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A STOCHASTIC PROGRAMMING FRAMEWORK FOR FINANCIAL INTERMEDIARIES LIQUIDITY MANAGEMENT IN SOUTH AFRICA

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I hereby declare that this thesis is my own work and that all sources that I have used or quoted have been indicated and acknowledged by means of complete references.

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Dedication

I dedicate my thesis to my lovely wife Asher Mareva, twin sons Atipaishe Daryl and Kupakwashe Dwayne, father and late mother. I wish she was alive. My dedication go to my family and those who have passion for Finance, Financial Engineering and Operations Research.

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Abstract

We provide a thorough overview of the current liquidity problem, discussing what are considered to be state-of-the-art approaches in both industry and in academia, and clearly establish our motivation to depart from current liquidity management standards. We noted that during 2007 to 2009 financial crisis different countries throughout the whole world faced serious challenges that ranged from chronic liquidity problems, deep-rooted risk management deficiencies and poor corporate governance practices. The liquidity crisis, especially in the USA, was caused by low real interest rates stimulating an asset price bubble fuelled by new financial products that were not stress-tested and that failed in the downturn. Large depository institutions face the question of how to optimally utilise funds and manage liquidity problems. The existing liquidity models are not standardised, and do not take into consideration the complexity and the nature of the bank. As evidenced by the late 2000 financial crisis, it is evident that nowadays there is not a metric that seems to be completely adequate to prevent liquidity crises.

Our contribution is fourfold. First we investigate appropriate scenario generation methods and perform a rigorous investigation on how to generate multistage scenario trees. Further, we investigate the inclusion of all qualifying liquid asset instruments into the portfolio optimisation. We propose a novel multistage stochastic programming methodology for liquid asset control. Thus we define how to construct and solve stochastic programming models for liquidity needs-driven sub-portfolios. Our approach is based on scenario trees and makes no assumption on the distributions of random variables. Finally, we investigate the inclusion of liquidity needs-driven strategies which are core liquidity, cash cushion, operational cash and discretionary liquidity into the overall liquidity portfolio.

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Stochastic programming is a multi-faceted problem, and even the most focused treatment necessarily incorporates techniques from a wide range of disciplines. Through the development of fully coherent models and a sufficiently robust solution methodology, we provide a thorough overview of the problem at hand, discussing approaches in both industry and in academia. We introduce practical and theoretical advances that are to our best knowledge unexplored in the current literature, and document the usefulness of these avenues through a systematic series of increasingly complex applications and experiments. The data used is from the South African Reserve Bank (SARB) and International Monetary Fund (IMF) from January 1988 to May 2014. Most corporations such as commercial banks generally hold a unitary liquidity portfolio and not necessarily segmented to focus on bank specific cash and liquidity needs. Banks do have different cash needs at different times. Financial intermediaries to manage liquidity efficiently and effectively, segmenting the optimal liquid asset portfolio is the best management strategy. We construct different stochastic programming models based on decision making under risk and provision of powerful paradigm for decision making under uncertainty. The stochastic programming models with recourse are clear, easy to implement, very efficient and provide the optimal solution according to future possible set of scenarios. In defining and constructing stochastic programming models with recourse, sensitivity analysis should be carried out to increase the decision maker's understanding of the problem and to show the effect of different assumptions. Constructing an SP model with more stages provides better approximations compared to a single-period model. We found that the use of the proposed models through segmenting the unitary liquidity portfolio improves the management of liquidity compared to current techniques which are based on simulation, experience and trial-and-error. Thus high quality liquidity buffers insure the bank against any adverse liquidity risk. We found that liquidity buffer is

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best modelled as a stochastic process than deterministic. High net cash flow enhance effective and efficient liquidity management. Finally, excess reserves improve country monetary policy and broaden the scope of central bank lending programmes to address conditions in credit markets but on the other hand, may lead banks to loosen standards by weakening lending criteria in an attempt to increase returns.

In designing the sub-portfolios, liquidity determinants such as liquid asset returns, loan returns, payment flow, interest rates and gross income are uncertain, and to avoid liquidity problems caused by these variables, we need to include randomness on them. To effectively and efficiently manage liquidity, a bank may be required to follow certain key liquidity principles. The first is that the bank needs to understand and categorise its cash needs into at least four liquidity sub-portfolios as explained in the research. In this study, we strongly recommend that the banks' management should design the following sub-portfolios; liquidity buffer, cash cushion, operational cash and discretionary liquidity. The bank should clearly maintain the holdings of high quality liquid assets that can provide reliable reserves under all conditions. In addition, strict and relatively comprehensive disclosure practices in relation to liquidity risk management objectives should be submitted to central banks. Finally, there should be improvement on funding markets and public confidence by broadening the scope of bank guarantees to ensure future financial stability. We need to emphasise the point that bank liquidity is restricted by capital adequacy, required reserves, liability and deposit insurance defined by the central bank. Research can therefore be done on models that can be used to efficiently and accurately forecast future cash outflow taking into consideration the behavioural cash flows and estimating the discretionary and excess reserves. Further research can also be done on comparing the benefits of the calculated strategies in the stochastic program-

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ming context to more traditional methods.

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List of Publications

(1) Managing liquidity buffer through core liquidity portfolio - *Investment Management and Financial Innovations Journal*, Volume 12, Issue 1, 2015, pp. 69-76 - Part of Chapter 5.

(2) Liquidity of Commercial Banks and its Determinants: A South African Perspective - *Journal of Commerce*, Volume.7, No.1, January 2015. - Part of Chapter 2.

(3) A Cash Cushion Portfolio Management with Stochastic Programming Models - *33rd Conference of the Southern Africa Mathematical Sciences Association* - SAMSA2014, November 24 - 28, 2014, Victoria Falls, Zimbabwe (Presentation) - Part of Chapter 6

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Abbreviation

$EVPI$	Expected value of perfect information
EWS	Expected wait-and-see model's objective
$EVMU$	Expected value of modeling uncertainty
EV	Expected value of objective
EM	Expected value of policy based on mean outcome

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CHAPTER 1

1 INTRODUCTION

1.1 Background of the Study

"A banker is a fellow who lends you his umbrella when the sun is shining and wants it back the minute it begins to rain"(Pirbhai; 2007). Bankers can demand their money at any time and predicting the future is hard, next to impossible. Various important traditional perceptions regarding liquidity risk in business were explained by Vladimirou (2003), such beliefs as liquidity risk is "bad". But can uncertainty about the future liquidity be ignored? An unstable liquidity can distress the banking industry. Extreme events can occur, and their effects can be catastrophic to the banks. It is true that uncertainty is "bad", and thus risk and uncertainty should be managed, but we cannot totally eliminate them. Yes, even if the bank can eliminate liquidity risk, is this always a preferable strategy? At what cost? Stochastic programming is a powerful tool which can be used to support improved financial risk management (Vladimirou, 2003).

Large depository institutions face the problem of how to optimally allocate and generate high or low levels of liquidity. Varying levels of sensitivity of depositors is making it very difficult for financial institutions to predict volume response and as a measure, most financial intermediaries are focusing on deposit rate and the volume response. So because of this reason, a central bank in any country is responsible for monitoring and determining the investment portfolio for all the depository institutions in that country. Most institutions have a statutory investment portfolio which consists of liquid assets, which are interest rate sensitive, low credit risk, money market instruments and short-term deposits, which all pro-

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vide maximum liquidity. The institutions do have constrained optimization portfolios which can be privately optimal reserve holdings or regulator imposed reserve holdings. The state of liquidity is usually used in the assessment of short-term solvency. If an institution's liquidity levels are low and barely meet its obligations, then the management maybe lacking foresight and ability to plan. Thus this may lead to the overall conduct of the institution being questioned. The serious problems of potential insolvency or mismanagement need to be controlled. To address that the stochastic programming techniques may be used to monitor and optimise the liquid asset portfolio levels. The institution cannot hold those assets solely for making specific payments, but for the purpose of generating sales, and to protect it from the unexpected developments or take advantage of the opportunities available.

A number of financial intermediaries in different countries throughout the world faced serious challenges in the years 2007 to 2009 that ranged from chronic liquidity problems, deep-rooted risk management deficiencies and poor corporate governance practices. According to Subhanij (2010), a well known reason for the severity of financial crisis lies in the propagation of the original shock that is compounded by extreme bank funding fragility, forcing fire-sale across all markets. The funding of some banks has shifted towards a greater dependence on the capital market. In the USA, the loss of investor confidence in a wide range of structured securities markets led to risks flowing onto banks' balance sheets. The shock started in the credit market that was transmitted through a fall in asset market liquidity, which led to an increase in funding risk. This forced money markets to tighten internationally as banks built up liquidity to meet contingent claims. Banks in South East Asian Central Banks (SEACEN) countries remain resilient to the global financial crisis as a result of ample liquidity and traditional businesses

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pursued prior to the crisis.

After the introduction of Basel Accords 1, 2 and 3 to curtail liquidity risk, banks are still exposed to high liquidity risk. A number of failed banks have huge loan exposures and high concentration risks in their deposits. Insider loans are also a major concern for the banking sector. Current bank's portfolios are not performing and use only a limited amount of their resources to grant loans to businesses and customers. Most of the funds used to fund operations come from liabilities to third parties, usually deposits. There is less empirical evidence on how banks can manage liquidity risk successfully and current liquidity management models are readily seen to be inadequate when protecting against many associated risks and levels of liquid asset yields movements. In addition, the current models fail to take advantage of the banks and banks' clients into consideration, where things are not going their way; they can make an adjustment to secure client position. The current liquidity risk models undervalue extreme events affecting funding and market risk in global scenarios. In our research we highlight the most significant features to consider to implement an effective liquidity risk management and to achieve a more supervisory framework for financial intermediaries. We empirically analyse the way banks should manage their liquidity risk. We propose a risk-minimising strategy by subdividing the liquidity portfolio into four sub-portfolios which are core liquidity, cash cushion, operational cash and discretionary liquidity portfolios. We consider the use of simulation and two-and multi-stage stochastic programming in the optimisation of liquid asset portfolios. The multi-stage stochastic programming is a multi-faceted method that incorporates techniques from a wide range of disciplines. Through the development of fully coherent models and a sufficiently robust solution methodology, we provide a thorough overview of the current liquidity management strategies and discuss approaches in both industry

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and academia. We introduce practical and theoretical advances that are to our best knowledge unexplored in the current literature, and document the usefulness of these avenues through a systematic series of increasingly complex applications and experiments.

Against this backdrop, during the financial crisis, it has been seen that lack of cash flow analysis, lack of coordination of strategic planning, lack of tactical execution and poor liquidity management strategies at some institutions has led to liquidity problems. Some institutions were over-dependent on outdated static liquidity ratios which are not based on forward looking projected sources and uses of funds and thus were exposed to liquidity risk. In some cases, some financial institutions employed less than robust analysis of liquidity risk profiles and management practices and were not reflecting the true liquidity position. Thus the traditional methods of liquidity measurement and management are no longer valid due to ever-changing asset liquidity and financial innovation. The changes in asset liquidity include increased liquidity of loans through pledging and securitisation, loan products with increased optionality and increasing concentrations in particular loan types. The other sources of liquidity risk include increasing competition for retail deposits, changing liability liquidity due to more options and increased use of alternative funding. Thus liquidity risk may be a result of changing funding sources and uses. Some banks make use of structured funding products without understanding risks thereby exposing themselves to liquidity risk. The increasing concentration of one liquidity source has been regarded as one of the source of liquidity risk. Little or no asset liquidity in financial intermediary investment securities, and no or few risk limits for liquidity may trigger to liquidity risk. Finally, some financial intermediaries are holding all liquid collateral pledged to one source and this increases their exposure to liquidity risk.

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1.2 Framework of Financial Risk Management

Over the recent years, financial intermediaries became increasingly complex institutions, being exposed to an intertwined set of risks. Throughout the several types of services a bank offers such loans to businesses and individuals, and issuing money among other services, it is exposed to wide array of risks. Among these include the risk that loans will not be repaid, customers will suddenly withdraw tons of cash, the interest rate changes, and the securities market behaves poorly. Thus financial intermediaries are subjected to financial, business, and event risks. Risk refers to, according to Bessis (2002), Chaplin (2005), Christoffersen (2012), Horcher (2005), Jorion (2007), Saunders and Allen (2002), Schroeck (2002), the possibility that something unexpected or not planned for will happen. In financial issues, risk is seen as possibility that something that is not in conformity to expected outcomes might happen. Thus risks are uncertain future events that could influence the achievement of a bank's objectives. In the financial world, risk is often measured in terms of volatility of expected returns, but the bank should be protected against avoidable losses. Classification of risks is subjective and here we give an overview of risk classes. Risks can be classified as systematic or non-systematic according Bessis (2002), Jorion (2007), and Saunders and Allen (2002). Systematic risk relates to market factor and are not specific to any bank's asset or portfolio while non-systematic risk is specific risk that relates to factors that affect a specific bank portfolio that is not related to the market as a whole. A risk can be classified as continuous due to sources and or factors that can change continuously; or event risk which is a response due to the influence of a specific event. Banks (2004) classified risk as either financial risk or operational risks. Drigă (2012) defined financial risk as losses arising from financial variables while operational risks are losses arising from variables that have impact on the operations of a bank. Finally, risk can be downside risk or upside risk. Downside risk

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is a risk that actual events will turn out worse than expected, while upside risk is the opposite of downside risk, which is a risk that actual event will turn out better than expected. Therefore, risk can be defined as a measure of uncertainty associated with future payoff to an investment, measured over some time horizon and relative to a benchmark.

In our thesis we focus on financial risk that can be classified into two groups viz; pure and speculative risks. The pure risks have the prospect of downside that is they can result in loss for a bank; while speculative risks have the possibility of upside or downside. In other words, speculative risks can result in gain or loss. Pure risks include credit, liquidity and solvency risks; while speculative risks include interest rate, currency, price and market position risks. Hence financial risk according to Banks (2004) and Van Greuning and Bratanovic (2003) is a loss arising from the financial instruments of a bank and the bank might be certain or uncertain about the financial risks. The certainty financial risks are the expected losses the bank knows with reasonable certainty will occur, and prepare for them through holding reserves. On the hand, the uncertainty risks are the unexpected losses with unforeseen events, and banks rely on capital as a buffer to absorb them. Financial risks are managed through a process of ongoing identification, measurement and monitoring all types of risks the bank is exposed to.

Risk management in banking involves the process of evaluating risks faced by a bank and minimising the costs accordingly. As has been explained above, banks are exposed to a set of risks and we give an overview of each risk. Banks face credit risk that some borrowers or counter-parties will not honour their obligations when they fall due. Therefore, credit risk can be defined as the risk that a financial contract will not be honoured according to the original set of terms, and there

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will always be some risk of default. Credit risk has two important dimensions namely transaction risk and portfolio risk. Transaction risk refers to individual loans while portfolio risk is risk of the entire loan portfolio, that is the summation of all individual loan risks. Default occurs when counter-parties are not able or willing to pay interest, repay capital or fulfil their contractual obligations under loan agreements or other credit facilities. According to Dowd (1999), credit risk can be decomposed into arrival, timing, recovery and default dependency risks. Arrival risk can be defined as the risk connected to whether or not a default will happen in a given time-period, for an obligator. We also have the risk connected to the uncertainness of the exact time-point of the arrival risk and this is the timing risk. Sometimes the institution may be able to define the size of the actual loss if default occurs and this is called the recovery risk. Lastly, we have the default dependency risk, which is the most crucial risk factor that has to be considered in a credit portfolio framework. According to Avram *et al* (2009), and Dowd (1999) it can be defined as the risk that several obligators jointly defaults during some specific time period. To manage this risk, banks use a variety of options. As has been elaborated by Santomero (1997) and State Bank of Pakistan (2010), banks tend to stay well-diversified by using several different types of loans by setting guidelines on asset allocation. Banks also specialise in credit risk analysis to help identify the most creditworthy loan applicants before giving out a loan. The most difficult aspect of lending is problems of asymmetric information. Banks attempt to control these problems with careful screening and the use of collateralized loans.

