well as Allenspach and Monnin (2006). Allenspach and Monnin (2006) conducted a detailed study concerning the link between common exposure and systemic risk. The authors mention that several studies declare that higher correlations lead to higher systemic risk without formally testing this assumption. Their data in the study are the correlations between the asset-to-debt ratios of large international banks over a period from 1996 to 2006 (Allenspach and Monnin, 2006). In their simulations, Allenspach and Monnin (2006) find no trends in the systemic risk indices they create, but rather *two* peaks. One is the combination of the Long-Term Capital Management (LTCM) and Russian crises in 1998 and the other the stock market downturn in 2002–2003. They conclude their study by finding that higher correlations between banks do not necessarily lead to higher systemic risk rather, and that systemic risk is driven by *individual* risk taking by banks (Allenspach and Monnin, 2006).

The systemic risk index computed by Allenspach and Monnin (2006) is based on the systemic risk index created by Lehar (2005), which uses Monte Carlo simulations. The systemic risk index measures the probability of a systemic crisis given that there is multiple defaults in the system at any point in time. According to Lehar (2005:2581) the method used in his study is

uncomplicated and relatively easy to implement and it allows supervisors to monitor risk in the banking system frequently. The method also allows supervisors to compare risk for different time periods and between countries. Finally, Lehar (2005:2598) concludes that the model can be enhanced using advanced value-at-risk (VAR) models in order to estimate the volatility of expected shortfall. According to Huang *et al.*, (2009), the market-based measures used in these studies have two distinct advantages over traditional risk measures. The first is that they are more frequently updated than traditional risk measures, with certain market information being updated daily. Secondly, they are more forward looking since the anticipation on the performance of underlying assets is reflected in the movements of asset prices within financial markets (Huang *et al.*, 2009).

The assessment of a financial systems vulnerability to downside risks, identified by Huang *et al.*, (2009) as an essential part of determining a financial systems health, is addressed by means of stress testing. Stress testing has for a long time formed part of the risk management practice, as financial market participants have always wanted to know the resilience of market positions, instruments and even entire portfolio's (Schuermann & Wyman, 2012). It usually takes the form scenarios or sensitivities.<sup>2</sup> The lack of stress testing on financial systems as a whole has received extensive criticism in post-crisis times. However, in the past several studies have stress tested financial systems as a whole for several types of risks.

The studies of both Basurto and Padilla (2006) and Avesani *et al.*, (2006) used market-based information to conduct stress testing on entire financial sectors. Basurto and Padilla (2006) implemented and combined two methodologies with the goal of improving the measurement of portfolio credit risk. The two methodologies are the conditional probability of default (CoPoD) and the consistent information multivariate density optimising (CIMBO) (Basurto & Padilla, 2006). In short, the CoPoD includes the effects of macro-economic shocks into credit risk by recovering estimators when only a short time series of loans are available (Basurto & Padilla 2006). The methodology is used to model the empirical frequencies of loan defaults as functions of certain financial and macro-economic variables. The CIMBO methodology may be used to recover multivariate distributions that explain the probability of changes in credit risk quality for loans making up a portfolio. It is possible for

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<sup>2</sup> Sensitivities represent price, volatility and spread changes, whereas scenarios represent recessions, stagflation and post-Lehman bankruptcy for instance.

this methodology to do so without enforcing unrealistic parametric assumptions and by only using partial information available (Basurto & Padilla, 2006). For a full description of how CoPoD and CIMBO is developed and implemented see Segoviano and Padilla (2006) and Segoviano and Goodhart (2009) respectively. These methodologies are straightforward to implement in any data-constrained environment and improves the measurement of portfolio credit risk (Basurto & Padilla, 2006).

Applying a Risk Assessment Model for Systemic Institutions (RAMSI), Aikman *et al.*, (2008) illustrate the effects of liability-side feedbacks on liquidity and systemic risk. The RAMSI model they implement is only in its development phase and the authors state that there is still significant room for extension of the model, particularly with regard to the cash flows of banks and the incorporation of feedback effects arising from the banking sector onto the real economy (Aikman *et al.*, 2008). Their RAMSI model is based on balance sheet information gleaned from UK banks and it incorporates macro-credit risk, both interest and non-interest income risks, network interactions and feedback effects. Funding liquidity risk is introduced in the model by allowing for rating downgrades. The rating changes in the model do not arise from data by external providers, but is rather modelled using a framework where concerns over solvency, funding profiles and confidence levels may trigger the complete closure of funding markets to certain institutions (Aikman *et al.*, 2008). The RAMSI model assesses systemic risk by means of the liability-side feedbacks, which may intensify the already existing losses of banks, and which may ultimately lead to system-wide instability. This study of Aikman *et al.*, (2008) sheds light on how increased liquidity concerns and funding costs can effect and increase other forms of risks associated with institutions. The authors illustrate how defaulting financial institutions can, through the interbank market and asset fire sales amongst others, increase contagion within a financial system.

Other work also focussing on the liquidity shortages arising from the liabilities of banks include Allen and Gale (2000:2-3) and Freixas *et al.*, (2000:612). Both of these studies focus on major deposit withdrawals, but the latter through the withdrawals of interbank deposits. Freixas *et al.*, (2000:612) adopt a similar model as developed by Diamond and Dybvig (1983) wherein they assume that agents have to make payments in other locations from where they have deposits, thus providing the need for an interbank market or payment system. Their study establishes that payment systems are efficient under normal conditions, but are



exposed to liquidity crises that may freeze markets and ultimately depend on central bank interventions (Freixas *et al.*, 2000:612). The work of Allen and Gale (2000) builds on their previous study, Allen and Gale (1998) and it also adopts the model of Diamond and Dybvig (1983). In the model they allow for an aggregate demand for liquidity at given times in order to test several types of market structures. They conclude their study by suggesting that the completeness of an interbank market structure and connectedness between banks are conducive to contagion. They argue that within completed markets all banks have linkages with central banks and if central banks intervene appropriately the inefficiency of liquidation associated with contagion may be avoided (Allen & Gale, 2000:27-33).

The work of Von Peter (2004) uses an uncomplicated monetary macro-economic model that has the ability to distinguish between financial and macro-economic stability, which ultimately sheds light on the role that asset prices play in monetary policy. This flexible model studies the effect of shocks on prices, borrowers and the banking sector as a whole. Von Peter (2004) found that asset price movements driven by market liquidity indirectly affected balance sheets through financial accelerators. Von Peter (2004), however, concludes by suggesting that due to the stylised nature of the model, it has its limitations, which should be addressed in future research.

Cifuentes *et al.*, (2005:558) further studied the effects of the amplification of asset prices on interbank defaults. They explored liquidity risk for a financial system with interconnected institutions that mark their assets to market and are exposed to regulatory solvency constraints. Their study found that under certain circumstances more interconnected systems may be at higher risk to systemic problems than less connected systems are (Cifuentes *et al.*, 2005:564). They argue that asset prices of illiquid assets will fall when sold by troubled institutions if the demand for these assets is not perfectly elastic, thus inducing losses for other institutions. These losses can then be amplified when assets are marked to market, which would encourage further sales of these assets and would ultimately reduce prices further. They conclude by suggesting that liquidity buffers can play a similar role as capital buffers and in some instances they can be more effective in absorbing systemic effects.

A combination of studies compiled by Leinonen (2005) focuses on liquidity requirements, systemic risk and the impact of shocks on the performance of a system, amongst other things. Further focuses of Leinonen (2005) include settlement speeds, gridlock situations,

gridlock resolving methods, liquidity economising and payment and settlement systems as a source of liquidity shocks and contagion between banks. The studies compiled in Leinonen (2005) mostly use the BoF-PSS2 simulator developed by the Bank of Finland, used by several central banks and financial institutions around the world.

Work investigating the behavioural reactions to these liquidity shocks includes Ledruth (2007) and Bech *et al.*, (2008). Ledruth (2007) uses a payment and settlement simulator developed by the Bank of Finland to assess the operational failure of participants in the Dutch interbank payment system. With this the author shows that the reactions by participants can mitigate the effects of disruptions for themselves and the banking system as a whole. However, it is not that simple, because reactions and the speed of these reactions by participants can significantly influence or aggravate the secondary effects of market disruptions (Ledruth, 2007). Furthermore, the author emphasises the importance for participants to control their exposure to counterparties by means of bilateral limits,<sup>3</sup> in order to reduce possible costs arising from market disruptions. Bech *et al.*, (2008) examines the Canadian Large Value Transfer System via payment networks defined by the credit controls. They estimate payment-processing speeds of individual banks using a similar technique to Google's PageRank procedure.<sup>4</sup> They suggest that when taking into account the processing speeds of payments, their measure is a good estimator of daily average liquidity holdings in individual banks.

In contrast to Aikman *et al.*, (2008), Alessandri *et al.*, (2008) focus on asset-side feedback effects when using the RAMSI model.<sup>5</sup> Despite this, Van Vuuren (2011:40) suggests that there is still a lack of the feedback effects arising from market and funding liquidity in the macro stress testing models of central banks. The RAMSI model captures the effect of post-default fire sales of assets on asset prices ultimately affecting the balance sheets of banks. The study found that the combination of credit and trading losses has the ability to induce defaults and trigger additional defaults associated with network effects and the fire sale of assets (Alessandri *et al.*, 2008). The work of Brunnermeier and Pedersen (2009) models two possible sources of contagion for banks. The first is market liquidity where higher margins may constrain funding in markets as participants may be more reluctant to take in positions,

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<sup>3</sup> Limits used to control exposures to counterparties. See Ledruth (2007).

<sup>4</sup> Google PageRank procedure is a mathematical method of ranking web pages on a search engine.

<sup>5</sup> The model also allows for macro credit risk, interest income risk, market risk and network interactions.

thus withholding liquidity from markets. Secondly, funding shocks and margin increases may reduce the ability of participants to take in market positions, hence reducing trading positions and contributing to market illiquidity. Adapting a similar model to Grossman and Miller (1988), Brunnermeier and Pedersen (2009:2201) link market and funding liquidity and provide evidence that market liquidity has the ability to dry up suddenly, it has communality across securities, it is correlated with volatility, it is subject to flight to quality and since funding conditions move with the market, so does market liquidity.

The work (Van den End, 2010) is an extension of Brunnermeier and Pedersen's (2009) work into a more practical mechanical algorithm that uses real data and embraces first and second round effects of a liquidity event in simulations. Van den End's (2010) work explores the role of banks in the transition and amplification of shocks within the financial system, as well as the role of liquidity risk when it comes to interaction and contagion between banks in the interbank market.

Chapter 2 reviewed the literature concerning liquidity risk and highlighted how this risk has evolved and how it has been managed and measured throughout its evolution. The construction of the LST follows in Chapter 3. A detailed description of the data used in this study will also be provided in this chapter as well as a description of how to model the LST using Microsoft Office Excel.

## Chapter 3: Model Construction and Data

This chapter provides a detailed description of how the LST is constructed and modelled in Microsoft Office Excel and provides a rationale as to why the chosen periods and economies were used.

### 3.1 Model methodology

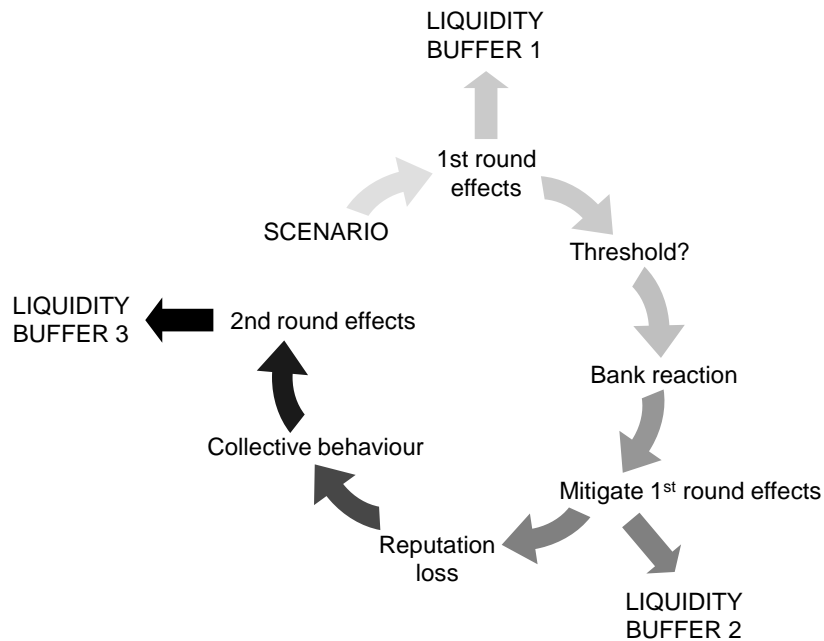
The original LST developed and employed by Van den End (2010) employs buffer restoration as a mitigating action in order to reduce the first round effects of a liquidity scenario. However, by adjusting the LST, different mitigating actions by banks in reaction to these initial liquidity shocks, as well as the effect of severe haircuts and increasing systemic risks, can also be modelled. A description of how these actions and circumstances are modelled is also presented in this chapter.

The LST is based on a practical, mechanical algorithm, which not only makes it operational for simulations with real data, but also has the advantage of modelling the first- and second-round<sup>6</sup> effects of liquidity shocks. The LST focuses on the liquidity positions of banks by means of Monte Carlo simulations of univariate shocks to risk factors, which can affect market and funding liquidity. These risk factors can then be combined in the LST to produce multi-factor scenarios that may affect a bank's liquidity position. The LST assumes that a liquidity stress scenario unfolds in two rounds. However, the effect of these scenarios on the liquidity positions of banks is modelled over three stages within the LST. It is worth mentioning that the interbank- and asset-markets through which banks are affected are not directly modelled. The LST rather focuses on the effect that the mitigating reactions of banks may have on market volumes and prices to which other banks may also be exposed.

The process of the LST is illustrated in Figure 3.1

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<sup>6</sup> Second-round effects are also known as feedback effects. These effects disturb market prices due to the behavioural reactions by heterogeneous banks, as well as idiosyncratic reputation effects.



**Figure 3.1:** Flow chart showing the assumed cycle that follows from a liquidity 'event' and the stages at which buffers should be initiated.

The first round effects of the LST are modelled after a specific scenario, which may affect the liquidity position of any bank, transpires within the banking system. The magnitude of the first round effects determine whether the banks will react by mitigating these effects, depending on reaction thresholds set by banks. These mitigating actions<sup>7</sup> by banks to restore their liquidity positions through buffer restoration are the second stage of the LST. The third stage in the LST is where the second-round feedback effects on banks are modelled. These feedback effects spawn from the reactions by banks to restore their liquidity positions and consist of two components. The first is the idiosyncratic reputation risks that a bank might face. This is caused by the risk that banking sector participants, including banking customers, might sense that the bank may be in financial trouble, possibly causing significant deposit withdrawals and a lack of trust towards the bank.<sup>8</sup> The second component is systemic risk, which is caused by the impact that the collective reactions by banks in the scenario can have on the banking sector ultimately affecting all banks. According to Van den End (2010:43) the LST is of such nature that it does take in to account that systemic risk would be higher if:

<sup>7</sup> Mitigating actions imply that banks instigate specific actions with balance sheet items to restore liquidity buffers.

<sup>8</sup> Extreme deposit withdrawals are also known as bank runs.

- The number of reacting banks is higher since collective reactions lead to increased disturbance in the market.
- Crowded trades due to mitigating actions trigger more reactions that are similar.
- Larger banks react to first round effects since larger banks are more likely to cause a disturbance in the banking sector.

The LST generates distributions of buffer outcomes for every bank in the model over the three stages. Distributions include tail outcomes and the probabilities of a liquidity shortfall in the scenario. With the LST contributing to the ease of creating multi-factor scenarios it provides the flexibility to model various possible liquidity shock scenarios. The construction of different scenarios is deterministic and is based on economic judgement and historical experience of events, which may initiate a liquidity crisis.

### **Liquidity horizon**

The Financial Stability Forum (FSF) (2008) asserts that although banks usually only allow for a one or two month liquidity horizon,<sup>9</sup> the losses stemming from the liquidity crisis stretched far beyond this period. The LST developed by van den End (2010), however, has the ability to extend the liquidity horizon, with van den End (2010:54) estimating the LST with a horizon of up to six months. His estimations of the LST with this liquidity horizon showed significant effects on the scenario outcomes, especially on the tail outcomes of the LST estimations. However, van Vuuren (2011) suggests that the significant impact of a six-month liquidity horizon can be explained by certain liability payments realising after one month.

Similar to the study of van Vuuren (2011:43), the liquidity horizon in this study is limited to one month due to data restriction in the form of a lack of suitable weights for longer liquidity horizons. Van Vuuren (2011:43) suggests that this may underestimate the potential impact of these extended liquidity horizons on the liquidity buffer outcomes.

### **First round effects**

It is assumed that the fixed weights in the LST are 0.1% tail events, which is illustrated by:  $w_i \approx 3\sigma$ . The first-round effect on an item  $i$  in a scenario is determined by the weights ( $w_{sim_{1,i}}$ ) that are simulated based on Monte Carlo simulations, calculated by obtaining ran-

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<sup>9</sup>Liquidity horizon can refer to the frequency at which transactions and portfolios are rebalanced or adjusted.

dom draws from a standard normal distribution  $N(0,1)$  scaled by  $w_i/3$ . Transforming the scaled normal distribution to a log-normal distribution is determined using  $\exp\left(N(0,1) \times \left(\frac{w_i}{3}\right)\right)$ , so that  $w_{sim_{1,i}} \sim \log N(\mu, \sigma^2)$ . According to Van den End (2010:46) the use of a log-normal distribution is motivated by the non-linear features of severe liquidity stress events. Van den End (2010:46) argues that because the log-normal distribution is right skewed it captures the non-linear features of extreme liquidity stress events and that its asymmetric shape fits well with high volatility regimes of financial market data. In the model the log-normal distribution, similar to the weights, is bounded below by 0. The weights are furthermore truncated at  $w_{sim_{1,i}} \leq 100\%$ . This is appropriate for the model, since haircuts on assets and withdrawal rates on liabilities cannot exceed a 100%.

The initial or baseline liquidity buffer in normal market conditions  $B_0$  is

$$B_0^b = \sum_{i=1}^{nc} I_{non-cal,i}^b \quad (3.1)$$

where:

- $b$  represents the individual bank; and
- $I_{non-cal,i}^b$  is the amount of available assets of non-calendar items (the stock items of liquid assets  $1, \dots, nc$ ).

The initial buffer ( $B_0$ ) is made up of deposits at the central bank, securities that have the ability to be easily converted into cash, regulatory SARB eligible collateral, interbank assets immediately available, as well as receivables due from other professional money market participants.  $B_0$  thus provides a counterbalancing capacity against the effect of liquidity scenarios.

The first round effect ( $E_1$ ) of a liquidity scenario is calculated using

$$E_1^b = \sum_{i=1}^{nc} I_i^b \times w_{sim_{1,i}} \quad (3.2)$$

where

- $I_i$  is the amount of all the liquid asset and liability items that include non-calendar and calendar items.

The impact of  $E_1$  on  $B_0$  of a liquidity scenario is determined by,  $B_1$ . This is the buffer that initiates after the first round effects:

$$B_1^b = B_0^b - E_1^b \quad (3.3)$$

### **Banks' mitigating actions**

If the first round of effects of a liquidity shock is of such size that it exceeds the reaction threshold, banks will react in an attempt to restore their liquidity buffers to as close to  $B_0$  as possible. The mitigating actions that banks rely on are attempts to safeguard their stability, as well as their reputation within the banking sector. Through these actions, the banks attempt to meet the liquidity risk criteria of regulators and the rating agencies. In the LST a reaction threshold ( $\theta$ ) is used to determine whether banks would react to the impact of the first round effects of a liquidity scenario. The size of the first round of effects relative to the original liquidity buffer determines whether mitigations actions will be triggered. If this ratio exceeds the reaction threshold, mitigating actions do occur. The trigger  $q(0,1)$  for the mitigating actions is based on the following probability condition:

$$q = \begin{cases} 1 & \text{if } \frac{E_1^b}{B_0^b} > \theta \\ 0 & \text{otherwise.} \end{cases}$$

$\theta$  acts as a measuring tool arising from self-imposed liquidity risk controls and regulatory requirements by banks and can be calculated using the average correlation between the value changes of balance sheet items and the declines of the bank's liquidity buffers lagged by one month:

$$\text{Corell} \left( \frac{B_{t=0}^b - B_{t=-1}^b}{B_{t=-1}^b}, \frac{I_{i,t=1}^b - I_{i,t=0}^b}{I_{i,t=0}^b} \right),$$

conditioned by:

$$\frac{B_{t=0}^b - B_{t=-1}^b}{B_{t=-1}^b} < 0.$$

The liquidity buffers are lagged to control for the possible influence of endogeneity in the relationship between liquidity buffers and balance sheet items. Van den End (2010:47-48), using data from 82 Dutch banks, estimates the reaction threshold at 40%, suggesting that



significant balance sheet changes only occur at above 40%. This reaction threshold indicates whether banks react, and not in which direction they react (Van den End, 2010:48).

Using the same technique, van Vuuren (2011:45) calculates  $\theta = 28\%$  from data collected from January 2004 to January 2010 for large UK banks. Like van den End's (2010) study, van Vuuren (2011) does not investigate the sensitivity of results to the threshold parameter, but keeps the threshold at 28% throughout the study. This study investigates two different periods for two different economies respectively and thresholds are determined in the same way as that used by van den End (2010) and van Vuuren (2011). However, in contrast to these studies, each economy has a separate reaction threshold for both the crisis and non-crisis periods.

The reaction thresholds for the developing South African economy are determined at 3% and 9% in the non-crisis and crisis periods respectively. For the developed UK economy, however, reaction thresholds are determined at 80% for the non-crisis period and 9% for the crisis period of 2009. The high reaction threshold of 80% indicates that banks would only have reacted to losses exceeding 80% of their liquidity buffer, a clear warning signal that should have been heeded at the time. This might reflect either the confidence of the banking system and its participants in the non-crisis period of 2005, or an underestimation of risk in this period, or both.

Equation 3.4 indicates the size of the transactions that a bank would perform with a particular instrument ( $i$ ) in the process of attempting to restore the liquidity buffer. The number of transactions with a particular instrument by a bank is expressed as:

$$RI_i^b = (B_0^b - B_1^b) \times \left( \frac{I_i^b}{\sum_i I_i^b} \right) \quad (3.4)$$

With the buffer after restoration being smaller than the original buffer ( $B_1 \leq B_0$ ), the number of transactions with an instrument ( $RI_i^b$ ) should by definition be positive. Van den End (2010:48), however, suggests that this does not at all indicate the direction of the transactions in terms of buying or selling, it merely gives an indication of the size of the transactions needed to generate liquidity. The variable  $RI_i^b$  is thus only a size factor contributing to the calculation of the liquidity buffer after mitigating actions ( $B_2$ ), which is derived from:

$$B_2^b = B_1^b + \sum_i RI_i^b \times (100 - w_{sim_{1,i}}) \quad (3.5)$$

With  $RI_i^b$  being positive, the buffer after mitigating actions would exceed the buffer prior to these actions ( $B_2 > B_1$ ). This is according to Equation 3.5. However, if markets were to be gridlocked ( $w_{sim_{1,i}} = 100\%$ ) no mitigating action would be able to occur and  $B_2^b$  would be equal to  $B_1^b$ .

If mitigating actions do occur, the buffer after these actions would be smaller than the original buffer for the relevant bank ( $B_2 < B_0$ ). This is due to the market disturbances arising from the first round of a scenario that prevent the buffer from being fully restored. These market disturbances are reflected in  $w_{sim_{1,i}}$ . The most severe stress situations may be presented by  $w_{sim_{1,i}} = 100$ . This implies a drying up of all the available liquidity in financial markets. With financial markets unavailable banks will not be able to raise additional liquidity to service their needs, and in situations like these, if there is no liquidity in repo markets the collateral used by banks may be of no use (van den End, 2010:49).

## Second-round effects

The reactions by banks to mitigate the first round of effects of a liquidity scenario may lead to wider disturbing effects on markets that banks operate within. These effects can feed-back on banks within markets and cause further impact on their liquidity positions. This realises in the markets where banks react through further haircuts on liquid assets and increasing withdrawals of liquid liabilities. These are the second round simulated weights ( $w_{sim_{2,i}}$ ) and its increased effect can be calculated using,

$$w_{sim_{1,i}} \leq w_{sim_{2,i}} \leq 100.$$

Feedback effects on banks may increase if their reactions are more similar and if the number of reacting banks increases ( $\sum_b q$ ). This increased effect is expressed in the model by the sum of reactions by a particular instrument ( $\sum_b RI_i^b$ ). When dividing the sum of reactions of a particular instrument ( $\sum_b RI_i^b$ ) with the sum of all reactions ( $\sum_i \sum_b RI_i^b$ ) the ratio indicating the similarity of reactions ( $\sum_b RI_i^b / \sum_i \sum_b RI_i^b$ ) is derived. When banks participate in deep liquid markets, the size of  $w_{sim_{2,i}}$  is reduced. This is due to the wider range of instruments available to service liquidity needs in liquid markets than illiquid markets. The actual estimation of the simulated second round weights ( $w_{sim_{2,i}}$ ) for the third stage of the LST is as follows,

$$w_{sim_2,i} = w_{sim_1,i} \times \frac{\left( \sum_b q \left( 1 + \frac{\sum_b RI_i^b}{\sum_i \sum_b RI_i^b} \right) \times s \right)}{\sum_b q} \quad (3.6)$$

$RI_i^b$  indicates the size of the transactions conducted with instruments to generate liquidity and this implies that higher values of  $RI_i^b$  arise when there is a higher demand for liquidity. If banks have a higher demand for liquidity, it will result in a negative impact on the markets that provide liquidity to banks. The inclusion of  $RI_i^b$  into Equation 3.6 provides evidence that larger transactions (caused by collective behaviour or reactions by large banks) will have a greater impact on market liquidity than smaller transactions. Thus, the inclusion of  $RI_i^b$  in Equation 3.6 substantiates that the LST takes into account that feedback effects arising from systemic risk increases when banks react similarly and reacting banks are larger.

The relationship between asset prices and the sale of assets by banks in Equation 3.6 compares to those used in the work of Alessandri *et al.*, (2008) and Nier *et al.*, (2008). In the models of these two authors, the price of banking assets is a decreasing function of liquidated assets. Furthermore, the authors suggest that the elasticity of price effects can be referred to as a measure of market illiquidity. In the LST, the simulated weights ( $w_{sim_1,i}$ ) and the market stress variable ( $s$ ) account for the elasticity of price effects.

The variable  $s$  in the LST is a market stress indicator. Van den End (2010:50) derives this variable using several risk aversion indicators as proxies, including implied stock, price volatility and US corporate bond spreads. Van den End (2010:50) indicates that in order to determine the range of  $s$  in the LST, it is assumed that normal market conditions are expressed by  $-1 \leq s \leq 1$ , which represents  $\frac{2}{3}$  of market conditions according to a standardised distribution of risk indicators. Severe market conditions can be expressed by  $s = 3$ . The  $s$  variable is, however, not limited to 3 and can be even higher. Van Vuuren (2011:51) used  $s = 3.4$  to observe how enhanced contagion can impact second-round effects of the model. With the intent to observe liquidity stress situations the restriction of  $s \geq 1$  applies when using the LST. Van den End (2010:50) also suggests that using these risk aversion indicators allows for periodic estimations of the LST in which market conditions play a role.

Market conditions play an essential role in the LST by contributing to the impact second-round effects may have on liquidity positions. Increasing market stress ( $s$ ) leads to increased

second-round effects in the LST, which may reduce liquidity buffers even further. This increased effect is due to the impact of  $s$  on the number of and the similarity of reactions by banks.

Van den End (2010:51) illustrates the exponential relationship between  $w_{i\text{sim}_{1,i}}$  and  $w_{\text{sim}_{2,i}}$ , as well as how these variables are dependent on the number of reacting banks, the similarity of mitigating actions and the level of market stress ( $s$ ). The model assumes that the similarity of bank reactions have a greater effect on markets than the number of reacting banks does. The insight behind this assumption is that similar reactions by banks expose the market to crowded trades, ultimately affecting asset prices in the market and ultimately the balance sheets of banks participating in these markets.

Banks face reputation risk when they attempt to restore their liquidity buffers through mitigating actions. The application of sensible measures as mitigating actions should theoretically strengthen the financial positions of banks and provide comfort to counterparties in times of stress. However, the adverse signalling effect of transactions (mitigating actions) can reverberate on the conditions banks already face in the markets (van den End, 2010:51). This could introduce to even greater haircuts on liquid assets and increased withdrawals of liquid liabilities held by banks in the third stage of the LST. This is reflected in  $w_{\text{sim}_{2,i}}^*$  in Equation 3.7 where  $w_{\text{sim}_{2,i}} \leq w_{\text{sim}_{2,i}}^* \leq 100\%$ . It is clear in Equation 3.7 that the reputation effect is dependent on  $s$  affecting second-round effects, since in stressed circumstances the signalling effect of reactions adversely feedback on banks. Van den End (2010:52) suggests that this is proven by the stigma surrounding the liquidity crisis of 2007 where the accessing of central bank standing facilities played a significant role in the contagious abilities of the crisis. Equation 3.7 illustrates how the simulated second round weight accounting for reputation effects is derived,

$$W_{\text{sim}_{2,i}}^* = w_{\text{sim}_{2,i}} \times \sqrt{s} \quad (3.7)$$

The additional impact of second-effects ( $E_2^b$ ) on banks, arising from idiosyncratic reputation and systemic risk, is determined in Equation 3.8,

$$E_2^b = \sum_i [(I_i^b + RI_i^b) \times (w_{\text{sim}_{2,i}} - w_{\text{sim}_{1,i}})] \quad (3.8)$$

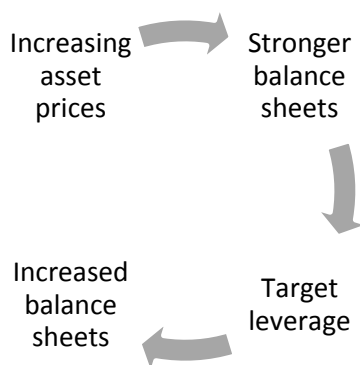
In Equation 3.8  $w_{sim_{2,i}}$  may be replaced with  $w_{sim_{2,i}}^*$  for banks that react, which causes them to face reputation risk. Once the second round effects have been determined, the liquidity buffer ( $B_3$ ) after the second-round effects of the model can then be derived as,

$$B_3^b = B_2^b - E_2^b. \quad (3.9)$$

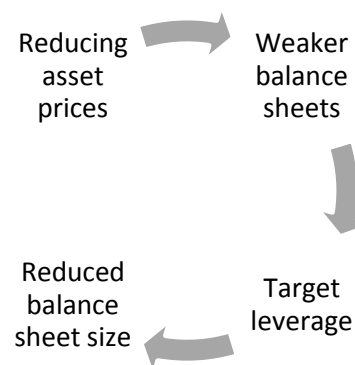
### *Leverage targeting*

The assumptions of the domino model of financial contagion suggest that asset prices are fixed at book values and only defaults have the ability to affect balance sheets. However, the domino model of financial contagion is flawed since it assumes that balance sheets are not actively managed and it does not fully account for how asset prices and measured risks change (Adrian and Shin, 2008). Adrian and Shin (2008) further argue that price changes affecting balance sheets are more likely to cause distress than defaults in a banking system. Their work with evidence gathered directly from the market shows that during and prior to the liquidity crisis banks used leverage targeting to actively manage their balance sheets to obtain desirable leverage ratios. Furthermore, credit ratings are essential for banks in order to ensure low cost funding and these desired credit ratings are achieved through the active management of balance sheets.