The second type of risk is market risk and can be defined as the risk that the fair value or the future cash flows of a financial instrument will fluctuate because of changes in market prices. In other words, it is the adverse deviations of the marked-to-market value of the trading portfolio due to market movements. It can

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be referred to as systematic risk which is the risk of asset value change associated with systematic factors, see Jorion (2007) and Oldfield and Santomero (1997). Market risks arise from open positions in interest rate, currency, commodity and equity products, all of which are exposed to general and specific market movements and changes in the level of volatility of market rates or prices. Therefore market risks include interest rate risk, foreign exchange risk, commodity risk and equity risks and in some instances, the liquidity risk. According to Kupper (1999), Santomero (1997), and State Bank of Pakistan (2010), banks use different techniques to measure market risk such as; daily value-at-risk, stress tests and sensitivity analysis, annual net interest income at risk, economic value of equity and economic capital. The foreign exchange risk is related to market risk and has been defined by Avram *et al* (2009), Oldfield and Santomero (1997) as the risk that the value of financial liability or asset denominated in foreign currency will fluctuate due to changes in the exchange rate. The institution takes on exposures to the effects of fluctuations in the prevailing foreign currency exchange rates in the financial position and cash flows. Foreign exchange is managed through the use of daily value-at-risk and stress test. In addition, banks minimise the mismatches on foreign exchange assets and liabilities through daily monitoring of the net foreign exchange exposure by the treasury department.

Fluctuations in the prevailing levels of market interest rates affect banks' financial position and cash flows and the risk is referred to as interest rate risk. Interest rate risk is the exposure of a bank's financial condition to diverse movements in market interest rate and arises from mismatch in maturity between assets and liabilities. The source of interest rate risk are the repricing mismatches, unanticipated shifts of the yield curve and imperfect correlation in the adjustments of the rates earned and paid on different instruments. Excessive interest rate risk has a negative effect

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on the financial institution's future cash flows and can pose a significant threat to a bank's earnings by changing its net interest income and the level of other interest sensitive income and operating expenses. Changes in interest rates also affect the underlying value of the bank's assets, liabilities and off-balance sheet instruments because the present value of future cash flows change when interest rates change. In banks, the interest rate risk is managed by the bank's asset and liability management committee (ALCO) through matching maturity of assets and liabilities and use of derivatives such as interest rate swaps, see Avram *et al* (2009), Berkowitz and O'Brien (2001), Oldfield and Santomero (1997), and Santomero (1997). If interest rates rise, lenders suffer from the 'opportunity cost' of not lending at these higher interest rates. However, if interest rates decline, they suffer from not taking advantage of lower interest rates. Interest rate risk is linked to refinancing risk and reinvestment risk. Refinancing risk is the risk that mortgage borrower will not be able to refinance an existing mortgage at a future date under favourable terms. Reinvestment risk is the risk that future coupons from a bond will not be reinvested at the prevailing interest rate when the bond was initially purchased. Reinvestment risk is more likely when interest rates are declining.

A bank can be exposed to operational risk, and according to the Basel Committee on Banking Supervision (2010) and (2011), and Samad-Khan (2008), is the risk of direct or indirect loss resulting from operational failure that is inadequate or failed internal processes, people or systems or from external events. In other words, operational risk covers the entire range of failures in the operational part of transactions business, stopping the system from executing transactions as planned or adding unwanted consequences to executed transactions. In the absence of operational failure, the other risks are much less significant. Operational risk, according to Samad-Khan (2008) was associated with a low capital charge; there-

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fore, many banks viewed it as a low-priority issue. It can be distinguished in three types viz; operations risk, legal risk and system risk. Operational risk is much more than just operations risk. Operations risk is a subset of operational risk and is characterised by unconscious execution errors and processing failures. Operational risk, by contrast, is driven primarily by "non-normal" operational failures, particularly conscious violations of professional or moral standards and excessive risk taking. Operations risk includes possibility of process breakdown, and system shut down. Legal risk implies liabilities incurred through the execution of transactions or inability to fulfill a signed contract. On the other hand, system risk are problems that result from technology issues, system capability, connectivity or data integrity.

All banks face the risk that their customers will want to cash out their deposits. This is called liquidity risk and can be defined according to the Basel Committee on Banking Supervision (2010) and (2011), Burucs (2008), Cai and Thakor (2008), Dowd (1999), Ericsson and Renault (2006), Varroto (2011), Vento and La Ganga (2009), as the risk that operations cannot be funded and financial commitments cannot be met timeously. Banks face liquidity risk on both sides of their balance sheet. The threat of sudden deposit withdrawals is a liability side liquidity risk and the asset side of liquidity risk comes mostly from the off-balance sheet activities. Whenever a bank makes a loan commitment, it needs to make sure that the cash for the commit is ready and available for withdraw. If a bank cannot meet the funds requested by its customers, it runs the risk of bank failure. Because of this threat, bank managers are constantly trying to manage liquidity risk. The Basel 3 Accord has clearly defined the minimum liquidity risk management requirements and techniques that are supposed to be adopted by all financial institutions in the world. In our research, we trim down to focus on liquidity risk.

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1.3 Liquidity Risk Management

Liquidity is often used in loose and imprecise way because it covers many aspects. According to Buschmann and Heidorn (2011) the meaning of the term liquidity itself is not commonly agreed. Its complexity is based upon the fact that several different definitions of liquidity can be identified in literature and in practice. According to Alzahrain (2011), liquidity can be defined as the ability to buy or sell significant quantities of security quickly, anonymously and with little price impact. Subhanij (2010) defines liquidity as the ability to fund increases in assets and meet obligations as they come due. The two definitions seem to have a small difference, where Alzahrain's (2011) definition emphasises on price impact while Subhanij (2010) does not explicitly state that. Taking closer look at the existing and commonly used definitions, several dimensions will be recognised. Within the financial system three paradigms to liquidity management are distinguished by Subhanij (2010) and Valla *et al* (2006) which are the funding liquidity, market liquidity and central bank liquidity. According to Cecchetti and Disyatat (2010), it is useful at the outset to distinguish three types of liquidity. The first paradigm according to Ślazak (2012), is the neoclassical concept of banking activity, which implies that banks structurally create funding liquidity and leads to maturity transformation. Brunnermeier and Pedersen (2008), and Sarr and Lybeck (2002) point that funding liquidity is agent-specific, and was the original narrow definition of liquidity. The IMF defines funding liquidity as the ability of solvent institutions to make agreed upon payments in a timely fashion. On the other hand, the Basel Committee on Banking Supervision (2009) defines funding liquidity as the ability of banks to meet their liabilities, unwind or settle their positions as they come due. The bank is liquid if the difference between the cash inflow and cash outflow is positive.

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The market liquidity is the second paradigm, and is asset-specific. Funding liquidity drives market liquidity and, according to Sarr and Lybeck (2002) this refers to the broader definition of bank liquidity and in particular refers to the ability to trade an asset at short notice, at low cost and with little impact on its price. Brunnermeier and Pedersen (2008), Garcia (2009) and Subhanij (2010) state that there are three forms of defining market liquidity which are depth, tightness and resiliency. According to Subhanij (2010), the third paradigm is the central bank liquidity which can be defined as the ability of the central bank to supply liquidity to the financial system when needed. In other words, this is the flow of monetary base provided to the system by central banks via central bank operations either for routine or emergency liquidity facilities. Acute shortage of funding liquidity at specific institution occurs when a particular institution experiences an acute shortage of funding liquidity associated with solvency. However if the bank fails to secure official assistance, this may result in contagion and spill-over effects that could put the entire financial system at risk. Therefore the link among these liquidity types are quite dynamic, complex and strong. Funding and market liquidity relate to the mix of assets a bank holds and various funding sources, and systemic shortage of funding and market liquidity is potentially the most destructive. It involves tensions emanating from an evaporation of confidence and from coordination failures among market participants that lead to a breakdown of key financial markets.

Financial intermediaries may experience liquidity excess or inadequate liquidity. Liquidity excess is preferred by all depository institutions, but is it a good position? Lamoo and Casey (2005) argued that excess liquidity can lead to damaging financial instability by encouraging speculative activities such as momentum trading. Due to liquidity destabilisation property, liquidity needs should be con-

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strained or harnessed all the time. Liquidity can be "too much of a good thing". In this case depository institution management may be tempted to put a fair amount of that liquidity to good work by converting liquid assets into riskier ones, that is, less liquid assets that yield higher returns. Thus assets that are liquid today are not necessarily going to be liquid on the date that the institution management expects them to be liquid. On the other hand, low liquidity levels are a threat to institutions. Low liquidity levels lead to certain risks that have contagion effect.

Inadequate liquidity leads the bank to be exposed to liquidity risk. Neu and Vogt (2010) segmented liquidity risk into maturity mismatch risk, contingency liquidity risk and market liquidity risk. Maturity mismatch risk is concerned with losses that a bank may experience due to different asset and liability maturity transformation. The adverse movements in the capital markets change the availability of funds to the bank and leads to funding liquidity risk factor. The contingency liquidity risk can be referred to as funding liquidity risk and according to Burucs (2008) and Vento and La Ganga (2009), it is the risk that the bank will not be able to efficiently meet both determined and stochastic current and future cash flow. According to Drehmann and Nikolaou (2009), funding liquidity risk focuses on an entity and is concerned with the liability side of the balance sheet. Bhaduri *et al* (2007) stressed that market liquidity risk results if assets in or close to default typically become very illiquid. Financial institutions are especially sensitive to funding liquidity risk since debt maturity transformation is one of their key business areas. There are three forms of funding liquidity risk according to Garcia (2009), which are margin funding risk, rollover risk and redemption risk. Margin funding risk is risk that margins will change while rollover risk is risk that it will be more costly or impossible to roll over short-term borrowing. Redemption risk is risk that demand depositors of banks withdraw funds. The market liquidity risk

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factor lies outside the control of a bank and is the risk that the market liquidity worsens when the bank needs to unwind a position. When a bank experiences market liquidity risk, the bank asset prices may fall significantly such that the bank cannot easily offset or eliminate a position without significantly affecting the market price due to inadequate market depth or market disruption. According to the Basel Committee on Banking Supervision (2009), liquidity risk can emanate from incorrect judgment and complacency by the institution.

For the bank to be able to manage liquidity, literature that is widely available explains different sources of bank liquidity. The sources of liquidity, according to Ali (2004) can be nicely grouped into internal and external sources. Internal causes of liquidity risk emanate within the institution itself and on the other hand, external causes emanate from outside the institution. According to Ali (2012), liquidity risk emanates from the nature of banking business, from the macro factors that are exogenous to the bank, from financing and operational policies that are internal to the banking firm. Alzahrain (2011) identified the sources of liquidity problems that a bank may put under check. The first line of defence is managing liquidity risk in the management of cash flow and this one has been addressed in the research. The bank may invest in short-term investments, medium-term asset, and residential mortgages portfolios that have regular payments of principal and interest, and borrowing from the interbank market. Banks like any other business, cannot make enough money without taking on risk. Risk-taking, may lead to bank failure, but is an essential part of the type of the business. This makes banking business to become more and more portfolio information driven and thus we are concerned with managing liquid asset portfolio (Espenilla *et al*, 2005).

Liquidity risk, according to Cornett *et al* (2011) depends not only on the final

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maturity of assets and liabilities, but more on exposure to undrawn loan commitments, maturity of each intermediate cash flow, the unexpected withdrawal of funds from wholesale deposits and the loss of other sources of short-term financing. A notable example is the failure of Lehman Brothers due to liquidity risk from loan commitments. The bank's judgment on cash out-flows can turn out to be incorrect, and may result in liquidity risk. Due to unforeseen circumstances, the institution's cost of capital may change (Ali, 2004). This unanticipated change in cost of capital can happen due to causes general to the banking sector or bank specific such as credit squeeze or a rating downgrade. Different measures have been developed focusing on the sources of liquidity risk; that is on the liability side, asset side and off balance sheet operations. Moore (2009) pointed out that one can measure liquidity by stock approach or flow approach.

The stock approach focuses on the asset and liability sides of the balance sheet employing ratios to identify liquidity trends. The common liquidity metrics a bank can use are liquidity ratios and see Chagwiza *et al* (2015a), Moore (2009) and Vodová (2011), (2013a) and (2013b) provided balance-sheet related five liquidity ratios. On the other hand, the flow approach focuses on comparing the variability in bank's inflows and outflows to determine the amount of reserves that are needed during a period. To strengthen the liquidity framework, Basel 3 introduced two minimum international standards for funding liquidity. Delfiner *et al* (2006) studies the sound practices for management of liquidity risk at financial institutions and reviews best practices suggested by the Basel Committee on Banking Supervision. The standards are; the liquidity coverage ratio and the net stable funding ratio. The liquidity coverage ratio intends to promote short-term resilience to potential liquidity disruptions over a 30-day horizon. In this case, the standard ensures that the banks have sufficient unencumbered high quality liquid

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assets to offset the net cash outflows it could encounter under an acute short-term stress scenario. Thus the high quality liquid asset portfolio should contain assets that are unencumbered and liquid in the markets during stress times and eligible to redeem at central bank, according to Basel Committee on Banking Supervision (2010) and (2011). According to Jorion (2009), good risk management does not guarantee that big losses will not occur, and points that big losses can occur due to business decisions and bad luck.

The concept of liquidity is complex and banks should manage different strategies. We need to point that both lenders and borrowers are exposed to liquidity risk. To lenders, it means the potential inability to sell a loan or raise money against it to the full value of the expected repayments. From the borrower's perspective, it is the fear of not receiving financing or getting a loan with terms that elevates the cost of financing. Banking activities create liquidity risk, intimately linked with the other types of risk directly or indirectly influencing the liquidity position of a bank. Liquidity risk is inter-related to other financial risks as shown in Figure 1.1, see Chagwiza *et al* (2015a), Jorion (2007), Vento and La Ganga (2009), Vodová, (2011) and (2013b). Liquidity risk does not exist in isolation but is linked to other risks. It can compound other risks and, also can be a consequential risk implying that it follows the increase in other risks. Liquidity risk is therefore occasionally also referred to as derived risk or in some cases secondary risk. Empirical literature which stresses the relationship between liquidity risk and other risks is innumerable. These interactions have gained in significance and involve that banks more progressively need to adapt their systems to control liquidity risks in a manner consistent with their business models. According to Vento and La Ganga (2009), the relationships with other risks tend to create uncertainty with regard to liquidity risk measurement and to the management of a bank's liq-

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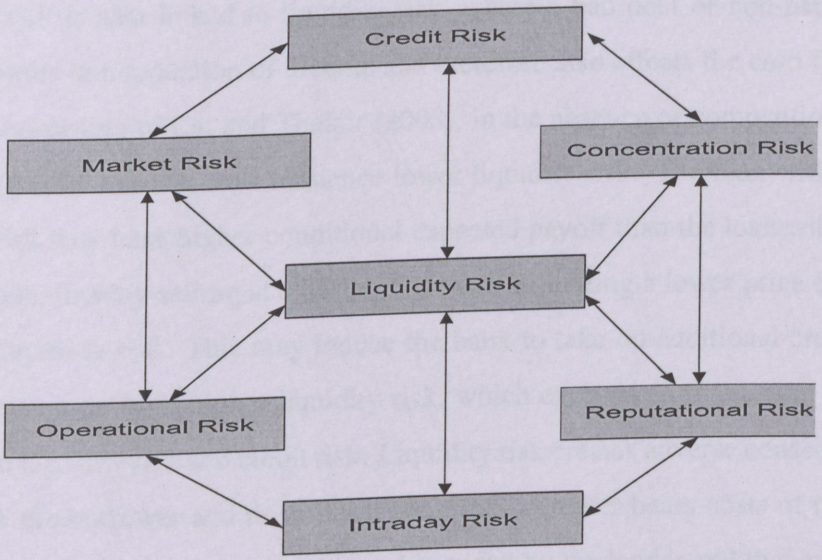
Figure 1.1: Liquidity Risk Interaction with Other Risks



uidity gap profile. Operational risk permeates all aspects of the risk universe, that is to say it overlaps with and exacerbates all other types of risks, such as market, credit, liquidity and underwriting risk. Interest rate risk and liquidity risk come together where maturities of assets and liabilities are mismatched. The interest rate risk that results from mismatches of maturities or the dates for interest rate adjustments may appear as either market or refinancing risk. In this context, liquidity risk refers to the diverging timing of the asset and liability cash flows. Generally under normal circumstances; banks may try to increase the net interest income by sacrificing a degree of liquidity, thereby exposing itself to liquidity risk. The link between foreign exchange risk and liquidity risk is that the profile of foreign exchange assets and liabilities should be monitored to capture the cash flow consequences of the foreign exchange positions, so that short-term liquidity needs and surpluses are identified for each currency. An increase in foreign exchange liabilities increases bank's liability and is exposed to liquidity risk. However, an

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increase in foreign exchange assets increases bank's liquidity.

Credit risk is also linked to liquidity risk, where a bad debt or non-performing loan results in a reduction of income and therefore also affects the cash flow of a bank. According to Cai and Thakor (2008), in the absence of competition, loans with higher credit risk may influence lower liquidity risk. The loan with higher credit risk may have higher conditional expected payoff than the loan with lower credit risk, thereby selling at a higher price and exhibiting a lower price discount due to liquidity risk. This may induce the bank to take on additional credit risk in order to cope with higher liquidity risk, which exposes an interesting tension between liquidity risk and credit risk. Liquidity risk creates adverse consequences for both the borrower and the lender. Here the borrower bears costs of illiquidity, including a higher return premium demanded by the lender and that may lead to possible liquidation, while the lender may face an inability to sell the loan at its full value and may even take on higher credit risk in order to cope with its liquidity need. Reputational risk is linked to liquidity risk, and is the risk of a loss of business due to negative public opinion (Santomero, 1997). Reputational risk can result in an increase in the general cost of funds, increase in the amount of secured transactions required to make deals, reduced credit lines and bank runs.

In managing liquidity, according to the Basel Committee on Banking Supervision (2010) and (2011), the banking institutions should at least consider the following three stress scenarios; the idiosyncratic, market-wide and combination of both stresses. Idiosyncratic stress scenarios are institutionalised and include the institution's financial position, market position, and credit rating. The key underlying assumption here is that the banks' liabilities cannot be replaced or rolled over and the banks must pay the liabilities at the time of maturity. Then the market-

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wide stress scenarios are market-specific and mainly focus on assets volatility. The market specific scenarios solely focus on asset price movements in collaboration with the interest rate shifts. Market-wide stress scenarios are very important because cash flows can be deterministic or stochastic. The market wide-stress scenario, also known as general market crisis scenarios, affect liquidity of all banks in one or more markets. The key underlying assumption that banks have to make is that, differences in funding access among banks or classes of financial institutions would widen, benefiting some and harming others. With these scenarios, banks can prevent the impact of temporary constraints and manage their net funding requirements. Basel 3 Accord encourages all financial intermediaries to carry regular stress tests on its liquid assets. There are three main approaches that can be used for stress testing which are; the historical scenarios, the statistical approach and the judgmental based approach. The statistical approach uses historical data to infer probability distribution of risk factors to estimate potential shocks. The characteristics of each scenario depend on period of time whether short or long; and severity, whether mild or severe.

1.4 Statement of the Problems

(a) The first problem deals with the investigation of appropriate scenario generation methods. In stochastic programming, uncertainty is represented in the form of a scenario tree. The scenario tree is a discrete approximation of the joint distribution of these random variables. A realisation of all uncertain parameters gives rise to a distinct scenario with an associated probability. In dynamic problems that involve decisions at multiple successive periods, the evolution in the outcomes of the random variables can be visualized as a path through the scenario tree, and the nodes as future decision points. The scenarios constitute the primary inputs to the stochastic programming mod-

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els. We specifically investigate an appropriate scenario generation method to generate joint scenarios for dynamic deposit, and dynamic withdrawals and net deterministic deposit drains since they are the early indicators of liquidity problems. The generated scenarios are integrated to find the overall scenarios for net deposit drains. The problem is presented in Chapter 3.

(b) The second problem deals with the investigation the inclusion of all qualifying liquid assets instruments into the portfolio optimisations. Banks face costs associated with controlling liquid assets below and above the defined liquidity level threshold. The central bank in each country requires depository institutions to keep a minimum amount in liquid assets. For this purpose institutions keep a statutory portfolio, also called a liquid asset portfolio presented in Chapter 4.

(c) The third problem looks at the construction of stochastic programming models and the determination of solutions to the problems. To manage this portfolio in an 'optimal' way the institution will need to re-balance or change the composition of the portfolio on a regular basis. Changing the portfolio composition will depend on certain factors such as expert views on risk factors movements, legislation and regulations. The aim of this work is to construct scenario trees and stochastic programs to determine the portfolio positions. The optimisation methods will also be used to investigate the viability of incorporating certain institutional considerations and determine a solution that is optimal according to specific objectives under different economic scenarios. Financial intermediaries are exposed to dynamic information structure and thus we need to determine dynamic contingency decisions under changing economic factors. The sub-portfolios are dedicated in Chapters 5 to 8. Chapter 5 is dedicated to core liquidity portfolio, the cash cushion portfolio

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presented in Chapter 6, Chapter 7 dedicated to operational cash portfolio and Chapter 8 presents the discretionary liquidity portfolio.

(d) The fourth problem is investigating the inclusion of liquidity needs-driven strategies (core liquidity, cash cushion, operational cash and discretionary liquidity) into the overall liquidity portfolio. The aim of this part is to investigate whether segmenting the overall liquidity portfolio can add value in effectively and efficiently managing liquid asset portfolio. Chapter 9 is dedicated to an integrated liquidity risk management model.

1.5 Methodologies

Financial intermediaries are constantly confronted with the situation of making decisions at any time that involve a degree of uncertainty such as cash flow planning, and portfolio investment hence we employ scenarios that will also capture those uncertainties. Financial decisions require forward looking parameter distributions which account for uncertainty in the economy and financial markets. Thus in this thesis different models are developed for generation of scenarios for effective management of liquidity. However, the scenarios do not follow any statistical distribution or stochastic process. Stochastic programmes with recourse are roped-in because of their suitability. The input parameters are assumed to be discrete. The stochastic programmes have been chosen because of their flexibility and capability to handle multiple assets as compared to linear programmes. In addition, the stochastic programmes are more versatile than linear programming because they are dynamic and can accommodate institutional, market specific and regulatory constraints. Multiple risk factors are considered simultaneously to make concrete and informed decisions. The data to calibrate different models was obtained from the International Monetary Fund, the Johannesburg Stock Ex-

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change and the South African Reserve Bank. Stochastic programming explicitly recognises uncertainty by using random variables for some aspects of the problem and defining the sequence of decisions in relation to the realisation of the random variables. Given the sequence of probable decisions, an objective function is defined that reflects a rational criterion for evaluating the decisions made before the realisation of randomness and may be feasible after the realisation. Therefore, stochastic programming provides information necessary for decision making subject to risk.

1.6 Scientific Contributions

Most financial institutions are finding it difficult to meet the central banks operational requirements relating to statutory reserve and optimal liquid assets portfolio. The financial intermediaries do not know what optimal liquid assets portfolio they should have in order to enhance the overall level of investor confidence and their creditworthiness. Stochastic programming models provide a powerful tool for decision making under uncertainty. The financial institutions' investment objective is to preserve capital and liquidity. They desire to preserve capital and invest in low-risk portfolios, and as a result highly liquid securities are very common amongst financial institutions. Hence achieving higher portfolio returns is always a secondary objective for a financial intermediary. The main focus will be on optimally managing a liquid asset portfolio of a financial intermediary to reduce the risk of bank failure. In this thesis we want to look at:

(a) Constructing new scenario generation models for net deterministic deposit drain, dynamic deposit and dynamic withdrawals. Further, we propose a liquid asset return model;

(b) Constructing stochastic programming models for four liquid asset sub-portfolios

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which are core liquidity, cash cushion, operational cash and discretionary liquidity. To the best of our knowledge, these have not been researched and presented in any internationally recognised journals;

(c) Developing an integrated simulation and optimization framework for liquid asset portfolio management;

(d) Implemention of portfolio stochastic programming models that jointly select the appropriate investments and determine the levels of each sub-portfolio;

(e) Adaptating a suitable method for constructing sub-portfolios in scenario-based stochastic programming setting;

(f) Developing an integrated liquidity risk management framework where risks and trading strategies of liquid assets to interest rate are used to minimise the risks. The need for an integrated risk management approach is as a result of contagion effect of liquidity risk (market, funding, interest rate and credit risks); and

(g) Assessing alternative risk minimisation strategies in terms of their effectiveness to control liquidity risk while enabling the attainment of goals.

1.7 Thesis Structure

The whole thesis is organised as follows; Chapter 2 mainly focuses on the relevant literature to enhance the research. The related literature includes general theory on setting up of stochastic programming and current scenario generation models and their applications in the financial field. In addition, we give a brief explanation on traditional scenario generation approaches and testing methods for reliability. The first statement of the problem is addressed in Chapter 3. The chapter focuses on scenario generation methods for net deterministic deposit drain and net dynamic

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deposit drain of the overall bank liquidity analysis. We determine net dynamic deposit drain as the difference between dynamic deposits and dynamic withdrawals. To determine net deterministic deposit drain scenario generation model, we employ statistical approaches. To compute the net dynamic deposit drain scenarios, we assumed that the dynamic deposit follows a stochastic differential equation with jump diffusion while the dynamic withdrawals follow GARCH (1, 1) process. Chapter 4 addresses the second statement of the problem. A comprehensive liquid asset control model is presented in this chapter. The chapter explains the overall liquid asset portfolio management and not defining the sub-portfolios as presented in Chapter 9. Most current stochastic programming models to control liquid assets mainly focus on minimising general costs and maximising available liquid assets. In our multi-stage stochastic programming model with recourse, we introduce and specifically define two sources of costs which are inadequate liquidity costs and excess liquidity costs. In our model, we define the required threshold the bank should maintain to minimise overall liquidity management costs. A scenario generation model is constructed and assets are classified according to maturity as short-term liquid assets, medium-term liquid assets and long-term liquid assets. The statistical characteristics of historical data and testing the effectiveness of scenario generation are presented in this chapter.

Explorations of four liquid asset sub-portfolios are presented in Chapters 5, 6, 7 and 8 and address the third problem. Chapter 5 explores the core liquidity portfolio management stochastic programming model with recourse, its composition and uses. We present the first of its kind core liquidity management stochastic programming model and a scenario generation model. The aim of the model is to maximise liquidity buffer. In Chapter 6, we present a unique scenario generation model and a cash cushion management stochastic programming model. From the

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literature widely available, none has ever developed a cash cushion management stochastic programming model with recourse that maximise interest rate spread. An operational cash management stochastic programming model is presented in Chapter 7. We construct a new cash flow scenario tree and a stochastic programming model. The model is used to maximise after-tax net cash flow. The discretionary liquidity management stochastic programming model with recourse is presented in Chapter 8. The main purpose of the portfolio is to maximise excess reserve. We define a bank reserve scenario tree model, the associated risk and a stochastic programming model with recourse. The total bank reserve is partitioned into three categories and incorporated into the model. Chapter 9 integrates all the four constructed sub-portfolios of liquidity management presented in Chapters 5, 6, 7 and 8. The main aim of Chapter 9 is to maximise the optimal weighted difference between threshold and shortfall. Here we construct a two-stage model to address the fourth problem. The integrated model is the first of its kind, and has not been published to my best knowledge anywhere in the internationally recognised journals. Finally, Chapter 10 summarises and concludes the research. We present areas of further research that can be pursued to improve the models constructed.

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CHAPTER 2

2 A FRAMEWORK FOR STOCHASTIC PROGRAMMING FOR LIQUIDITY MANAGEMENT

2.1 Introduction

Liquidity risk is one of the least understood and most underestimated risks that financial markets participants are exposed to. A rapidly growing body of literature has focused on credit risk but liquidity remains a relatively unexplored topic. Liquidity risk is said to be the assassin of banks. Liquidity risk is typically considered a type of market risk. The increase in the complexity of financial instruments, the securitisation, the growth of collateral usage and the trend to raise funds has led to the complexity of liquidity management in financial institutions. According to Daykin and Hey (1991), traditional accounting models are of limited value in assessing the financial strength of a bank partly because of difficulties of measurement and valuation and partly because they do not help the user to understand the inherent uncertainty. Accounts are concerned with what has happened in the past and while it is important for the bank management to view the bank as a dynamic entity. The challenge related to liquidity management is that it represents the final cap-stone in a pyramid of inter-connected aspects of bank management. Whatever the financial intermediary does will eventually lead to cash inflow and cash outflow and impact on bank liquidity position. Therefore, liquidity management should be forward looking. However the question is how to derive reasonable estimates of future cash flow and manage liquidity. This overview of the literature is by no means exhaustive. It has primarily focused on works from which we draw

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for the developments presented in this thesis. The research reviewed comes from two distinct, yet related, scientific disciplines; namely, finance and operations research. The financial literature presented in this chapter covers bank risks and their relation to liquidity risk, and liquidity management for financial intermediaries.

On the hand, the operations research literature covered especially stochastic programming models and related scenario generation methods, particularly, their applications to financial problems. Financial engineering, financial modelling and risk management have been particularly fertile application domains for scenario generation and stochastic programming as is evident by the rapidly growing body of literature on stochastic programming in finance. The thesis spans across the two scientific disciplines. The thesis aims to bring stochastic programming models with recourse to bear on the challenging and practically important problem of bank liquidity management. Through bringing financial and operations research disciplines, this work develops a framework to analyse, in a unified manner, the decisions involved in managing liquid assets. An extensive numerical test is done through the use of historical data. The stochastic programming models constructed are not merely tools for experimental analysis, but can also be effective decision support tools in practical settings in banks.

2.2 Liquidity Management Models

A number of liquidity related management models were investigated by Fielitz and Loeffler (1979), Pokatta and Schmaltz (2010), Raubenheimer and Kruger (2010) and Sigauke *et al* (2012). A linear programme to manage commercial banks liquidity was investigated by Fielitz and Loeffler (1979). We introduce randomness in the Fielitz and Loeffler (1979)model. Pokatta and Schmaltz (2010)

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researched on whether liquidity management should be centralised on one branch in several regional ones or decentralised to each branch. Pokatta and Schmaltz (2010) proposed that banks should establish liquidity centres and is deemed cheaper and provides just-in-time liquidity. A mixed integer linear programming is used to minimise the expected cost if a bank-run occurs whether the bank has a liquidity centre or not. In the model, Pokatta and Schmaltz (2010) identified low production cost as a centralisation factor, and decentralisation factors as high transportation costs, production costs and penalty costs, time zones and demand volatility. However the weakness of their model is that it does not capture liquidity constraint from monetary policy that is, the minimum reserves. In addition, Pokatta and Schmaltz (2010) model does not capture minimum liquidity buffers. Voloshyn and Voloshyn (2013) developed an integrated risk management in market-maker commercial banks on the basis of cash flow at risk. The effects of liquidity management on profitability in Jordanian commercial banks during the time period 2005 to 2012 was investigated by Alshatti (2015). Jasiené *et al* (2012) builds a liquidity risk management model for commercial banks and appraises the importance of risk to the economy, and the model influence to solve commercial banks liquidity problems. Topcu *et al* (2008) determine the investment policy that maximises the net profit over the investment horizon, taking into account associated risk and cost of transaction.

A model that divides liquidity management into internal and external factors was developed by Mohamad *et al* (2013). Mohamad *et al* (2013) examined the relationship between liquidity management, bank specifications, economic supervision and cycle. In their model, Mohamad *et al* (2013) found that control variables do not directly produce the results but can provide vital information in predicting the economic cycle route. Malik and Rafique (2013) examines the

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bank specific and macro-economic determinants of commercial banks liquidity in Pakistan using an econometric model. Pagratis and Topaloglou (2012) proposed a framework for analysing bank liquidity risk using stochastic dominance method. In their model, Pagratis and Topaloglou (2012) considered liquidity risk diversification across asset and liability classes of US commercial banks and provide evidence of banks' heterogeneous response to the Lehman crises. Pagratis and Topaloglou (2012) found that small banks relied extensively on securities to meet liquidity needs while large banks appeared unconstrained by loan illiquidity and able to scale down loan exposures more aggressively than smaller banks. Deeper 2007 to 2009 financial crisis problems, according to Neu and Vogt (2010), stemmed from bank's reliance on purely quantitative approaches which lack business judgement. Some bank liquidity risk management models fail due to known unknowns, according to Jorion (2009), which include the regulatory changes and structural changes in capital markets. In our thesis, the quantitative model constructed should be analysed and implemented in collaboration with qualitative data.

A multi-stage SP model that minimises downside risk of liquid asset portfolio is presented by Raubenheimer and Kruger (2010). In their model, the aim is to manage a liquid asset portfolio in an optimal way, such that it keeps the minimum required liquid assets to comply with regulations. Raubenheimer and Kruger (2010) assumed that any shortfall will be funded by the bank, and funds provided by the bank for the purpose of the liquid asset requirement will carry some sort of liability payment equal to inter-divisional borrowing rate. They use simulated future yield curves to construct a scenario tree. They found that the model performed as expected with average shortfall decreasing and cost increasing as the weight increases, and average shortfall and cost increasing as liquid asset requirement

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growth rates increase. The current liquidity models are not standardised, which take into consideration the complexity and the nature of the bank. As evidenced by late 2000s financial crisis, it is evident that, nowadays there is not a metric that seems to be completely adequate to prevent liquidity crises. We propose a similar framework to Raubenheimer and Kruger (2010) in Chapter 4 but we differ in that in their model, the objective function is minimising downside risk. In our case, we minimise both costs below the lower threshold and costs above the upper threshold. Sigauke *et al* (2012) presented an SP framework for liquidity management of commercial banks in Zimbabwe and the model minimises costs associated with funding assets, funding earning assets, average interest expenses on deposits and average cost of borrowed funds. Recent SP model on bank liquidity management by Sigauke *et al* (2012) performed as expected but focused primarily on a unitary liquidity portfolio. Common liquidity management models deal with the maximising of the financial well being of an institution. We differ with Sigauke *et al* (2012) model in that instead of formulating a single liquid asset portfolio, we construct four sub-portfolios and are presented in Chapters 5, 6, 7 and 8. The Asian Development Bank (2013) proposed five liquidity sub-portfolios but no SP model has been constructed. To the best of our knowledge, this is the first thesis that applies SP models in managing the four liquidity sub-portfolios.