Figures 3.2 and 3.3 illustrate the process of leverage targeting in both an economic boom and economic bust.



**Figure 3.2:** Leverage targeting during financial boom

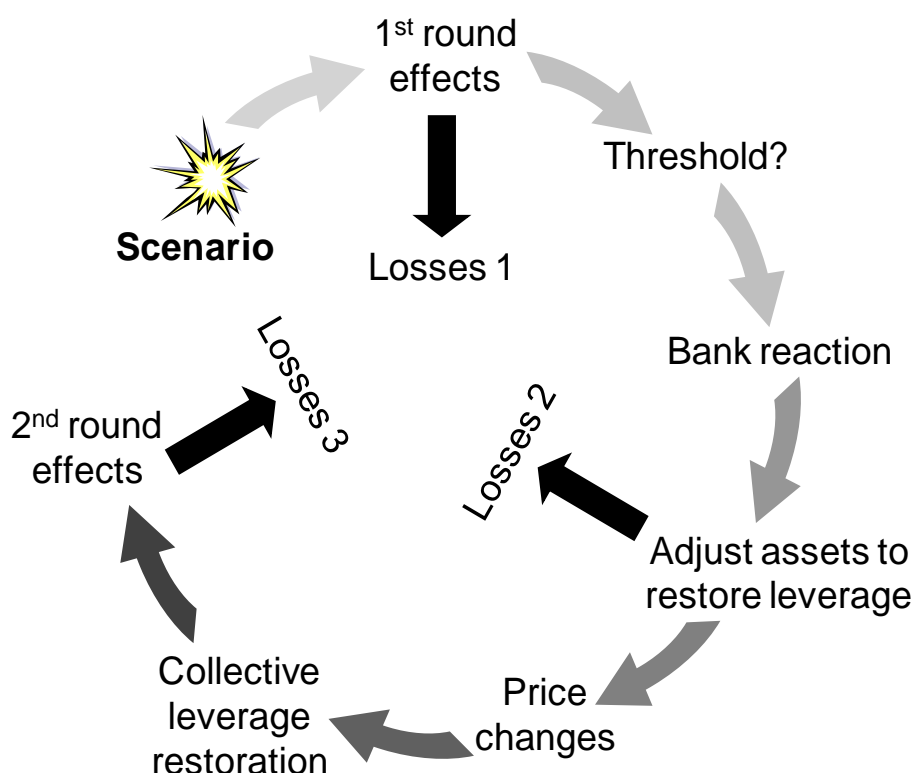


**Figure 3.3:** Leverage targeting during financial busts

Figures 3.2 and 3.3 illustrate how leverage targeting is employed by banks in both financial booms and busts in order to actively manage balance sheets. Increased asset prices in Fig-

ure 3.2 would understandably lead to banks having stronger balance sheets in times of economic boom. An increased leverage ratio would further increase the exposure of banks to favourable market conditions, possibly increasing net worth and balance sheet strength. Reduced assets prices in Figure 3.3 would leave banks with weaker balance sheets. Through leverage targeting the banks can reduce their leverage ratio and balance sheet size, protecting them from market conditions and possibly shielding their current net worth.

The LST adjusted for leverage targeting as a mitigating action is displayed in Figure 3.4.



**Figure 3.4:** An alternative cycle to that proposed by van den End (2010:42) in which leverage targeting rather than buffer restoration is the mitigating action.

The process of how leverage is affected by changing asset prices and restored is explained with the following example:

Using the balance sheet in Table 3.1 as an example, the institution holds 200 units assets,<sup>10</sup> which is funded by 180 units of debt and 20 units of equity. Leverage is defined as the ratio of total assets to equity (Adrian and Shin, 2008) and can thus be illustrated as:

<sup>10</sup> These assets are assumed to be available-for-sale securities just for the simplicity of the example

$$\text{Leverage ratio } (L) = \frac{\text{Assets}(A)}{\text{Equity}(E)}$$

The leverage ratio in this example is thus:

$$L = \frac{A}{E} = \frac{200}{20} = 10.$$

ASSETS		LIABILITIES	
SECURITIES	200	DEBT	180
		EQUITY	20

**Table 3.1:** Original balance sheet

If for instance there were an increase of 2% in the value of securities, the leverage ratio would change to:

$$L = \frac{A}{E} = \frac{204}{24} = 8.5$$

ASSETS		LIABILITIES	
SECURITIES	204	DEBT	180
		EQUITY	24

**Table 3.2:** Balance sheet after asset price increase

The value change in securities in Table 3.2 leads to a lower leverage ratio. On the liabilities side of the balance sheet the balancing factor comes from equity and this is due to the value of debt remaining approximately constant. If the bank wishes to maintain their original leverage ratio of 10 they will have to take on more debt and use this debt to purchase additional securities and restore the leverage ratio. The additional debt the bank has to acquire equals 36 units, which are used to purchase additional securities of 36 units. By doing this in Table 3.3, the leverage ratio is restored to 10 since:

$$L = \frac{A}{E} = \frac{204 + 36}{24} = 10.$$

ASSETS		LIABILITIES	
SECURITIES	240	DEBT	216
		EQUITY	24

**Table 3.3:** Balance sheet after leverage targeting

This increase in security prices leads to increased holding of securities when leverage targeting is used as a mitigating action and thus indicates upward sloping demand curves and downward sloping supply curves in case of security price increases. Van Vuuren (2011:48)

states that in order to use leverage targeting as a mitigating action in the LST, the assumption that banks have to restore their liquidity buffer back to the original level has to be relaxed. Instead, an assumption should be imposed that banks purchase additional assets (regardless of worsening prices) to restore their leverage ratio after the first round of a liquidity.

The haircuts on assets and run off rates on liabilities play a significant role in the LST and are some of the key determinants of the effects of a liquidity event. As mentioned, both economies have two sets of weights arising from haircuts and run-off rates on balance sheet items with one for the non-crisis period and another for the crisis period. The effect of these weights on balance sheet items is investigated in the study by introducing a haircut factor defined as  $f$ . An increased  $f$  implies increased simulated weights in the LST as  $f$  is multiplied with the original weights each time the LST is estimated. The ability of incrementally increasing the simulated weights to see the effect of these weights in the study is gained.

Using haircut data gleaned from UK banks for January 2004 to January 2008 and January 2008 to January 2010, van Vuuren (2011:49-50) also investigates the effects of increased haircuts. His simulated results found that the increased haircuts from the latter period applied by banks in order to constrain further losses and penalise for the lending on riskier financial instruments significantly reduced the possible liquidity buffer losses.

### *Enhanced contagion*

Market conditions play a significant role in contributing to how extent second-round effects can influence the liquidity positions of banks. In the LST the contagion parameter is set by  $s$  as used in Equations 3.6 and 3.7. The reputation effects that banks are exposed to are driven by stressed market conditions ( $s$ ) in the second-round effects the model. The reputation risk to banks arises by the introduction of  $\sqrt{s}$  in Equation 3.7.

In the LST van den End (2010:53) sets  $s = 1.5$  and van Vuuren (2011:50) sets  $s = 2$  as their baseline levels of market stress. Both authors also estimate their models using  $s = 2$  and van Vuuren (2011:50) also estimates his model at  $s = 3.4$  to observe how an increased  $s$  can further contribute to second-round effects in the LST. By increasing  $s$  the reputation effect banks are exposed to will also increase, thus leading to greater possible feedback effects on the liquidity positions of banks.



The next section describes the relevant data used in this study. Furthermore, it also describes why the relevant periods were used and why the South African and UK economies were chosen.

## **3.2 Data**

The empirical study is conducted via the reconstruction of van den End's (2010) LST, calibrated using data from five leading South African, as well as five principal UK banks. This section of Chapter 3 assesses why the data used in the study are appropriate and relevant. Five key characteristics regarding the data are taken into consideration and discussed in this section. The usage of bank data are the first characteristic discussed in terms of why it is appropriate and important, followed by an assessment of the South African and UK banking data respectively. This aims to identify the characteristics that make each economy unique and thus comparable under liquidity stress and non-stress situations. This section of Chapter 3 concludes with an assessment of the crisis and non-crisis periods used in the LST simulations, possibly identifying why these periods are different from each other and may yield different results in simulations.

### **3.2.1. Banks**

Using banking data is supported by the assumption that banks can be considered as a measure of a specific economy's health, as several characteristics of banks represent the local economy. The health of a bank's balance sheet can reflect several characteristics of an economy. Allen and Carletti (2008) identify several positive and negative aspects regarding the roles of banks in economies and financial systems. They suggest that banks play a vital role in solving several informational problems throughout an economy. This is achieved by banks serving as delegated monitors of the financial system, ensuring effective resource allocation between borrowers and lenders (Allen & Carletti, 2008). Through this process banks can also be seen as liquidity creators in financial systems as they allocate funds from lenders into markets where borrowers can access it.

This might possibly also spur on growth within the economy due to the effective allocation of financial resources. Furthermore, the study of Levine and Zervos (1998:537) also suggest that a greater level of bank development leads to higher growth irrespective of how markets develop. Banks also play a vital role in terms of sharing and smoothing risk fluctuations

within an economy (Allen & Carletti, 2008). They can smooth risks that cannot be diversified by building up reserves when returns on banking assets are high and reducing them in times when returns are low. This averages these un-diversifiable risks, which may reduce risks for depositors and other banking system participants (Allen & Carletti, 2008).

Trust is considered as one of the fundamental aspects regarding financial market activities, including trade and investment, as it is the place where individuals depart from their money in exchange for promises (Sapienza & Zingales, 2009:124). A lack of trust in banks can reveal to a certain extent investor perceptions towards banks and the banking system. The financial crisis also saw a decrease in the level of trust towards banks in Austria when investigated by Knell and Stix, (2010). Thus, the level of trust in banks can also shed light on the stability and state of a financial system.

Since the onset of the credit crisis in 2008 and its severe effects on the global financial system, the topic of contagion and interconnectedness between banks has become increasingly important. A shock has the ability to affect a certain sector of the economy or specific institutions and spreads through links between banks and other financial institutions, ultimately affecting an entire financial system and the economy (Allen & Carletti, 2008). The effects arising from the relatively small sub-prime mortgage sector that affected the entire financial system in the crisis of 2008 serves as prove (Adrian & Shin, 2008). The ability of contagion to affect the banking system through traditional defaults and more recently, price changes in market-to-market systems is explored by Adrian and Shin (2008). The work of Upper and Worms (2004:827) finds that in the German banking system the failure of a single bank can in terms of assets breakdown 15% of the banking system. With more recent work focussing on how asset price changes can encourage contagion within a financial system, Cifuentes *et al.*, (2005:564) found contagion effects to be severe if significant price changes occur. As the entire economy has some sort of connection to the banking system and banks can act as measures of economic health and stability, banking data can effectively represent the economy in non-crises and crises times.

Associating with contagion is the concept of banks becoming too big to fail. Banks labelled too big to fail usually carry high levels of systemic risk and if they were to fail, they would significantly affect other institutions in financial markets and possibly cause further defaults (Joines, 2010). Central banks and governments prefer not to get involved when financial in-

stitutions fail, except when these institutions are considered as *too big to fail*. Central banks would further consider whether the stability of the financial system outweighs the costs associated with moral hazard issues and investor perception arising when they intervene (Joines, 2010). Preferably, banks should not get too big to fail through proper risk management and regulation activities. However, the effects of activities<sup>11</sup> leading up to the crisis significantly increased interconnectedness within the global banking system, ultimately increasing the exposure of financial institutions to the crisis (FCIC, 2011).

### 3.2.2 The South African banking system

The South African banking system forms a small percentage of the global financial system and is rather tiny compared to the banking systems of the UK, USA and Japan (Financial Centre Authority (FCA), 2013).<sup>12</sup> The FCA ranks financial systems according to infrastructure, general competitiveness within the financial system, access to markets, as well as people and the business environment amongst other. However, South African banks are respected globally as they are ranked amongst the top ten in the world regarding the soundness of banks within the economy (World Economic Forum (WEF), 2009). Furthermore, the WEF (2009) also ranks South African financial market sophistication sixth out of the hundred and thirty-three economies assessed. Thus, although the South African banking system is small, the sophistication of the economy possibly ensures that South African data would fully represent the effects of the data periods used. This is important, as data from less sophisticated economies might possibly not capture all the effects arising from crisis periods within a year. It is thus essential to compare economies that could have been similarly exposed and affected by certain events in order for the study to have merit.

With the South African economy being branded as an emerging economy, the use of these data offer insight into how an emerging economy compares to a well-developed economy in either a crisis or a non-crisis period. Also emphasising the sophistication and development of the South African banking sector is the fact that a South African bank was voted as the most innovative bank in the world at the BAI-Finacle Global Banking Innovation Awards in 2012 (First National Bank, 2013).

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<sup>11</sup> Boom in the housing markets and securitisation of subprime mortgages.

<sup>12</sup> The FCA ranks the London Financial system 1<sup>st</sup> and South Africa 54<sup>th</sup> as of January 2013.

Compared to other developed economies the South African banking sector weathered the worst effects of the global financial crisis (The Banking Association South Africa (BASA), 2010, Moody's Investors Service, 2011 & Verster, 2012). The papers cited above further suggest that the heavy regulation of the South African banking sector significantly contributes to these limited effects. Several acts<sup>13</sup> along with the King Code on Corporate Governance and Basel Regulatory Standards have contributed to the intense regulations of the South African banking system. This supports the use of the South African data set in the study as it is comparable to the UK banking system, which suffered more severely from the financial crisis.

Exchange controls, which have been relaxed in the past decades, is still present in the South African financial system (Aron, Elbadwi & Kahn, 1997). The South African Reserve Bank (SARB) regulates these exchange controls by managing all in- and out-flows of foreign exchange in the South African economy. These controls apply to all transactions involving foreign exchange and South Africa is amongst a few countries still employing these controls. These controls proved an advantage for the South African financial system in the crisis period as banks could better control their exposure to toxic assets, especially foreign sub-prime structured products (Moody's Investors Service, 2011). Preventing exposure to the financial crisis along with the exchange controls is The National Credit Act (NCA) 34 of 2005, implemented in June 2007. This act restricts banks from entering into reckless lending activities, as well as possibly reducing banks' exposures to foreign market activities and risky instruments prior to the crisis.

The South African data are thus suitable to use as they reflect a unique, sophisticated, globally respected – although small – banking system. Furthermore, the South African Economy was not as severely affected by the crisis compared to other developed countries such as the USA and the UK (BASA, 2010, Moody's Investors Service, 2011 & Verster, 2012). The estimations of the LST illustrate the possible liquidity buffer losses of the banking system and not an individual bank. Thus, results illustrated do not implicate any individual bank; they merely illustrate the possible and not certain losses of the entire banking system. The data are gleaned from the financial statements of Standard Bank, ABSA, FirstRand Bank, Nedbank

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<sup>13</sup> These acts include: The Banks Act, The National Payment System Act, The Financial Intelligence Centre Act (FICA), The Financial Intermediary and Advisory Service Act (FAIS), The National Credit Act, The Consumer Protection Act, The Home Loan and Mortgage Disclosure Act and The Competition Act (The BASA, 2010).

and Investec. These banks were chosen as they represent the biggest percentage of the South African banks in terms of their assets. Their market share equals more than 90% of the South African banking system (BASA, 2010). The data include the relevant haircuts and liquidity thresholds needed in the LST and these haircuts on assets and liabilities are illustrated in the Appendix

### **3.2.3. The UK banking system**

The UK banking system, contrary to the South African banking system, is one of the world's largest, along with New York in the USA and Tokyo in Japan (FCA, 2013). It is considered as the hub of global finance, attracting some of the world's finest bankers, furthermore, acting as a gateway to the rest of Europe. Compared to the South African banking system the UK severely suffered the effects of the global financial crisis, with banks failing in the crisis period, forcing the UK government to acquire in some cases majority stakes in banks, including the Royal Bank of Scotland (RBS) and the Lloyds Banking Group amongst others (House of Commons Treasury Committee (HCTC), 2009). Furthermore, Barclays resorted to raising funds through sovereign wealth stemming from the Qatar Investment Authority amongst others. They were criticised for this because they did not attempt to raise capital through its existing shareholders (HCTC, 2009). These severe effects of arising from the financial crisis gave way to the introduction of the Asset Protection Scheme (APS) in January 2009, which allowed banks and other financial institutions to insure against future value losses of certain assets (HCTC, 2009). This partly emphasises the severe effects of the financial crisis on the UK banking system.

Another characteristic distinguishing the UK economy from the South African economy is the housing boom that was hugely present in the UK prior to the crisis. This does not imply that the housing boom did not occur in the South African market at all, however, house prices increased by a 175% in Britain between 1997 and 2006 (Anon, 2006). However, significantly affecting the UK financial sector prior to the onset of the crisis was the vast amount of subprime mortgages in the UK banking system. A Financial Crisis Inquiry Report in 2011 suggests that the UK had the highest percentage of subprime mortgages outside the US, peaking at 8% in 2006 (FCIC, 2011). This confirms how exposed the UK banking system might have been prior to the onset of the financial crisis. This is in contrast to the South African

banking system where banks were restricted by intense regulation and acts from participating in risky lending (BASA, 2010).

The Bank of England does not employ any exchange controls like the SARB. This distinguishing the banking systems of the two economies compared in this study even more. The new conservative government abolished exchange controls in 1979, with Artis and Taylor (1989) investigating the effect of this abolishment on UK portfolio investments controls and monetary controls. With no exchange controls in place banks in the UK would have had more freedom to participate in foreign markets in the economic boom period prior to the crisis. This would most likely have led to the increased exposure of the financial crisis compared to an economy like South Africa. Further increasing the exposure of UK banks to the financial crisis is the high level of interconnectedness between these banks prior to the crisis (Buiter, 2009; IMF, 2011). The work of Aikman *et al.*, (2008), as discussed in Chapter 2, illustrates how liability-side feedback affects their RAMSI (quantitative model for systemic risk) model. They illustrate how funding liquidity problems at one bank can affect other banks within the banking sector when estimating with data gleaned directly for the balance sheets of UK banks.

The severe effects of the crisis, the housing boom and the interconnectedness of UK banks prior to the crisis all distinguish the South African banking sector from the UK's. However, there are further unique characteristics of the UK banking sector. London is the home of the London Interbank Offered Rate (LIBOR), which is an interest rate used in the London interbank market. However, millions of transactions across the globe also rely on the LIBOR interest rate, including the USA, Canada and Switzerland (Haubrich, 2001). Although South Africa has the Johannesburg Interbank Agreed Rate (JIBAR), it is not nearly as widely used in the rest of the world as LIBOR.

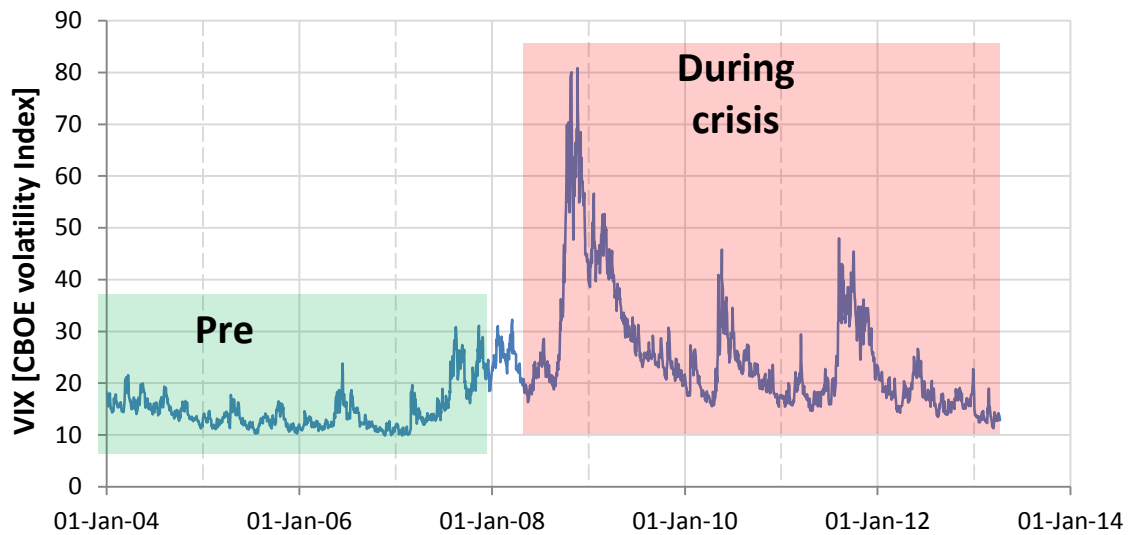
The UK financial system on its own is hugely complex and developed and houses activities involving complex derivatives used by the world's biggest multinational corporations (FCA, 2013). The size of the South African banking sector cannot nearly compare to that of the UK. However, after the onset of the crisis the soundness of UK banks were ranked at 126<sup>th</sup> out of a 133 countries compared to South African banks, which were ranked 6<sup>th</sup> (WEF, 2009).

Apart from comparing the banking systems of South Africa and the UK there are several other characteristics of these economies separating them from each other. The economy of

the UK had a Gross Domestic Product (GDP) three times that of South Africa with a population of just about ten million more in 2006 (World Bank, 2013). The GDP growth rates of South Africa and the UK economies were 4.87% and 1.82% respectively in the economic boom of 2005. However, in the first quarter of 2009 both economies achieved negative GDP growth, emphasizing the effects of the financial crisis (World Bank, 2013). The South African economy, however, recovered easier than the UK economy, with the UK economy still reporting negative GDP growth in 2012 (World Bank, 2013). On the contrary, the South African economy achieved GDP growth rates exceeding 4% in 2011. However, in 2012 the economy achieved lower growth rates, although still positive (World Bank, 2013). The GDP growth rate is an appropriate indicator of how the crisis affected both economies and it may show how the crisis crippled performance of both economies. The data for the UK banking system are gleaned directly from the balance sheets of five principal UK banks including Barclays, RBS, The Lloyds Banking Group, HSBC and Standard & Chartered bank. Again, as mentioned for the South African data, results do not implicate any single bank mentioned. Results in the Chapters 4 through 6 indicate possible liquidity buffer losses for the entire banking system under the specific scenario.

#### **3.2.4. The non-crisis period of 2005**

The reason 2005 was chosen as a suitable period in which to explore liquidity requirements is that it marks the middle of the largest economic boom in post-war history, spanning from approximately 2003 to 2007 (Kirkland, 2007). Figure 3.5 clearly distinguishes the non-crisis and crisis periods, with 2005 being in the midst of the pre-crisis period and arguably the least volatile.



**Figure 3.5:** CBOE Volatility Index (VIX), showing the pre-crisis and severe crisis periods.

Source: Chicago Board Options Exchange (2013)

The two periods illustrated in Figure 3.5 differ significantly from each other. The pre-crisis period saw significant growth in several industries with very little volatility obscuring this growth. The boom in the housing market encouraged positive growth in other sectors of economies around the world as well (FCIC, 2011). The success of the housing markets was positively correlated with construction industries (FCIC, 2011). Further supporting the positive growth in the mentioned markets was amongst other things the relaxation off credit standards that allowed financially unfit consumers to acquire credit (FCIC, 2011). At the time this encouraged growth as the majority could afford homes without any income or assets backing their mortgages (FCIC, 2011). Essentially these major capital injections into these sectors fuelled growth without the consequences being considered (FCIC, 2011). The term moral hazard has been thrown around a lot since the onset of the liquidity crisis and the activities prior to the crisis period are mostly to blame for this. The Financial Times Lexicon (2013) defines moral hazard as the insured taking more risk and being more careless because they are covered and that this concept can be applied to any contract. Banks across several economies performed reckless lending activities and increasingly financed their asset holdings with shorter maturity instruments in order to increase their exposure to the booming economy (Brunnermeier, 2009:78).

Brunnermeier (2009:78-80) identifies two characteristics of the non-crisis period that laid the platform for the financial crisis. The first is the *originate to distribute* model that banks



used to pass on the risk by repackaging and removing loans from their balance sheets. This was done through the practice of securitisation<sup>14</sup> by banks, which was enormous prior to the financial crisis. Along with the securitisation came instruments referred to as Credit Default Swaps (CDS), which investors in securitised products purchased to insure them against default of the underlying tranche or bond they invested in. Investors in AAA tranches backed by a CDS had no reason to fear default as the risk of default under these high ranking tranches were small, which emphasises the calmness in the markets prior to the crisis. However, Brunnermeier (2009:78) suggests that although securitisation passed on risk to other investors, the risks never left the banking sectors, as banks remained the majority investors in these products. The problem with these products was that several of them were backed by the NINJA (No Income, No Job or Assets)<sup>15</sup> loans banks provided to clients and when defaults on these loans realised, rating downgrades were inevitable (Brunnermeier, 2009:87). Rating downgrades along with defaults first noted in the US economy in 2007 triggered the liquidity crisis and significant declines in the Mortgage Credit Default Swap ABX Indices (Brunnermeier, 2009:83).

The second characteristic Brunnermeier (2009:79-80) identifies is that banks increasingly used shorter maturity instruments to finance their asset holdings in the non-crisis period. This was done using short-term asset-backed commercial papers and reverse repurchased agreements, which significantly increased the maturity mismatch on the balance sheets of banks, ultimately increasing the exposure to liquidity funding risk (Brunnermeier, 2009:80). The use of the 2005 period captures a significant part of these activities that laid the foundations for the liquidity crisis.

What further encouraged the use of the 2005 period was the fact that this period was undoubtedly before the onset of the crisis. In 2005, there were no signs of markets slowing down or turning for the worse and furthermore, the markets were unsurprisingly calm in this period in contrast to the panic of the 2009 period used in the study. Figure 3.5 illustrates the calmness experienced in global markets in the non-crisis period spanning from 2003 to 2007 by means of the VIX index. The NCA of 2005 was only implemented in 2007 in South Africa, which brings the ability to explore how the NCA might have contributed in pro-

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<sup>14</sup>For more on securitisation see Brunnermeier (2009:78-79).

<sup>15</sup>Banks offered these loans to customers with no creditability and they did not fear the risks as they would within a couple of months offload these risks through securitisation.

protecting the South African banking system from the effects of the crisis. Thus possible liquidity buffer losses before and after the implementation of the act can be simulated.

### 3.2.5. The crisis period of 2009

The financial crisis of 2008, which showed its first signs in 2007, has been labelled as the worst financial meltdown since the great depression (Nastase *et al.*, 2009:691). Figure 3.5 illustrates the volatile nature of global finance in this crisis period. There are several characteristics of the crisis period that serve as motivation for using the 2009 period in this study. Many economies experienced negative GDP growth rates in 2009 due to suffering the severe effects of the financial crisis, with a decline of 7.4% and 9.8% in GDP in the UK and the Euro area respectively (Nastase *et al.*, 2009:695).

The turn of the housing market in 2006 precipitated the start of the financial crisis. House prices that reached their peak in 2006 in the US declined, on average 28% up until 2009. Cities like Las Vegas experienced a decline of 55%, with even cities not experiencing home price increases prior to the crisis suffering the effects in their housing markets (FCIC, 2011). The first signs of the housing crisis came to light when a rise in early payment defaults occurred in 2006 with 1.5% of loans less than one year old were in default. This was followed by first payment defaults<sup>16</sup> rising above 1.5% in early 2007 (FCIC, 2011). The crash of the housing markets was followed by rating downgrades on tranches of securitised products backed by subprime mortgages. This occurred to such an extent that in the first 10 months of 2007, 92% of the mortgage backed securities had at least one tranche downgraded or put on watch by rating agencies (FCIC, 2011). In the end 76% of security tranches issued in 2006 and 89% of those issued in 2007 initially rated as high as investment grade (Baa3), were downgraded to junk. This entire process caused the prices of almost all mortgage-backed securities to plummet, along with runs on money market funds, tighter credit, as well as higher interest rates (FCIC, 2011).

There has been a significant amount of speculation regarding the total losses of the financial crisis, with the International Monetary Fund (IMF) estimating that losses in 2009 would exceed US\$4 trillion dollars (Dattels & Kodres, 2009). Mark Adelson, former chief credit officer of Standard & Poor's recently made possibly the broadest loss estimation of the crisis. Attracting some criticism, he estimated total losses of the global financial crisis at US\$15 tril-

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<sup>16</sup> First payment defaults refer to mortgages on which not one payment was made.

lion (Yoon, 2012). Regardless of the exact number of the losses arising from the crisis, it is clear that the crisis has had a significant effect on the global economy with effects still visible in economies across the globe at present. The crisis saw several financial institutions around the globe fail despite the massive direct capital injections into some institutions by central banks, as well as support within markets by central banks. In the US institutions including Bear Stearns, Fannie Mae, Freddie Mac, the Lehman Brothers and American International Group (AIG) amongst others experienced significant financial difficulties (FCIC, 2011). Bear Stearns experienced runs from hedge fund customers, repo lenders and derivative counterparties and was eventually rescued when purchased by JP Morgan assisted by the US government. Financial institutions Fannie May and Freddie Mac were taken over by the government, costing taxpayers a \$151 billion up until 2011. Dubbed the kings of leverage, Fannie May and Freddie Mac significantly exposed themselves to the boom and eventually the bust of the financial crisis<sup>17</sup> (FCIC, 2011). The Lehman Brothers, one of the US's largest investment banks, had roughly \$200 billion exposure in repo markets prior to its collapse, whereas Bear Stearns only had \$50 to \$80 billion and they also collapsed (FCIC, 2011). The Lehman Brother collapse in September 2008 caused panic in the markets, as the government did not rescue them as they saved Bear Stearns, Fannie May and Freddie Mac before them and AIG after them (FCIC, 2011). The question in the markets was who would not be saved next. The mega insurance institution AIG collapsed shortly after Lehman Brothers, sparking further panic within markets as there was uncertainty regarding the balance sheets of major financial institutions across the globe. The government ultimately committed more than \$180 billion to AIG due to the fear that if AIG should fail it would have significant repercussions in the global financial system (FCIC, 2011). These are only a few of the US financial institutions that suffered the effects of the financial crisis, with several other financial market participants reporting severe losses throughout the crisis period.

With the UK banking system thoroughly involved in subprime mortgage backed securities prior to the onset of the crisis, several UK financial institutions also severely suffered the effects of the crisis. The market turmoil in the US forced the UK government to intervene and provide support to Northern Rock, which was one of the first UK financial institutions to severely suffer the effects of the financial crisis in the UK. Northern Rock came under severe

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<sup>17</sup> Fannie May and Freddie Mac's leverage stood at 75 to 1 when including the loans they owned and garmented at the end of 2007.

pressure to fund their operations when wholesale funding markets tightened up in the middle of 2007 as their business model was highly dependent on wholesale funding (HCTC, 2009). The fact that Northern Rock was one of the first UK banks requesting public funds placed them under severe pressure as the bank fell victim to a bank run. The bank was taken into temporary public ownership in February 2008, but not without constructing a restructuring plan with the goal of returning to the private sector and repayment of the debt owed to the Bank of England (HCTC, 2009).

Following soon after Northern Rock was Bradford and Bingley (a UK-based building society), which was taken into public ownership in September 2008. Bradford and Bingley had almost £17 billion more in loans compared to assets, which was funded through wholesale markets prior to the crisis. Similar to Northern Rock, the moment wholesale markets tightened up Bradford and Bingley also came under severe pressure. They were taken into public ownership with the goal of winding down operations in contrast to Northern Rock. Further consequences of the crisis were the merger between Lloyds TSB and HBOS to form the Lloyds Banking Group in January 2009. Lloyds TSB was one of the UK financial institutions that weathered the effects of the financial crisis the best, as they reported steady profits in 2007 and 2008 (HCTC, 2009). However, the institution also has other segments, including insurance and investment, as well as wholesale and international banking respectively, which throughout the market turmoil period did not perform as well, reporting significantly lower profits in 2007 and 2008. Nevertheless, Lloyds TBS adamantly suggested that they entered the crisis in a strong position due to a strong business model, prudent risk approaches and anticipation that the favourable market conditions would not last forever (HCTC, 2009).

The Royal Bank of Scotland (RBS) became partly publically owned after the £20 billion capital raising program they announced failed to attract investors, ultimately seeing the government acquiring a majority stake in RBS. The crisis affected RBS significantly due to the bank having leveraged itself too much in the good times and their untimely acquisition of Dutch bank ABN Amro in 2007 (HCTC, 2009). The takeover of ABN Amro opened up RBS's funding gap as their leverage increased further, exposing them significantly if wholesale markets were to tighten up. RBS was further criticised for conducting due diligence in May 2007, six months prior to the completion of the takeover. In these six months financial insti-

tutes including Northern Rock failed and markets took a severe turn for the worse (HCTC, 2009).

It is clear that some of the leading banks were significantly affected throughout the financial crisis devastating the global financial system in the crisis period. However, it did not end there, as several market participants thought it would.

The liquidity crisis experienced by banks was followed by a boom in equity markets during which several financial institutions around the world were assisted by central banks and governments in order to fight the effects arising from the global financial crisis. In the Euro area the probability of countries defaulting on the sovereign debt increased due to several macro-economic misalignments in the middle of 2007 (Haidar, 2011). These macro-economic misalignments included budget deficits spurred on by the recession and several bailout motivated fiscal measures of specific Euro area countries. Haidar (2011) determines which countries are in sound fiscal positions by illustrating debt as a percentage of their 2009 GDP. He suggests that countries including Luxembourg, Norway, the Slovak Republic, Denmark, Finland and Slovenia are some of the safest countries, with their debt as a percentage of their GDP being less than 50%. However, countries such as Greece, Italy and Iceland fared worse with this figure exceeding 110% (Haidar, 2011). Haidar (2011) suggests that the global recession significantly affected European economies as fiscal expenses arising from the crisis including bailout packages amongst other significantly pressured sovereign debt services of European countries. He further states that European economies experienced significant fiscal revenue decreases after the onset of the crisis due to the real estate and asset market collapses mentioned above. The crisis increased several fiscal expenditures, including unemployment benefits, further increasing pressure on fiscal deficits (Haidar, 2011). These are only a few of the core effects arising from the financial crisis that significantly pressured European economies in the build-up to the sovereign debt crisis that emerged in 2009 and is still ongoing, as several countries continues to suffer severe financial distress. Several countries, including Cyprus and Greece, are still in severe financial distress. Cyprus has requested a bailout of €10 billion, provided by the European Union (EU), European Central Bank (ECB) and the International Monetary Fund (IMF) albeit attached to certain austerity measures (Inman, 2013). Greece continues to suffer the effects of a 5-year-old recession and an economic contraction of 4.2% forecast for 2013 (Avent, 2012).

The SWEAP<sup>18</sup> countries received a further bailout package during the sovereign crisis from the IMF, European Central Bank (ECB) and the European Commission (EC) totalling more than €750 billion (Haidar, 2011). These are only some of the bailouts that have occurred so far in the European debt crisis, and they are accompanied by several austerity and reform measures (Haidar, 2011). The measures and conditions have been applauded and criticised alike and remain a heated discussion in finance. The European sovereign debt crisis is still not over as possible contagion effects between Euro zone members remains a concern, with Santis (2012) indicating that spill-over effects from Greece arising from rating downgrades on sovereign bonds can significantly affect countries including Ireland, Portugal, Italy, Spain, Belgium and France as a result of contagion.

With regard to South Africa, it might have taken time for the NCA introduced in South Africa in June 2007 to fully take effect in the South African economy and balance sheets of banks. This further motivates the use of 2009 banking data, as 2008 data might not have fully captured the effects that stem from the implementation of this act.

The next section describes how Van den End's LST is developed and transformed in Microsoft Office Excel based on the fundamentals of the model discussed in the model methodology section of this chapter.

### **3.3 LST construction**

This section illustrates how the LST is constructed using Microsoft Office Excel screenshots, as well as the LST basics. Most importantly, this section illustrates how to transform the equations in the model methodology section of this chapter into Microsoft Office Excel formulas, which may assist future research with the LST.

Figure 3.6 shows the construction of the first round effects for the LST.

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<sup>18</sup> South-West Euro zone Periphery and includes Portugal, Italy, Ireland, Greece and Spain.

	D	E	F	G	H	I	J	K	L
1		Tenor	Amount	$W_{sim_{1,i}}$	$W_{sim_{1,i}}(Const)$	$I_1 * W_{sim_{1,i}}$	$Ri_b$	$100\% - W_{sim_{1,i}}$	Product
2	<b>Assets</b>	Asset A	15.04	0.0%	0.0%	0.00	0.21	100.00%	0.21
3			=EXP(NORMSINV(RAND()))*E123/3	0.6%	0.6%	0.15	0.32	99.35%	0.32
4		Asset C	=IF(G3<100%,G3,100%)	0.8%	0.8%	0.08	0.01	99.23%	0.01
5		Asset D	17.09	1.6%	=F4*H4	0.28	0.24	98.38%	0.23
6		Asset E	20.81	1.5%	=(B8-B9)*(F5/F23)	0.29	0.29	98.49%	0.28
7		Asset F	306.86	0.8%	0.8%	2.33	4.24	99.24%	4.21
8		Asset G	16.29	0.3%	0.3%	0.01	=100%-H6	99.74%	0.22
9		Asset H	3.55	0.2%	0.2%	0.01	0.05	99.77%	0.05
10		Asset I	0.90	0.3%	0.3%	0.00	=PRODUCT(J7:K7)		0.01
11		Asset J	0.19	1.1%	1.1%	0.00	0.00	98.91%	0.00
12	<b>Liabilities</b>	Liability A	25.75	0.3%	0.3%	0.08	0.36	99.68%	0.35
13		Liability B	303.95	2.2%	2.2%	6.79	4.20	97.76%	4.11
14		Liability C	0.00	1.0%	1.0%	0.00	0.00	98.99%	0.00
15		Liability D	20.92	0.7%	0.7%	0.15	0.29	99.27%	0.29
16		Liability E	0.49	0.3%	0.3%	0.00	0.01	99.69%	0.01
17		Liability F	3.46	1.8%	1.8%	0.06	0.05	98.17%	0.05
18		Liability G	2.74	1.4%	1.4%	0.04	0.04	98.56%	0.04
19		Liability H	2.98	0.5%	0.5%	0.01	0.04	99.55%	0.04
20		Liability I	11.81	2.4%	2.4%	0.29	0.16	97.55%	0.16
21		Liability J	=SUM(G2:G22)	0.1%	0.1%	=SUM(J2:J22)	0.09	99.88%	0.09
22	<b>Equity</b>	Shareholder's equity	26.00	2.4%	2.4%	0.62	0.36	97.63%	0.35
23	<b>Total</b>		809.12	0.20	0.20	11.19	11.19	20.80	11.04

Figure 3.6: Construction of the first round effects of the LST.

The first round effects in the LST start with the determining of the liquidity buffer for each individual bank within normal market conditions. Van den End (2010:46) also calls this the baseline buffer and denotes it as  $B_0$ . The original buffer for each bank is determined by the sum of the non-calendar asset items available as in Equation 3.1. In Figure 3.6, the sum of cells F2 to F11 determines the liquidity buffer as it is the amount of all liquid non-calendar assets available. Cell B8 illustrates the liquidity buffer for Bank 1 in Figure 3.7.

The second step in constructing the first round effects of the LST is determining the first round simulated weights ( $w_{sim_{1,i}}$ ) for each balance item used in the LST. The fixed weights for balance sheet items gleaned from banks are shown in cells E123 to E143 in Figure 3.10. These weights are used to determine the simulated weights for the first round effects of the model. The formula in cell G2 in Figure 3.6 shows how the simulated weights are estimated in Microsoft Office Excel. The (NORMSINV(RAND())) formula represents the normal distribution from which random draws are taken, basing the weights on Monte Carlo simulations. These weights are scaled ( $w_i/3$ ) and the normal distribution is transformed into a log-

normal distribution using the EXP() formula in order to capture the non-linear features of extreme liquidity stress events (Van den End, 2010:46). Cells G2 to G22 illustrate all the simulated weights for the balance items of each individual bank. Cells H2 to H22 represent the upper bound of simulated weights, as these weights cannot exceed a 100%. The IF() formula in cell H3 is used to implement the upper bound.

The initial shock of the liquidity event is the sum of cells I2 to I22, which is displayed in cell I23 in Figure 3.6. These values are determined by multiplying columns F and H, which show the value of each asset and its simulated weights respectively. This summary of Bank 1 in Figure 3.7 in cell B4 also shows this first round effect. Cell B5 illustrates the effects stemming from the second round contagion effects and is calculated in cell Q23 in Figure 3.8.

Figure 3.7 illustrates a summary of a liquidity event for each bank within the LST.

	A	B	C
2	<b>Bank 1</b>		
3	Variable	Value	
4	$E_1$	38.6	=I23
5	$E_2$	160.7	=Q23
6	$E_1/B_0$	9.5%	=B4/B8
7	Bank reacts?	1	=IF(B6>B12,1,0.0000000000000001)
8	$B_0$	404.6	=SUM(F2:F11)
9	$B_1$	365.9	=IF(B8-B4<B14,0,B8-B4)
10	$B_2$	402.7	=IF(B9=0,0,B9+B7*L23)
11	$B_3$	242.0	=IF(B5>B10,0,B10-(B7*B5))
12	Buffer <sub>threshold</sub>	3.0%	0.03
13	$I_{threshold}$	75.0%	=B122
14	Insolvency	303.4	=B8*B13

**Figure 3.7:** Summary of the LST.

The LST used in this study has two distinct thresholds with the first one displayed in cell B12 and the second in cell B13 in Figure 3.7. The threshold in B12 is the buffer threshold set by Bank 1, which determines whether they react to the initial shock of the liquidity event. The second threshold in cell B13 is the insolvency threshold, which if breached would indicate that a bank would become insolvent in the particular liquidity event. The insolvency threshold is not bank specific and is set the same for all banks at 75%. The insolvency threshold can be set as desired in the LST regardless of the banking system used in the model. The formula in cell B14 in Figure 3.7 multiplies the original liquidity buffer with the insolvency



threshold. This produces the minimum liquidity that a bank must have in the LST to stay solvent after the initial shock of a liquidity event. The calculation in cell B9 for the liquidity buffer after the initial shock of the liquidity event shows how the IF() formula is applied to account for the insolvency threshold. If  $B_1$  in cell B9 is less than the required buffer in cell B14 the bank would become insolvent.

The second stage of the LST models the banks responses to the initial shock of the liquidity event. The buffer threshold determined by banks by means of their own liquidity risk controls and regulatory requirements plays a significant role in whether banks would react to the initial effects of the liquidity event. Cell B6 in Figure 3.7 estimates the size of the first round effects relative to the original liquidity buffer. This equation is used in Cell B7 to determine whether the bank reacts to the initial effects of the liquidity event. If the percentage in cell B6 exceeds that of the threshold, the bank would react to the first round effects of the liquidity event. A value of 1 or 0 in cell B7 indicates whether the bank reacts or does not react to first round effects respectively. The IF() formula in cell B7 in Figure 3.7 determines whether banks would react to the liquidity event.

The buffer threshold is determined by the correlation between the value changes of balance sheet items and the declines of the liquidity buffer lagged by one month. This method is shown in the model methodology section of this chapter. Following the estimation of the buffer threshold and the determination of whether a particular bank reacts, the number of transactions the bank conducts with each specific instrument is determined as in Equation 3.4. Cells J2 to J22 in Figure 3.6 estimate this by multiplying the losses of the first round effects ( $B_0^b - B_1^b$ ) with the percentage that the specific instrument contributes to the balance sheet ( $I_i^b / \sum_i I_i^b$ ). The formula in cell J5 gives the calculation of each instrument's number of activities to restore the liquidity buffer in Microsoft Office Excel. Cell J9 indicates the full restoration of the buffer as it equals the losses arising from the first round effects of the liquidity event. However, Van den End (2010:49) states that the buffer cannot be fully restored due to the market disturbances caused by the first round effects of the liquidity event. Hence, cells K2 to K22 calculate the remaining percentage of each balance sheet item and multiply it with its corresponding cell in column J to produce the values in column L. This process follows Equation 3.5 in the model methodology section of this chapter. The formula in cell L7 shows how the final restoration ability of each instrument is calculated. The sum of

cells L2 to L22 is thus the final restoration ability of Bank 1 in this crisis period as displayed in cell L23. Adding the restoration value in cell L23 to the buffer after the first round effects ( $B_1$ ) in cell B9 in Figure 3.7 produces the liquidity buffer after restoration attempts ( $B_2$ ) by Bank 1. This liquidity buffer after restoration ( $B_2$ ) is shown in cell B10 in Figure 3.7.

The final step in the LST is to determine the second round contagion effects. The first step in determining these effects would be to calculate the simulated weights ( $w_{sim_{2,i}}$ ) for each instrument for the second round of the liquidity event. Figure 3.8 indicates the estimation of the second round effects for Bank 1.

	N	O	P	Q
1	$w_{sim_{2,i}}$	$w_{sim_{2,i}}(Const)$	$w_{sim_{2,i}}-w_{sim_{1,i}}$	$(I_i+Ri_i)*(w_{sim_{2,i}}-w_{sim_{1,i}})$
2	0.0%	0.0%	0.0%	0.00
3	13.4%	13.4%	9.8%	2.35
4	$=H2*\$B\$129*SQRT(\$H\$122)$		0.9%	0.00
5	0.6%	0.6%	0.4%	0.08
6	20.0%	20.0%	14.6%	3.11
7	9.6%	9.6%	7.0%	21.98
8	1.1%	$=IF(N6<100\%,N6,100\%)$		0.13
9	0.9%	0.9%	0.7%	0.02
10	4.6%	4.6%	3.4%	0.03
11	7.2%	7.2%	5.3%	0.01
12	4.4%	4.4%	$=O10-H10$	0.84
13	7.6%	7.6%	5.6%	17.38
14	12.1%	12.1%	8.8%	$=(F12+J12)*P12$
15	5.1%	5.1%	3.8%	0.81
16	4.7%	4.7%	3.5%	0.02
17	2.7%	2.7%	2.0%	0.07
18	12.3%	12.3%	9.0%	0.25
19	2.0%	2.0%	1.4%	0.04
20	15.5%	15.5%	11.3%	$=SUM(Q2:Q22)$
21	0.7%	0.7%	0.5%	0.03
22	4.8%	4.8%	3.5%	0.94
23				49.48

**Figure 3.8:** Construction of the second round effects of the LST.

Cells N2 to N22 illustrate the simulated second round weights ( $w_{sim_{2,i}}$ ) for each instrument in the balance sheet of Bank 1. The Formula in cell N2 shows how the first round weights ( $w_{sim_{1,i}}$ ) are multiplied by the alpha in cell B129, determined for each individual bank in Figure 3.9.

	A	B	C
121	Threshold	%	
122	$\theta_1$	75%	0.75
123	$\theta_2$	75%	
124	$\theta_3$	75%	
125	$\theta_4$	75%	
126	$\theta_5$	75%	
127			
128	Bank	$\alpha$	
129	Bank <sub>1</sub>	3.52	$=(\$H\$123*(1+J23/\$H\$124)*\$H\$122)/\$H\$123$
130	Bank <sub>2</sub>	2.08	
131	Bank <sub>3</sub>	2.91	
132	Bank <sub>4</sub>	2.90	
133	Bank <sub>5</sub>	2.60	

**Figure 3.9:** Insolvency thresholds and Alphas ( $\alpha$ ).

The thresholds in cells B122 to B126 is the insolvency thresholds adapted from Van Vuuren (2011:45), which can be set to the modeller's desire depending on the banking system and stress situation being tested.

The alphas determined for each bank in Figure 3.9 forms part of Equation 3.6 and are the feedback effects that arise from the activities conducted with each balance sheet instrument in the buffer restoration period. These alphas in Figure 3.9 are created using cells J23, H122, H123 and H124, with several of them found in Figure 3.10. Thus, Equation 3.6 is split into cells N2 and B129 to simplify the modelling process. However, Equation 3.7 introduces the reputation effects, which are dependent on the market conditions by multiplying the second round simulated weights with the square root of the market stress factor ( $s$ ). This process is also done in cell N2, thus cell N2 can be describe as follows,

$$\text{Cell } N2 = \text{Cell } H2 \times \text{Cell } B129 \times \text{Cell } H122$$

$$\text{or} \tag{3.10}$$

$$w_{sim_{2,i}}^* = w_{sim_{1,i}} \times a \times \sqrt{H122}$$

Equation 3.10 is illustrated in cell N2, incorporates Equation 3.6 and Equation 3.7 to determine the second round simulated weights for the LST. Figure 3.10 illustrates cell H122 where the market stress variable is located along with the total of reacting banks and the total of all reactions with all balance sheet items by all banks.

	D	E	F	G	H	I	J
121	1st Round			2nd Round			
122	Asset	Haircut		s	2.00		
123	W <sub>1</sub>	0%		Sum q	4		
124	W <sub>2</sub>	5%		Sum <sub>i</sub> Sum <sub>j</sub> RI <sub>ij</sub> <sup>2</sup>	87.84		
125	W <sub>3</sub>	2%		=J\$23+J\$47+J\$71+J\$95+J\$119			
126	W <sub>4</sub>	5%		=B\$7+B\$31+B\$55+B\$79+B\$103			
127	W <sub>5</sub>	2%					
128	W <sub>6</sub>	8%		HC_increase	1.00		
129	W <sub>7</sub>	2%					
130	W <sub>8</sub>	2%					
131	W <sub>9</sub>	5%					
132	W <sub>10</sub>	8%					
133	W <sub>11</sub>	2%					
134	W <sub>12</sub>	8%					
135	W <sub>13</sub>	3%					
136	W <sub>14</sub>	3%					
137	W <sub>15</sub>	2%					
138	W <sub>16</sub>	8%					
139	W <sub>17</sub>	3%					
140	W <sub>18</sub>	3%					
141	W <sub>19</sub>	8%					
142	W <sub>20</sub>	2%					
143	W <sub>21</sub>	3%					

**Figure 3.10:** Original haircuts, Market stress factor, Sum of reacting banks, Sum of reactions and Haircut increase factor.

Figure 3.10 also indicates the original haircuts on assets and run-off rates on liabilities as used to derive the first round simulated weights ( $w_{sim_{1,i}}$ ) displayed in cells G2 to G22. The haircut increase factor in cell H128 is used in the estimation of the three-dimensional graphs in the results chapters. Each time after the model is estimated,  $f$  is increased with the desired increment level. The number of estimations can also be set as desired, which would ultimately deliver the three-dimensional graphs that illustrate the effects of an increased  $f$ .

The value of  $s$  in cell H122 can work similar to  $f$  as it can be set to the modeller's desired level, with 1 indicating stress free markets and 2 severely stressed markets. Using macros, this variable can also be increased after each simulation, producing three-dimensional graphs that illustrate the effects of market conditions.

The second round contagion effects can be determined once the second round simulated weights have been estimated. Cells O2 to O22, similar to cells H2 to H22, implement the up-

per bound on the second round simulated weights, as these weights cannot exceed 100%. Since second round effects arise from the buffer restoration activities with balance sheet items, the original amount of each balance sheet item is added to the amount of activities conducted with the particular instrument. The formula in cell Q12 and the first part of Equation 3.9 shows this process. The second part of Equation 3.9 is where the first round simulated weight ( $w_{sim_{1,i}}$ ) is subtracted from the second round simulated weight ( $w_{sim_{2,i}}$ ) as the goal is to only measure the additional impact that arises from second round effects. The simulated second round weights that account for reputation risk ( $w_{sim_{2,i}}^*$ ) is replaced by the one that does not ( $w_{sim_{2,i}}$ ), since a reacting bank can also face reputation risk. The subtraction of the two respective weights is illustrated in cells P2 to P22. The final step in the model is to estimate the impact of contagion effects on the liquidity buffer after restoration ( $B_2$ ). The entire second round effect on Bank 1 is displayed in cell Q23 in Figure 3.8, as well as in Figure 3.7, which displays the summary of the LST for Bank 1 in cell B5.

The IF() formula in cell B11 in Figure 3.7 determines whether the second round effects exceed the liquidity buffer after restoration  $B_2$ . Furthermore, the formula in cell B11 again confirms whether the particular bank reacts to the first round effects and accordingly determines the final liquidity buffer  $B_3$ .

This chapter discussed the data used in this study and used relevant economies, industries and periods as arguments. The original LST model developed by van den End (2010) was reviewed and a further detailed discussion was provided regarding the development of the model using Microsoft Office Excel. Chapter 4 presents the results of the implementation of the model and details potential liquidity buffer losses for the South African banking system for the non-crisis and crisis periods.

## Chapter 4 Stress testing: Developing economy results

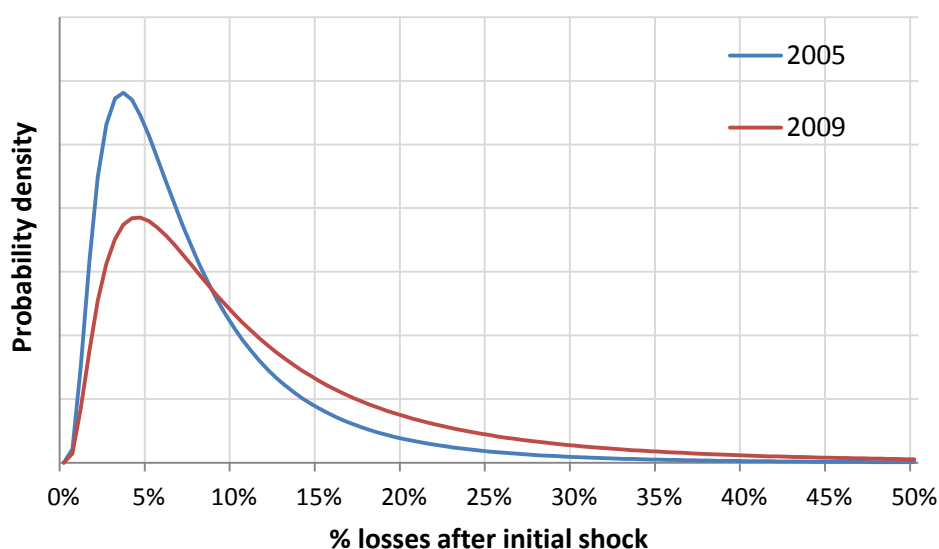
Chapter 3 discussed the construction of the LST and the relevance of the data used in the study. Chapter 4 examines the results obtained from the LST for South African data.

### 4.1 Individual Stage Analysis

Similar to van Vuuren (2011:45), the figures in this study illustrate the percentage losses of the original liquidity buffer and not the remaining percentages of the original buffer. As discussed in Chapter 3, the driver of the initial shock is the haircuts on balance sheet items.

#### 4.1.1 Initial Shock

Figure 4.1 shows the effect of the original haircuts ( $f = 1$ ) by means of the initial shock of a liquidity event on the original liquidity buffer.

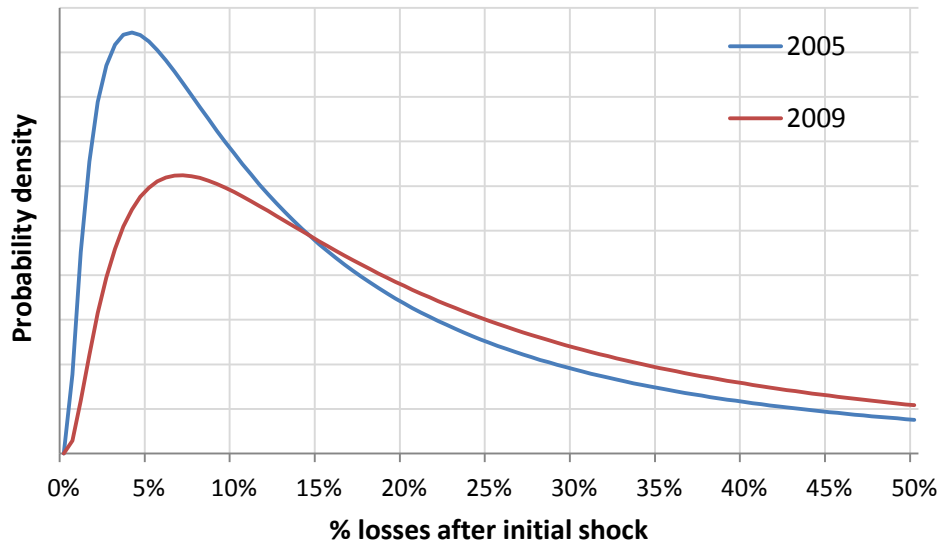


**Figure 4.1:** SA buffer losses at original haircuts ( $f \times 1$ ).

The blue line in Figure 4.1 above represents the probability of losses for the 2005 period and the red line represents the 2009 period. This is the case for all the two dimensional line graphs in Figures 4.1 to 4.6. It is clear that the probability density of losses between 0% and 10% are significantly higher for 2005 than 2009. As drivers of the initial shock, haircuts play a significant role in Figure 4.1. Average haircuts were 4% in 2005 and 6% in 2009. Understandably, larger haircuts will lead to increased possible losses of the liquidity buffer. The

increased size of haircuts over the two periods may be due to the increased volatility in markets since the onset of the 2007 liquidity crisis.

The effect of haircuts twice their original size (i.e  $f = 2$ ) on the liquidity buffer is displayed in Figure 4.2.

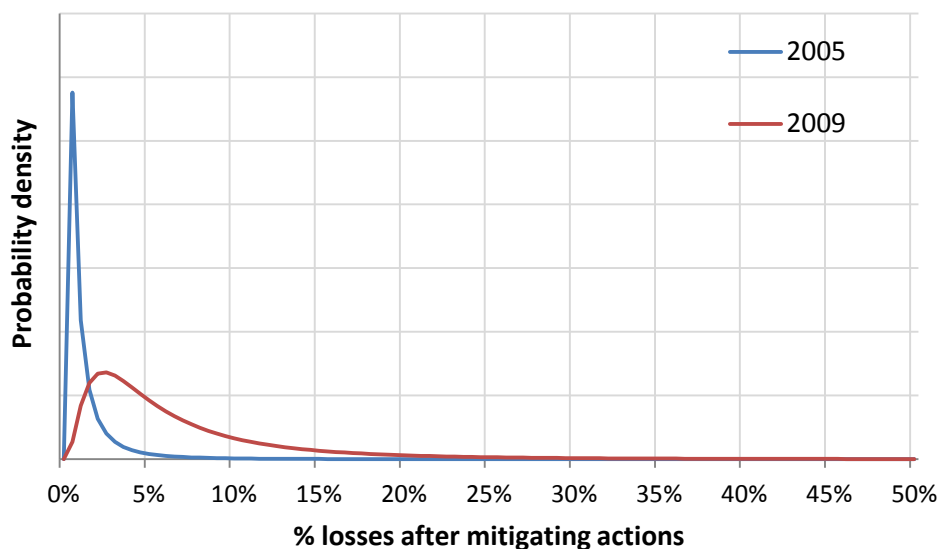


**Figure 4.2:** SA buffer losses with increased haircut factor ( $f \times 2$ ).

The lines in Figure 4.2 are similar to those of Figure 4.1, showing that larger haircuts in 2009 would have increased possible buffer losses of the original buffer. The possibility of losses greater than 50% becomes likely as haircuts increase to twice their original size. The mode of the red line shifts to beyond losses of 5% in 2009, where it was initially below 5% at  $f = 1$ . For the blue 2005 lines, however, the modes of the lines stay approximately constant.

#### 4.1.2 Mitigating Actions

The effect of mitigating actions to the initial shock of a liquidity event is illustrated in Figure 4.3. As discussed in Chapter 3, buffer restoration and leverage targeting are the two methods of mitigating actions with Figure 4.3 illustrating the former.



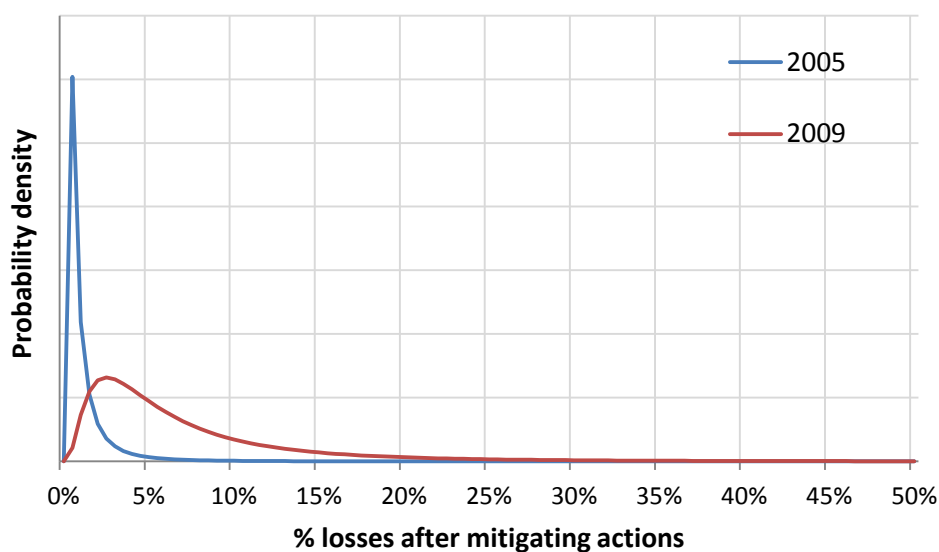
**Figure 4.3:** SA buffer losses after buffer restoration as a mitigating action.

The difference between the ability to restore the original liquidity buffer over the two periods is clearly visible in Figure 4.3. The blue line indicates that nearly all the possibilities of losses are below 5% in 2005. This is an indication of the health of financial markets in this period, with losses suffered being easily mitigated and buffers comfortably restored. The fact that banks set thresholds for reactions at an average of 3% may also have contributed to the high probability density of losses below 5%. Low thresholds would allow banks to notice smaller losses, which they would react to, instead of only reacting to greater losses of the liquidity buffer and merely absorbing smaller losses.

The red line, however, shows that losses up to 20% after buffer restoration were possible in 2009. This indicates the inability of buffer restoration after the onset of the financial crisis and the state of financial markets in this period. There is thus a significant decrease in the ability of buffer restoration over the two periods. Furthermore, thresholds of banks also increased from 3% to 12% on average over the two periods, which may be due to the cost of mitigating actions. Restoring the liquidity buffer frequently involves transaction costs and in a stable and healthy market (2005) this may not be a problem. However, in a volatile market (2009) transaction costs may become costly. The increased haircuts over the two periods might also contribute to buffer restoration's lack of effectiveness, as greater possible losses due to larger haircuts increases the role mitigating actions have to play. Furthermore, increased haircuts may affect the markets adversely and reduce the ability to mitigate original effects of the liquidity event. As discussed in Chapter 3, leverage targeting can also be used



as a mitigating action in the second stage of the LST and its ability to do this is shown in Figure 4.4 below.