2.3 Stochastic Programming Framework

The theory and framework of stochastic programming models have been explained and applied to different fields, for detailed explanation see Birge and Louveaux (1997), Haneveld and Van Der Vlerk (2009), Kall and Wallace (2003), and Shapiro *et al* (2009). SP is an optimisation model that involves uncertainty. According to Di Domenica *et al* (2003), SP can be classified as distribution, recourse or chance-constrained models. Figure 2.1 represents the taxonomy of SP models.

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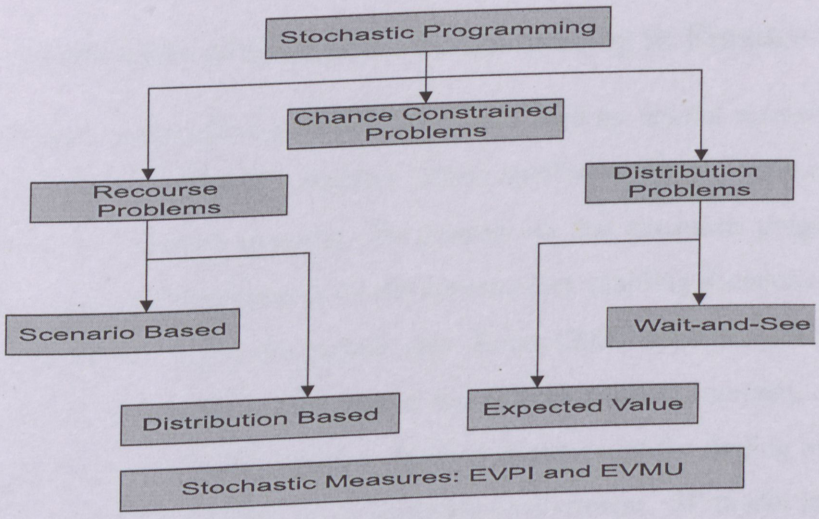
Distribution models are optimisation models which provide the distribution of the

Figure 2.1: Taxonomy of SP Models



objective function value for different realisations of the random parameters. The model is constructed by replacing the random parameters with their expected values. On the other hand the problem can be a wait-and-see type where we assume that the decision maker is somehow able to wait until the uncertainty is resolved before implementing the decisions. For a distribution model to work efficiently, it relies on perfect information about the future. Recourse problems are here-and-now models which can be distribution-based or scenario-based models. In the thesis we use the recourse model since the distribution has got drawbacks. Distribution problems produce solutions that are far from optimal since the decision makers do not know how to choose between expected value and best scenario from a set of scenarios. The choice of SP method has been made considering different factors. The first reason is that simple deterministic analysis may suggest a solution that is far from being optimal therefore, in our case, leading banks to hold exactly expected liquidity demand and not considering high liquidity de-

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mand in the near future. The second reason is that an optimal solution may be obtained when all scenarios are taken into account but may not be optimal for any scenario-by-scenario analysis.

2.4 Application of Stochastic Programming in Finance

The stochastic programming models have been used by several researchers and decision makers in finance. Ibrahim (2008) applied stochastic optimisation to solve portfolio selection problem. He pointed out that stochastic programming provides a generic framework to model uncertainties enabling decisions that will in general perform well in the general case. Koivu (2004) applied stochastic programming in asset-liability management of a Finnish pension company. Stochastic programming has been used as a decision support tool for finding long-term dynamic investment decision in an uncertain environment. SP model is used in bond portfolio management by Bertacchi *et al* (2006). According to Frauendorfer and Schürle (2008), SP models allow for the reflection of uncertainty in future liquid asset prices and yields, by generating scenarios of their possible future outcomes. In general, SP models yield a large scale program since it has to include a high number of scenarios to reflect the entire universe of possible future outcomes of risk factors and cash flows. Wang *et al* (2002) used a multistage SP in portfolio management. The model is more effective in assisting the property-liability insurer to determine the optimal composition of insurance and investment portfolio.

Stochastic programming has been used in the management of investment portfolios for large financial institutions such as pension funds, insurance companies and hedge funds. Ziemba (2003) pointed out that multi-stage stochastic programming models provide superior alternatives to other approaches such as mean-variance, simulation, control theory and continuous time finance; and take into account

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investor preferences in a simple, understandable way. According to Topalaglou (2004), the stochastic programming models have been used for risk management of international portfolios. He developed, implemented and validated a scenario-based stochastic programming model for actively managing international investment portfolios of stock and bond indices in multiple currencies. Further, Topalaglou (2004) incorporated forward contracts and European options in stochastic programming models as risk hedging instruments. Li-Young *et al* (2003) used stochastic programming for asset allocation, fixed-income securities management and asset-liability management. Zenios (1993) explained how stochastic programming can be incorporated and useful in financial decision making. Bertacchi *et al* (2006) discussed ways of selecting horizon and stages in financial applications and their impact on optimal first-stage solutions. In validating the solutions from stochastic programming, Dupačová (1999) defined methods for analysing the results obtained and the approaches are based on asymptotic and robust statistics. Now we explain the two-stage and multi-stage stochastic programming models.

2.4.1 Two-Stage Stochastic Programme with Recourse

According to Laurent (2006) and Li-Young *et al* (2003), a recourse model is a dynamic model that involves a combination of anticipative models and adaptive models. An anticipative model is a static model in which a decision does not depend on future decisions. At the decision making time we have to take into account all possible future realisations since the opportunity to adapt our decisions later on is not considered at the initial decision making stage. However as information related to uncertainty becomes partially available, before decision making, we implement an adaptive model in a learning environment. Thus the recourse model combines the two models in a common mathematical framework, which seeks a policy that does not only anticipate future observations but also

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takes into account temporarily available information to make recourse decision. In a financial framework, banks are always dealing with recourse models. In our research, we formulate two-stage SP models of the same nature as presented below for Chapters 5, 6, 7 and 8. In liquidity management, banks consider future liquid assets yield and liquidity demand as well as possibility of re-balancing the liquid asset portfolio positions as liquid asset yield changes. The general two-stage model can be represented as:

$$\max \; f(x) + \mathbb{E}_{\omega}[Q(x,\omega)] \tag{2.1}$$

$$\text{s.t} \quad Ax \leq b \tag{2.2}$$

$$x \geq 0 \tag{2.3}$$

where x is an n_1-dimensional vector of decision variables and represents the first-stage anticipative decision, which is made before the vector of random variables ω is observed, $\mathbb{E}_{\omega}$ is the mathematical expectation with respect to ω, and $f(x) : \mathbb{R}^{n_1} \rightarrow \mathbb{R}$ is a function and does not depend on ω. Corresponding to x are the first-stage constraint matrix and vector A and b of size m_1 x n_1 and m_1 x 1, respectively. In the second-stage a number of random events $\omega \in \Omega$ may realise. $Q(x,\omega)$ is the optimal value, for any given Ω of the following non-linear program:

$$\max \; q(y,\omega) \tag{2.4}$$

$$\text{s.t} \quad Wy(\omega) \leq h(\omega) - T(\omega)x \tag{2.5}$$

$$y \geq 0 \tag{2.6}$$

where $q(y,\omega)$ is the second-stage function, and $y \in \mathbb{R}^{n_2}$ is the second-stage recourse decision, which depends on the decision x taken in the first-stage, and on the random variable ω. The dependence of y on ω is of a completely different

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nature than the dependence of q or other parameters on ω. For a given realisation of ω, the second-stage problem constraint matrix $T(\omega)$ and vector $h(\omega)$ become known, where $T(\omega)$ has size m_2 x n_1 and $h(\omega)$, m_2 x 1 is less than the vector $Wy(\omega)$. To find the optimal first-stage decision x, we consider a set of all possible future realizations Ω and the best second-stage decision y given all possible information we could have at stage two. To find the first-stage optimal solution, we work recursively, first solving the second-stage problem over the whole set of possible random variable realisations and the set of all possible first-stage optimal solution which maximises the overall optimisation problem.

2.4.2 Multi-Stage Stochastic Programme with Recourse

Most practical decision problems involve a sequence of decisions that react to outcomes that evolve over time (Laurent, 2006 and Li-Young *et al*, 2003). However increase of the number of stages in the optimisation raises the difficulty of finding an optimal solution consequently. We adopt the properties of a multi-stage SP model in Chapter 4 to control liquid asset portfolio. Therefore, the general form of the multi-stage stochastic programming models with recourse is the following;

$$\max \; c_0x_0+\mathbb{E}_{\omega_1}[\max[c_1(\omega_1)x_1(\omega_1)+..+\mathbb{E}_{\omega_T|\omega_{T-1}}[\max[c_T(\omega_T)x_T(\omega_T)]..)]] \quad (2.7)$$

$$\text{s.t} \quad A_0x_0 \leq b_0 \quad (2.8)$$

$$B_1(\omega_1)x_0 + A_1(\omega_1)x_1(\omega_1) \leq b_1(\omega_1) \quad (2.9)$$

$$B_2(\omega_2)x_1(\omega_1) + A_2(\omega_2)x_2(\omega_2) \leq b_2(\omega_2) \quad (2.10)$$

.....

$$B_T(\omega_T)x_{T-1}(\omega_{T-1}) + A_T(\omega_T)x_T(\omega_T) \leq b_T(\omega_T) \quad (2.11)$$

$$x_0 \geq 0, \;\; x_1(\omega_1) \geq 0, \;\; ....., \;\; x_T(\omega_T) \geq 0 \quad (2.12)$$

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where the first-stage decisions are represented by vector x_1 and the stage t decisions are represented by vector $x_t(\omega_t)$, for $t = 2, ..., T$. In the objective function $\mathbb{E}_{\omega_T|\omega_{T-1}}$ denotes the conditional expectation of the state ω_t of the data process $\omega = (\omega_2, ..., \omega_T)$ at time t given the history of the process up to time $t-1$.

2.5 Scenario Generation Approaches

Scenario generation for stochastic programming has been the subject of extensive research. There are different approaches that can be used to generate scenario trees for stochastic programming problems, and for a detailed list of scenario generation methods see; Erlwein *et al* (2012), Kaut and Wallace (2007), Mitra (2008), Mitra *et al* (2009) and Vázsonyi (2006). Currently there exist four main categories for scenario generation which are sampling, simulation, statistical property matching and hybrid methods. According to Kouwenberg (1998), a stochastic process's simulation results in a "path by path" production of the scenario tree. The number of paths can be reduced by a process referred to as scenario reduction. Simulation method involves the process of inputting random numbers into an econometric model such as error correction model and vector auto-regressive model (Gülpinar *et al*, 2004). Different econometric models are used to generate a number of scenarios in this research. A dynamic deposit scenario generation model is presented in Chapter 3. In Chapter 4, we formulate a model to generate liquidity level changes scenarios. Liquid asset yield scenario generation model is presented in Chapter 5.

In scenario generation by sampling, we sample values from a distribution and the sampled value represents the scenario's value. Sampling methods include random sampling, importance sampling, bootstrap sampling, internal sampling, conditional sampling, Markov Chain Monte Carlo sampling and stratified sampling.

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The bootstrap method is able to estimate measures of variability and bias. It can be employed in nonparametric or in parametric mode. In generating scenarios using statistical properties, the general principle behind applying statistical methods is to determine the values of particular statistical properties of some given data. Approaches that can be used in statistical methods are mainly statistical moment (mean, variance, skewness and kurtosis), principal component analysis, copula presented by Sutiene and Pranevicius (2007), regression and its variant. Hoyland *et al* (2003) describe a scenario generation method using moment matching. However, there are other scenario generation methods such as mixing scenario generation of sampling with moments matching, artificial neural networks, clustering, hidden Markov models and scenario reduction. Hidden Markov models based scenario generation was used by Erlwein *et al* (2012) and Gregory *et al* (2008). Erlwein *et al* (2012) used hidden Markov models based scenario generation for an investment problem. Roman *et al* (2008) consider modelling financial time series by Hidden Markov models which are regime switching type models and used their model as a scenario generator to describe the future realisations of asset prices. In this research, we employ statistical methods in Chapter 3 to find the scenarios for net deterministic drains and dynamic withdrawals. Scenarios used in Chapters 8 and 9 were generated using statistical methods.

Betran-Royo *et al* (2010) present three approaches to deal with multistage linear programming under uncertainty. The first approach is to use the event-wood type of a scenario tree. In the event-wood approach, the uncertainty representation is simplified by using a sequence of two-stage trees, which amounts to a linear number of nodes. The uncertainty associated with each future stage is represented by means of one of these small trees. The second is the expected value approach where a single scenario is used. Finally, Betran-Royo *et al* (2010) presented a

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general scenario tree using scenarios recognised through simulation.

An advantage of a scenario tree is that it makes it possible to obtain a visual portrayal of sequential decisions. Only the important decisions and events are included provided the chance event outcomes are not continuous. A scenario tree has decision nodes, chance event nodes and terminating nodes. Each decision node represents a possible decision alternative at that decision point. The chance event nodes represent a possible event at that chance event point. Here the decision maker has no control over these chance events. Finally, the terminating nodes represent the end of the sequence of decisions and chance events.

2.5.1 Single-Stage Scenario Formulation

The formulation of a single-stage scenario was presented by Hoyland and Wallace (2001). To formulate a single-stage scenario tree, we suppose that s_0 denotes the state of the system at time $t = 0$. The state becomes the initial condition for the simulations and the initial decision variable is $x(s_0)$ being directly influenced by the outcome process. We set Ω to be the set of all scenarios we generate, so $N = |\Omega|$ is the number of scenarios and $\omega \in \Omega$ represents a single drawn from Ω. The realisation of each scenario is observed at the end of the horizon and for any ω, a value-function $V(x(s_0), \omega)$ can be assigned to the terminal node of the path. Therefore, the outcomes can be used to estimate the true expected value of the value-function by averaging over all the scenarios:

$$\mathbb{E}[V(x(s_0))] = \frac{1}{N} \sum_{\omega \in \Omega} V(x(s_0), \omega) \tag{2.13}$$

where the value of $x^*(s_0)$ that maximises this expectation is the optimal decision.

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2.5.2 Two-Stage Scenario Formulation

A two-stage scenario tree is a modification of a single-stage scenario tree. Given the initial state s_0 we define an initial decision $x_1(s_0)$ and produce $N_1 = |\Omega_1|$ independent scenarios $\omega_1 \in \Omega_1$ that span the time of first-stage. However, we cannot evaluate the value-function because we have not yet arrived at the horizon. Then the second-stage decisions $x_2(s_0, \omega)$ are influenced by the outcome of the first-stage scenarios and this information is used to make our decisions for the second-stage. Each node of the tree represents a distinct scenario. The two-stage scenario tree were adopted in Chapters 5, 6, 7, 8 and 9.

2.5.3 Multi-Stage Scenario Formulation

The multi-stage scenarios according to Hoyland and Wallace (2001), is an extension of a two-stage scenario model. In particular, the multi-stage scenario tree is very important in recourse models in that it gives us the freedom to make changes to our strategy based upon our initial decisions and the observed realisation of any random variables that evolve during the lifetime of the problem. We need to note that a multi-stage can be viewed as a nested n-stage problem, allowing some creative methods of iteratively solving them. In our research, the multi-stage scenario tree is used in generating net deterministic deposit drains and net dynamic deposit drains in Chapter 3.

2.6 Summary

Different liquidity management model formulations are explained along with their assumption and findings are presented. In making decisions, the bank should consider the following stress scenarios: the idiosyncratic, market-wide and combination of both stresses. The literature on stochastic programming and scenario

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generation is explained. Different classes of stochastic programming programming are explained and, formulation of two classes of stochastic programming, which are the two-stage and multi-stage models. Stochastic programmes have been used in the fields of financial modelling, financial engineering and risk management. Four scenario generation methods which are sampling, simulation, statistical property matching and hybrid methods are explained. Other scenario generation methods which were proposed and used by researchers are hidden Markov models, artificial neural networks, clustering and scenario reduction. Finally, we explain how a scenario tree can be constructed starting from single-stage, then two-stage and finally a multi-stage scenario tree. Three types of scenario trees are defined which are the wood-event, expected scenario and the general scenario trees. In our thesis, different classes of stochastic programming models with recourse and different classes of scenario trees are used. The next chapter looks at scenario generation methods for net deterministic deposit drains, dynamic withdrawals and dynamic deposits. Reduction method is used to formulate final net deposit drains.