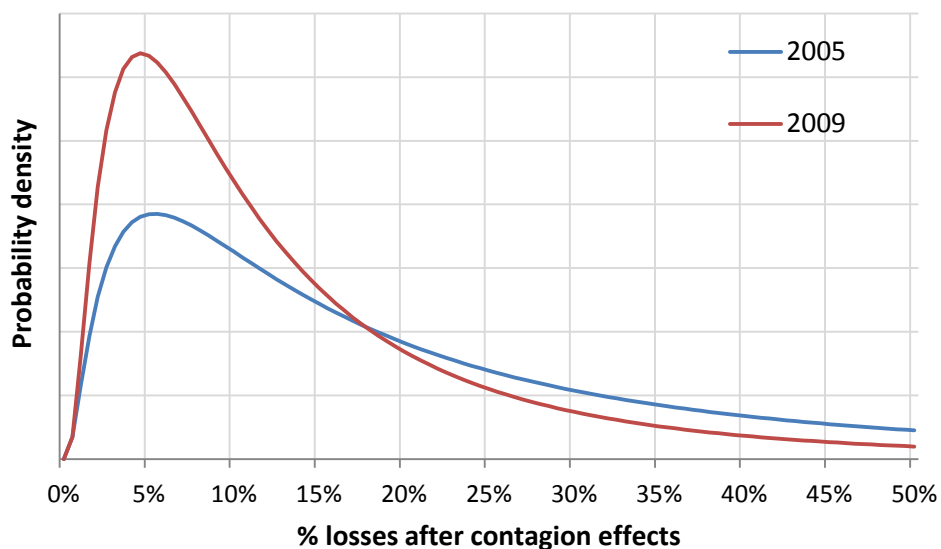


**Figure 4.4:** SA buffer losses after leverage targeting as a mitigating action.

At first glance Figures 4.3 and 4.4 seem to be identical. However, it is clear how the peaks of the two blue curves differ. The loss statistics in Tables 4.1 and 4.2 confirm that these two methods are not identical. These statistics and the line graphs for the two methods do not differ by much, which shows that for the developing economy buffer restoration and leverage targeting are equally effective in restoring the liquidity buffer. However, the leverage ratios in Table 4.5 suggest that the effect of the initial shock on leverage ratios were small, indicating that leverage targeting would not be significantly different from buffer restoration. Chapter 3 discusses how leverage targeting entails the purchasing of assets, albeit at falling prices in order to restore the leverage ratios. However, if the original leverage ratio is not significantly affected fewer assets need to be purchased, thus minimising the effect of falling asset prices.

#### 4.1.3 Second Round Feedback Effects

The feedback effects resulting from mitigating actions are the third stage of the model as discussed in Chapter 3 and are illustrated in Figures 4.5 and 4.6. Although there is only a small difference between the two methods of mitigating actions it is possible that feedback effects arising from these actions will be different. Figure 4.5 illustrates the feedback effects for the South African data by using buffer restoration as a mitigating action.

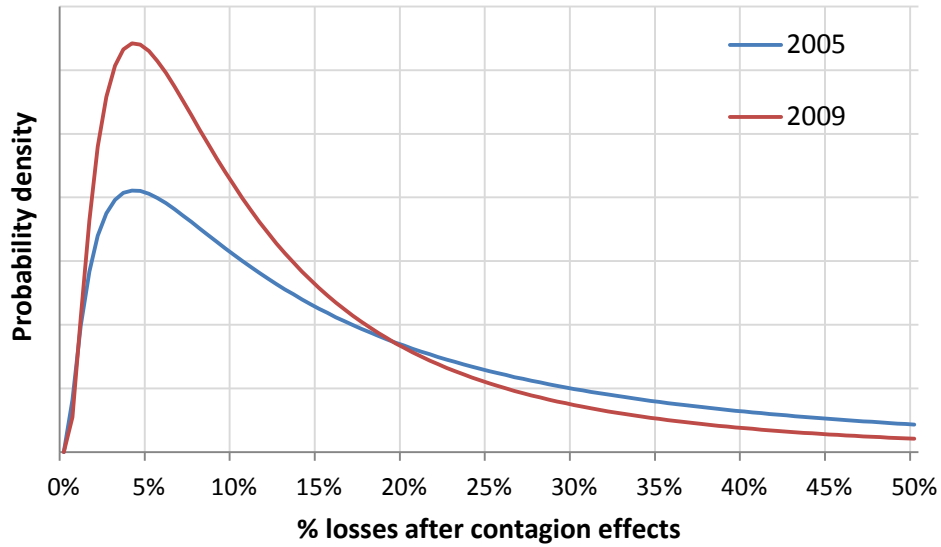


**Figure 4.5:** SA buffer losses for buffer restoration model after contagion effects.

Figure 4.5 shows that South Africa would have been more susceptible to contagion in 2005 than in 2009. The probability of losses below 15% is significantly higher in 2009 and losses above 20% are less likely in 2009 compared to 2005.

Numerous factors might contribute to the decline in exposure of banks to contagion in 2009 than in 2005. Firstly, the mixture of assets and liabilities within the balance sheets of banks may have changed, as banks might have resorted to less riskier items in their balance sheets, ultimately reducing contagion. Furthermore, the introduction of the NCA of 2005 in 2007 might have reduced the interconnectedness between banks. The act was introduced to promote responsible credit granting in order to reduce reckless lending and reckless use of credit. The act furthermore promotes the re-organisation of debt where over-indebtedness has occurred and transparency and proper regulation of credit information.<sup>19</sup> Up until 2009, the act might have had sufficient time to reduce the interconnectedness between banks and possible contagion exposure of banks. The mixture of assets and liabilities in the balance sheets of banks might also have been affected, as banks would not be able to acquire certain assets due to the restrictions of the NCA of 2005. The effect of contagion on the liquidity buffer after using leverage targeting as a mitigating action is shown in Figure 4.6.

<sup>19</sup> For further insight regarding the purpose of the National Credit Act see: South Africa. 2005. National Credit Act 34 of 2005 published in the Government Gazette 15 March 2006 Vol. 489 No. 28619.



**Figure 4.6:** SA buffer losses for leverage targeting model after contagion effects.

Similar to Figure 4.5, Figure 4.6 again shows that banks were more susceptible to liquidity risk in 2005 than 2009. A comparison of Figures 4.5 and 4.6 indicates that there would have been no significantly different results when using either of the methods as a mitigating action to liquidity shocks. However, the effect of the liquidity shock on the original leverage ratio is quite small and falling asset prices might not have a significant effect on the liquidity buffer. This insignificant effect on the leverage ratio is shown in Table 4.5.

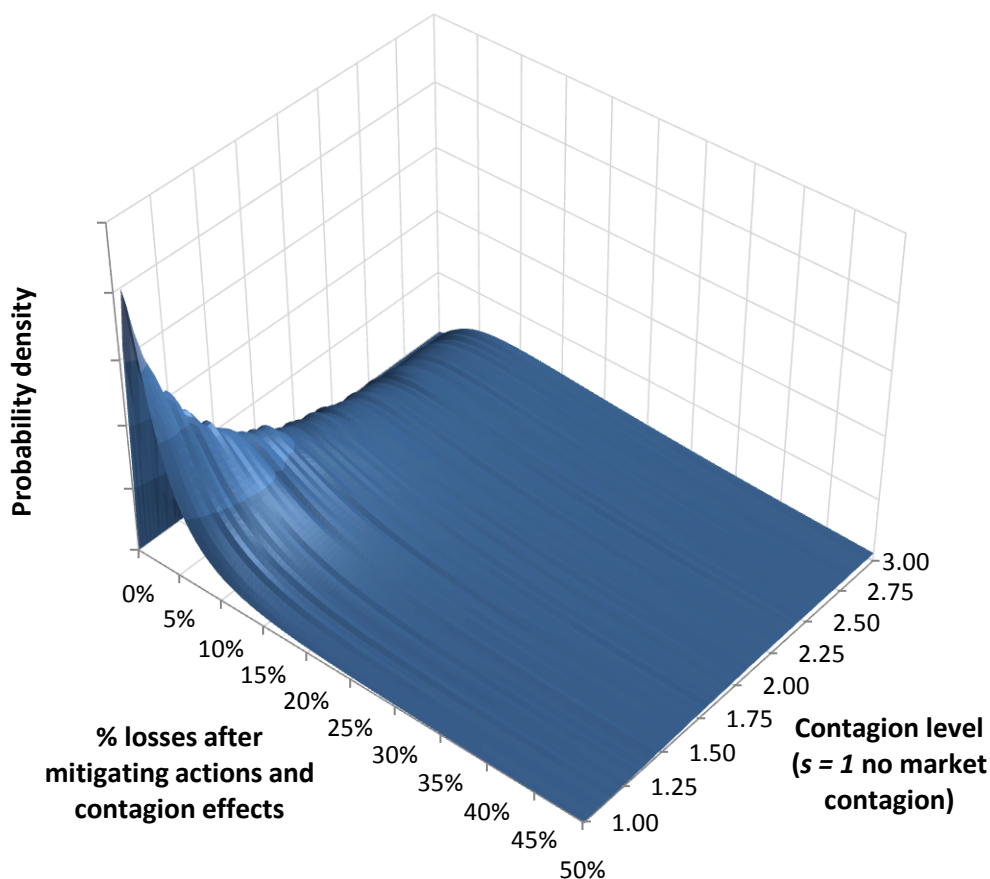
The two-dimensional line graphs estimated in figures 4.1 to 4.6 suggest that, firstly, losses after the initial shock would have been more severe in 2009 than in 2005, which is due to the increased haircuts on assets and liabilities. Secondly, the graphs through figures 4.1 to 4.6 suggest that buffer restoration and leverage targeting would have been equally effective in restoring the liquidity buffer. Finally, South African banks might have been more susceptible to contagion in 2005 than in 2009.

## 4.2 Consolidated Analysis

The three-dimensional graphs in figures 4.7 to 4.14 illustrate the effect of increasing  $s$  and  $f_s$  in the LST respectively. These graphs provide the ability to evaluate possible buffer losses with respect to both of these variables.

### 4.2.1 Buffer Restoration Models

The effect of an increased level of contagion on the liquidity buffer of South African 2005 data is illustrated in Figure 4.7. This model is estimated using the original haircuts for assets and liabilities.<sup>20</sup>

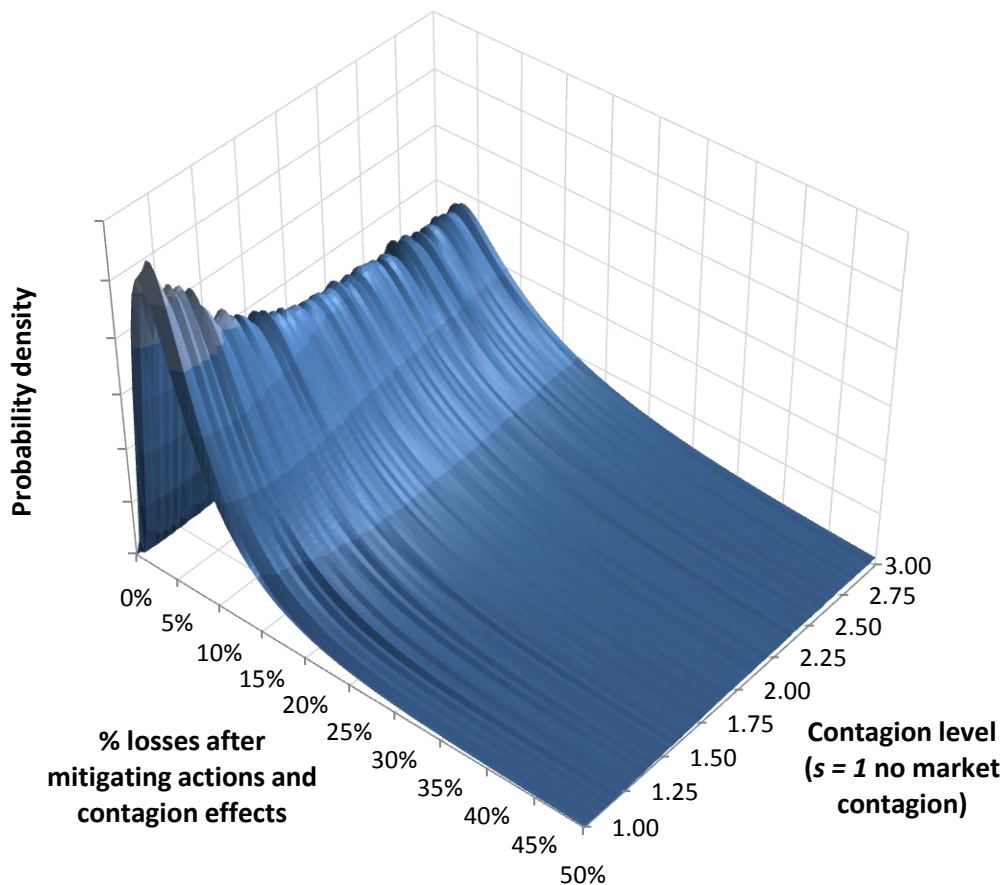


**Figure 4.7:** SA 2005, buffer restoration model output showing the dependence of loss probabilities on  $s$ .

In Figure 4.7 the effects of increasing the contagion level within the market from a stress-free market to a severely stressed market are clearly visible. As discussed in Chapter 3,  $s = 1$  represents a virtually stress-free market and  $s = 3$  a severely stressed market. Initially, at  $s = 1$ , the distribution in Figure 4.7 peaks between 0% and 5%, indicating minimal effects arising from contagion. However, the graph in Figure 4.7 never completely flattens out and losses up to 50% are always a possibility, albeit very small. As  $s$  is increased in the mod-

<sup>20</sup> All the three dimensional figures illustrating the effects of increased contagion were estimated using the original haircuts of assets and liabilities.

el, the distribution in Figure 4.7 flattens out and shifts to the right giving way to increased possibilities of greater losses. Contagion is most severe at  $1 < s < 2$ , with losses less than 5% significantly decreasing as  $s \rightarrow 2$ . The contagion axis (depth axis) shows how possible losses of up to 50% increase as  $s$  increases. A similar model in Figure 4.8 with the exception of using 2009 data, illustrates buffer losses as  $s$  is increased.

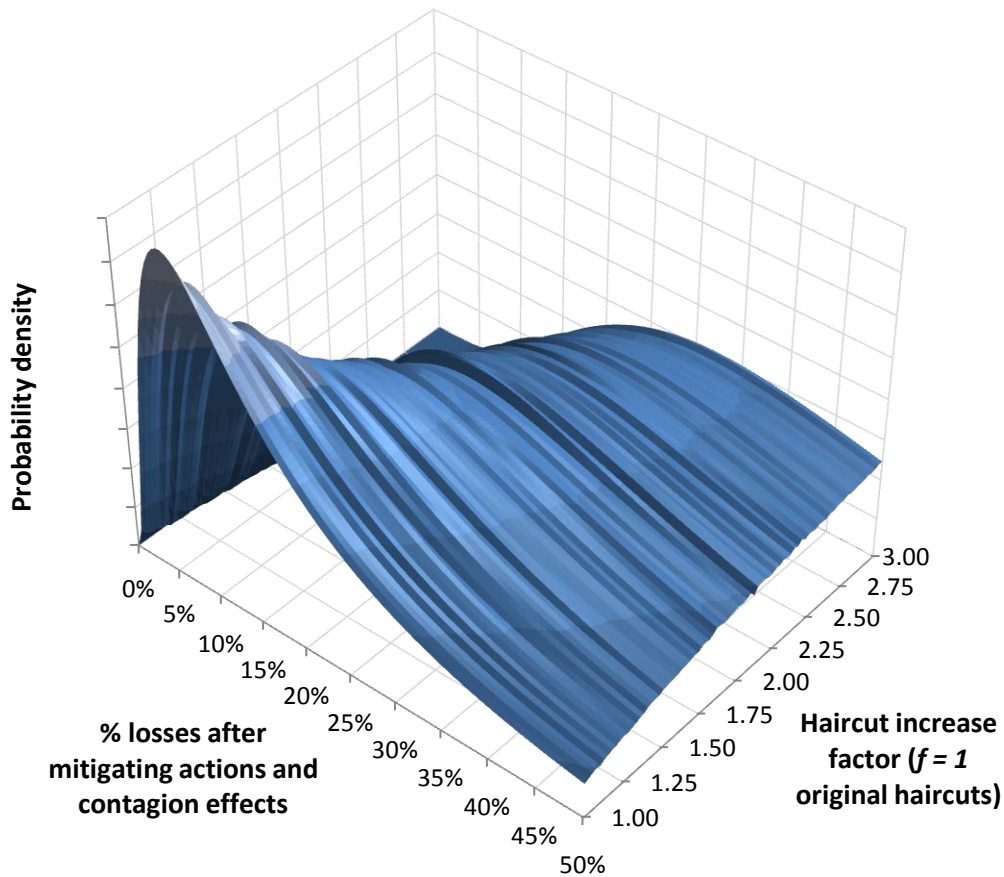


**Figure 4.8:** SA 2009, buffer restoration model output showing the dependence of loss probabilities on  $s$ .

Comparing Figures 4.7 and 4.8 suggests, similar to the two dimensional graphs that South African banks may have been more susceptible to contagion in 2005 than in 2009. The effect in 2009 is clearly not as significant as in 2005, with the probability density of losses predominantly remaining between 0% and 20%. The distribution does not flatten out as significantly in 2005 as in 2009. Similar to Figure 4.7, contagion has the greatest effect between  $1 < s < 2$  and at  $s > 2$  the effect of contagion stays approximately constant. Furthermore,

the possibility of losses up to 50% is always present at any given level of contagion. Again, the reduced exposure to contagion in 2009 may be due to several factors, including the introduction of the NCA (34 of 2005) in 2007.

Increased haircuts on assets and liabilities may possibly lead to more severe losses of the liquidity buffer. Figure 4.9 shows the effect of increasing  $f$  on the liquidity buffer after the third stage of the LST, using South African 2005 data.



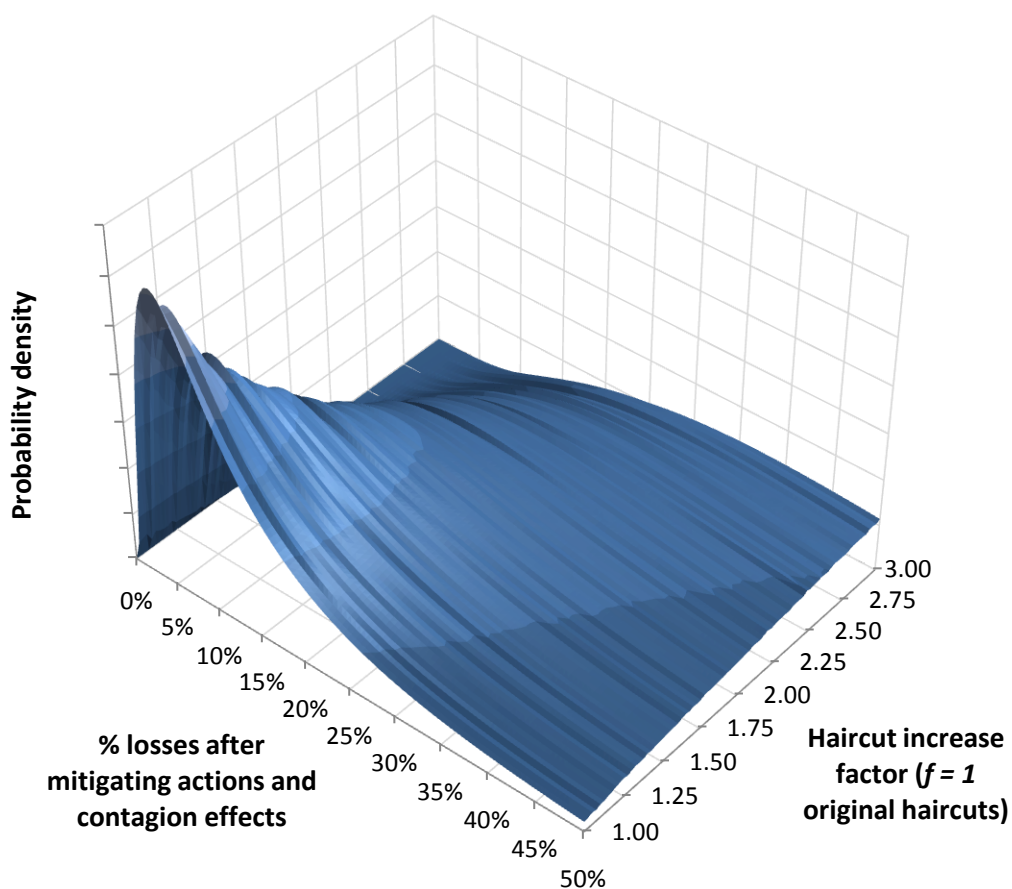
**Figure 4.9:** SA 2005, buffer restoration model output showing the dependence of loss probabilities on  $f$ .

The distribution of possible buffer losses in the Figure 4.9 shows that an increased  $f$  has a significant effect on the liquidity buffer. The model, estimated at  $s = 2$  and  $f$ , is gradually increased to eventually produce haircuts three times their original size.<sup>21</sup> At  $f = 1$ , the probability density of possible losses peak at approximately 5%. However, as  $f$  is increased

<sup>21</sup> All the three dimensional figures illustrating increased  $f$ s were estimated at  $s = 2$ .

this peak shifts to the right, indicating increased possible losses of the liquidity buffer. As  $f$  increases to  $f = 3$  losses lower than 5% vanish, indicating that either buffer restoration is ineffective in restoring the buffer after the increased initial shock or the exposure to contagion after the third stage of the model is very high. Consequently, as the possibility of small losses decrease, losses exceeding 50% become more likely as the graph in Figure 4.9 peaks at roughly 30%.

Figure 4.10 shows the effect of increasing  $f$  for South African 2009 data using buffer restoration as a mitigating action.



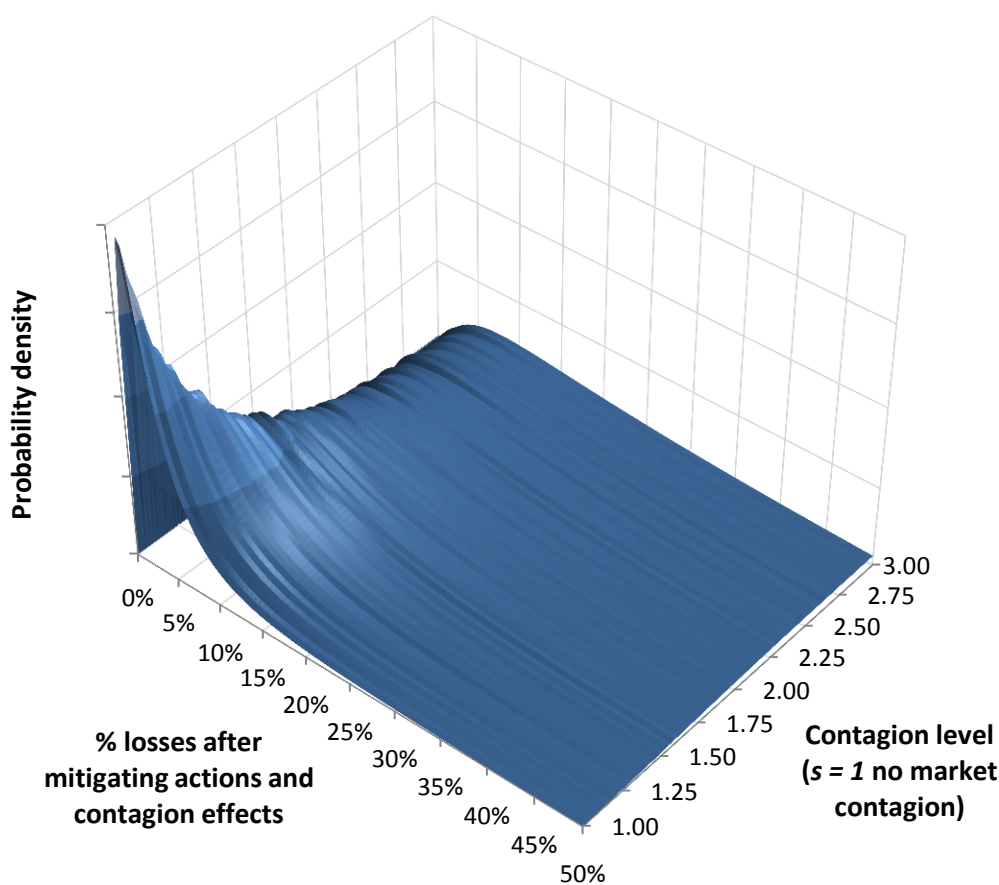
**Figure 4.10:** SA 2009, buffer restoration model output showing the dependence of loss probabilities on  $f$ .

Figure 4.10 represents a similar distribution to that of Figure 4.9, illustrating a significant effect on the liquidity buffer when increasing  $f$ . There are no possibilities of losses below 5%

of the original buffer as  $f$  reaches 3. The possibility of losses exceeding 50%, however, becomes more likely as  $f$  increases, but is not as significant as the 2005 data in Figure 4.9.

#### 4.2.2 Leverage Targeting Models

As mentioned earlier, there is little difference between the two methods of mitigating actions as the leverage ratios are not severely affected. It is, however, important to illustrate these results as the increased haircuts may affect leverage ratios, leverage targeting as a mitigating action and ultimately liquidity buffer losses.

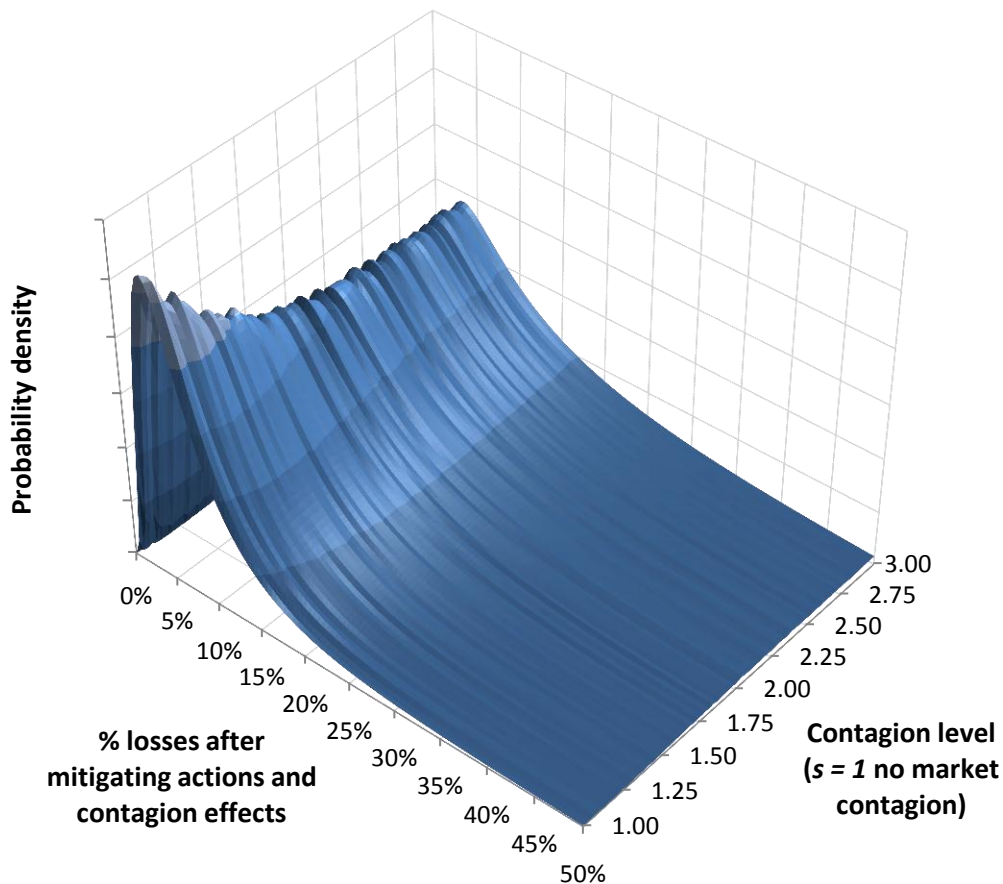


**Figure 4.11:** SA 2005, leverage targeting model output showing the dependence of loss probabilities on  $s$ .

Figure 4.11 above appears to be similar, though not identical to Figure 4.7. A closer inspection of the graph in Figure 4.11 and analyses of the loss statistics in Tables 4.1 and 4.3 confirm that these figures are not identical. As discussed with the two dimensional graphs, the reason for this is the minimal effect of the initial shock on the leverage ratio. The leverage



ratios in Table 4.5 illustrate the small effect of the initial shock to the original leverage ratio and how, through leverage restoration, the leverage ratio is restored. Yet again the effect of an increased level of contagion is most significant at  $1 < s < 2$ , with the distribution staying approximately the same at  $2 < s < 3$ . Figure 4.12 displays possible buffer losses for South African 2009 data using leverage targeting as a mitigating action after increased levels of contagion are applied.

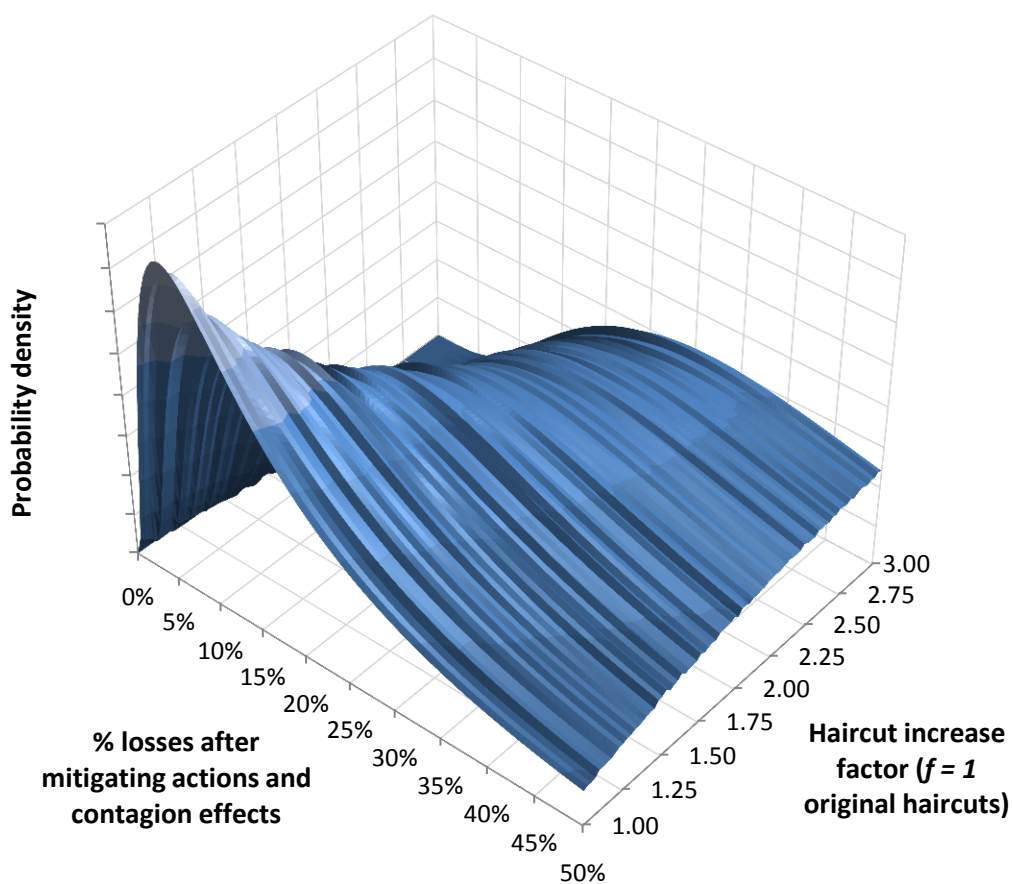


**Figure 4.12:** SA 2009, leverage targeting model output showing the dependence of loss probabilities on  $s$ .

Figure 4.12 illustrates a similar outcome to that of Figure 4.8, which uses buffer restoration as a mitigating action. Considering both methods of mitigating actions evaluated throughout this chapter, it is evident that neither of these methods increases the banks' exposure to contagion. Again, this does not suggest the two methods are equally effective as a mitigating method. The estimations simply illustrate that for the data used, contagion would not be

more severe when using either of these methods due to both methods equally restoring the buffer in stage two of the LST. Furthermore, Figure 4.12 shows that South African banks would have been less susceptible to liquidity risk in 2009 than in 2005. Similar to the 2005 graph in Figure 4.7, contagion is most severe at  $1 < s < 2$  and stays approximately constant at  $2 < s < 3$ . The possibility of losses up to 50% is always present, similar to 2005, although it is very small.