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CHAPTER 3

3 SCENARIO GENERATION MODELS

3.1 Introduction

To manage banks' liquidity risk effectively, we need to know the evolution of banks' net deposit drain. The ability to observe and understand the ways in which net deposit drains change over time is vital to our approach. The clients' consumption and savings rates are random. Thus the varying levels of sensitivity of depositors make it very difficult to predict volume response. This exposes banks to stochastic liquidity demand. The management of net deposit drain can be very difficult because of the underlying variables driving the exposures which can be dynamic and unpredictable. Therefore the banks' net deposit drain can be divided into deterministic and stochastic.

Banks need to be well acquainted with the timing of individual's withdrawals and deposits. Often, depositors tend to withdraw their money at short notice whereas borrowers prefer to repay their loans over a longer term. Depository institutions need to be able to predict the distribution of net deposit drains. In addition, the institutions need to understand the nature of the depositor base. In this chapter we will formally introduce the notion of net deposit drains and define related concepts that are essential if we are to begin to understand how banks manage liquidity. We look at how we should go about dividing our horizon into stages, and investigate the options we have when deciding on the best path for us to use to arrange and store paths through the various scenarios. We begin by applying simulations to introduce deposits and withdrawals associated with each scenario. Finally, we use this information to establish a tree of net dynamic deposit and net

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dynamic deposit drain. However, to establish this, we must establish a method of simulating dynamic deposits and dynamic withdrawals. We need to pay attention to dependencies between various stochastic parameters, for generation of possible realizations.

3.2 Scenario Generation Models

Scenario generation involves identification of plausible events that are possible future events. In other words, scenario generation is identification of plausible evolution of net deposit drains over time and assignment of probabilities to these events. According to Parpas and Rustern (2006), we need to specify the possible states of the world and the probability of each state. Thus the scenarios are represented by a scenario tree with probabilities assigned to each node of the tree. The scenario trees must represent the underlying distribution and the model should produce good decisions. In building scenario trees some statistical properties should be retained such as expectations and correlations between the stochastic variables. Hochreiter and Flug (2002), Kaut and Wallace (2007), Kouwenberg (1998), Mitra (2008), Sutiene and Pranevicius (2007) pointed out that estimating scenario trees for stochastic programming problems consists of choosing the topological structure of the tree process. The trees must represent the underlying distribution such that the model produces good decisions. As has been echoed by Casey and Sen (2009), the scenario tree needs to account for low probability, high cost events.

We construct scenario generation models in order to compute the net deposit. The net deposit drain, according to Saunders and Cornett (2009), and Rose and Hudgings (2008), is the amount by which the cash withdrawals exceed the cash inflows over a given period of time. Net deposit drain can be positive implying

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that withdrawals are greater than inflows. Likewise, net deposit drain can be negative, implying that inflows are greater than withdrawals. Therefore in our scenario generation models we choose to use continuous time in a discrete model.

3.2.1 Net Deterministic Deposit Drain Scenario Generation Models

The net deterministic deposit drains are known with certainty by the bank at time t. Here the depository institution knows the periodic withdrawals and deposits at time t. We assume that the institution is in a position to predict the net deterministic deposit and withdrawal through observations and data analysis. Due to net deposit drains' deterministic property, the institution is in a position to schedule the cash flows in time t. In our model, the deterministic deposits include credit card payments, loan payments, and company salaries and wages, tuition fees, and coupon payments and deposits. On the other hand, deterministic withdrawals include maturing repurchase agreements, notified fixed deposits, government and company employees' salaries. Now we estimate the net deterministic deposit drain model by the following equation.

$$\vartheta_t = \varphi_t^d - \eta_t^d, \qquad \forall t \in T \tag{3.1}$$

where ϑ_t is the net deterministic deposit drain, φ_t^d is the deterministic withdrawals, η_t^d is the deterministic deposits. We assume that the net deterministic deposit drain ϑ_t follows a normal distribution, that is

$$\vartheta_t \sim N(\overline{\vartheta_t}, \delta_{\vartheta_t}^2), \qquad \forall t \in T \tag{3.2}$$

We assume the time series $\{\vartheta_t\}$ is based on independent Gaussian white noise $\{\epsilon_t\}$ with variance 1 and mean 0, so that

$$\vartheta_t = \overline{\vartheta_t} + \delta_{\vartheta_t}\epsilon_t, \qquad \forall t \in T \tag{3.3}$$

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Therefore, the conditional net deterministic deposit drain, is given by;

$$\vartheta_{t+1}|\tilde{\vartheta}_t = E[\vartheta_{t+1}|\tilde{\vartheta}_t] + \epsilon_{t+1}\sqrt{Var[\vartheta_{t+1}|\tilde{\vartheta}_t]}, \qquad \forall t \in T \tag{3.4}$$

where, according to Betran-Royo *et al* (2010), we have the mean and variance as follows; respectively,

$$E[\vartheta_{t+1}|\tilde{\vartheta}_t] = \overline{\vartheta_{t+1}} + \rho_{\vartheta_t}\frac{\delta_{\vartheta_{t+1}}}{\delta_{\vartheta_t}}[\tilde{\vartheta}_t - \overline{\vartheta_t}], \qquad \forall t \in T \tag{3.5}$$

$$Var[\vartheta_{t+1}|\tilde{\vartheta}_t] = \delta^2_{\vartheta_{t+1}}(1-\rho^2_{\vartheta_t}), \qquad \forall t \in T \tag{3.6}$$

Then substituting equations (3.5) and (3.6) into equation (3.4) we obtain the following equation:

$$\vartheta_{t+1}|\tilde{\vartheta}_t = \overline{\vartheta_{t+1}} + \rho_{\vartheta_t}\frac{\delta_{\vartheta_{t+1}}}{\delta_{\vartheta_t}}[\tilde{\vartheta}_t - \overline{\vartheta_t}] + \delta_{\vartheta_{t+1}}\epsilon_{t+1}\sqrt{1-\rho^2_{\vartheta_t}}, \qquad \forall t \in T \tag{3.7}$$

where $\overline{\vartheta_t}$ is the mean. The $\tilde{\vartheta}_t$ is the realisation of ϑ_t and ρ_{ϑ_t} is the correlation coefficient between the successive net deterministic deposit drains ϑ_t and ϑ_{t+1}. Therefore, the scenario generation model is represented by the equation:

$$\vartheta^s_{t+1}|\tilde{\vartheta}_t = \overline{\vartheta_{t+1}} + \rho_{\vartheta_t}\frac{\delta_{\vartheta_{t+1}}}{\delta_{\vartheta_t}}[\tilde{\vartheta}_t - \overline{\vartheta_t}] + \delta_{\vartheta_{t+1}}\epsilon_{t+1}\sqrt{1-\rho^2_{\vartheta_t}} \qquad \forall s \in S, \forall t \in T \tag{3.8}$$

where s denotes the scenario at time t.

3.2.2 Net Dynamic Deposit Drains Models

The bank may not be able to determine with certainty the actual deposits and withdrawals in a given period of time and therefore, there is a portion of both deposits and withdrawals which is unknown by the bank in that given time. The difference between the unexpected withdrawals and deposits is referred to as net dynamic deposit drain. We start by defining notations used in our model. The net deterministic deposit drain is less significant in most of the institutions than net

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dynamic deposit drains. However, net deterministic deposit drains set the minimum level a bank should consider when determining minimum liquidity level. The following are the model variables:

φ_t^D	Dynamic withdrawals, $\forall t \in T$
η_t^D	Dynamic deposit, $\forall t \in T$
φ_t^f	Floating deposit withdrawal, $\forall t \in T$s
φ_t^v	Virtual deposit withdrawals, $\forall t \in T$
φ_t^h	Hypothetical deposit withdrawals, $\forall t \in T$
η_t^d	Scheduled deposit additions, $\forall t \in T$
η_t^f	Floating deposit additions, $\forall t \in T$
η_t^v	Virtual deposit additions, $\forall t \in T$
η_t^h	Hypothetical deposit additions, $\forall t \in T$
ψ_t	The net dynamic deposit drain, $\forall t \in T$

The net dynamic deposit drain can be computed by the equation:

$$\psi_t = \varphi_t^D - \eta_t^D, \qquad \forall t \in T \tag{3.9}$$

We define dynamic withdrawal by:

$$\varphi_t^D = \varphi_t^f + \varphi_t^v + \varphi_t^h, \qquad \forall t \in T \tag{3.10}$$

We assume that $\varphi_t^f = \alpha\varphi_t^D + \epsilon_t$, $\varphi_t^v = \beta\varphi_t^D + \epsilon_t$, and $\varphi_t^h = \xi\varphi_t^D + \epsilon_t$ where $\alpha \in (0,1)$, $\beta \in (0,1)$ and $\xi \in (0,1)$. Then the dynamic withdrawal weights should satisfy the condition $\alpha + \beta + \xi \leq 1$. Further, we define dynamic deposit by the equation:

$$\eta_t^D = \eta_t^f + \eta_t^v + \eta_t^h, \qquad \forall t \in T \tag{3.11}$$

Also we assume that $\eta_t^f = \pi\eta_t^D + \epsilon_t$, $\eta_t^v = \varrho\eta_t^D + \epsilon_t$ and $\eta_t^h = \gamma\eta_t^D + \epsilon_t$, where $\pi \in (0,1)$, $\varrho \in (0,1)$ and $\gamma \in (0,1)$. Then the dynamic deposit weights should

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satisfy the condition $\pi + \varrho + \gamma \leq 1$.

The variables ϖ_t^f and η_t^f are assumed to be determined by the floating interest rates in the markets. The interest rates can move up and down or may not change. Actually, ϖ_t^v and η_t^v are the discrepancies between banks' ex-post estimates and its original forecasts. Finally, the ϖ_t^h and η_t^h are expertise' semi-discretionary forecasts. The hypothetical variables are linked to unknown new depositors' needs.

Dynamic Deposit Scenario Generation Model

To determine dynamic deposit drain scenarios, we assume that dynamic deposits follow the stochastic differential equation represented by:

$$d\eta_t^D = \mu_{\eta^D} dt + \delta_{\eta^D} dW_t + \phi J_F dF_t, \qquad \forall t \in T \tag{3.12}$$

where μ_{η^D} is the dynamic deposit drift component of the model, and δ_{η^D} is the dynamic deposit diffusion component. dF_t is the stochastic differential of Poisson process with intensity $\lambda > 0$ as the average number of jumps in the period of one year. $\{J_f\}_{f=1}^{\infty}$ is a sequence of independently and identically distributed random variables that are drawn from $\mathbb{R}_+$ according to exponential distribution with mean $\frac{1}{\sigma} > 0$. Over an infinitesimal time interval, there is a probability $\lambda\sigma e^{-\sigma j} dt$ that the bank deposits shift by $j \geq 0$. W_t is the Brownian motion with a continuous path and normally distributed with mean 0 and variance t. Therefore, dW_t is the increment of Brownian motion that represents small and frequent shocks to the bank deposits. The ϕ can take any of the three values indicated below:

$$\phi = \begin{cases} 1 & ; \text{if jump is positive,} \\ 0 & ; \text{if no jump,} \\ -1 & ; \text{if jump is negative} \end{cases}$$

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Now equation (3.12) can be approximated as the change in deposits and denoted by:

$$\Delta\eta_t^D = \mu_{\eta^D}\Delta t + \delta_{\eta^D}\Delta W_t + \phi J_f \Delta F_t, \qquad \forall t \in T \tag{3.13}$$

where $\Delta\eta_t^D$ and ΔF_t are the changes in η_t^D and F_t in a small interval Δt. The Wiener process $\Delta W_t = \epsilon\sqrt{\Delta t}$ and ϵ is the error term. If given the interval $[t-1, t]$, the change in deposit change is:

$$\Delta\eta_t^D - \Delta\eta_{t-1}^D = \mu_{\eta^D}[\Delta t - \Delta(t-1)] + \delta_{\eta^D}\epsilon\sqrt{\Delta t - \Delta(t-1)} + \phi J_f[\Delta F_t - \Delta F_{t-1}], \quad \forall t \in T \tag{3.14}$$

We denote the change in deposit change by $\eta_t^* = \Delta\eta_t^D - \Delta\eta_{t-1}^D$. The components μ_{η^D} and δ_{η^D} are constants. Therefore we assume that the dynamic deposit values can be approximated by the following scenario generation model:

$$\eta_{t+1}^s = \eta_0^D + e\eta_t^* + \iota\Delta\eta_t^s, \qquad \forall s \in S, \forall t \in T \tag{3.15}$$

where η_0^D is the initial amount deposited to the bank, $\iota \in (0,1)$ and $e \in (0,1)$ are user-defined constant values and $s \in S$ is the scenario.

Dynamic Withdrawal Scenario Generation Model

To compute scenarios for dynamic withdrawals, first we construct a dynamic withdrawals model given by the equation:

$$\varphi_t^D = \overline{\varphi_t^D} + \kappa\varphi_{t-1}^D + \theta\delta_t, \qquad \forall t \in T \tag{3.16}$$

where κ and θ are weights. The monthly dynamic withdrawal mean $\overline{\varphi_t^D}$ considered mainly depends on the period of observation but also on bank clients' confidence and country's financial stability. The variance of dynamic withdrawal δ_t^2 is not stable and it is assumed to follow GARCH(1,1) and is given by:

$$\delta_t^2 = c + \varsigma\epsilon_{t-1}^2 + \tau\nu_{t-1}\epsilon_{t-1}^2 + \chi\delta_{t-1}, \qquad \forall t \in T \tag{3.17}$$

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where ν_{t-1} can take any of the two options indicated below:

$$\nu_{t-1} = \begin{cases} 1 & ;\text{if} \quad \epsilon_{t-1} \leq 0 \quad \text{the bank's news are bad,} \\ 0 & ;\text{if} \quad \epsilon_{t-1} > 0 \quad \text{the bank's news are good,} \end{cases}$$

and c is a constant, ς is the good news impact on volatility and the effects are given by $\varsigma\epsilon_{t-1}^2$. We also have $(\varsigma + \tau)\epsilon_{t-1}^2$ which is the effect of bad news on volatility and the value of τ is expected to be positive to have large impact. In other words, $\varsigma + \tau$ measures the rate at which this effect dies out over time. The χ is the impact of previous standard deviation. Then the scenario generation model for dynamic withdrawal is denoted by the equation:

$$\varphi_t^{Ds} = \overline{\varphi_t^D} + \kappa\varphi_{t-1}^D + \theta\delta_t, \qquad \forall s \in S, \forall t \in T \tag{3.18}$$

Therefore, the net dynamic deposit drain scenario is the difference between models denoted by equations (3.18) and (3.15) represented by the equation

$$\psi_t^s = \varphi_t^{Ds} - \eta_t^s, \qquad \forall s \in S, \forall t \in T \tag{3.19}$$

where s denotes a scenario at time t. A bank with insufficient funds could still meet its withdrawal needs provided ψ_t^s is sufficiently large. Thus a bank can raise funds from liquidating the assets at fire sale prices or borrowings but with high borrowing costs.

3.2.3 Net Deposit Drains Scenario Generation Model

The overall net deposit drains model is derived from the general accounting methods that are used to determine bank's cash flow. Vento and La Ganga (2009) proposed an accounting method to determine cash flows and this model is built on the basis of their model. The overall net deposit drain is total of net deterministic deposit drain and net dynamic deposit drain and is represented by the equation;

$$x_t = \vartheta_t + \psi_t, \qquad \forall t \in T \tag{3.20}$$

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where x_t is the overall net deposit drain, ϑ_t is the net deterministic deposit drain and ψ_t is the net dynamic deposit drains. Therefore, the scenario generation model for net deposit drain is denoted by equation (3.21).

$$x_t^s = \vartheta_t^s + \psi_t^s, \qquad \forall s \in S, \forall t \in T \tag{3.21}$$

where s denotes a scenario, ϑ_t^s and ψ_t^s are as computed in equations (3.8) and (3.19), respectively. We need to note that the net deposit drain can be either negative or positive. The quality of managing liquidity risk on the liability side is heavily dependent on the accuracy in the prediction of the distribution of the net deposit drains x_t^s and that must ensure good planning in order to raise the required funds.

3.2.4 The Scenario Trees

In general, a scenario generation procedure for multistage problems involves three steps. The first step is collecting historical observations of the parameter values, assumptions of a model, which explain the behaviour of the random parameters. Here we estimate the following moments: mean, variance, kurtosis and skewness. The second step is calibration of parameters for the chosen model, which uses historical data and the statistical properties should be the same as the ones computed in the first step. However, given that our interest is on real world applications, we recognise that there may not always be a distribution that matches the calculated statistical properties. Finally, we generate data trajectories according to the chosen model using approximation of statistical properties. To simulate and generate scenarios, we applied the scenario generation work-flow strategy shown in Figure 3.1. The first step is to set up periods and stages. We restrict ourselves to three stages which are; 2 years, 4 years and 7 years. We then simulate future outcomes of net deterministic drain, dynamic deposit and dynamic withdrawals using models in equations (3.8), (3.15) and (3.18), respectively. After that, we then run an

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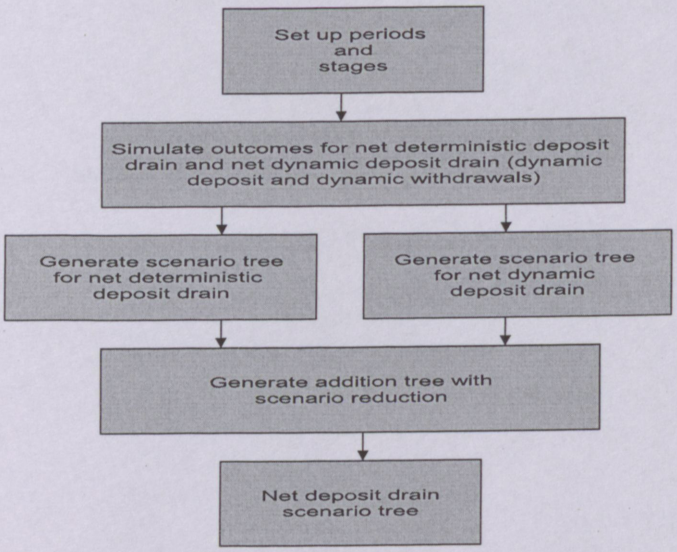
Figure 3.1: Scenario Generation Workflow



expert view and use judgemental view to ascertain the actual net deposit drain. From equations (3.15) and (3.18) we deduce equation (3.19). Then we generate univariate 3-2-2 scenario trees first for both dynamic withdrawal and dynamic deposit before univariate 3-2-2 scenario trees for net deterministic deposit drains and net dynamic deposit drains. Finally, we build a multivariate scenario tree with reduction based on the historical correlation of net deterministic deposit drains and net dynamic deposit drains. The Figure 3.1 shows the scenario simulation and generation strategy used for dynamic withdrawals and dynamic deposits, and then the final net dynamic deposit drains.

3.3 Empirical Results

The scenario tree generation approach is applied to construct net deposit drains. We use equations (3.8) and (3.15) to generate data, which consists of a finite number of scenarios, representing realisations of net dynamic deposit drains ψ_t. Let us

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assume that n branches are desired from each scenario tree node. Here, the scenarios generated should mimic the original data. First we generated a scenario tree for dynamic deposit and dynamic withdrawals independently and then compute the difference between the two outcomes. The correlation between the dynamic deposits and dynamic withdrawals is 0.47207919.

Table 3.1: Dynamic Deposit and Withdrawal Scenario Tree (R'0000)

Dynamic	Deposit		Dynamic	Withdrawal	
Stage 1	Stage 2	Stage 3	Stage 1	Stage 2	Stage 3
	54.4779	32.7465		53.2909	98.9523
2.2558		13.3818	5.1083		87.7316
	4.6095	11.3997		50.9462	108.9795
		15.0619			116.6595
	5.0273	25.1156		53.8878	91.4599
2.5471		32.0789	2.6574		124.6264
	4.6691	23.7484		52.5363	116.9701
		33.3508			158.8862
	5.9777	27.8415		49.6650	93.0426
1.8091		28.4013	4.4849		97.8503
	5.8028	32.5798		55.0550	154.6592
		30.9919			161.8209

We then combine the dynamic deposit scenario with the dynamic withdrawal scenario tree to have a combined scenario tree in Table 3.2. A scenario reduction is used to reduce the number of final scenarios. Therefore, the combined scenario tree shows the possible combination of dynamic deposit and dynamic withdrawals. So to compute the net dynamic deposit drain, we find the difference between the dynamic deposit and the dynamic withdrawal per node with associ-

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Table 3.2: Combined Scenario Tree for Dynamic Deposit and Dynamic Withdrawal (R'0000)

Stage 1		Stage 2		Stage 3	
Value	Probability	Value	Probability	Value	Probability
		5.44779/50.9462	0.5913	32.7465/116.6595	0.5161
2.2558/5.1083	0.2241			13.3818/108.9795	0.4839
		4.6095/53.2909	0.4087	11.3997/87.7316	0.7418
				15.0619/98.9523	0.2582
		5.0273/50.9462	0.6076	25.1156/116.6595	0.2042
2.5471/5.1083	0.1672			32.0789/108.9795	0.7958
		4.6691/53.2909	0.3924	23.7484/87.7316	0.5280
				33.3508/98.9523	0.4720
		5.0273/52.5363	0.6471	25.1156/158.8862	0.8381
2.5471/2.6574	0.1991			32.0789/116.9701	0.1619
		4.6691/53.8878	0.3529	23.7484/124.6264	0.3872
				33.3508/91.4599	0.6128
		5.0273/55.0550	0.3206	25.1156/161.8209	0.2899
2.5471/4.4849	0.1537			32.0789/154.6592	0.7101
		4.6691/49.6650	0.6794	23.7484/97.8503	0.8887
				33.3508/93.0426	0.1113
		5.9777/50.9462	0.8262	27.8415/116.6595	0.6745
1.8091/5.1083	0.1333			28.4013/108.9795	0.3255
		5.8028/53.2909	0.1738	32.5798/87.7316	0.4361
				30.9919/98.9523	0.5639

ated probability. The Figures 3.2 and 3.3 shows the net deterministic deposit drain and net dynamic deposit drain trends from July 1988 to March 2014, respectively.

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Figure 3.2: Net Deterministic Deposit Drain

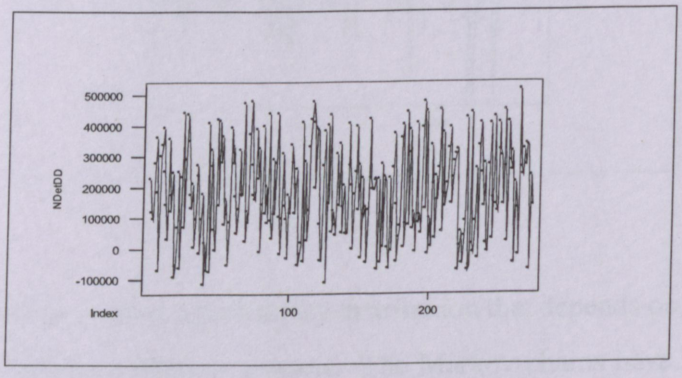

Figure 3.3: Net Dynamic Deposit Drain

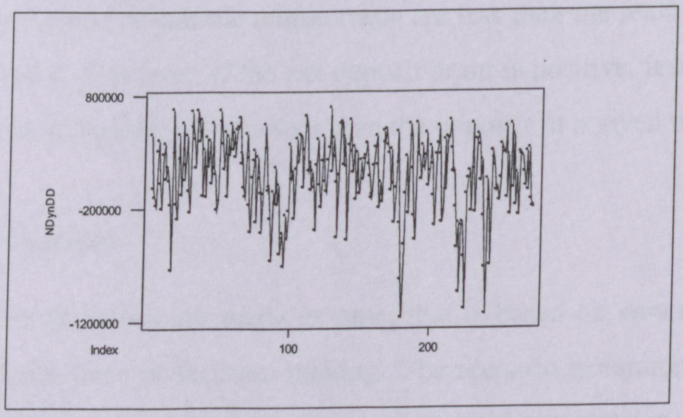

Figure 3.4 shows the possible net deposit drain. The nature of the simulated historical data depicts that the institution is experiencing higher withdrawals than the anticipated. Therefore, the institution needs to be well prepared for the unexpected withdrawals to reduce liquidity risk. The scenarios depend on period t defined and the number of scenarios per node. The spread around its median expands as the time increases, signifying that uncertainty increases with time. The

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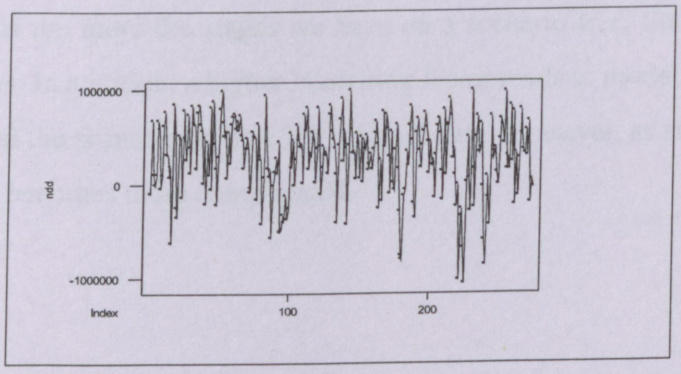
Figure 3.4: Net Deposit Drain



random variables ψ_t have a probability distribution that depends on an underlying state which follows a Markov process. The Markov chains have been used for simulating net dynamic deposit drains ψ_t states. Therefore, the Markov chains states of the net deposit drains can be; negative, zero or positive. The negative net deposit drain indicates that the withdrawals are less than the realised deposits on the given month. However, if the net deposit drain is positive, it implies that the bank experienced higher withdrawals than the deposits at a given time.

3.4 Conclusion

The cash flow decisions are made ex ante, that is based on parameters that are not known at the time of decision making. The scenario generators are used not only in the models for optimal decision making under uncertainty, they are also used for evaluation of cash flow decisions through simulation modelling. In the present chapter, we described the procedure based on both using the statistical model to generate the scenario trees out of data paths. The computational experiment showed that the size of generated scenario trees is much smaller than the dimension of scenario fan. However, they are good approximations with respect to the Euclidean distance used to measure the time-dependent data paths. We can

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conclude that the more the stages we have on a scenario tree, the better the approximations. In addition, a higher branching factor tends to model more extreme scenarios and the scenarios mimic the original data. However, as stages increase, the problem becomes more complicated.

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CHAPTER 4

4 STOCHASTIC PROGRAMMING MODELS FOR LIQUID ASSET CONTROL

4.1 Introduction

Stochastic programming approach has previously been used for decision making under uncertainty in the financial field. Financial optimisation models have been presented by Infanger (2006), Li Young *et al* (2003), Zenios (1993) and Ziemba and Mulvey (1998). The cash management in automated teller machines (hereinafter, ATMs), was researched by Castro (2007) and Garcia (2013), specifically focusing on the optimal amount of money that can be placed in ATMs to minimise opportunity costs. In compensation of credit card transactions and cash management in ATMs, Castro (2007) presented the short-term and the mid-term models with fixed and staircase costs. A multi-stage stochastic linear programme was used by Ferstl and Weissensteiner (2008) in minimising the conditional value at risk of final wealth.

A robust optimisation method was constructed by Glasserman and Xu (2013) and in their model, parameter ranges are defined by uncertainty sets and optimise against the worst-case configuration consistent with these ranges. In the Glasserman and Xu (2013) model, returns are driven by factors that evolve stochastically and are subject to model error. A stochastic programming in managing liquid asset portfolio was constructed by Raubenheimer and Kruger (2010) and their objective function is minimising downside risk. Motivated by Glasserman and Xu (2013) and Raubenheimer and Kruger (2010) objective functions weaknesses, we construct an objective function that minimises both costs below the lower threshold

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and costs above the upper threshold. Sigauke *et al* (2012) constructed a stochastic programming framework for liquidity management of commercial banks in Zimbabwe. The paper sets out to explain an important financial planning model for liquidity management; in particular it discusses why in practice optimum planning models are used. Sigauke *et al* (2012) model seeks to minimize costs the bank is exposed to with regard to liquidity needs. In our model, we explicitly define costs at not meeting the minimum requirement and costs of excess liquidity which includes holding costs and opportunity costs. The research is of prime importance to fund managers, portfolio managers, financial analysts and researchers to maintain an aggregate liquidity level. Using liquid assets tend to overestimate liquidity level since some assets that are liquid today may not necessarily be liquid when needed for trading. So to reduce the bias, we ought to use current liquidity level estimated by central bank at hand and not cash invested in doubtful assets. Assets defined as liquid by one bank may not be the same assets defined as liquid by a peer bank.

In spite of the fact that many applications of the multistage stochastic programming problems can be found in the literature, this type of the problem introduces some variables not considered in existing models. The aim of the chapter is to maintain the liquid asset portfolio at an optimal level to minimise extra costs to stay within the defined threshold. Thus the model constructed minimises average costs over all periods as well as satisfying the institution's clients stochastic demand. The optimisation of influence functioning in liquidity management is significant in improving cash management as this may have positive effects in reducing liquidity tensions. The chapter is organised as follows; first we develop a scenario generation method and then a multi-stage stochastic programming model with recourse. In our stochastic programming model, we intend to minimise over-

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all below lower threshold and over upper threshold costs. Then the next part is devoted to methods used to collect data and analysis of its statistical characteristics. Finally, the stochastic solutions are presented and we give meaning to the presented empirical results in conjunction with data characteristics and conclusion.

4.2 Model Formulation

Bank management need to decide how many liquid assets are to be released at each instant time to maintain an optimal liquid asset portfolio. We assume that the institution has a defined minimum and maximum liquidity level in relation to net stable funding ratio for a year. So we assume that the bank's liquid asset portfolio is currently above minimum liquidity level but below the maximum liquidity level. Further, we assume that the bank is capable of lowering liquid assets by a certain level per month but is affected by liquid asset return. The yield depends on interest rates and inflation movements. With this information, the process can then be modelled as a multi-stage stochastic programming problem with the objective to minimise overall costs. We start by defining the variables we used in the model as follows:

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Definitions of Sets

T	Set of time space
N	Set of scenario number
s_n	Set of scenarios at instant time $\forall n \in N$
$\Omega_1 = \{H, N, L\}$	Set of event space for the unknown liquid asset yield
$\Omega_2 = \{\Delta_c^+, \Delta_c^0, \Delta_c^-\}$	Set of event space for the unknown change in costs
$P_2 = \{p_{\Delta_c^+}, p_{\Delta_c^+}, p_{\Delta_c^+}\}$	Set of probabilities of event space for the unknown change in costs
$P_1 = \{p_H, p_N, p_L\}$	Set of probabilities of event space for the unknown liquid asset yield
P_{s_n}	Set of scenario probabilities, $\forall s_n \in S$

Input Data Parameters

φ_0	Initial cost price of initial liquidity
x^{min}	Expected minimum liquidity level
x^{max}	Expected maximum liquidity level
c^F	Penalty on liquidity shortage
c^E	Penalty on excess liquidity
$\tau_1 \in [0, 1]$	Destabilising factor on $A^1_{ts_n}$, $\forall n \in N, \forall t \in T, \forall s_n \in S$
$\tau_2 \in [0, 1]$	Destabilising factor on $A^2_{ts_n}$, $\forall n \in N, \forall t \in T, \forall s_n \in S$
$\tau_3 \in [0, 1]$	Destabilising factor on $A^3_{ts_n}$, $\forall n \in N, \forall t \in T, \forall s_n \in S$

Random Variables

$A^1_{ts_n}$	Short-term liquid assets held , $\forall n \in N, \forall t \in T, \forall s_n \in S$
$A^2_{ts_n}$	Medium-term liquid assets held, $\forall n \in N, \forall t \in T, \forall s_n \in S$
$A^3_{ts_n}$	Long-term liquid assets held, $\forall n \in N, \forall t \in T, \forall s_n \in S$

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Decision Variables

x_{ts_n} Liquid asset level holdings , $\forall n \in N, \forall t \in T, \forall s_n \in S$

y_{ts_n} The liquid assets released, $\forall n \in N, \forall t \in T, \forall s_n \in S$

z_{ts_n} Bank's liquidity level change, $\forall n \in N, \forall t \in T, \forall s_n \in S$

Having defined the parameters and the variables, we can then proceed to develop the scenario generation model and the stochastic programme using the defined models parameters.