The final three-dimensional graph employing South African 2005 data illustrates the effect of increasing  $f$  in Figure 4.13.



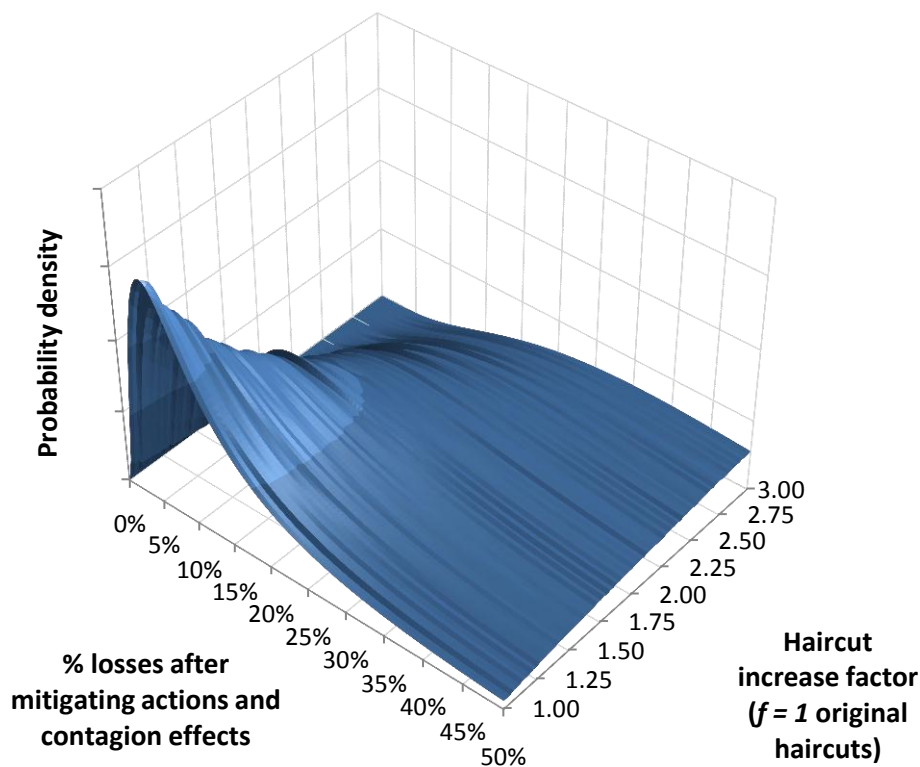
**Figure 4.13:** SA 2005, leverage targeting model output showing the dependence of loss probabilities on  $f$ .

The effect of increasing  $f$  is clearly visible in Figure 4.13, with the peak shifting to the right as  $f$  increases. As  $f$  is increased it eventually produces haircuts three times their original size, the probability of losses less than 5% of the original liquidity buffer vanish and losses

exceeding 50% become more likely. With original haircuts being 4% on average in 2005, increasing them to an average of 12% generates greater initial shocks to the liquidity buffer. This increases the need for mitigating actions, which increases activity in markets. The exposure to contagion may also increase, explaining the possibility of increased losses.

The four three-dimensional (Figures 4.7, 4.9, 4.11 and 4.13) graphs estimated using 2005 data above suggest, firstly, that buffer restoration and leverage targeting would have been equally effective as a mitigating action in this period. Secondly, increasing the level of contagion in the market does not affect buffer restoration or leverage targeting as a mitigating action. This is sensible as the contagion only affects the liquidity buffer in the third stage of the LST, were mitigating actions take place in the second stage. Finally, an increase of  $f$  does not affect the abilities of the two methods of mitigating actions differently. This does not suggest that increased haircuts do not have any effect on the mitigating actions, just that the insignificant difference between buffer restoration and leverage targeting in this study is responsible for similar results.

Figure 4.14 illustrates the effect of an increasing  $f$  on the liquidity buffer for 2009 data.



**Figure 4.14:** SA 2009, leverage targeting model output showing the dependence of loss probabilities on  $f$ .

Figure 4.14 illustrates, similar to the 2005 results in Figure 4.13, that an increase in  $f$  has a significant effect on liquidity buffer losses. At  $f = 1$ , the probability density peaks at approximately 5%. However, the distribution flattens out and shifts to the right as the  $f$  increases. The contagion axis (depth axis) shows how the possibility of losses exceeding 50% increases along with  $f$  and how the peak of the probability density shifts to the right as well.

There are also four three-dimensional graphs (Figures 4.8, 4.10, 4.12 and 4.14) that are estimated by using the 2009 data. These graphs suggest similar results to that of the 2005 period concerning mitigating actions, increased contagion and increased  $f$ s respectively. The introduction of an increasing level of contagion does not affect either of the methods of mitigating actions differently. As discussed, this is due to contagion only taking effect in the third stage of the LST after mitigating actions. Increasing the  $f$  does not produce different results for either of the methods of mitigating actions. This is due to the insignificant difference between the buffer restoration and leverage targeting in this study and does not suggest that the level of ( $f$ ) does not affect mitigating actions at all.

### **4.3 Results Loss Statistics**

As some of the lines and graphs illustrated in this chapter suggest little difference between methods of mitigating actions, Tables 4.1 to 4.4 below illustrate that methods used are not identical and, furthermore, it sheds light on statistics for all three stages of the LST.

#### **4.3.1 Buffer Restoration Statistics**

Table 4.1 below shows the loss statistics for the three stages of the LST, gleaned from South African 2005 data in the model using buffer restoration as a mitigating action.

		BUFFER RESTORATION		
		original	...and contagion	...and haircuts
Scenario	Statistic	Loss (%)		
Initial shock	Mean	5.65%	5.81%	11.72%
	Mode	4.20%	4.00%	10.00%
	95 <sup>th</sup> percentile	17.58%	18.79%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
Buffer restoration	Mean	0.24%	0.26%	0.71%
	Mode	0.05%	0.05%	0.00%
	95 <sup>th</sup> percentile	2.73%	2.81%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
2 <sup>nd</sup> round losses (feedback effects)	Mean	2.70%	18.03%	36.44%
	Mode	2.00%	3.00%	20.00%
	95 <sup>th</sup> percentile	22.99%	82.62%	100%
	99 <sup>th</sup> percentile	100%	100%	100%

**Table 4.1:** Models using S.A. 2005 data and buffer restoration as a mitigating action.

The column labelled as original in Table 4.1 shows the loss statistics for the LST estimated with all the original data<sup>22</sup> and  $s = 1$ . As mentioned in Chapter 3,  $s = 1$  represents a stress free market where the exposure to contagion is less. The ability of buffer restoration as a mitigating action is shown here as the mean reduces from 5.65% to 0.24% after mitigating actions. The mean of loss possibilities after the third stage of the model is only 2.70, thus indicating minimal effect arising from contagion in a stress free market.

The second column of loss statistics represents the buffer restoration model with the effects of an enhanced level of contagion. Noticeably, the statistics do not differ a great deal from those in the original column up until the end of the buffer restoration rows. This makes sense as contagion only affects the third stage of the LST, leading to 2<sup>nd</sup> round losses. There is more than a 15% increase in the mean loss possibilities if  $s$  is changed from 1 to 2, which indicates that South African banks may have been significantly affected by contagion in 2005 within stressed markets. The final column presents the loss statistics for the model with an increasing  $f$ , which is estimated at  $s = 2$ . The mean of possible liquidity buffer losses at the initial shock increases to 11.72% at  $f = 2$ . However, mitigating actions are still effective enough to almost completely restore the liquidity buffer with the mean decreasing to 0.70%. However, most concerning is the mean of possible losses after the third stage of the model, showing that 2<sup>nd</sup> round losses may reach up to 36.44%. This may be due to the

<sup>22</sup> These data refer to balance sheet information, thresholds and haircuts.

increased buffer restoration activities that may contribute to the severe 2<sup>nd</sup> round losses. Increased activities in already stressed markets may amplify a bank's exposure to contagion. The loss statistics for South African 2009 data follows, confirming the decrease in exposure due to contagion over the two periods.

#### 4.3.2 Leverage Targeting Statistics

		BUFFER RESTORATION		
		original	...and contagion	...and haircuts
Scenario	Statistic	Loss (%)		
Initial shock	Mean	8.05%	7.95%	16.00%
	Mode	6.00%	6.00%	10.00%
	95 <sup>th</sup> percentile	23.07%	22%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
Buffer restoration	Mean	5.79%	5.87%	6.97%
	Mode	1.00%	1.00%	1.00%
	95 <sup>th</sup> percentile	11.79%	11.45%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
2 <sup>nd</sup> round losses (feedback effects)	Mean	6.47%	7.95%	42.95%
	Mode	5.00%	6.00%	10.00%
	95 <sup>th</sup> percentile	14.15%	61.82%	100%
	99 <sup>th</sup> percentile	100%	100%	100%

**Table 4.2:** Models using S.A. 2009 data and buffer restoration as a mitigating action.

The loss statistics for the original model indicates that at  $s = 1$ , a slight increase in the exposure of South Africa banks to the initial shock from 2005 to 2009. This is expected, as mentioned previously the haircuts, which drives the original shock increases from an average of 4% to 6%. Furthermore, these statistics show that buffer restoration appears to be less effective in 2009, supporting the two-dimensional lines in Figure 4.3. In a stress-free market, South African banks show insignificant exposure to contagion, as the mean of possible losses increase from 5.79% to 6.47% after the third stage of the LST. As expected, similar to Table 4.1 the statistics stay identical between the original and contagion columns up until the third stage of the model. The effect of an increased level of contagion in a stress market at  $s = 2$  is considerably less in 2009 compared to 2005. The mean of possible losses after buffer restoration is 5.87% and only increases to 7.95% after the effects of contagion. Increasing  $f$ , however, has a significantly adverse effect on the liquidity buffer, similar to 2005. The increase of the mean at the initial shock shows the increase of  $f$ . Similar to 2005,

buffer restoration mitigates the increased effect of the initial shock just as effective as in the original model. The mean of possible 2<sup>nd</sup> losses exceeds that of 2005 reaching 42.95%. The reduced ability of buffer restoration along with the increase of average haircuts from 4% to 6% contributes to these severe losses of the liquidity buffer.

The loss statistics in Table 4.3 below represent the model, using leverage targeting as a mitigating action for South African 2005 data.

		<b>LEVERAGE TARGETING</b>		
		original	...and contagion	...and haircuts
Scenario	Statistic	Loss (%)		
<b>Initial shock</b>	Mean	5.67%	5.63%	11.28%
	Mode	5.30%	3.00%	10.00%
	95 <sup>th</sup> percentile	18.07%	17.93%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
<b>Buffer restoration</b>	Mean	0.26%	0.25%	0.65%
	Mode	0.06%	0.05%	0.00%
	95 <sup>th</sup> percentile	2.80%	2.77%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
<b>2<sup>nd</sup> roundlosses (feedback effects)</b>	Mean	2.72%	17.29%	34.90%
	Mode	2.70%	2.00%	2.000%
	95 <sup>th</sup> percentile	22.05%	81.79%	100%
	99 <sup>th</sup> percentile	100%	100%	100%

**Table 4.3:** Models using S.A. 2005 data and leverage targeting as a mitigating action.

As observed and discussed previously in the chapter, leverage targeting was effective in restoring the liquidity buffer to the same extent as buffer restoration. However, leverage ratios were not significantly affected, reducing the effect that falling asset prices might have had on the liquidity buffer if leverage ratios were more adversely affected. The loss statistics of the original model are thus more or less the same than of the LST using buffer restoration as a mitigating action. Increasing the level of contagion in the model ( $s$ ) and  $f$  respectively also produces similar results to that of Table 4.1. Leverage targeting is just as effective as buffer restoration throughout all three models and 2<sup>nd</sup> round losses are just as severe at  $f = 2$ .

Table 4.4 represents the loss statistics for the LST using leverage targeting as a mitigating action for 2009 data.

		<b>LEVERAGE TARGETING</b>		
		original	...and contagion	...and haircuts
Scenario	Statistic	Loss (%)		
<b>Initial shock</b>	Mean	7.84%	7.86%	15.84%
	Mode	5%	7%	10%
	95 <sup>th</sup> percentile	23.24%	23.42%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
<b>Buffer restoration</b>	Mean	5.76%	5.99%	5.82%
	Mode	1%	1%	1%
	95 <sup>th</sup> percentile	11.81%	11.77%	100%
	99 <sup>th</sup> percentile	100%	100%	100%
<b>2<sup>nd</sup> roundlosses (feedback effects)</b>	Mean	6.37%	7.86%	41.64%
	Mode	5%	7%	10%
	95 <sup>th</sup> percentile	12.89%	70.60%	100%
	99 <sup>th</sup> percentile	100%	100%	100%

**Table 4.4:** Models using S.A. 2009 data and leverage targeting as a mitigating action.

The loss statistics in Table 4.4 confirm that leverage targeting would have been just as effective in restoring the liquidity buffer in 2009. The statistics presented in Table 4.4 illustrate similar results to that of Table 4.2, again confirming no significant difference between the two methods of mitigating actions in this study. Tables 4.1 to 4.4 illustrated above confirm the results of the two- and three-dimensional graphs illustrated in Figures 4.1 through 4.14. The leverage ratios of the models using leverage targeting as the mitigating action is shown below in Table 4.5.

			<b>LEVERAGE TARGETING</b>	
Leverage ratio	2005	2009		
<b>Original</b>	16.10	16.78		
<b>After shock</b>	15.61	15.09		
<b>Restored</b>	16.10	16.78		

**Table 4.5:** Leverage ratios for leverage targeting models

The leverage ratios displayed in Table 4.5 for both periods are average leverage ratios for the five South African banks used in this study. These leverage ratios are estimated using the method discussed in Chapter 3 and the relevant balance sheet information of the banks. The table shows that leverage targeting as a mitigating action effectively restores the leverage ratio to its original level. However, it also shows the small effect the initial shock has on the original leverage ratios.



This chapter provided detailed results for the South African banking sector estimated using the LST model described in Chapter 3. It was found that either form of mitigating action used would have been equally effective in mitigating first round effects of a liquidity shock. Most importantly the chapter also indicates that the South African banking sector might have been significantly exposed to liquidity risk in either period. Chapter 5 presents the results estimated using data from a developed economy's principal banks with the same methods applied in this chapter.

## Chapter 5 Stress testing: Developed economy results

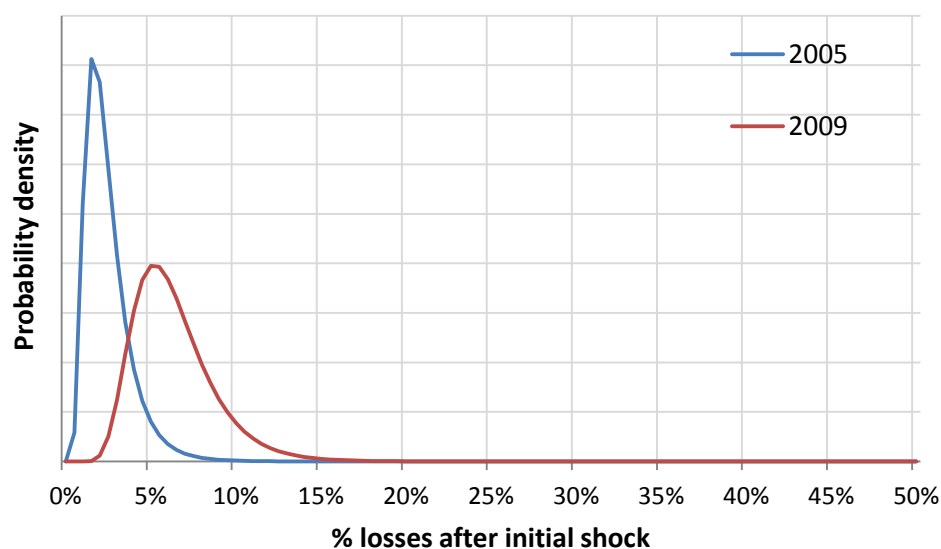
This chapter illustrates possible liquidity buffer losses for all three stages of the LST using the data gathered from five United Kingdom (UK) banks. The model producing these results is identical to the one discussed in Chapter 3 and used in Chapter 4, with the exception of implementing UK banking sector thresholds and haircuts on balance sheet items. This chapter follows a similar structure to that of Chapter 3 and the figures illustrate the percentage losses of the original liquidity buffer and not the remaining liquidity buffer.

### 5.1 Individual Stage Analysis

Figures 5.1 to 5.6 illustrate two-dimensional line graphs for the three stages of the LST. The ability to illustrate the effect of an increased level of contagion and increasing  $f$  is gained through the three-dimensional graphs in Figures 5.7 to 5.14. Tables 5.1 to 5.5 conclude the chapter by illustrating loss statistics and leverage ratios for the relevant models.

#### 5.1.1 Initial Shock

Figure 5.1 illustrates the effect of the initial shock on the original liquidity buffer for both the 2005 and 2009 period.

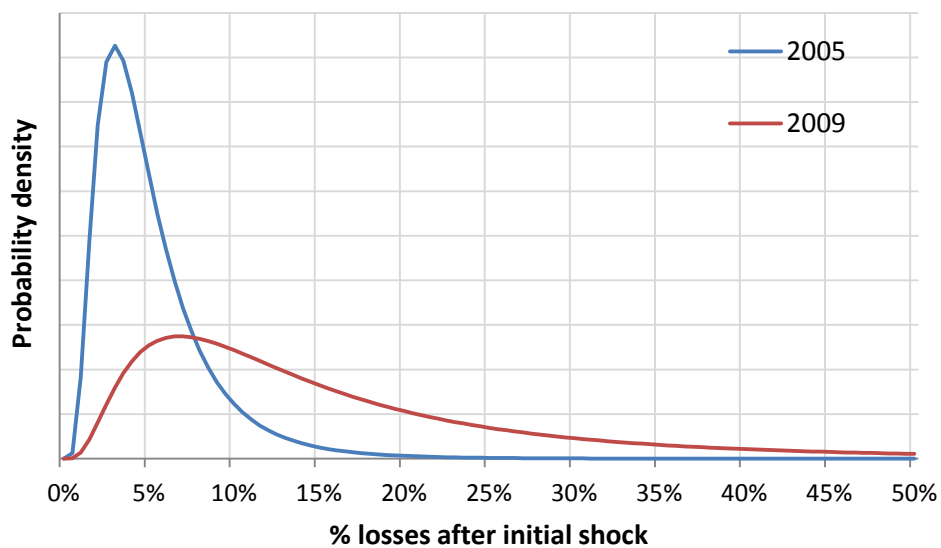


**Figure 5.1:** UK buffer losses at original haircuts ( $f \times 1$ ).

Estimating the LST at  $s = 2$  and using original haircuts ( $f = 1$ ) produce the lines in Figure 5.1 above.<sup>23</sup> The blue graph estimated using 2005 UK data indicates that the initial shock of a liquidity event would have had a less significant effect on the liquidity buffer compared to

<sup>23</sup> Similar to Chapter 3, all the two-dimensional graphs in this chapter are estimated at  $s = 2$ .

the red line of 2009. The mode of possible liquidity buffer losses shifts significantly to the right in 2009 compared to 2005. Losses do not exceed 10% in 2005, whereas in 2009 losses of up to 15% of the original buffer are possible. Chapter 3 reasons how the haircuts on balance sheet items drive the initial shock of a liquidity event. These haircuts averaged at 1% in the U.K. financial system in 2005 and contribute significantly to the high probability density of small losses in this period. The average haircuts increased to 4% in 2009, with the effect of this shown in the red line of 2009. The line shows that the initial shock of a liquidity event in 2009 would have been significant enough to eradicate any possibilities of losses smaller than 2% of the original liquidity buffer. The mixture of assets and liabilities in the balance sheets of banks contribute significantly to the effect of the initial shock. Banks may have had several assets in their balance sheets linked to significant haircuts, as the 4% only indicates the average of haircuts in this period. This may prevent losses being less than 2% of the original liquidity buffer. The effect of increasing  $f$  to produce haircuts two times their original size is illustrated in Figure 5.2 for both the periods used in this study.



**Figure 5.2:** UK buffer losses with increased haircut factor ( $f \times 2$ ).

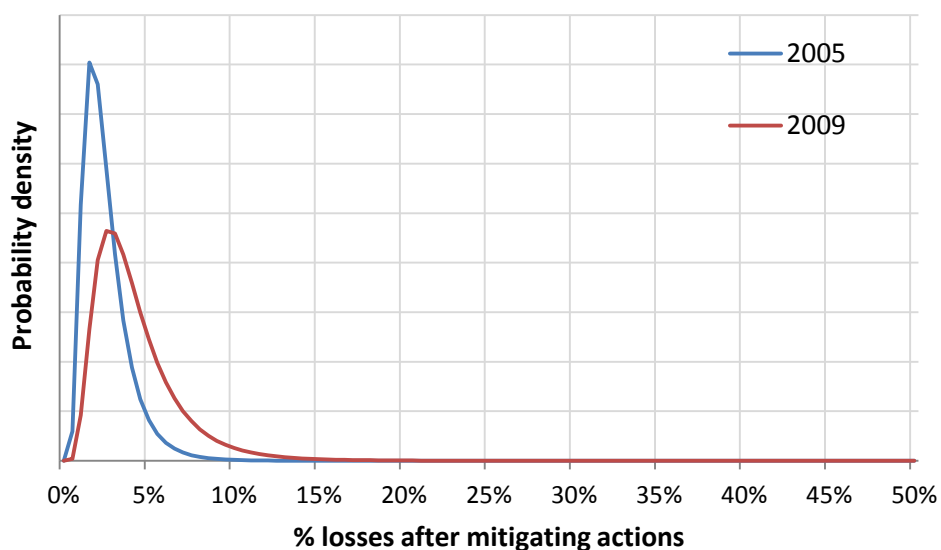
As discussed in Chapter 3 and applied in Chapter 4, an increase of  $f$  affects the initial shock of the liquidity event as this shock is to a certain extent dependent on the haircuts of balance sheet items. Comparing the line of Figure 5.2 to those in Figure 5.1, it is evident that the mode of both lines shifts to the right giving way to increased possible losses of the liquidity buffer. In 2005, possible losses of the liquidity buffer may have reached approximately 20%, however, still peaking at less than 5% with the increased  $f$  only producing a

longer tail of the blue line. In 2009, losses of up to approximately 50% of the original liquidity buffer would have been possible, with the line peaking at about 7%. The longer tail of the line graph allows for a threefold increase of possible losses when estimating the LST at  $f = 2$  in 2009. This significant increase in possible losses shows that an increase of  $f$  would have had a more severe effect in 2009 than in 2005. This is expected, as there was a 300% increase in average haircuts over the two periods, thus increasing the possible losses of the liquidity buffer. However, according to the methodology of the LST in Chapter 3, the mixture of assets and liabilities in the balance sheets of banks also contribute significantly to the losses produced by the initial shock.

The results displayed in this chapter make use of identical mitigating actions to those discussed in Chapter 3 and utilised for South African data in Chapter 4.

### 5.1.2 Mitigating Actions

The possible buffer losses for the LST, using UK 2005 and 2009 data and buffer restoration as a mitigating action follows in Figure 5.3.



**Figure 5.3:** UK buffer losses after buffer restoration as a mitigating action.

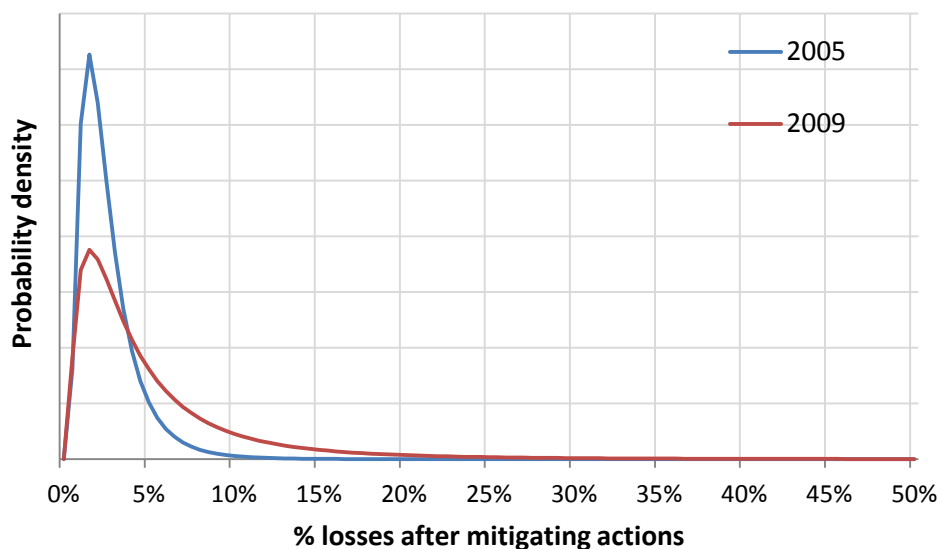
The lines above in Figure 5.3 illustrate possible liquidity buffer losses after mitigating actions have taken place. Buffer restoration seems to have no effect on the liquidity buffer in the blue line for the 2005 period. However, taking into consideration that reaction thresholds were set at an average of 80% for UK banks there most likely were no mitigating actions in this period. The loss statistics in Table 5.1 confirm a lack of mitigating actions by showing identical statistics for both the first and the second stage of the model. These results sug-

gest that banks would only have reacted to losses greater 80% of the original liquidity buffer and any losses smaller than this would be absorbed by the liquidity buffer. However, a loss of 1% of the liquidity buffer might amount to a loss of billions of Great British Pounds (GBP). A threshold of 80% is significantly high and indicates an underestimation of risk as losses far below this level may still put banks in deep financial distress. The effects of the high reaction threshold are visible throughout this chapter and Chapter 6 offers a detailed discussion on the possible consequences of this.

The red line representing the 2009 period, however, does differ when compared to the one in Figure 5.1, indicating that mitigating action would have taken place in 2009. This is due to the threshold decreasing to 9% in 2009, which is significantly lower when compared to 2005. The red line indicates that the possible losses reduce from 15% to approximately 13%. However, the mode of the line decreases significantly, shifting the line to the left and reducing the possibility of significantly high losses of the liquidity buffer.

The significant decrease in reaction thresholds of UK banks over the two periods is possibly to a certain extent due to most UK banks being public companies. Public companies have the obligation to disclose significantly more financial information compared to privately owned companies. In the UK, the government does have the controlling stake in some banks and minority stakes in other. Pressure from the public and the governmental stakeholders may have led to a reduction in the reaction thresholds, as these high reaction thresholds would appear to be an underestimation of risk. The effects of the 2007 liquidity crisis along with pressure from stakeholders after the crisis would most certainly also have contributed to the reduction in the reaction thresholds. The effects of these significantly high reaction thresholds on the UK economy and banks are further assessed in Chapter 6.

As mentioned above, similar to Chapter 3, this chapter also employs leverage targeting as a mitigating action and the effect of this method is displayed in Figure 5.4.



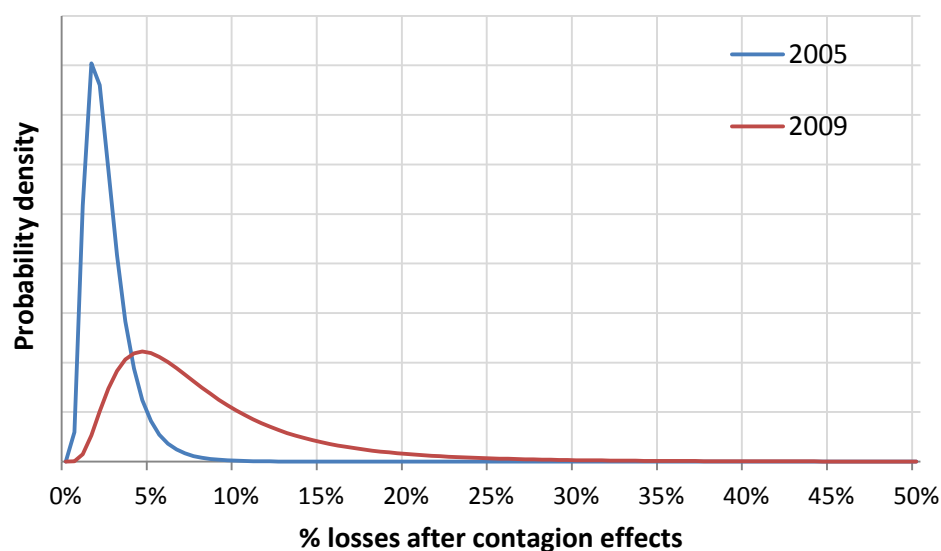
**Figure 5.4:** UK buffer losses after leverage targeting as a mitigating action.

The line representing the LST using leverage targeting as a mitigating action for the 2005 period in Figure 5.4 above is similar to the buffer restoration blue line in Figure 5.3. Again, this is due to the reaction thresholds being an average of 80%, which causes no mitigating actions to take place. The losses of the blue line thus still only illustrates the initial shock to the liquidity buffer. A comparison of the loss statistics across Tables 5.1 and 5.3 again confirms that no mitigating actions take place, producing similar statistics for the first and second stages of the liquidity models.

The lines for the two methods of mitigating action, however, differ in 2009, as mitigating actions do take place. There are increased possible losses of the liquidity buffer when leverage targeting is used as mitigating actions to restore the buffer. In Figure 5.4, the red line has a longer tail compared to the one in Figure 5.3, indicating that falling asset prices do have an effect on the liquidity buffer. However, the mode of the line for leverage targeting in Figure 5.4 is smaller compared to that of the buffer restoration red line in Figure 5.3. This indicates increased possibilities of smaller losses, with the line being flatter compared to the one using buffer restoration as a mitigating action. These results are similar to those found by Van Vuuren (2011:47-49) for UK banks in terms of leverage targeting, producing increased possible losses of the liquidity buffer. However, he estimates results for a different period and uses a different data set.

### 5.1.3 Second Round Feedback Effects

The third stage of the LST estimates the effects of contagion on the liquidity buffer after mitigating actions have taken place and Figure 5.5 illustrates these effects for the model using buffer restoration mitigating action.