4.2.1 Scenario Tree

To construct a stochastic programming model, we need to model the random variable liquidity level change as input to the model. We consider the case where the random vector S has a discrete and finite distribution, with scenario s in a set $S_t = \{s_1, ..., s_n, ..., s_N\}$. We assume that the scenario probability $p_{s_n} \geq 0$ for all $s_n \in S$ and that $\sum_{n \in N} p_{s_n} = 1$. Then we assume that the scenario generation model for liquidity level change is represented by the equation follows:

$$z_{ts_n} = (1 - \tau_1)A^1_{(t-1)s_n} + (1 - \tau_2)A^2_{ts_n} + (1 - \tau_3)A^3_{ts_n} + \epsilon_t \delta_z \qquad (4.1)$$

The destabilising factors τ_1, τ_2 and τ_3 are the economic and market impacts on different liquid assets classes held by the bank. In the economy these factors include clients' behavioural liquidity demand and economic change, and are assumed to have different effects on different classes of liquid assets the institution held. The volatility of the liquid asset portfolio is denoted by δ_z. The ϵ_t is the standard error with mean 0 and variance 1. In the scenario tree in Figure 4.1, x_0 represents the initial liquidity level decision at stage 0. However, the liquid asset portfolios held by the institution are subject to unknown liquid assets yield on event space $\Omega_1 = \{H, N, L\}$ with respect to probabilities p_H, p_N and p_L. At the beginning

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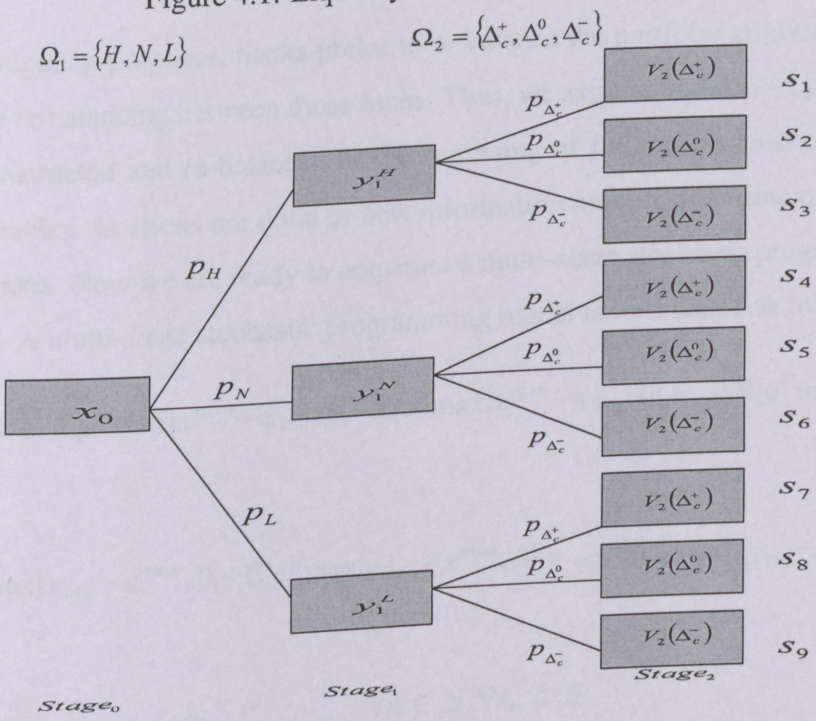
Figure 4.1: Liquidity Demand Scenario Tree



of stage 1, the liquid asset yield is revealed. At the end of stage 1, a recourse decision $y_1 = \{y_1^H, y_1^N, y_1^L\}$ is made to maintain the required liquidity level at unknown change in costs. The change in costs are determined by event space $\Omega_2 = \{\Delta_c^+, \Delta_c^0, \Delta_c^-\}$ with corresponding probabilities $p_{\Delta_c^+}, p_{\Delta_c^0}$ and $p_{\Delta_c^-}$. Then at the beginning of stage 2, the changes in costs are revealed and the overall change in costs $V_2(\Delta_c) = \{V_2(\Delta_c^+), V_2(\Delta_c^0), V_2(\Delta_c^-)\}$ can be computed. In all cases, the conditions $p_H + p_N + p_L = 1$ and $p_{\Delta_c^+} + p_{\Delta_c^0} + p_{\Delta_c^-} = 1$ are valid. We need to note that the scenario probability p_{s_n} is a conditional probability of successive events.

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4.2.2 Multi-Stage Stochastic Programming Model

For budgeting purposes, banks prefer to re-balance the portfolio at given times t and no re-balancing between those times. Thus, we assume liquid asset portfolios are constructed and re-balanced at the beginning of future time interval. Thus re-balancing decisions are done as new information unfolds over time on market conditions. Now we are ready to construct a multi-stage stochastic programming model. A multi-stage stochastic programming model is formulated as follows:

$$\text{Min } \varphi x_0 + \mathbb{E}[c^F \max[x^{min} - x_{1s_n}, 0] + \mathbb{E}[c^F \max[x^{min} - x_{2s_n}, 0] + ... + \mathbb{E}[c^F \max[x^{min} - x_{Ts_n}, 0]]]]$$

$$+$$

$$\mathbb{E}[c^E \max[x_{1s_n} - x^{max}, 0] + \mathbb{E}[c^E \max[x_{2s_n} - x^{max}, 0] + ... + \mathbb{E}[c^E \max[x_{Ts_n} - x^{max}, 0]]]] \tag{4.2}$$

$$\begin{aligned}
\text{s. t} \qquad x_0 - z_0 &\leq x_{1s_n}, \quad \forall n \in N, \forall s_n \in S && (4.3)\\
x_{(t-1)s_n} - z_{(t-1)s_n} &\leq x_{ts_n}, \quad t \geq 1, \forall n \in N, \forall s_n \in S && (4.4)\\
x_{ts_n} + y_{ts_n} &\leq x_{(t-1)s_n}, \quad t \geq 1, \forall n \in N, \forall s_n \in S && (4.5)\\
x_{ts_n} - x^{max} &\leq \max[x_{ts_n} - x^{max}, 0], \quad t \geq 1, \forall n \in N, \forall s_n \in S && (4.6)\\
x^{min} - x_{ts_n} &\leq \max[x^{min} - x_{ts_n}, 0], \quad t \geq 1, \forall n \in N, \forall s_n \in S && (4.7)
\end{aligned}$$

$$x_{ts_n} \geq 0, z_{ts_n} \leq 0, 0 \leq y_{ts_n} \leq Y_t(x_{ts_n}), \quad (t = 1, .., T) \tag{4.8}$$

The objective function denoted by equation (4.2) minimises the total cost of maintaining the liquid asset portfolio. Our objective is to minimise the expected value of the sum of the cost of inadequate liquidity and the cost of excess liquidity. The first-stage constraint (4.3) denotes the initial liquidity level at the beginning of a state and is equal to the liquidity level at the end of the previous state less the liquidity level released in the previous state. The state transition function is represented by constraint (4.4) and is the liquidity re-balancing function which is

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observed per instant time t. At each stage, we start with an initial liquidity level. The liquidity level changes during the course of the set time interval and we get to the end-of-stage liquidity level. Then the bank releases some quantity of liquid assets and stipulates the initial liquidity level for the next stage. The initial liquidity level x_{ts_n} and the final liquidity level $x_{(t+1)s_n}$ are the free variables.

However, after anticipative decisions have been made, adaptive decisions are made after an event has happened. Here, the decision maker makes corrective measures, which are recourse decisions. The constraint (4.5) is the final liquidity level at the end of the state and is the same as the liquidity level at the beginning of the state plus the liquidity level change observed in that state. The constraint (4.6), if positive, is the amount by which the end-of-stage liquidity level exceeds the defined maximum liquidity level. The constraint (4.7), if positive, is the amount by which the end-of-stage liquidity level falls below the defined minimum liquidity level. Finally, constraint (4.8) specifies the variables as non-zero and some as having defined upper bounds. The upper bounds are defined by the decision maker.

4.3 Methodology

The developed stochastic programme is solved using Lingo 14 software and results are analysed. The constructed model is assessed for its viability and performance through extensive numerical tests using market data on required liquid assets and actual liquidity holdings. The monthly data used is from the South African Reserve Bank from January 1988 to March 2014. We start by computing the statistical characteristics of historical data. The Minitab software was used to compute the first four moments of the historical data. The characteristics of data used are as shown in Table 4.1 below. The changes in both historical required liquid assets and actual liquid asset holdings both exhibit negative skewed distri-

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Table 4.1: Statistical Characteristics of Historical Data

Statistical Measure	Required Liquid Assets Change	Actual Liquid Asset Holdings Change
Average	5.05379×10^2	9.64417×10^2
Standard Deviation	1.18129×10^3	3.53028×10^3
Kurtosis	14.9834	15.49727
Skewness	-0.65374	-0.56785
Minimum	-8.79×10^3	-2.7095×10^4
Maximum	5.688×10^3	1.7844×10^4

bution. Thus both required liquid assets and actual liquid asset holdings exhibit considerable variance in comparison to their mean. In addition, the changes in both required liquid assets and actual liquid asset holdings exhibit significant excess kurtosis since the calculated kurtosis ($K > 3$), implying heavier tails than the normal distribution. If the condition ($K > 3$), the historical data is laptokurtic implying that it is more peaked with fatter tails.

4.4 Results Analysis

Before we analyse the stochastic solution, first we compare the required liquid asset and the actual liquid asset holdings by banks as shown in Figure 4.2. The required liquid asset and actual liquid asset holdings are denoted by purple and green colours, respectively. As evidenced by the nature of the time series plots, the required liquid asset and actual liquid asset holdings were almost the same for more than 9 years, that is from January 1988 to June 1997 and then actual liquid asset holdings started to sharply decrease up to date while the required reserve increased at a steady rate. However in early 1988 and early 1990, the banks' actual liquid asset holdings were less than the required liquid assets. Thus during

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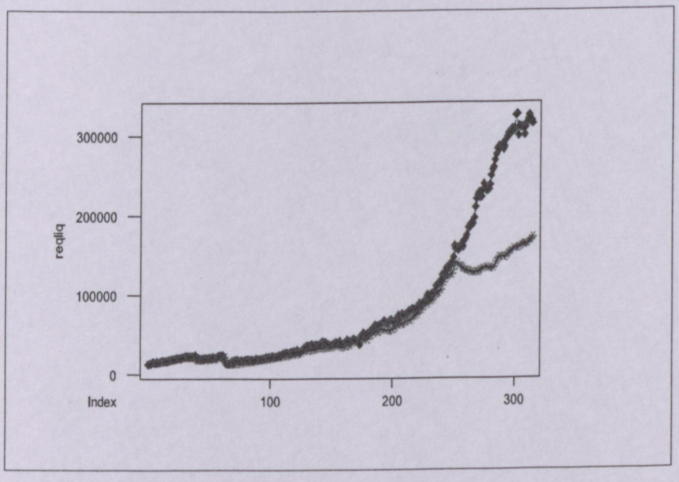
this period, banks were exposed to liquidity risk. Figure 4.3 shows the monthly

Figure 4.2: Comparison Between Required Liquid Asset and Actual Liquid Asset Holdings



change in required liquid asset. In the 1990s and early 2000s the change was very small and in some cases it decreased, but in March 1993, there was a massive fall in required liquid assets. However, in late 2000s and thereafter, the required liquid asset changes are more pronounced and very significant. This might have been a result of Basel 2 Accord. In 1990s and 2000s, the change in actual liquid asset holdings shown in Figure 4.4 are very close to zero and insignificant. However from 2008 to date, the change is very significant and has an impact on bank liquidity status. The increase in actual liquid asset holdings may have been triggered by new bank regulations and liquidity requirements after the US 2007 - 2008 financial crisis. Now we present and discuss the performance of the stochas-

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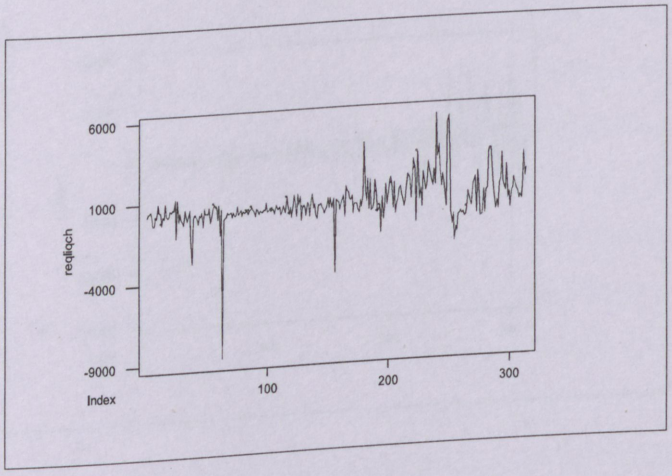
Figure 4.3: Required Liquid Asset Monthly Change



tic programming model through six different stages. The first step is meant to determine the stochastic programming solution status. In this case, the solution status is globally optimal implying that the results are valid. Now we turn to Table 4.2 where results of different components are shown. Of prime importance are the stochastic objective values, which are the expected objective values over all different cases and scenarios. As the number of stages increase, the scenarios also increase and it leads to increase in objective value. We need to note that the optimal cost is the objective value in our model. The advantage of using a stochastic programming model is that the bank is always well-hedged against worst-case scenarios. The value of infeasibilities is zero in all the stages implying that no constraints were violated in the deterministic equivalent model. The EV of the costs is the same as the reported optimal costs for the model, further giving

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Figure 4.4: Monthly Change: Actual Liquid Asset Holdings

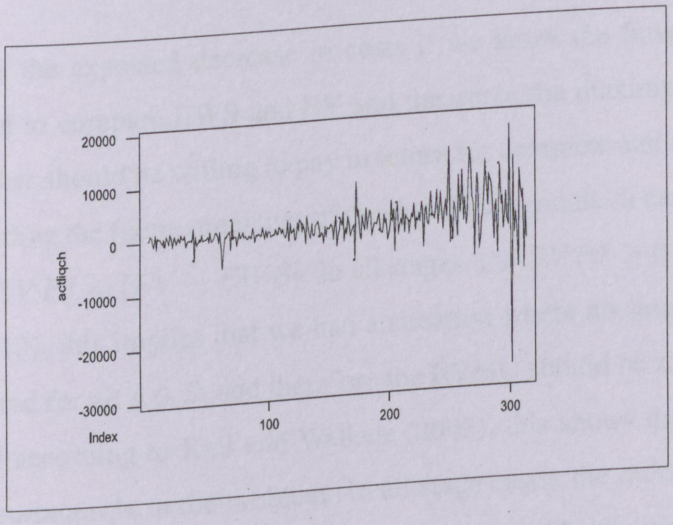

Table 4.2: Comparison of Stochastic Programming Solutions at Different Stages

Stages	Scenarios	Obj	Inf	EV	EWS	EVPI
2	9	1.346762×10^6	0	1.346762×10^6	6.178373×10^4	1.284978×10^6
3	27	4.950131×10^6	0	4.950131×10^6	6.423671×10^5	4.307764×10^6
4	81	9.508095×10^6	0	9.508095×10^6	1.688664×10^6	7.819431×10^6
5	243	1.467176×10^7	0	1.467176×10^7	3.094596×10^6	1.157717×10^7
6	729	2.041685×10^7	0	2.041685×10^7	4.741850×10^6	1.567500×10^7
7	2187	2.657819×10^7	0	2.657819×10^7	6.607284×10^6	1.997091×10^7

weight to the results. The EWS costs reports the EV of the optimal costs if we could wait and see the outcomes of the unknown liquid asset yield and change in costs before making decisions. However, in reality it is not possible to wait and

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make decisions after an event has happened. Comparing the EWS and EV, we expect $EWS \leq EV$ since we are minimising.

The EVPI is the expected decrease in costs if we know the future in advance. EVPI is used to compare EWS and EV and measures the maximum amount the decision maker should be willing to pay in return for complete and accurate information regarding the future outcomes of the liquid asset yields. It can be computed as follows; $EVPI = |EV - EWS|$. In all stages, the $EVPI \geq 0$ and according to Birge (2013), this implies that we had a situation where no single optimal solution s existed for all $s \in S$, and therefore the EVMU should be zero. The EVPI is large, and according to Kall and Wallace (2003), this shows that randomness plays an important role in the problem. In all stage cases, the ratio of total EVPI to total costs of stochastic value is between 75.1% and 95.4% implying that the decision maker is willing to pay an average of 81.7% per given instant time t. We can observe that $WS \leq SP \leq EV$, and $EVPI \geq 0$ which are consistent with Barbaro and Bagajewicz (2004) and Birge (1997) conditions. This means that lower optimal costs of maintaining liquid assets is best achieved under EWS than EV. Therefore, at this level, we can infer that the scenarios generated are reliable and valid.