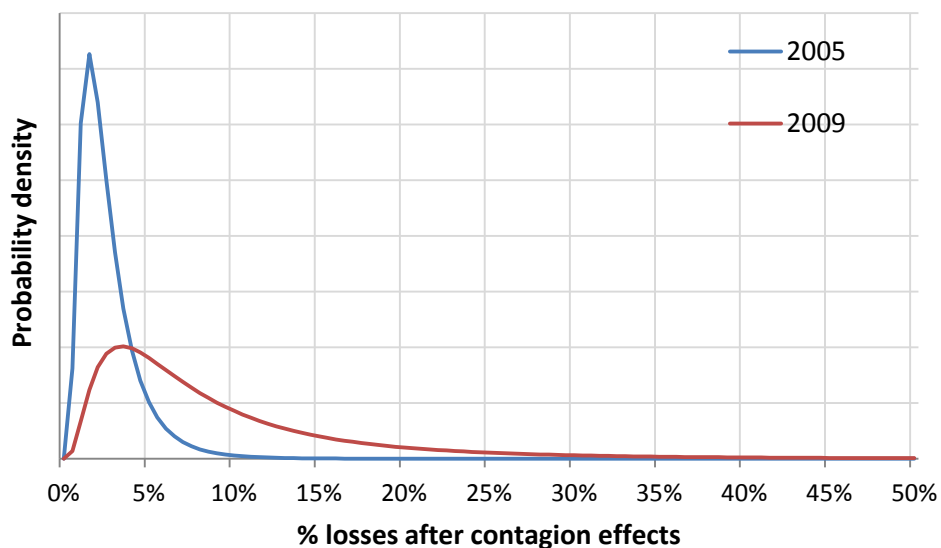


**Figure 5.5:** UK buffer losses for buffer restoration model after contagion effects.

The blue line in Figure 5.5 that represents 2005 is identical to those that represent the first and second stages of the model for this period. Again, the lack of mitigating actions leads to the similarity of lines for the 2005 period. Equation 3.8 in Chapter 3 shows how the second round effects are dependent on the size of transactions conducted with various instruments (*RI*) by banks by means of mitigating actions. With no mitigating actions taking place there are no second round effects and this creates the illusion that banks may have not been exposed to contagion. Chapter 6 further discusses how the activity in markets can affect balance sheets of banks even if they do not react to liquidity shocks. The loss statistics in Table 5.1 for 2005 again show identical statistics compared to the first and second stages of the LST. However, for the 2009 period contagion does affect the liquidity buffer in the third stage of the model with possible losses increasing from approximately 12% to above 20%. The line also flattens out, indicating fewer possibilities of smaller losses with the mean of the line also shifting slightly to the right. This increase of the mean of possible losses is visible in the loss statistics illustrated in Table 5.2. The effect of contagion is, however, not as significant as in Chapter 4 and this is possibly due to the amount of toxic assets present in the UK financial sector. It is widely accepted that UK banks were more severely affected by

the 2007 financial crisis, compared to South African banks and this possibly increased the amount of toxic assets in the financial system (Madubeko, 2010). Banks would avoid activities with these toxic assets in the system, which may reduce activity in the market and ultimately exposure to contagion as well. However, with the hope of a future recovery in financial markets, banks may also hold on to these assets, anticipating an increase in their value. Chapter 6 compares the results of both Chapters 4 and 5 and discusses why the results found may be possible.

Figure 5.6 illustrates the effect of contagion on the LST using leverage targeting as a mitigating action.



**Figure 5.6:** UK buffer losses for leverage targeting model after contagion effects.

As expected, the distribution of losses for 2005 is identical in both the first and second stage of the LST. Similar to the Figures 5.1 and 5.3 to 5.5, the lack of mitigating actions (due to the extremely high reaction threshold) by banks causes Figure 5.6 not to illustrate any contagion in the third stage of the model. Furthermore, the loss statistics in Table 5.3 again confirm the lack of any contagion effects. There is, however, a contagion effect in 2009 with possible losses reaching above 25% of the original liquidity buffer. This is approximately 5% more than the model using buffer restoration as a mitigating action in Figure 5.5.

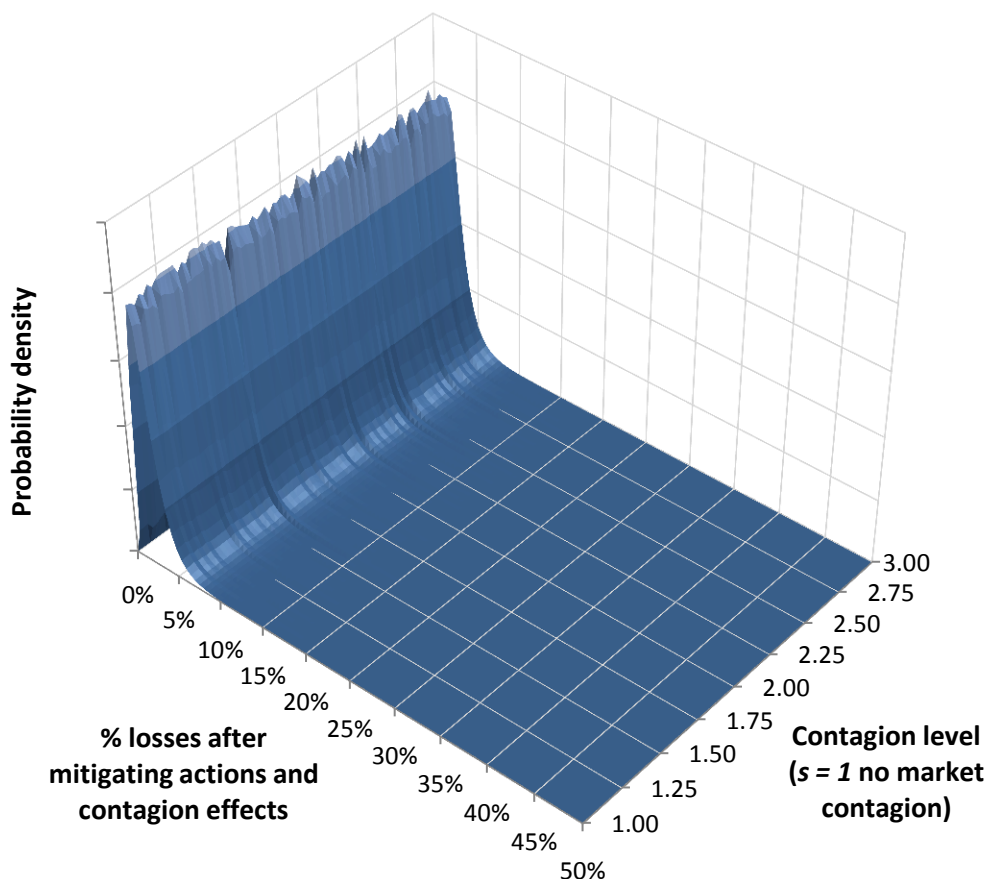
## 5.2 Consolidated Analysis

The ability to vary  $s$  and  $f$  in the LST allows for the estimation of three-dimensional graphs, illustrating the effect of these variables respectively.



### 5.2.1 Buffer Restoration Models

Figure 5.7 illustrates the effect of an increased  $s$  on the liquidity buffer for the model using UK 2005 data and buffer restoration as a mitigating action.



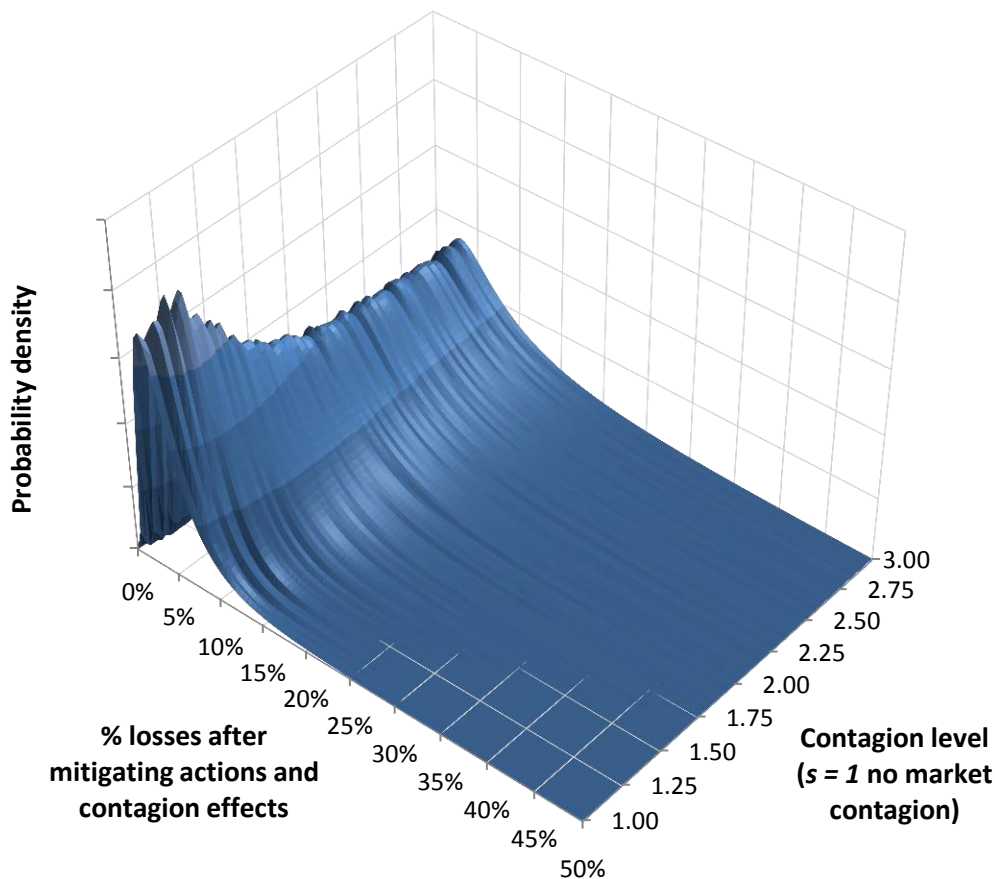
**Figure 5.7:** UK 2005, buffer restoration model output showing the dependence of loss probabilities on  $s$ .

Figure 5.7 above illustrates that increased levels of contagion does not have any effect on the distribution of the liquidity buffer. The possible losses of the liquidity buffer remain less than 10% at  $1 < s < 3$  and original haircuts ( $f = 1$ ) is used to estimate the model.<sup>24</sup> The reason for the  $s$  having no effect on the liquidity buffer is due to the buffer losses illustrated in Figure 5.7, being the effect of the initial shock only. Yet again, the high reaction threshold (80% on average in the UK) in 2005 led to a lack of mitigating actions. In the LST, the second round contagion effects depend on the mitigating actions<sup>25</sup> and since neither of these is

<sup>24</sup> All three-dimensional graphs illustrating an increased level of contagion are estimated with original haircuts ( $f = 1$ ).

<sup>25</sup> See Equation 3.8.

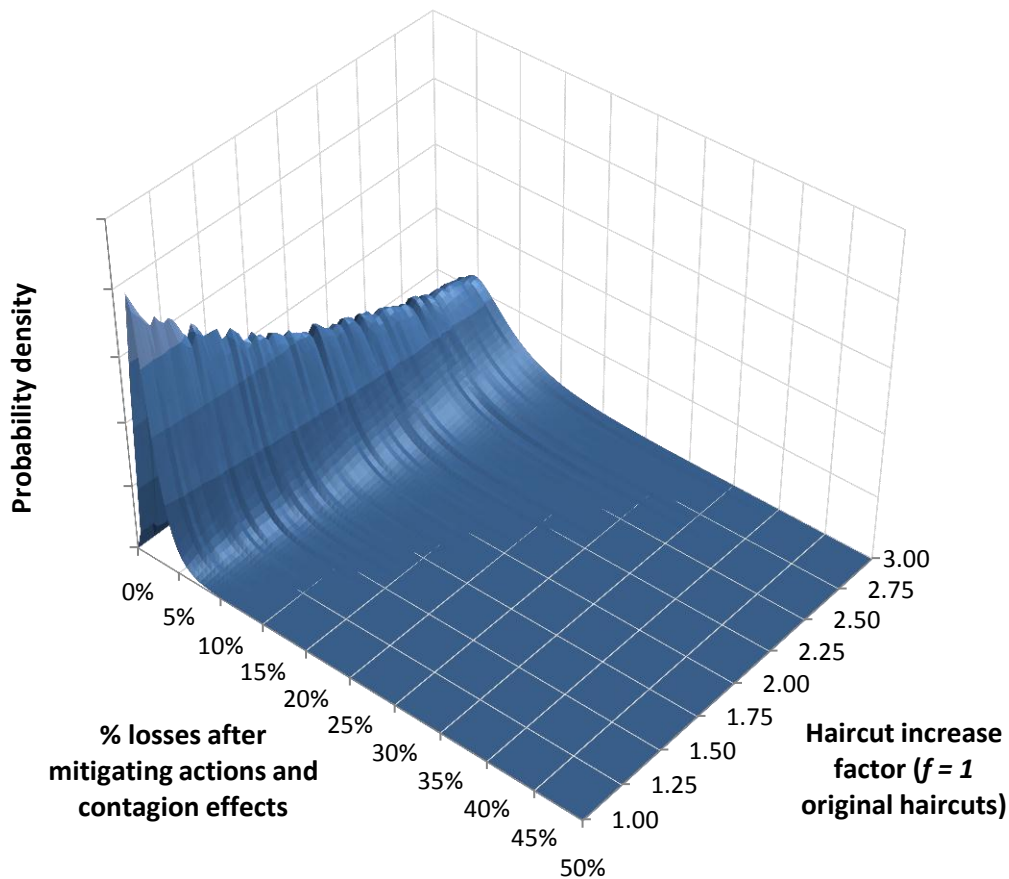
present, the initial shocks are the only possible losses the liquidity buffer may suffer. This is, however, an illusion, as banks would still be susceptible to contagion through their balance sheets as a result market risk. Chapter 6 offers further discussion on this. Also illustrating the effects of an increased level of contagion, Figure 5.8 uses UK 2009 data and buffer restoration as a mitigating action.



**Figure 5.8:** UK 2009 buffer restoration model output showing the dependence of loss probabilities on  $s$ .

In contrast to Figure 5.7, Figure 5.8 illustrates that the level of contagion in the market would have had an effect on the liquidity buffer in 2009. As the level of  $s$  increases it is clear how the tail of the distributions lengthens, giving way to losses up to 50% at  $s = 3$ . Similar to Chapter 4, contagion has the most severe effect at  $1 < s < 2$  and the peak of distribution stays approximately constant at  $s > 2$ . Figure 5.8 differs significantly from Figure 5.7 due to mitigating actions and the contagion that affect the liquidity buffer in 2009.

An increase of  $f$  increases the initial shock of the LST, and since all three stages of the model are interconnected; this will affect the liquidity buffer in all three stages of the model. Figure 5.9 illustrates the effect of increasing  $f$  for the model, using UK 2005 data and buffer restoration as a mitigating action.

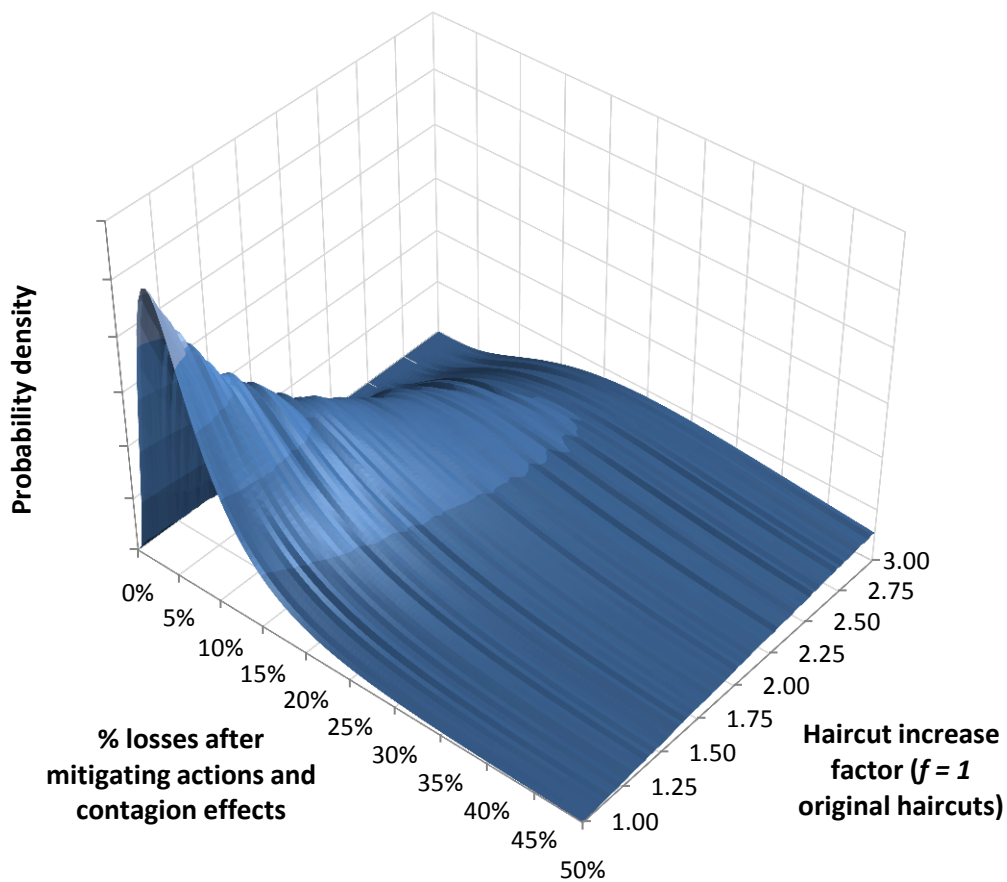


**Figure 5.9:** UK 2005 buffer restoration model output showing the dependence of loss probabilities on  $f$ .

The distribution in Figure 5.9 illustrates the effect of the increasing  $f$ , showing that losses of up to 30% of the original liquidity buffer are possible at  $f = 3$ . For the estimation of Figure 5.9 the level of contagion is set at  $s = 2$ , which is the case for all the three-dimensional graphs (Figures 5.9, 5.10, 5.13 and 5.14), illustrating the effect of the increased  $f$  in this chapter. The distribution in Figure 5.9, however, is yet again only the effects of the initial shock on the liquidity buffer as no mitigating actions took place in 2005. Furthermore, as no mitigating actions would have taken place, no contagion effects arising from these actions

would occur. It is sensible for the graph in Figure 5.9 to change as the haircuts affect the liquidity buffer through the initial shock in first stage of the LST and the distribution illustrates this gradual increase of  $f$ .

Figure 5.10 illustrates the effect of increasing  $f$  on a model using 2009 UK data and buffer restoration as a mitigating action. This is the final figure using buffer restoration as a mitigating action, which is followed by results for models using leverage targeting as a mitigating action.



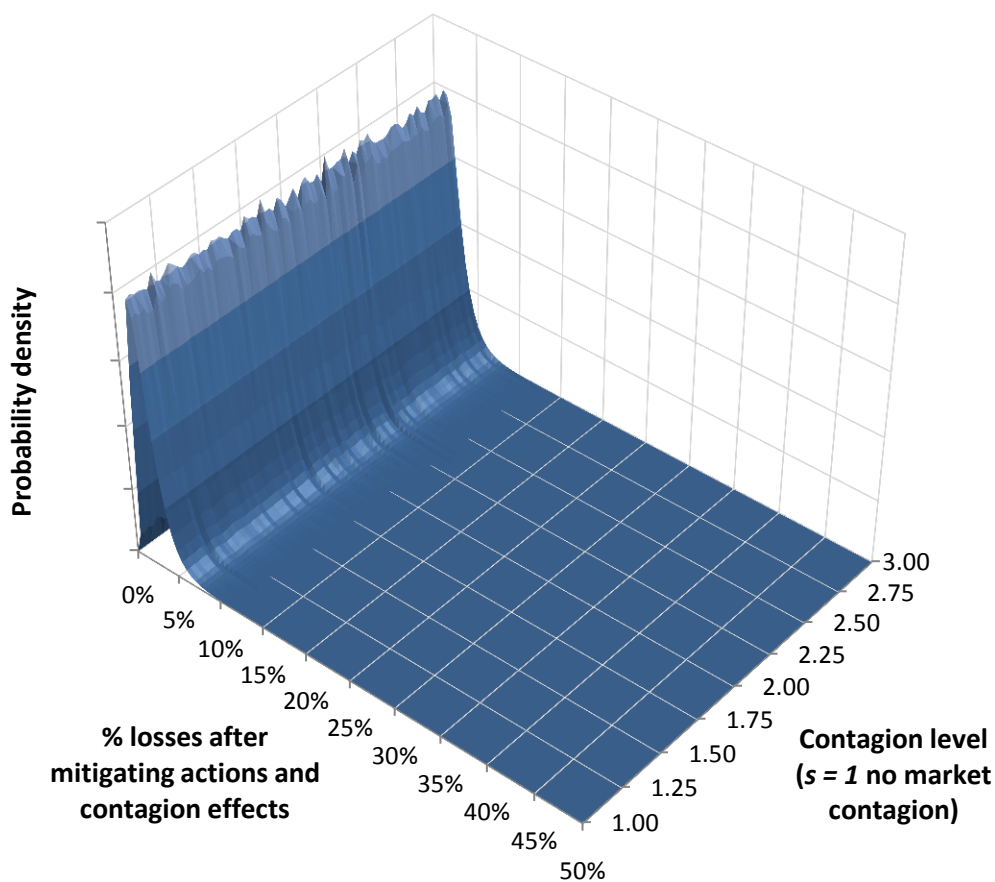
**Figure 5.10:** UK 2009 buffer restoration model output showing the dependence of loss probabilities on  $f$ .

The effect of the changing  $f$  is clearly visible in Figure 5.10 as losses exceeding 50% become increasingly possible as  $f$  reaches 3. Increasing the haircuts to this size eradicates the possibility of losses below approximately 2% of the original liquidity buffer. As  $f$  is increased, the distribution significantly flattens out and the mode of possible liquidity buffer losses in-

crease as well. This indicates increased possibilities of larger losses of the liquidity buffer. The interconnectedness of all three stages of the LST causes an increase in  $f$  to have a significant effect on the liquidity buffer in Figure 5.10.

### 5.2.2 Leverage Targeting Models

Leverage targeting as a mitigating action is also evaluated to assess how an increased  $f$  would affect its ability to restore the liquidity buffer and, furthermore, the effect of leverage targeting on contagion in the market. Figure 5.11 illustrates the effect of an increased  $s$  on a model using 2005 UK data and leverage targeting as a mitigating action.

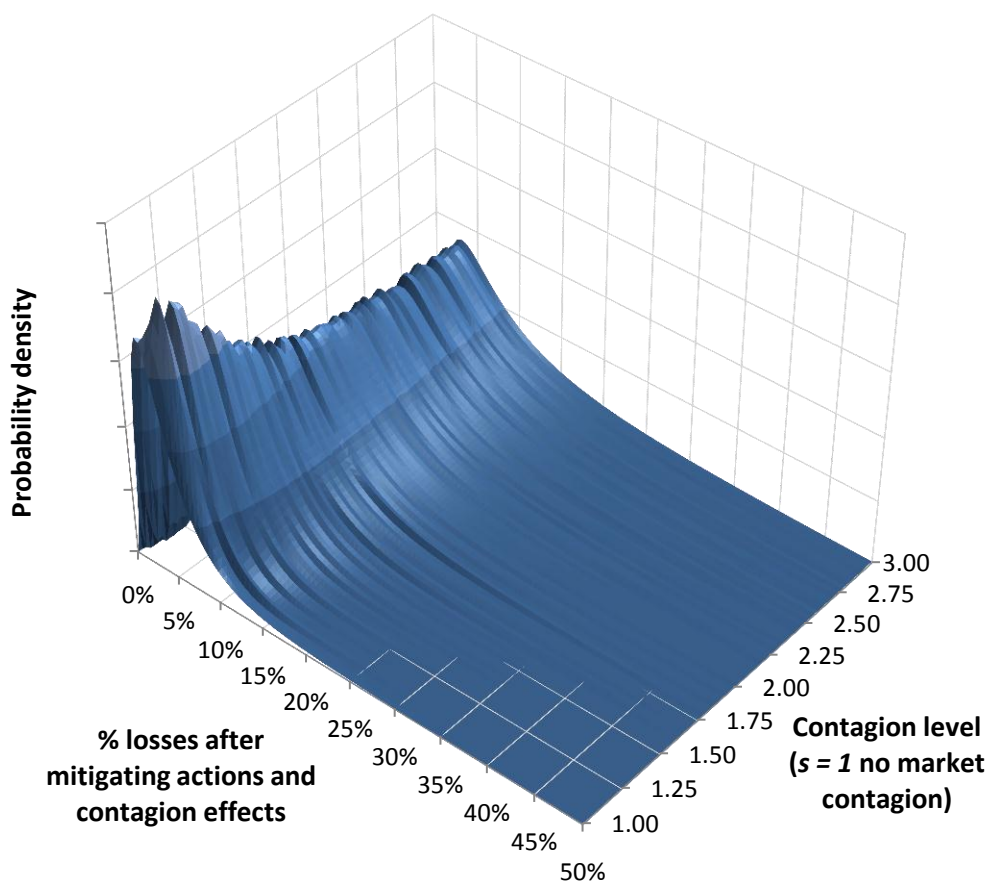


**Figure 5.11:** UK 2005, leverage targeting model output showing the dependence of loss probabilities on  $s$ .

Similar to Figure 5.7, the distribution in Figure 5.8 shows no susceptibility to contagion. However, the buffer losses are only that of the first stage of the LST, with the significantly high reaction threshold causing no mitigating action and thus no contagion effects arising

from these actions. The possible losses are thus limited to the initial shock of the LST. However, as discussed it is highly unlikely that banks can show no exposure to contagion and that estimations like this might have misled banks in the UK financial sector. The liquidity buffer of banks comprising of balance sheet items will most likely always be susceptible to contagion as these items are affected by market risk factors linked to assets and liabilities. Chapter 6 provides further explanation on the susceptibility of UK banks to contagion in this period.

Figure 5.12 illustrates how contagion can affect the liquidity buffer in the LST when using 2009 UK data and leverage targeting as a mitigating action.

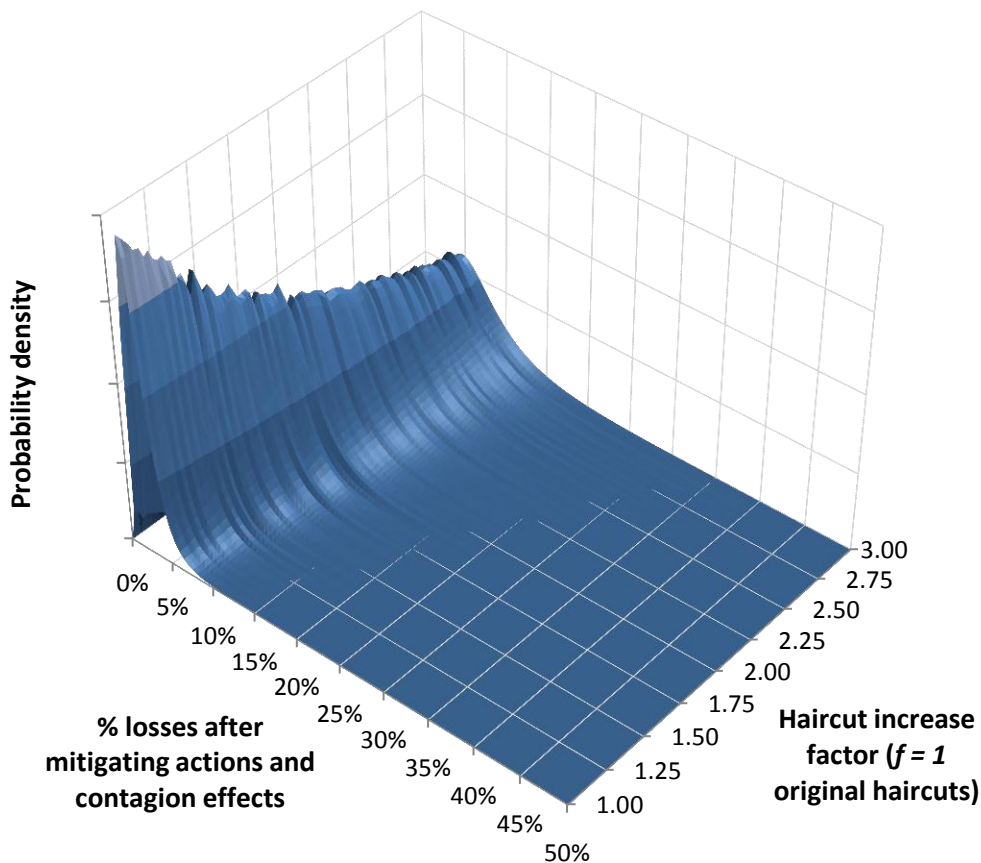


**Figure 5.12:** UK 2009 leverage targeting model output showing the dependence of loss probabilities on  $s$ .

The distribution in Figure 5.12 above illustrates how the increased level of contagion might have affected the liquidity buffer in the 2009 period. The graph in Figure 5.12 is similar to

that of Figure 5.8, illustrating the most severe effect arising from contagion at  $1 < s < 2$ , with the distribution staying quite constant at  $s > 2$ . At  $s > 2$  losses up to 50% of the liquidity buffer, become a reality. However, the majority of losses remain between 0% and 10%. The lower average reaction thresholds of banks' in 2009 allows for the assessment of effects arising from contagion, as a mitigating action did take place in this period. Although buffer restoration and leverage targeting three-dimensional graphs appear very similar, the two-dimensional line graphs displayed above do illustrate the difference between the methods of mitigating action.

The effect of increasing  $f$  for a model using UK 2005 data and leverage targeting as a mitigating action follows in Figure 5.13.



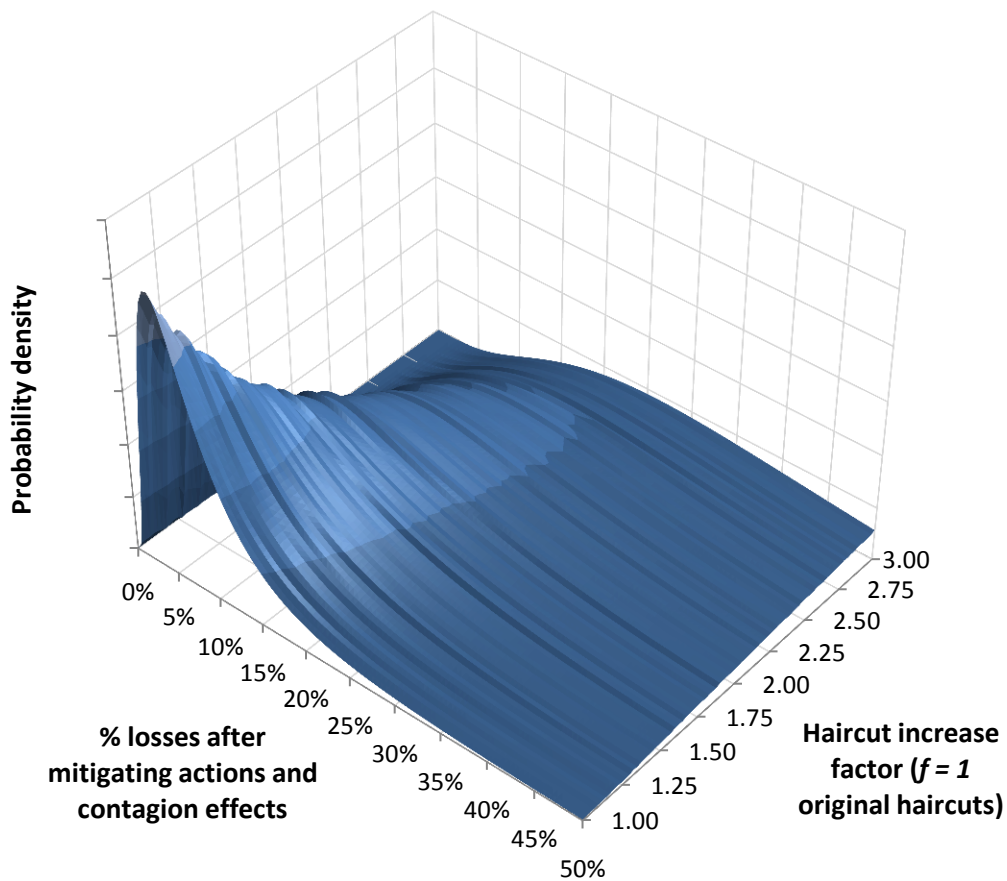
**Figure 5.13:** UK 2005 leverage targeting model output showing the dependence of loss probabilities on  $f$ .

Gradually increasing  $f$  produces Figure 5.13, which shows the effect of increased haircuts on the liquidity buffer. This figure is almost identical to that of Figure 5.9, with only the loss sta-



tistics across Tables 5.1 and 5.3 differing slightly. This is expected, due to the losses in both these figures only presenting losses arising from the initial shock of the model. Again the significantly high reaction thresholds of banks in 2005 led to no mitigating actions and contagion effects arising from these actions that take place in this period. The possible losses of the LST for this period are thus limited to the initial shock of the liquidity event and since no mitigating actions take (with mitigating actions being the distinguishing factor in the models) the distributions in Figure 5.9 and 5.13 should be very similar.

The estimation of the LST in Figure 5.14 represents the effects of increasing  $f$  for a model using UK 2009 data and leverage targeting as a mitigating action.



**Figure 5.14:** UK 2009, leverage targeting model output showing the dependence of loss probabilities on  $f$ .

Figure 5.14 is significantly different compared with Figure 5.13, which is mostly due to all three stages of the LST affecting the liquidity buffer in Figure 5.14 compared to only the ini-



tial shock affecting the buffer in Figure 5.13. The possibility of losses up to 50% of the liquidity buffer is a reality at any level of  $f$  and the possibilities of these losses increase as  $f$  is increased. Again, similar to Figure 5.10, as  $f$  approaches 3 the possibility of losses less than 2% of the liquidity buffer vanish, indicating the severity of the increased haircuts along with the effects of contagion. Again the graph in Figure 4.14 significantly flattens out as  $f$  is increased, giving way to increased possibilities of greater losses of the original liquidity buffer.

### 5.3 Results Loss Statistics

The tables below present loss statistics and leverage ratios for the relevant models used in this chapter and they contribute to the ability to statistically evaluate the difference between the models.

#### 5.3.1 Buffer Restoration Statistics

Table 5.1 illustrates the loss statistics for all three stages of the LST using U. K. 2005 data and leverage targeting as a mitigating action.

Scenario	Statistic	BUFFER RESTORATION		
		original	...and contagion	...and haircuts
		Loss (%)		
Initial shock	Mean	2.07%	2.06%	4.04%
	Mode	1.74%	2.50%	3.40%
	95 <sup>th</sup> percentile	5.53%	5.58%	10.81%
	99 <sup>th</sup> percentile	9.50%	9.51%	16.87%
Buffer restoration	Mean	2.07%	2.06%	4.04%
	Mode	1.74%	2.50%	3.40%
	95 <sup>th</sup> percentile	5.53%	5.58%	10.81%
	99 <sup>th</sup> percentile	9.50%	9.51%	16.87%
2 <sup>nd</sup> round losses (feedback effects)	Mean	2.07%	2.06%	4.04%
	Mode	1.74%	2.50%	3.00%
	95 <sup>th</sup> percentile	5.53%	5.58%	10.81%
	99 <sup>th</sup> percentile	9.50%	9.51%	16.87%

**Table 5.1:** Models using UK 2005 data and buffer restoration as a mitigating action.

The loss statistics in Table 5.1 above illustrates the effect of the significantly high reaction thresholds set by UK banks in 2005. In the column representing the original model loss statistics for all three stages of the LST are identical indicating the lack of mitigating actions and contagion arising from these actions. The models introduce enhanced contagion and an increased  $f$  present similar loss statistics in terms of all three stages of the models having identical loss statistics.

Furthermore, the loss statistics of the original model and the one employing enhanced contagion are almost identical. This is expected as contagion arising from mitigating actions only takes effect in third stage of the LST and since no mitigating actions were conducted in this period, there will be no effects from enhanced contagion. However, the loss statistics for the model representing the effects of increasing  $f$  do differ from the loss statistics illustrated for the first two models. This is due to the increased haircuts taking effect in the first stage of the model and thus affecting the initial shock of the liquidity event. The effects of increasing  $f$  to produce haircuts twice their original size is not that significant as haircuts were only an average of 1% in 2005 in the UK banking sector. Furthermore, these statistics (caused by the reaction threshold of 80%) prevents the investigation of how effective mitigating actions might have been in 2005 in the UK.

Table 5.2 presents the loss statistics for the LSTs using UK 2009 data and buffer restoration as a mitigating action.

		<b>BUFFER RESTORATION</b>		
		<b>original</b>	<b>...and contagion</b>	<b>...and haircuts</b>
<b>Scenario</b>	<b>Statistic</b>	<b>Loss (%)</b>		
<b>Initial shock</b>	Mean	5.72%	5.66%	11.43%
	Mode	5.20%	4.10%	8%
	95 <sup>th</sup> percentile	14.23%	14.31%	100%
	99 <sup>th</sup> percentile	21.65%	23.78%	100%
<b>Buffer restoration</b>	Mean	4.61%	4.58%	1.57%
	Mode	0.43%	0.50%	0.50%
	95 <sup>th</sup> percentile	8.34%	8.23%	100%
	99 <sup>th</sup> percentile	8.92%	8.94%	100%
<b>2<sup>nd</sup> round losses (feedback effects)</b>	Mean	4.71%	5.66%	27.19%
	Mode	5.20%	4.10%	8%
	95 <sup>th</sup> percentile	8.40%	32.43%	100%
	99 <sup>th</sup> percentile	8.96%	49.13%	100%

**Table 5.2:** Models using UK 2009 data and buffer restoration as a mitigating action.

The loss statistics in Table 5.2 illustrate the effect of a liquidity event on the liquidity buffer for all three stages of the relevant LST's. This table differs significantly compared to Table 5.1 with the effects of mitigating actions clearly visible along with the contagion effects arising from these actions. Buffer restoration in all three models is not that effective in restoring the liquidity buffer when compared to the loss statistics in Chapter 4. However, surprisingly

buffer restoration is most effective in the model with the increased  $f$  producing a more severe initial shock to the liquidity buffer.

Using original haircuts in the model with an increased level of contagion, the effects of contagion is not that severe compared to loss statistics observed in Chapter 4. As contagion effects arise from mitigating actions, the inability of buffer restoration to restore the buffer in this period may contribute to the reduced effects arising from the contagion in the third stage of the model. However, the effect arising from contagion in the model with an increased  $f$  is significantly high, indicating that increased activities to restore the liquidity buffer can increase the banks' exposure to contagion. Possible losses of the liquidity buffer due to contagion amount to a mean of 27.19%.

### 5.3.2 Leverage Targeting Statistics

Table 5.3 illustrates the loss statistics for the LSTs using UK 2005 data and leverage targeting as a mitigating action.

		<b>LEVERAGE TARGETING</b>		
		<b>original</b>	<b>...and contagion</b>	<b>...and haircuts</b>
<b>Scenario</b>	<b>Statistic</b>	<b>Loss (%)</b>		
<b>Initial shock</b>	Mean	2.05%	2.06%	4.18%
	Mode	2.12%	2.08%	2.95%
	95 <sup>th</sup> percentile	5.46%	5.39%	10.87%
	99 <sup>th</sup> percentile	8.85%	9.30%	17.66%
<b>Buffer restoration</b>	Mean	2.05%	2.06%	4.18%
	Mode	2.12%	2.08%	2.95%
	95 <sup>th</sup> percentile	5.46%	5.39%	10.87%
	99 <sup>th</sup> percentile	8.85%	9.30%	17.66%
<b>2<sup>nd</sup> round losses (feedback effects)</b>	Mean	2.05%	2.06%	4.18%
	Mode	2.12%	2.08%	2.95%
	95 <sup>th</sup> percentile	5.46%	5.39%	10.87%
	99 <sup>th</sup> percentile	8.85%	9.30%	17.66%

**Table 5.3:** Models using UK 2005 data and leverage targeting as a mitigating action.

The table illustrates similar results compared to that of Table 5.1 in terms of the loss statistics being similar for all three stages across all the models. As discussed above, the lack of mitigating actions (due to the high reaction threshold) and contagion arising from these actions cause the loss statistics to remain identical for all three stages of all the models in the table. Again, statistics for both the original and the model utilising an increased level of contagion are almost identical due to no mitigating actions and contagion taking place in either

of these models. The only reason why the final model illustrating the effect of increased haircuts differs from the other two models in the table is due to the initial shock, which is affected by increased haircuts.

Table 5.4 which follows illustrates the loss statistics for the LST's using UK 2009 data and leverage targeting as a mitigating action.

		<b>LEVERAGE TARGETING</b>		
		original	...and contagion	...and haircuts
Scenario	Statistic	Loss (%)		
<b>Initial shock</b>	Mean	5.75%	5.66%	11.36%
	Mode	5.30%	4.30%	9%
	95 <sup>th</sup> percentile	14.21%	13.97%	100%
	99 <sup>th</sup> percentile	23.26%	21.42%	100%
<b>Buffer restoration</b>	Mean	4.61%	4.56%	1.43%
	Mode	0.42%	0.49%	0.50%
	95 <sup>th</sup> percentile	8.33%	8.20%	100%
	99 <sup>th</sup> percentile	8.95%	8.88%	100%
<b>2<sup>nd</sup> round losses (feedback effects)</b>	Mean	4.70%	5.66%	27.08%
	Mode	0.50%	4.30%	8%
	95 <sup>th</sup> percentile	8.42%	31.05%	100%
	99 <sup>th</sup> percentile	9.00%	44.65%	100%

**Table 5.4:** Models using UK 2009 data and leverage targeting as a mitigating action.

The final loss statistics in Table 5.4 illustrates the possible effects of a liquidity event in the UK financial system and both the effects of increased haircuts and the level of contagion are visible. The original model and the model illustrating an increased level of contagion produce similar loss statistics for the first two stages of the LST as expected, as contagion only takes effect in the third stage of the model. The third stages of the models do differ slightly with contagion having an increased effect on the liquidity buffer. This effect is small compared to the results in Chapter 4 and this is likely due to the effect of the liquidity crisis and the amount of toxic assets present in the markets.

The table illustrates leverage targeting to be most effective in the third stage of the model, as the mean drops to 1.43% compared to 4.61 and 4.56 of the other models. This is similar to the loss statistics representing the buffer restoration models in Table 5.2. The final table in this chapter is Table 5.5, illustrating the leverage ratios for LSTs using UK data and leverage targeting as a mitigating action.

	<b>LEVERAGE TARGETING</b>	
<b>Leverage ratio</b>	<b>2005</b>	<b>2009</b>
<b>Original</b>	24.35	21.36
<b>After shock</b>	23.27	18.38
<b>Restored</b>	24.35	21.36

**Table 5.5:** leverage ratios for leverage targeting models.

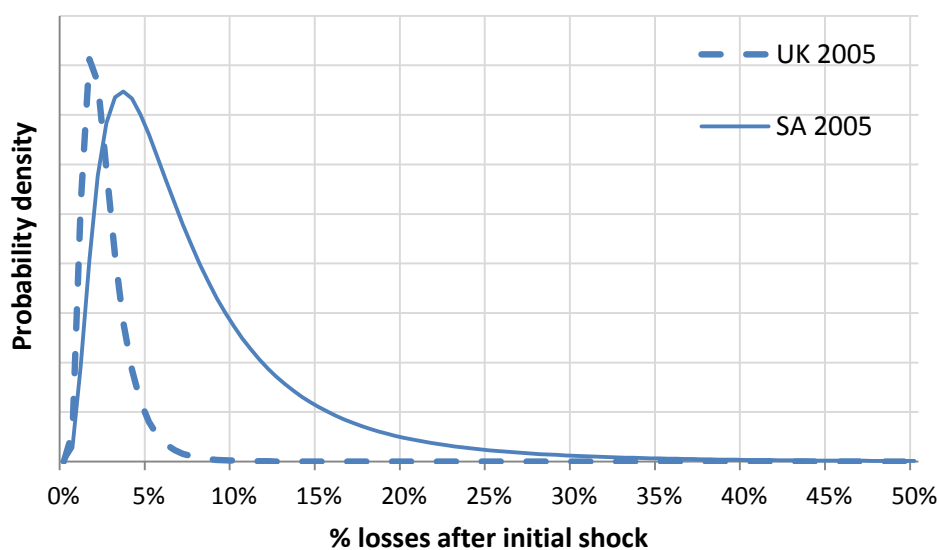
The set of leverage ratios in Table 5.5 above do not illustrate whether leverage targeting is effective as a mitigating action to restore the liquidity buffer. However, it does illustrate that the method is effective in its purpose of restoring the leverage ratio after a liquidity shock. The leverage ratios are averaged for the five UK banks used in this study for the relevant periods. The table shows that for both periods the leverage ratio is restored to what it was before the onset of the liquidity event. The drop in leverage ratios over the two periods is expected due to the effects of the liquidity crisis and Chapter 6 argues why this would have happened. Chapter 5, similar to chapter 4 illustrates through the results obtained that the UK banking system would not have been as sensitive to contagion compared to the South African banking system. However, results are constrained to a certain extent by the lack of mitigating actions and contagion effects arising from these actions in the non-crisis period. Chapter 6 further compares the buffer losses for both periods across the two economies used in the study and reason why these possible losses differ.

## Chapter 6: Comparison of economies

Chapters 4 and 5 illustrated results for LSTs using South African and UK data respectively for both the non-crisis and crisis periods. These two chapters also provide reasons why the possible losses of the liquidity buffer illustrated would have been likely to occur in the periods used in this study. This chapter compares the results for these economies and discusses why results may be so different. This comparison of the results attempts to identify which characteristics of the economies may have led to increased liquidity risk and ultimately increased possible losses of the liquidity buffer.

### 6.1 Initial Shock

Estimating the LST at  $s = 2$  and using original haircuts produce the line graphs in Figure 6.1, which illustrates the effect of the initial shock on the liquidity buffers for both economies in the non-crisis period.



**Figure 6.1:** SA and UK 2005 buffer losses at original haircuts ( $f = 1$ ).

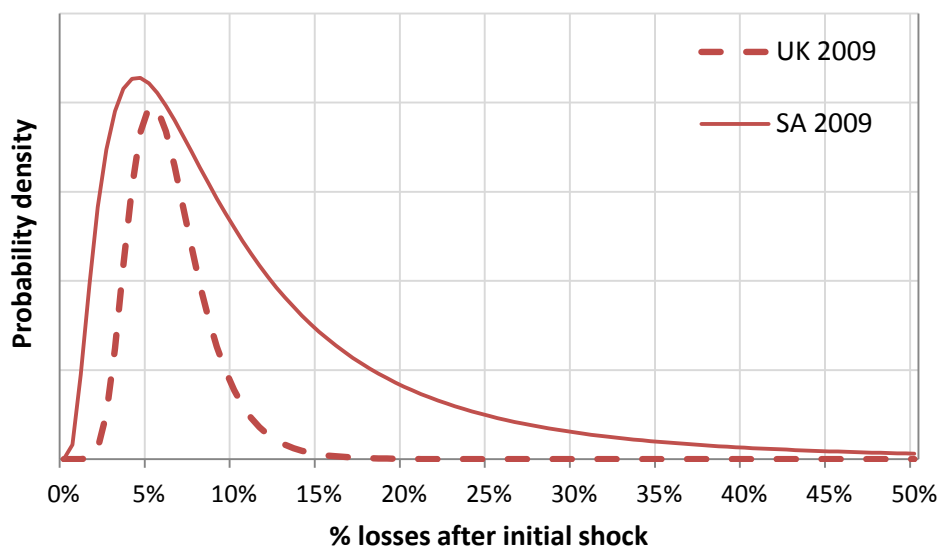
The solid line representing losses for the South African banks shows that the initial shock of a liquidity event in the LST would have been more severe compared to UK banks. Figure 6.1 shows how in South Africa losses may have possibly reached 35% compared to losses less than 10% of the liquidity buffer in the UK banking system. However, Chapter 3 discusses how the initial shock of the LST is dependent on the haircuts on balance sheet items, thus the size of these haircuts play a significant role in the severity of the initial shock. The hair-

cuts were on average 4% and 1% on South African and UK balance sheet items respectively in 2005, which explain the significant differences in the graphs in Figure 6.1.

The size of haircuts on balance sheet items can reflect to a certain extent several characteristics of an economy and the banking system. Van den End (2010:45), states that haircuts (weights) applied to balance sheet items represent a mixture of firm specific and market wide scenarios of liquidity risk. The weights are based on the best practices and values of haircuts and run-off rates for balance sheet items as used in the industry and by rating agencies (van den End, 2010:45). The haircuts per balance sheet item differ according to each item's sensitivity to liquidity stress. Larger haircuts on balance sheet items potentially increase the liquidity risk of banks as these haircuts produce greater initial shocks to the liquidity buffer. As 2005 was in the middle of one of the most significant economic booms in history (discussed in Chapter 3), haircuts on balance sheet items were expected to be low due to the health of the financial system. This possibly led to an underestimation of liquidity risk, which may arise through contagion caused by initial shocks.

Chapter 3 further discussed the significant differences between the South African and UK financial systems, stating that compared to the UK, which is considered the hub for global finance, South African banks make out quite a small percentage of the global banking system. The significant size of the UK financial system generates increased possibilities of diversification of balance sheets, which along with the health of global finance potentially explains the small haircut sizes linked to the balance sheets of UK banks in 2005. South African banks, although respected in global finance, is not nearly as exposed to the amount of financial activities as the UK banking sector and the South African banking sector is significantly smaller, since it operates in a emerging economy. This possibly contributes to the larger haircuts in the South African banking system as banks may not be able to diversify the risks arising from haircut exposures as comfortably as UK banks and would possibly not be able to generate liquidity as comfortably as UK banks.

Figure 6.2, similar to Figure 6.1, illustrates the first stage of the LST estimated at  $s = 2$  and with original haircuts, with the exception of using 2009 crisis data for both economies.



**Figure 6.2:** SA and UK 2009 buffer losses at original haircuts ( $f = 1$ ).

The effect of the initial shock would have been more severe in 2009 for both South African and UK banks when comparing the lines in Figures 6.1 and 6.2. In the UK, losses of the liquidity buffer double from 2005, exceeding 15% and losses less than 2% of the liquidity buffer are unachievable. The solid line representing South African 2009 data, illustrates a flatter distribution with a longer tail and possible losses, reaching 50% of the liquidity buffer compared to 35% in Figure 6.1.

By 2009 the effects of the financial crisis would have already been felt throughout financial systems globally, since 2009 was deep in the midst of the liquidity crisis, as explained in Chapter 3. The consequences of the financial crisis would most certainly have had an effect on the haircuts linked to balance sheet items, as haircuts reflect how economic conditions regarding liquidity risk would affect these particular assets and liabilities in times of stress. Haircuts on average were 6% and 4% for South African and UK banks respectively in 2009, indicating a significant increase over the two periods for the UK banks especially. The effects of these increased haircuts are clearly visible when comparing Figures 6.1 and 6.2. The significantly increased haircuts indicate the susceptibility of balance sheet items to liquidity risk in the crisis period. The effects of the financial crisis significantly contribute to the doubling of haircuts in the UK banking sector. Although the UK financial sector is one of the biggest in the world and banks might have had more diversification possibilities, their exposure to financial crisis would also have been higher compared to a smaller economy like South Africa. The crisis led to a significant amount of risky assets owned by banks turning toxic, which

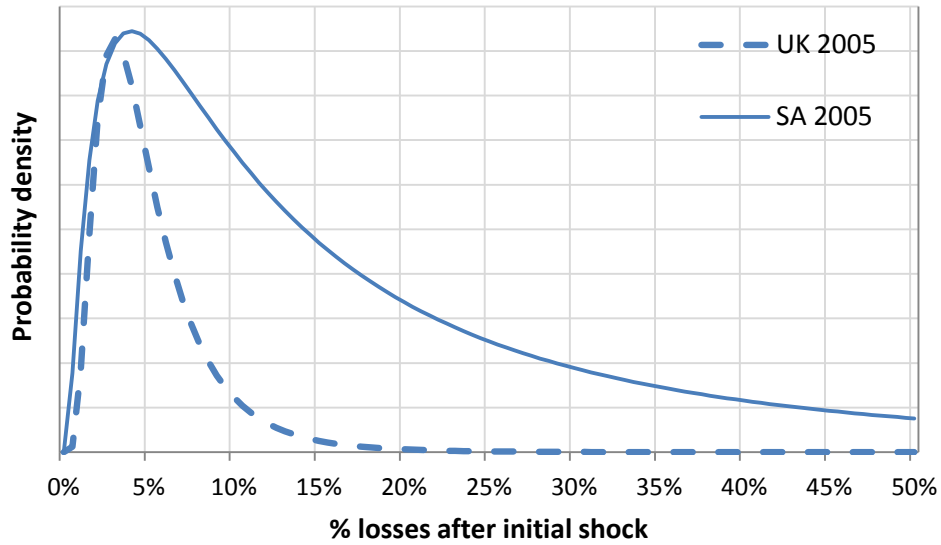


might still up until present be difficult to sell to other banking sector participants. Furthermore, banks might potentially have kept these toxic assets in their balance sheets with the hope of their value increasing when markets recover. Either of these scenarios would have kept toxic assets within balance of UK banks, possibly increasing liquidity risk through haircuts as these assets become riskier.

The South African banking sector, however, did not suffer as severely from the effects of the financial crisis, with growth rates not decreasing as significantly compared to developed countries (Ocaya, 2012:169). This possibly caused fewer assets within balance sheets to become toxic. This caused haircuts not to increase as significantly compared to UK banks, ultimately leading to a smaller increase in possible liquidity buffer losses after the initial shock within the South African banking sector. However, South African banks are still undoubtedly more at risk with possible liquidity buffer losses exceeding 50%. It is only the increase from the non-crisis to crisis period, which is not as severe. There may be several other reasons why the haircuts did not double in the South African banking system as they did in the UK banking system. However, the South African NCA of 2005 may have contributed to the lower level of interconnectedness between South African banks and also reduced reckless lending prior to the onset of the liquidity crisis. This would have prevented banks from obtaining risky assets with high haircuts linked to them, possibly explaining a smaller increase in average haircuts across the two periods.

## **6.2 Initial Shock at Increased Haircuts**

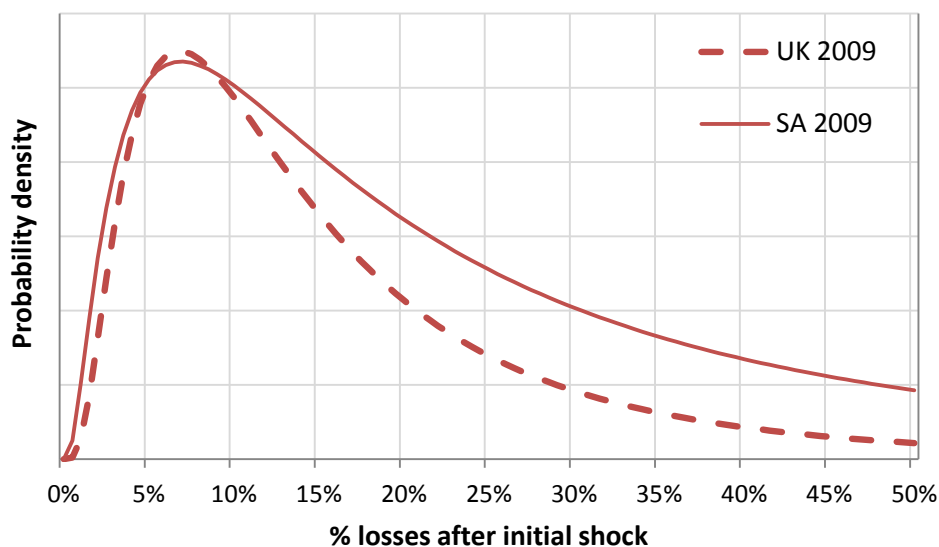
Increasing  $f$  in order to produce haircuts twice their original size and estimating the LST at  $s = 2$  produces the line graphs in Figure 6.3. This indicates the significant impact of haircuts through the initial shock on the liquidity buffers of both economies.



**Figure 6.3:** SA and UK 2005 buffer losses at original haircuts ( $f = 2$ ).

Estimating the LST with haircuts twice their original size illustrates in Figure 6.3 the significant effect of these haircuts on possible liquidity buffer losses in the initial shock of the LST. The solid line representing South African banks illustrates losses exceeding 50% of the original liquidity buffer. The possibility of buffer losses for UK banks does not increase as significantly and losses of up to 20% of the liquidity buffer become the maximum. However, original haircuts on balance sheet items of UK banks were on average 1% in 2005, thus no significant increase in possible first stage losses is expected as haircuts only increase to 2%. Haircuts on South African balance sheets items were 4%, which if doubled would significantly affect possible liquidity buffer losses in the first stage of the LST for this period.

Figure 6.4, illustrating possible liquidity buffer losses for both economies in 2009 is similar to Figure 6.3, estimated using haircuts twice their original size and at  $s = 2$ .



**Figure 6.4:** SA and UK 2009 buffer losses at original haircuts ( $f = 2$ ).

Figure 6.4 illustrates significant possible losses of the liquidity buffer for both economies in the 2009 crisis period, with both liquidity buffers exceeding possible losses of 50%.

The mixture of assets and liabilities play a significant role in determining the effects of the initial shock, as these balance sheet items have unique haircuts linked to each of them. Although haircuts were an average 6% and 4% for South African and UK banks respectively, this does indicate the amount of each asset in the balance sheet and its relevant haircut exposure.

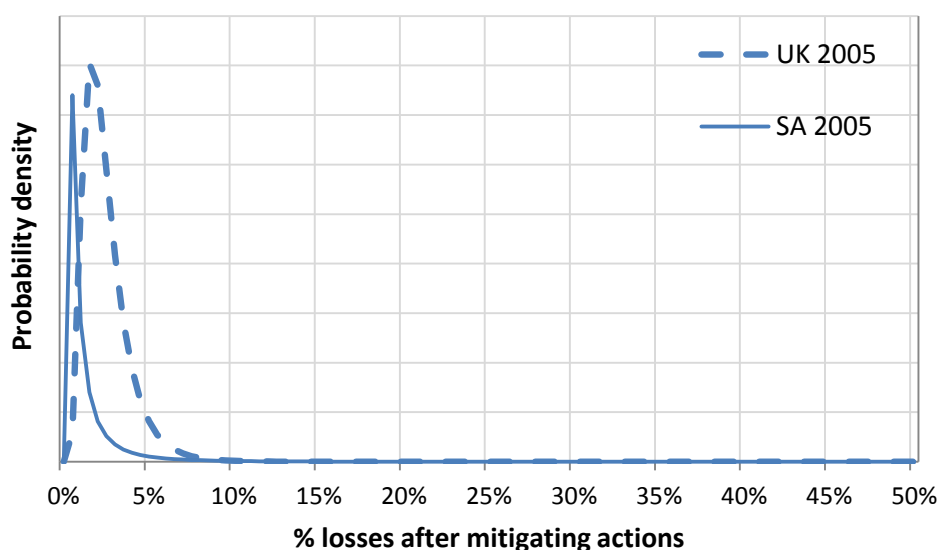
The line graphs in Figures 6.3 and 6.4 indicate how losses would have significantly increased at haircuts twice their original size for both periods. However, these figures do not indicate the effects of buffer restoration and an increased level of contagion on the liquidity buffer if haircuts were to be this high. Chapters 4 and 5, however, illustrate for both economies the effect of an increased  $f$  on the liquidity buffer after all three stages of the LST with the three-dimensional graphs. These graphs indicate how volatility in haircuts on balance sheet items effect all three stages of the LST, as they are interconnected.

The smaller increase in possible liquidity buffer losses from the non-crisis to crisis period in UK banks when compared to South African banks might possibly be due to the reduction of assets and liabilities with significant haircut exposures in balance sheets. In 2009, the effects of the financial crisis would have spread throughout global markets, affecting all participants differently. With the UK banks suffering quite severely from the crisis, their risk tolerance

most certainly would have decreased, causing banks to avoid balance items linked to risky severe haircuts.

### 6.3 Mitigating Actions

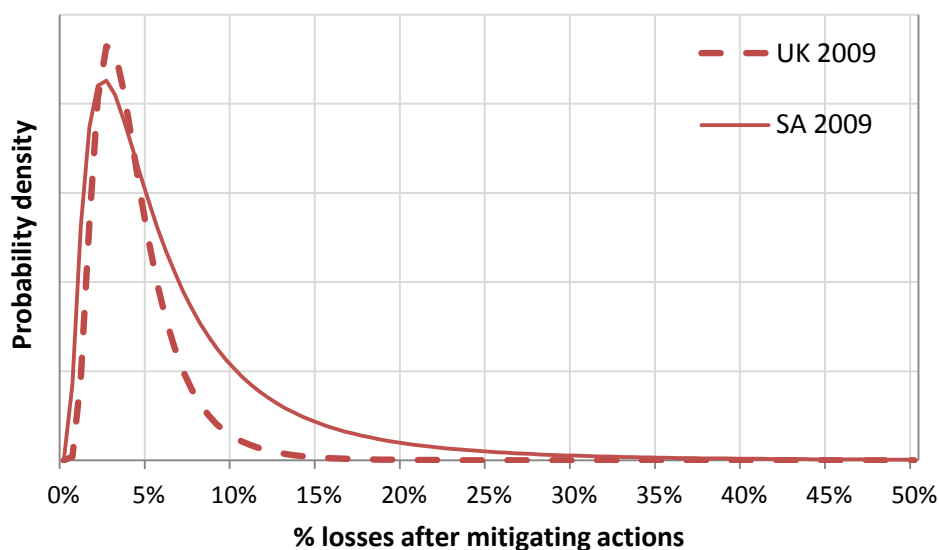
The effects of mitigating actions through buffer restoration are shown in Figure 6.5, which is also estimated at  $s = 2$  and with original haircuts. Due to similarity of buffer restoration and leverage targeting as mitigating actions in Chapters 4 and 5, only the comparison between buffer restoration for the two economies across the two periods is illustrated.



**Figure 6.5:** SA and UK 2005 buffer losses after buffer restoration as a mitigating action.

The line representing UK liquidity buffer losses for 2005 in Figure 6.5 is identical to that of Figure 6.1. This is due to no mitigating actions taking place in the estimations of simulations for UK banks in 2005. As discussed in Chapter 5 the significantly high reaction threshold of 80% set by banks is the cause of no mitigating actions taking place in the UK banking system for 2005. Compared to Figure 6.1, the solid line in Figure 6.5 does differ, however, for South African liquidity buffer losses after mitigating actions. Figure 6.5 illustrates the effectiveness of buffer restoration in the South African banking sector for the 2005 non-crisis period. Losses decrease from above 30% to less than 10% of the original liquidity buffer with losses higher than 5% becoming highly unlikely. The ability of buffer restoration is thus unobservable in the UK banking system and cannot be compared to mitigating actions in the South African banking system for the non-crisis period.

Figure 6.6 illustrates the effect of mitigating actions through buffer restoration on the initial shock of a liquidity event for both economies in the crisis period of 2009.



**Figure 6.6:** SA and UK 2009 buffer losses after buffer restoration as a mitigating action.

The line graph in Figure 6.6 illustrates that possible liquidity buffer losses after buffer restoration for the UK economy does differ from that in Figure 6.2. Although maximum losses remain approximately 15%, the mean of possible losses decreases from above 5% to roughly 3%. As discussed in Chapter 5, the lower reaction thresholds of banks in the 2009 crisis period causes mitigating actions to occur. Unfortunately, the ability of buffer restoration as a mitigating action for the UK banking system cannot be compared across the two periods. However, Figure 6.6 shows the inability of buffer restoration as a mitigating action in the UK banking system, with only the mean of possible losses decreasing slightly.

Buffer restoration in the South African banking system is more effective as a mitigating action in the crisis period as shown in Figure 6.6. Although losses after mitigating actions may still exceed 30%, losses before mitigating actions could potentially have reached 50% of the liquidity buffer. Within the South African economy, buffer restoration is not as effective in 2009 as in 2005, indicating the effect of the financial crisis on the ability of mitigating actions to restore the liquidity buffer. Mitigating actions reduce possible liquidity buffer losses by 25% in the non-crisis period, compared to 20% in the crisis period. Although the difference is only 5% across the two periods it would still have a significant effect on the liquidity buffers of banks, along with possible liquidity buffer losses remaining 30% in the crisis period after mitigating actions. Mitigating actions is effective in both the non-crisis and crisis peri-

ods, however, the effects of the liquidity crisis is clearly visible when comparing possible liquidity buffer losses after mitigating actions in the South African banking system.

Multiple reasons may have contributed to the slightly reduced ability of buffer restoration in the crisis period. For the three simulations where mitigating actions did occur, buffer restoration was least effective in the UK banking system in the crisis period of 2009. It is widely known and discussed in Chapter 3 how the UK economy severely suffered the effects of the financial crisis. The financial crisis would have influenced the UK financial system and markets within the system to such an extent that mitigating actions would have become extremely difficult as markets possibly froze up. Several factors can possibly effect mitigating actions within the UK banking system. In the midst of the crisis, the risk tolerance of market participants reduced, reducing the activity in markets to such an extent that markets froze up. This is due to market participants, including banks, possibly avoiding activities with risky balance sheet items or avoiding market exposure as much as possible. The reduced level of market activity reduces the opportunities to restore the liquidity buffer through mitigating actions. Furthermore, as the UK economy is one of the financial hubs of the world the risks of market participation may further increase as exposure to foreign markets increase as well. As discussed in Chapter 3, the level of interconnectedness was significantly high between UK banks before the onset of the crisis, which may have been difficult to reduce throughout the financial crisis. This may have contributed to the inability of mitigating actions, as several banks would have been similarly affected in terms of certain assets<sup>26</sup> losing value and leading to liquidity buffer losses. In the crisis period, participating with these assets in the market would have been difficult due to a possible significant supply, which may have led to several banks attempting similar activities in markets.

As mitigating actions occurred in both the crisis and non-crisis periods in the South African banking system a comparison of these actions ability is possible. The effectiveness of buffer restoration in 2005 illustrates the health of the South African financial system. It also illustrates how easy it would have been to participate in the markets, as losses could have been limited to a maximum of 5%. Several characteristics of the South African financial system could have contributed to the effective restoration of the liquidity buffer in both the crisis and non-crisis periods. Chapter 3 describes that South African banks make up a small per-

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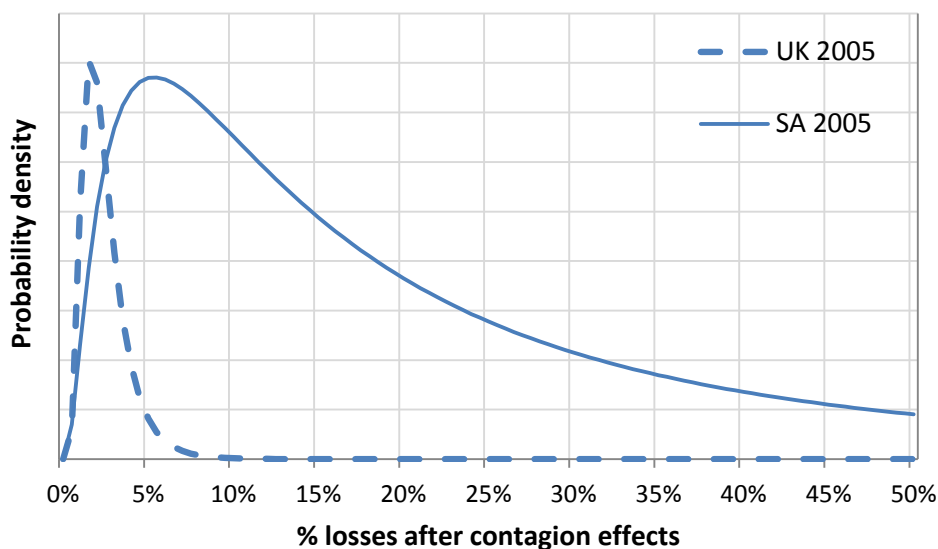
<sup>26</sup> Including the products brought on through securitisation that sparked the liquidity crisis as the mortgage bubble burst.

centage of the global banking system. This might be an advantage for South African banks as their losses would be small and easy recoverable in the global banking system. Furthermore, the South African NCA of 2005 was only assented to the President in March of 2006 and took effect on the 1<sup>st</sup> of June 2007. The restrictions of this act would thus not have prevented banks from restoring their liquidity buffers in the non-crisis period. This is known to be one of the characteristics of the South African financial system that protected the economy against the most severe effects of the liquidity crisis (Madubeko, 2010). However, although protecting South African banks against the effects of the liquidity crisis it may have affected the ability of mitigating actions throughout the crisis. Banks would not have been able to partake in activities with certain assets, as the NCA would have prevented them, possibly deeming these assets to risky.

Contrary to the UK banking system, there were much less toxic assets in the South African banking system with the balance sheets of South African banks not as severely affected in this period. The NCA would have contributed to the phasing out of risky assets within balance sheets after the act was implemented. The less risky assets in the balance sheets of banks reduce the average haircut sizes on balance sheet items. This might be one of the contributing factors as to why there was a smaller increase in average haircut sizes in the South African banking system compared to the UK banking system from the non-crisis to the crisis period.

### **6.3 Second Round Feedback Effects**

Liquidity buffer losses due to contagion effects arising from mitigating actions for both economies in the 2005 periods is shown in Figure 6.7 below. The lines were estimated using original haircuts and  $s = 2$ .



**Figure 6.7:** SA and UK 2005 buffer losses for buffer restoration model after contagion effects.

Figure 6.7 is the final figure illustrating possible liquidity buffer losses for the non-crisis period of 2005, however, similar to figures in Chapter 5 and Figures 6.1 and 6.5, the line graph representing the UK banking system is identical for all three stages of the LST. As mentioned the lack of mitigating actions in 2005 within the UK banking system produces the identical two-dimensional lines for all three stages of the LST throughout Chapters 5 and 6. All three stages of the LST representing 2005 illustrates only the effects of the initial shock caused by a liquidity event

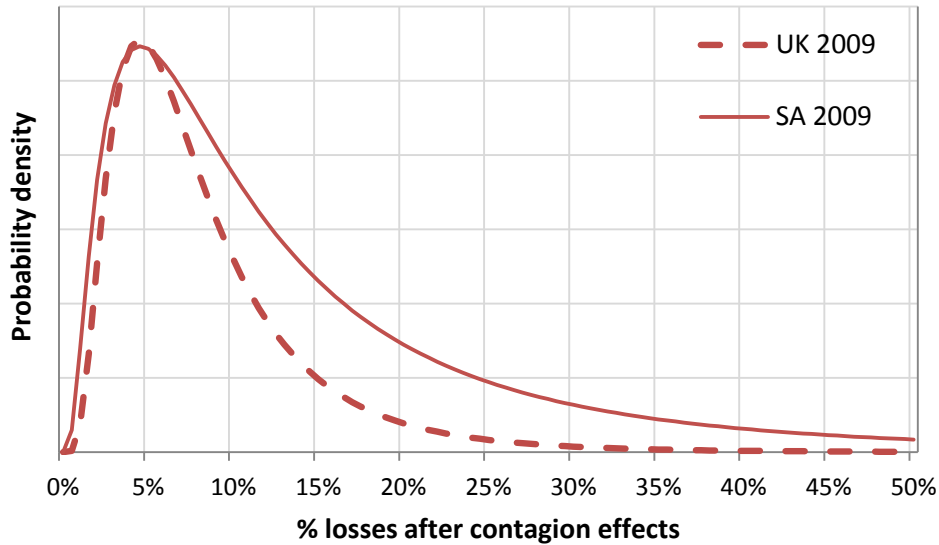
As discussed in Chapter 5, although the figures illustrating enhanced contagion do not differ from those representing the first two stages of the LST throughout the study, this does not necessarily indicate that UK banks were not exposed to contagion in the non-crisis period. The fact that there was a high level of interconnectedness between UK banks prior to the liquidity crisis indicates that contagion would have possibly affected banks in this period. However, the LST does not illustrate these effects, as contagion effects are dependent on the reactions by banks to the initial shocks of liquidity events. Although the LST does not illustrate contagion effects for UK banks in the non-crisis period, banks may have been exposed to these effects, albeit the exposure may still have been small. This is due to the high reaction thresholds possibly causing a lack of activities in markets.

The solid line in Figure 6.7 representing South African liquidity buffer losses after the effects of contagion indicates that even in the non-crisis period contagion would have had a significant effect on liquidity buffers. Mitigating actions illustrated in Figure 6.5 were highly effective



tive in restoring the liquidity buffer to a maximum of roughly 5%. However, contagion effects increase possible buffer losses to comfortably above 50% of the original liquidity buffer. A comparison of Figures 6.1 and 6.7 indicates that the effects of contagion would have been much more severe than the initial shock of the liquidity event. Contagion might thus have had the same effect on the UK banking system if mitigating actions had taken place in the non-crisis period. The significant effects of contagion in the South African banking system would have been caused by several characteristics of the South African financial system. Chapter 3's data section mentioned that South African banks form a small percentage of the global banking system. A liquidity crisis in a small banking system might have severe effects on banks within the system, as the effects arising from mitigating actions through contagion would have possibly been amplified in the small system. Figure 6.5 illustrates how effective mitigating actions would have been in the non-crisis period in the South African banking system. The effectiveness of mitigating actions would have possibly increased the contagion effects, as the simulated weights calculated for second round contagion effects are dependent on the amount of activities with balance sheet items. This is illustrated as  $RI_i^b$  in Equation 3.6. The significant amount of mitigating actions used to restore the liquidity buffer encourages the effects of contagion. Chapters 2 and 3 describe how mitigating actions may lead to asset fire sales, which would ultimately encourage contagion in the markets as supply of certain assets far outweighs the demand for them. This would theoretically reduce the value of these assets, affecting all banks with these assets in their balance sheets, hence the enhanced contagion effects.

Figure 6.8 illustrates the liquidity buffer losses arising from contagion effects in the third stage of the LST for the 2009 crisis period.



**Figure 6.8:** SA and UK 2009 buffer losses for buffer restoration model after contagion effects.

Figure 6.8 illustrates for both economies how contagion would significantly affect possible liquidity buffer losses in the crisis period. For the UK banking system liquidity buffer losses after mitigating actions double to approximately 30% after contagion takes effect. This is similar for the South African banking system with possible losses comfortably exceeding 50% of the original liquidity buffer. A comparison of Figures 6.2 and 6.6 shows that mitigating actions did not significantly reduce possible liquidity buffer losses in the UK economy in the crisis period. However, second round contagion effects still considerably increase the possible liquidity buffer losses in Figure 6.8, emphasizing the effects of the financial crisis in this period.

In the South African banking system mitigating actions would have been more effective in reducing possible liquidity buffer losses. However, similar to the non-crisis period of 2005, contagion effects would have considerably increased the possible liquidity buffer losses, ultimately to exceed 50%.

To conclude this chapter it is important to notice that even though there was a lack of mitigating actions in the UK banking system in the crisis period, second round contagion effects would have still caused significant possible liquidity buffer losses. The high level of interconnectedness between UK banks might contribute to the higher level of contagion in the crisis period, as well in the non-crisis period. Mitigating actions would have been more effective in the South African banking system for both periods, as possible losses are significantly reduced in Figures 6.5 and 6.6 respectively. However, Chapter 3 asserts that second round

contagion effects are dependent on the amount of activities conducted with balance sheet items through mitigating actions. The effectiveness of mitigating actions and too many of these actions would thus promote second round contagion effects in the LST.

Chapter 6 combined results of Chapters 4 and 5 attempting to compare and identify key differences between the two economies and periods throughout a liquidity shock or stress situation. Chapter 7 concludes the study with recommendations for further research regarding the LST and how it may be further developed and implemented. The chapter also provides a summary of the findings of this study.

## Chapter 7: Conclusions

The lack of liquidity risk management in terms measuring, monitoring and modelling prior to the financial crises experienced in this early part of the 21<sup>st</sup> century has most certainly been made clear by the effects arising from these crises. Post-crisis this has been severely criticised and liquidity risk has lately been receiving significantly more attention. Financial models concerning liquidity have shifted attention to financial systems as a whole and not only the failure of single institutions. This is of significant importance as the health of financial systems is essential to the health and growth of the global economy.

### 7.1 Literature Study

The data used in liquidity risk models are greatly important as they may serve as a core necessity for successful models. Chapter 2 addresses how traditional measures using certain balance sheet data suffer low reporting frequencies, as well as lags between market events and balance sheet changes. Work that is more recent focuses on data that rely on equity prices and CDS information. These data have a significantly higher reporting frequency and are more forward-looking.

Focussing on the funding liquidity of traders, Brunnermeier and Pederson (2009:2201) shows how the funding of traders can affect and is affected by market liquidity. This link between funding and market liquidity is of utmost importance as it clarifies how systemic risk can through the funding problems of one market participant, affect market liquidity and ultimately the funding liquidity of other market participants. This ability of systemic risk was experienced in the financial crisis of 2008 at significant costs when several financial institutions failed globally and forced central banks to intervene within their financial systems.

The evolution of the global financial system has caused institutions to become more funding liquidity thirsty as industries and financial systems expanded significantly. As markets developed the opportunities for institutions to expand and diversify, portfolios increased. These developments could help institutions to become more risk adverse or increase their risk tolerance depending on their needs and views of markets. The development of the global financial system possibly plays a significant part in the occurrences throughout the global economy in the last decade (2003-2013). The pre-crisis boom of the 2000's saw banks significantly investing in mortgage backed securities and CDO's, although they sold off their

mortgage books through securitisation. All these institutions exposed themselves to similar risks, ignoring and underestimating the risks involved.

The effects of the liquidity crisis saw liquidity risk being taken more seriously and the BCBS developed and suggested measurement and monitoring tools for liquidity crises. In their 2010 paper they developed the LCR and NSFR to manage liquidity for shorter and longer time horizons respectively. The LCR has been revised by the BCBS and changes to the measure regarding the characteristics of its variables were disclosed in January 2013. These measurement tools attempt to improve financial institutions resiliency to liquidity risk by serving separate but complimentary goals towards the management of liquidity risk. The BCBS further suggests monitoring tools to be implemented by banks in order to assist the process of correctly using and interpreting information regarding liquidity risk. A closer inspection of these monitoring tools reveals how they stem to a certain extent from the crisis experienced in the global economy. The BCBS sets out several guidelines for financial institutions to use when implementing these liquidity risk measurement and monitoring tools related to the characteristics instruments should have in order to qualify for these tools.

A review of previous financial models attempting to model liquidity risk indicates the lack of trying to assess the systemic risk of financial systems as a whole. A large amount of previous work focussed on the failure of single institutions. The lack of stress testing liquidity and systemic risks arising from market and funding liquidity also becomes noticeable when reviewing previous work on this field of risk management. Although essential to estimating a system's vulnerability to downward risks stress testing regarding market and funding liquidity has not been too common in the macro stress testing models of central banks. Previous work and several failing models of the crisis period mostly focus on point estimation and do not accommodate stress testing or scenario tests.

## **7.2 The LST Model**

The model in this study is similar to the LST developed by van den End (2010) and also used by van Vuuren (2011). The LST is an easily adaptable model that allows for the observation of several bank reactions under a variety of market conditions. The model furthermore allows for the assessment of second round effects stemming from reacting and non-reacting banks in a liquidity event. This whole process is modelled throughout the three stages of the

LST. The first stage of the LST test the initial shock of a liquidity event by looking at the hair-cuts and run-off rates assigned to balance sheet items. This is followed by the modelling of mitigating actions by banks within the financial system. The final stage of the LST simulates the second round feedback effects arising from the mitigating actions conducted by banks. These three stages of the LST are made possible by the Monte Carlo simulations that apply univariate shocks to risk factors, which can affect market and funding liquidity. The LST combines these factors to form multi-factor scenarios, which may affect a bank's liquidity position. This study provides a detailed description on how to model the LST in Microsoft Office Excel. This is important as it may assist future research and development with the LST.

The LST is highly flexible and allows for simulations with several different financial systems. The data in this study represent two very different economies and two significantly different periods. Data for a non-crisis and crisis period are gleaned from the balance sheets of banks for both an emerging market and a developed economy. As for the two time periods, 2005 represents one of the largest economic booms since post-war history. This period is used in the study as it represents the middle of the economic boom where no slowdown of markets was anticipated. This was the case to such an extent that even credit standards were relaxed in order further fuel the expansion of industries like housing markets and construction, amongst others. The calm and confidence in markets saw several industries grow significantly in the pre-crisis period. The crisis period to follow was a stark contrast to the non-crisis period. The 2009 period was chosen as it is assumed to have been in the midst of the crisis, with global statistics showing significantly low growth and negative percentages for some countries in this period. It has been labelled as the worst crisis since the great depression and the effects of this crisis are still present in the global financial system at this very moment. In the crisis markets collapsed, institutions failed and central banks were forced to intervene where possible. The total losses stemming from this crisis are still being debated, as there are so many views regarding the effects of the crisis.

### **7.3 Results**

The economies used in this study differ significantly from each other with one classified as an emerging economy and the other a developed economy. South Africa, representing the emerging market, has a considerably smaller banking system compared to that of the UK.

However, South Africa has a globally respected banking system, with the soundness of South African banks ranking well within the top ten of the world. Several other characteristics of the South African banking system make it suitable for comparison with the UK banking system. It is suggested that the NCA of 2005 prevented South African institutions from investing too heavily in risky securitised products prior to the crisis, thus shielding South African banks from the effects of the crisis. Furthermore, currency controls managed by SARB may also have contributed. The UK banking system representing the developed economy is known as a global hub for finance and is significantly larger than that of South Africa. In contrast to South Africa, the UK financial system did not have such stringent laws restricting banks from risky investments. The UK financial system does not apply currency controls like the SARB in South Africa. It is also widely recognised that the UK financial sector severely suffered the effects of the financial crisis. Prior to the crisis the UK housing market grew at significant rates and the UK was highly invested in subprime mortgage backed assets coming second only to the US. All of these characteristics differ significantly from the South African economy, making these two economies sufficient for comparison.

### 7.3.1 South Africa

The South African results simulated with the LST are illustrated in a combination of graphs in Chapter 4. The two-dimensional graphs simulated indicate possible liquidity buffer losses after each stage of the LST. The three-dimensional graphs estimated reveal the susceptibility of possible liquidity buffer losses of the financial system to increased market stress conditions and increased  $f$ s. The first stage simulations for the South African banking system reveal that possible losses incurred would severely affect the banking system. Not surprisingly, losses in the non-crisis period do not seem to be as severe when compared to the crisis period of 2009. However, possible liquidity buffer losses stemming from haircuts on balance sheet items still pose a significant threat to the banking system of South Africa, as possible losses can exceed 30% of a liquidity buffer even in a non-crisis period. Estimating the LST with haircuts twice their original size reveals and emphasises the significant role these haircuts and run-off rates can play in liquidity crisis, as possible losses exceed 50% for both the crisis and non-crisis periods.

The ability of mitigating actions through buffer restoration modelled in the second stage of the LST suggest that mitigating actions might have been highly effective in reducing possible

liquidity buffer losses for the non-crisis period in South Africa. These actions would not have been so effective in the crisis period, but would still have reduced possible losses significantly. Simulating mitigating actions in the form of leverage targeting reveals that there would have been an insignificant difference between the two methods, showing similar graphs for both methods. An analysis of the models reveals that the leverage ratios are not significantly changed, thus leverage targeting is not that different from buffer restoration as a mitigating action. The simulation of the contagious feedback effects arising from these mitigating actions is also very similar due to the two mitigating actions being very similar. However, simulations reveal contagious effects would be more severe in the non-crisis period compared to the crisis period. Several factors may contribute to this, including the fact that the implementation of the NCA of 2005 occurred after the non-crisis period. Furthermore, as contagion is dependent on the mitigating actions in the LST, the effectiveness of mitigating actions might have amplified the contagious effects in the non-crisis period.

As all three stages of the LST are interconnected, all three-dimensional graphs in this study can sufficiently illustrate the effect of increased market stress and haircuts on the entire LST. Estimating these graphs in Chapter 4 suggests that haircut increases in the first stage of the LST would significantly increase possible losses of the liquidity buffer once mitigating actions and contagion occurs. Increased levels of market stress also significantly effects the outcome of possible liquidity buffer losses. Again, three-dimensional graphs (Figures 4.7 to 4.14) estimated for both methods of mitigating actions do not differ significantly. However, the focus of the three-dimensional graphs is rather on the destructive ability of increased haircuts and market stress.

### **7.3.2 United Kingdom**

Similar to the South African results, the UK results representing the developed economy are illustrated in a combination of two- and three-dimensional graphs in Chapter 5. Again, two-dimensional graphs are estimated to illustrate the possible liquidity buffer losses after each stage of the LST. Estimating the first stage of the model reveals significant differences between the two periods for the UK banking system. Possible losses in the non-crisis period are not as severe compared to the crisis period, as haircuts and run-off rates on balance sheet items increased from the non-crisis to the crisis period. The estimates reveal that the initial shock of a liquidity crisis would be of such an extent that losses would be no less than



approximately 2% of the liquidity buffer, peaking at almost double compared to that of the non-crisis period. The first stage of the model is also re-estimated using haircuts twice their original size to illustrate the effect increased haircuts can have on possible liquidity buffer losses. Estimations show that losses are highly sensitive to haircut changes.

Throughout Chapters 5 and 6 the significantly high reaction thresholds set by UK banks in the non-crisis period obscure the ability to observe these actions. The two-dimensional graphs illustrating the non-crisis period of 2005 are all identical, as no mitigating actions or contagion arising from these actions occur. Mitigating actions in the form of buffer restoration for the crisis of 2009 do affect possible liquidity buffer losses, albeit slightly. The distribution shifts slightly to the left, reducing possible liquidity buffer losses marginally, but more importantly, illustrating how difficult it would have been to mitigate possible losses arising from the first stage of the LST. The two methods of mitigating actions differ slightly more in the crisis period for the UK banking sector when compared to the South African banking sector. Leverage targeting as a mitigating action reduces the mean of possible liquidity buffer slightly, but lengthens the tail, increasing possible liquidity buffer losses.

As for the third stage of the LST where contagious effects arising from mitigating actions are modelled, two-dimensional graphs representing the non-crisis period are again similar to those representing the other stages of the LST. For the crisis period, however, possible liquidity buffer losses increase for both models using buffer restoration and leverage targeting as a mitigating action. Contagion effects arising from the leverage targeting model, again has a longer tail, although the mean of possible losses is slightly less. Losses due to contagion effects in the UK financial system do not increase as significantly. However, very little mitigating actions would have taken place when assessing the two-dimensional graphs illustrated for the UK banking system. As discussed above concerning the South African results, third stage contagion effects are dependent on mitigating action in the second stage of the LST. The lack of or inability to conduct mitigating actions might have constrained possible liquidity buffer losses in the third stage of the LST.

Three-dimensional graphs for the UK banking system in the non-crisis period reveal how the high reaction threshold set by UK banks in this period restricts the LST from estimating the effects of the mitigating actions and contagion arising from these actions. For the crisis peri-

od, however, the three-dimensional graphs clearly illustrate the effects of increased market stress and haircuts. The graphs (Figure 5.9, 5.10, 5.13 and 5.14) suggest that, similar to results of the South African banking sector, increased haircuts would most severely affect possible liquidity buffer losses.

#### 7.4 Comparison

A comparison of the two economies showed that effects from the initial shock would have been more severe in the South African banking system in both the non-crisis and crisis times. As discussed, initial shock effects are mainly determined by the haircuts and run-off rates on balance sheet items. Thus, higher haircuts would understandably produce greater possible losses of the liquidity buffer in the first stage of the LST. Further research on the underlying factors determining haircuts on balance sheets items will explain why possible losses would have been greater in the South African banking system.

Unfortunately, a comparison of the second stage of the model for the two economies is only possible for the crisis period due to estimations of the second and third stages not being possible for the non-crisis period of the UK banking system. However, as shown mitigating actions in the form of buffer restoration would have been highly effective in restoring the liquidity buffer in the South African banking sector for the non-crisis period. Buffer restoration would have been more successful in the South African banking sector in the crisis period as well, significantly reducing possible liquidity buffer losses, compared to a marginal change in possible liquidity buffer losses for the UK banking system. However, the insignificant effect of mitigating actions in the UK banking system should not be seen as unwillingness to conduct these actions, rather it might be seen as a reflection of the state of the UK economy in this period.

Again, contagion effects across the two economies could not be compared for the non-crisis period. Contagion effects in the South African banking system for this period increased possible liquidity buffer losses to comfortably exceed 50% of the original liquidity buffer. This is concerning as it suggests that the South African banking system might have been severely at risk even in the non-crisis period. The crisis period sees a similar estimation for the South African banking system where contagion effects increase possible liquidity buffer losses to exceed 50%. The increase from the non-crisis period to the crisis does not seem too severe,

however, the risk is still very high as possible losses far exceed that of the UK banking system. The concern for the UK banking system is that although few mitigating actions occurred, losses increased significantly after contagion effects, possibly indicating that although institutions avoided market activities they would have still been severely affected by contagion.

The results of this study do not attempt to scrutinise or criticise the financial systems of the economies or their participants involved. It rather illustrates how exposed financial systems might have been to liquidity events even in a non-crisis period and what effect reactions by institutions might have had.

### **7.5 Future Research Possibilities**

Research with the LST is not completed, as there is still significant room for development of the model and its parameters. If possible, development of the LST in line with the BCBS suggestions and proposals may yield an even more valuable tool for central banks and individual banks to use. This developed model would allow banks to evaluate liquidity in the financial system simultaneously with the ratios (LCR and NSFR) proposed by the BCBS. The model, from a data point of view, may be further developed to employ higher frequency and more forward looking data.

Future research may also include the assessments of other economies, including the US, which is known to have been a highly interconnected banking system prior to the crisis of 2008 (Markose *et al.*, 2010). Linking sovereign Eurozone countries will also require the LST to be further developed in order to accompany all of these economies, but results may shed light on connected economies and how liquidity in the entire Eurozone is affected by liquidity shocks. Finally, results estimated in this study are only snapshots of the different periods in global finance for two different economies. Linking these periods would form a rolling liquidity measure that may illustrate interesting results on how liquidity in financial systems changes across different market conditions.

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## Appendix

Liquid asset haircut values and liability withdrawal/run-off rates of balance sheet items.

<b>ASSETS</b>		
<b>Bank notes/coins</b>	100	100
<b>Receivables from central banks</b>		
• Demand deposits	100	100
• Amounts receivable	100	100
• Receivables in respect of reverse repos	100	100
<b>Collection documents</b>		
• Available on demand	100	100
• Receivable	100	100
<b>Readily marketable debt instruments/FSA eligible assets</b>		
<i>Issued by public authorities and central banks</i>		
• FSA tier 1 and tier 2 eligible assets	92	92
• FSA tier 2 eligible assets, deposited	82	82
• FSA tier 2 eligible assets, not deposited	87	82
• Other readily marketable debt instruments	92	92
• Other readily marketable debt instruments, Zone B	65	65
<i>Issued by credit institutions</i>		
• FSA tier 1 eligible assets	88	88
• FSA tier 2 eligible assets, deposited	78	78
• Other qualifying debt instruments	87	88
• Other liquid debt instruments	68	68
<i>Issued by other institutions</i>		
• FSA tier 1 eligible assets	88	88
• FSA tier 2 eligible assets, deposited	79	80
• Other qualifying debt instruments	88	87
• Other liquid debt instruments	66	67
<b>Amounts receivable</b>		
<i>Branches and banking subsidiaries not included in the report</i>		
• Demand deposits	52	100
• Amounts receivable in respect of securities transactions	100	100
• Other amounts receivable	100	89
<i>Other credit institutions</i>		
• Demand deposits	46	100
• Amounts receivable in respect of securities transactions	100	100
• Other amounts receivable	100	88
<i>Public authorities</i>		
• Demand deposits	48	100
• Amounts receivable in respect of securities transactions	100	100
• Other amounts receivable	100	85
<i>Other professional money market players</i>		
• Demand deposits	45	100
• Amounts receivable in respect of securities transactions	100	100
• Other amounts receivable	100	85
<i>Other counterparties</i>		
• Demand deposits	0	0
• Amounts receivable in respect of securities transactions	100	88
• Other amounts receivable, including premature redemptions	45	37
<b>Receivables in respect of repo and reverse repo transactions</b>		
<i>Reverse repo transactions (other than with central banks)</i>		
• Receivables in respect of bonds	100	100
• Receivables in respect of shares	100	100
<i>Repo transactions (other than with central banks)</i>		
• Receivables in the form of shares	66	67
<i>Securities lending/borrowing transactions</i>		

• Securities stock on account of securities lending/borrowing transactions	100	100
• Securities receivable on account of securities lending/borrowing transactions	100	100
<b>Other securities and gold</b>		
• Other liquid shares	67	67
• Unmarketable shares	0	0
• Unmarketable bonds	100	100
<b>Gold</b>	88	89
<b>Official standby facilities</b>		
<i>Official standby facilities received</i>	100	100
<b>LIABILITIES</b>		
<b>Moneys borrowed from central banks</b>		
• Overdrafts (payable within one week)	100	100
• Other amounts owed	100	100
<b>Debt instruments issued by the bank itself</b>		
• Issued debt securities	100	100
• Subordinated liabilities	100	100
<b>Deposits and fixed term loans</b>		
<i>Branches and banking subsidiaries not included in the report</i>		
• Amounts owed in respect of securities transactions	100	100
• Deposits and other funding – fixed maturity	100	88
<i>Other credit institutions</i>		
• Amounts owed in respect of securities transactions	100	100
• Deposits and other funding – fixed maturity	100	82
<i>Other professional money market players</i>		
• Amounts owed in respect of securities transactions	100	100
• Deposits and other funding – fixed maturity – plus interest payable	100	87
<i>Other counterparties</i>		
• Amounts owed in respect of securities transactions	100	100
• Deposits and other funding – fixed maturity – plus interest payable	52	38
• Fixed-term savings deposits	22	22
<i>Repo transactions other than with central banks</i>		
• Amounts owed in respect of bonds	100	100
• Amounts owed in respect of shares	100	100
<i>Reverse repo transactions other than with central banks</i>		
• Amounts owed in the form of bonds	100	100
• Amounts owed in the form of shares	100	100
<i>Securities lending/borrowing transactions</i>		
• Negative securities stock on account of securities lending/borrowing transactions	100	100
• Securities to be delivered on account of securities lending/borrowing transactions	100	100
<b>Credit balances and other moneys borrowed with an indefinite effective term</b>		
<i>Branches and banking subsidiaries not included in the report</i>		
• Current account balances and other demand deposits	45	100
<i>Other credit institutions</i>		
• Balances on <i>vostro</i> accounts of banks	45	50
• Other demand deposits	45	100
<i>Other professional money market players</i>		
• Demand deposits	45	100
<i>Savings accounts</i>		
• Savings accounts without a fixed term	2.5	10
<i>Other</i>		
• Demand deposits and other liabilities	5	22
• Other amounts due and to be accounted for, including the balance of forward transactions and amounts due in respect of social and provident funds	5	22
<b>Official standby facilities</b>		
• Official standby facilities granted	100	100
<b>Liabilities in respect of derivatives</b>		
Known liabilities in respect of derivatives	89	89
Unknown liabilities in respect of derivatives	88	88

<b>Other contingent liabilities and irrevocable credit facilities</b>		
• Unused irrevocable credit facilities, including underwriting of issues	2.5	10
• Bills accepted	100	100
• Credit-substitute guarantees	2.5	10
• Non-credit-substitute guarantees	1.25	5
• Other off-balance-sheet liabilities	1.25	5