4.5 Conclusion

A multi-stage stochastic programming model with recourse was constructed to control banks' liquidity level. It is intuitively expected that as the randomness in the problem increases, the expected value of correct information and value of stochastic solution would increase by increasing variance. Different stages were used to determine the behaviour of the optimal cost. We assumed that at initial stage, the bank purchases liquid assets from the market, liquidate some to meet

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liquidity demands and hold some liquid assets for next instant time. We assumed that the following instant time, a bank can meet its liquidity needs from the portfolio held or purchase from the market. Thus the bank is facing the following set of decisions which are; how much liquid assets to hold and purchase and meet liquidity needs. It also needs to know how many liquid assets to purchase and hold up to the next instant time. Finally, the bank needs to know how many liquid assets to liquidate to meet its liquidity obligation at the beginning of each instant time. Therefore, the decision maker's decision depends on the state of liquidity level, liquidity demand, the asset price, holding and maintenance costs and the defined lower and upper liquidity thresholds. With this information, the problem can be modelled as a stochastic programme with the objective of minimising costs. From the results, we can infer that taking into account uncertainty is much of a benefit to the decision maker. We need to note that large EVPI might not necessarily show that the deterministic model cannot function well. The multi-stage stochastic programming model is clear, easy to implement, very efficient and provides the optimal solution according to future possible set of scenarios. The use of the proposed model may improve the current techniques used by banks, which are based on simulation, experience and trial-and-error. Further researches can be done on alternative scenario generation methods for generating liquidity demand scenarios.

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CHAPTER 5

5 CORE LIQUIDITY MANAGEMENT STOCHASTIC PROGRAMMING MODELS

5.1 Introduction

Banks are exposed to liquidity risk through maturity gap between assets and liabilities. To alleviate the maturity gap, the most traditional liquidity management method applied by commercial banks is the use of interbank loans and highly liquid securities such as treasury bonds and assets to insure against liquidity shocks. Basel 3 introduced several standards designed to reduce the likelihood of systemic crises caused by liquidity distress at individual financial institutions. The most prominent of these standards according to Kowalik (2013), was a requirement that financial institutions maintain liquidity buffers.

Until recently, liquidity was not the main focus of banking regulators. Bonner *et al* (2013) explained on the determinants of banks' incentives to hold liquid assets across countries whether the liquidity regulation or the bank's internal incentive. Present liquidity regulation renders most determinants insignificant. However, an institution's disclosure requirement and size remain significant. A number of liquidity-related management models have been developed, see Abraham (2011), Bolton *et al* (2008), De Alcântara (2008), Ratwovski (2013). Abraham (2011) proposed a method that can be used to calculate liquidity buffer. In his model, Abraham (2011) proposed two methods of calculating liquidity buffer requirement which involve calculating base requirement first and then secondly, apply the multiplier factors. The variables to be included in Abraham (2011) model are through summing the wholesale, retail, off-balance sheet, and intra-day and

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downgrade requirements. On the other hand, the multiplier factors are then multiplied by computed base requirement to have the liquidity buffer. The multiplier factors are divided into the scalar multiplier and glide-path multiplier. The liquidity demand model was considered by Bolton *et al* (2008), and computed a liquidity demand arising from a possible maturity mismatch between asset revenues and consumption. De Alcântara (2008) developed an integrated model for optimal asset allocation in commercial banks that incorporates uncertain liquidity constraints that are ignored in risk-adjusted return on capital and economic value added models. A model of bank liquidity risk driven by solvency was proposed by Ratwovski (2013. In his model, he defined the interaction between liquidity requirements, access to refinancing and liquidity risk.

Previous and most recent liquidity management models developed look at liquidity as a unitary portfolio. In this thesis, we construct a sub-portfolio that specifically focuses on preserving liquidity buffer. There is wide agreement that insufficient liquidity buffers are the root cause of the 2007 to 2009 liquidity crisis. The prominent approach to regulating liquidity in the financial industry is to require a buffer of liquid assets that financial institutions can use in a liquidity crisis. Thus in our research, the main aim of the core liquidity portfolio is to ensure that the created liquidity buffer is viable and provides the necessary security required to safeguard the institution against liquidity related problems. We construct a two-stage stochastic programming model with recourse to manage the core liquidity portfolio. The core part of core liquidity portfolio is the liquidity buffer.

5.2 Rationale for Liquidity Buffers

Liquidity buffer is a key component of any financial intermediary's liquidity risk management. Holding liquidity buffer is costly, since liquid assets provide lower

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returns than illiquid assets. According to Bonfim and Kim (2011), holding buffer may also be inefficient as it limits banks' ability to provide liquidity to businesses and customers. Liquidity buffer is defined as the short end of the counterbalancing capacity under a planned stress. It is dependent on three dimensions which are, according to the Committee of European Banking Supervisors (2009), the severity and characteristic of stress scenario, the time horizon fixed as the survival period, and the characteristics of the assets in the buffer. The Committee of European Banking Supervisors (2009) defined survival period as the period during which an institution can continue operating without needing to generate additional funds and still meet all its payments due under the assumed stress scenarios. Liquidity risk is largely institution-specific, and banks are expected to tailor their liquidity management, stress tests, and liquidity reserves to their specific needs. Institutions should develop cash flow projections covering expected cash inflows, expected cash outflows and expected counterbalancing capacity, broken down by major business lines, instruments and maturity buckets. In determining expected cash flows and counterbalancing capacity, institutions should distinguish between contractual and behavioural flows and choose the most conservative in estimating their liquidity situation overtime.

Berben *et al* (2010) pointed that high capital and liquidity buffers reduce liquidity risk and shareholders will therefore be prepared to accept lower returns. High buffers reduce the probability of crises and the amount of damage they may cause. There is ultimately a trade-off between the costs of additional capital and liquidity buffers and the economic benefits they produce. Buffers enhance the capacity of banks to absorb losses and uphold lending during a downturn. If liquidity holdings are much above the legal requirements according to Deléchat *et al* (2014), this may be costly in terms of foregone financial intermediation and excess liquid-

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ity also hinders the development of interbank and money markets.

According to Kowalik (2013), liquidity buffers may reduce the risk of systemic crisis in four ways. The first benefit is that substantial liquidity buffers may make an institution less vulnerable to runs into their creditors because the buffers increase the creditors' confidence in the institutions' ability to service their obligations. The second benefit, according to the Basel Committee on Banking Supervision (2010) is that if financial institutions experience stress event, liquidity buffers may give their management and supervisors time to find solutions to their liquidity needs. A liquidity buffer should be 'large enough' such that it can be used as a stop gap measure during which time, less extreme solutions to reduce the likelihood of supervisors having to trade-off disruptive bankruptcy and a bailout could be found. The third benefit of liquidity buffer is that it reduces the institution's dependence on central bank as a provider of liquidity in times of stress. Reliance on central bank is viewed as a source of moral hazard by investors. It is widely viewed that the central bank's role of lender-of-last-resort, according to Farhi and Tirole (2012) incentivises banks not to hold their own liquidity buffers in good times, which increases the likelihood of liquidity crisis and contributes to financial instability.

The final benefit of liquidity buffer is that it reduces financial institutions' overreliance on asset sales as a means of managing low liquidity environment. Instead of fire sale of assets, banks may hoard liquidity. However, both asset sales and liquidity hoarding create negative perception for other financial institutions and are therefore detrimental to the stability of the financial industry. Fire sale of less liquid assets on an immediate basis reduces asset prices either because buyers are uncertain about the value of the assets or because they need liquidity themselves. On

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the other hand liquidity hoarding is detrimental because when one financial institution stops providing liquidity to others, the other institutions also may be forced to hoard liquidity or sell assets leading to a chain effect that spreads throughout the system, see Acharya and Merrouche (2012), Heider *et al* (2010) and Kowalik (2013). The adverse effect is that financial institutions holding similar assets are forced to mark down their holdings because of accounting and regulatory rules. According to Brunnermeier and Pedersen (2008), marked down assets reduce the liquidity level and institutions end having to fund the gap through forced sell of assets, fuelling a cycle of falling prices.

The effectiveness of liquidity buffers depends on the institution's own characteristics such as the structure of their liabilities and capital, their risk profile, their size, their business activities, and the supervisory and political environments in which they operate. Liquidity buffers must be built using cash and assets that ensure the generation of liquidity within a short time at a predictable value. The buffer should be composed mainly of cash and the most reliably core liquid assets that are both central bank eligible and highly liquid in private markets even in stressed circumstances which banks can sell or repurchase regardless of their condition without accepting large 'fire sale' discounts. The Committee of European Banking Supervisors (2010) proposed that eligible cash exclude cash that is unavailable due to business-as-usual requirements such as automated teller machines. A financial institution needs to balance between eligible assets that are too broad and too narrow in terms of liquidity quality. However it is tricky for the bank to include too broad liquid assets since the assets may not be liquid when needed and may compromise the purpose of liquidity buffer. On the other hand, too narrow liquid assets may lead to limited supply of such assets and may result in several unintended consequences.

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As proposed by the Basel Committee, banks should impose limits on the inclusion of less-liquid assets in the buffer by setting a fixed limit on their share of the buffer and imposing haircuts on their market value. A haircut, according to the Basel Committee on Banking Supervision (2010) is discounting low liquid assets at their current market value. The buffer represents available liquidity covering the additional need for liquidity that may arise over a defined short period of time under stressed conditions and banks should avoid holding large concentrations in particular assets. The more liquid assets banks hold, the less liquidity risk they face. However the bank should balance between the two extreme situations that is excess liquidity and inadequate liquidity through skilful liquidity management which we propose in this thesis.

5.3 Model Formulation

The location and size of liquidity buffers within a banking group should adequately reflect the structure and activities of the group in order to minimise the effects of possible legal, regulatory or operational impediments to using the assets in the buffer. The management needs to decide on the size of the initial liquidity buffer to hold so as to protect itself against stochastic liquidity demand. We present visual components on how to construct a core liquidity portfolio. The core liquidity portfolio is funded by equity. The bank invests the proceeds in cash and core liquid assets that are both central bank eligible and highly liquid in private markets. Thus at each beginning of instant time, the bank decides on how much to invest in high quality liquid assets to satisfy the liquid asset reserve requirement. In between instant times, the bank is exposed to exogenous liquidity demand and the liquidity buffer is depleted. The bank needs to make recourse decisions to maintain the liquidity buffer. We start by defining the decision variables and pa-

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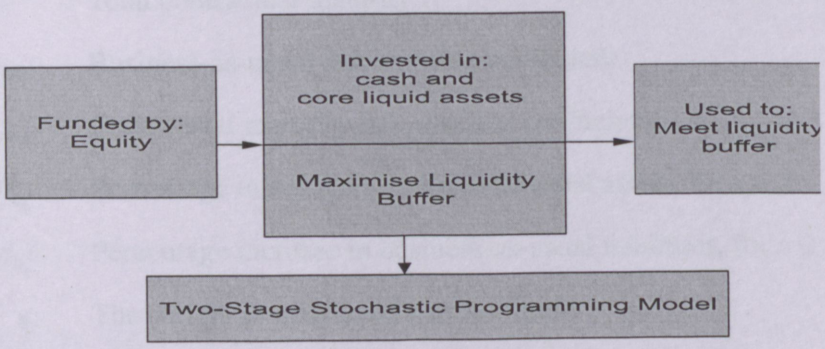
Figure 5.1: Core Liquidity Portfolio Formulation



rameters that we used as follows;

Definitions of Sets

T	Set of time space
I	Set horizon bands
s_n	Set of scenarios, for $n \in N$
Ω_1	Set of event space for the unknown liquid asset return
Ω_2	Set of event space for the unknown cost of liquid asset
$P_{\omega_j^1}$	Set of probabilities of event space for the unknown liquid asset return, where $j \in J$
$P_{\omega_k^2}$	Set of probabilities of event space for the unknown cost of liquid asset, where $k \in K$
P_{s_n}	Set of scenario probabilities, for $s_n \in S$

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Deterministic Data

F_0	Initial liquidity buffer
q_0^{AB}	Liquid assets held at stage 0 under uncertain liquid asset returns
C^M	Total contractual maturity
ϑ_{bau}	Business-as-usual risk aversion coefficient
ϑ_{cont}	Contractual maturity risk aversion coefficient
$\beta_{b_i^A}$	Percentage increase in business-as-usual assets, for $i \in I$
$\beta_{b_i^L}$	Percentage increase in business-as-usual liabilities, for $i \in I$
ψ	The weight of additional needed funds
λ	The coefficient of business-as-usual net funding gap

Random Data

$b_{its_n}^A$	Business-as-usual assets, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^L$	Business-as-usual liabilities, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^{Az}$	Business-as-usual asset advance, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^{Ad}$	Business-as-usual asset trading, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^{Aa}$	Business-as-usual other asset, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^{Le}$	Business-as-usual stable deposits, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^{Lv}$	Business-as-usual volatile deposits, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^{Lh}$	Business-as-usual trading and hedging instruments, for $i \in I$, $t \in T$, and $s_n \in S$
$b_{its_n}^{Ll}$	Business-as-usual other liabilities, for $i \in I$, $t \in T$, and $s_n \in S$
$c_{its_n}^A$	Contractual maturity of assets, for $i \in I$, $t \in T$, and $s_n \in S$
$c_{its_n}^L$	Contractual maturity of liabilities, for $i \in I$, $t \in T$, and $s_n \in S$
$c_{its_n}^{Az}$	Contractual maturity of assets advance, for $i \in I$, $t \in T$, and $s_n \in S$

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$c^{Ad}_{its_n}$ Contractual maturity of assets trading, for $i \in I$, $t \in T$, and $s_n \in S$

$c^{Aa}_{its_n}$ Contractual maturity of other assets, for $i \in I$, $t \in T$, and $s_n \in S$

$c^{Le}_{its_n}$ Contractual maturity of stable deposits, for $i \in I$, $t \in T$, and $s_n \in S$

$c^{Lv}_{its_n}$ Contractual maturity of volatile deposits, for $i \in I$, $t \in T$, and $s_n \in S$

$c^{Lh}_{its_n}$ Contractual maturity of trading and hedging instruments, for $i \in I$, $t \in T$, and $s_n \in S$

$c^{Ll}_{its_n}$ Contractual maturity of other liabilities, for $i \in I$, $t \in T$, and $s_n \in S$

$c^{M}_{its_n}$ Net contractual maturity, for $i \in I$, $t \in T$, and $s_n \in S$

r_{its_n} Liquid asset returns, for $i \in I$, $t \in T$, and $s_n \in S$

Decision Variables

$b^{G}_{its_n}$ The business-as-usual net funding gap, for $i \in I$, $t \in T$, and $s_n \in S$

$f^{D}_{its_n}$ Planned additional funds, for $i \in I$, $t \in T$, and $s_n \in S$

$q^{AE}_{its_n}$ Liquid asset bought to maintain liquidity buffer, for $i \in I$, $t \in T$, and $s_n \in S$

$q^{AB}_{its_n}$ Liquid assets held at stage t under uncertain liquid asset returns, for $i \in I$, $t \in T$, and $s_n \in S$

5.3.1 Liquidity Buffer Scenario Tree

We need to construct a scenario for a random variable liquid asset returns. Now consider a case where the random vector S_t, has a discrete and finite distribution, with s scenario set $S = \{s_1, s_2, ..., s_N\}$. Denote p_{s_n} as the probability of realization of the nth scenario s_n. We assume that $p_{s_n} \geq 0$ for all $s_n \in S$ and that $\sum_{n \in N} p_{s_n} = 1$. A scenario is defined as a path from the root of the tree to one of the leaves. The nodes visited by each path correspond to the values assumed by random parameters in the model. Now we assume liquid assets return can be

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computed as;

$$r_t = \frac{(1+r_a)(q_t^{AB} - C_{CB}) + (1+r_{CB})C_{CB} - q_t^{AB}}{q_t^{AB}} \tag{5.1}$$

where r_t is the liquid assets returns at time t. The r_a and r_{CB} are the interest rate on interest earning liquid assets and interest rate on cash reserves deposited with central bank, respectively. We assume that $r_a \geq r_{CB}$. The cash reserve deposited with central bank is C_{CB}. Now, we can define a scenario generation model by the equation;

$$r_{i(t+1)s_n} = \mu_{q_t^{AB}} + \gamma_{CI}\delta_{q_t^{AB}}\epsilon_{t+1} \tag{5.2}$$

where we assume ϵ_{t+1} to be the random error with mean 1 and γ_{CI} is the standard normal value at confidence interval level CI. The scenario tree is then constructed as shown in Figure 5.1. In the scenario tree at stage 0, the q_0^{AB} represents the initial liquid assets to be decided under the event space having three possibilities $\Omega_1 = \{\omega_1^1, \omega_2^1, \omega_3^1\}$, with corresponding probabilities $p_{\omega_1^1}, p_{\omega_2^1}$ and $p_{\omega_3^1}$. The event space Ω_1 represents uncertain liquid asset returns. At the beginning of stage 1, the liquid asset returns are revealed. A recourse decision to buy additional liquid assets $q_1^{AE}(\omega_j^1)$ is made at the end of stage 1 under event space $\Omega_2 = \{\omega_1^2, \omega_2^2, \omega_3^2\}$ with corresponding probabilities $p_{\omega_1^2}, p_{\omega_2^2}$ and $p_{\omega_3^2}$. At the beginning of stage 2, the money market announces the cost of liquid assets. We need to note that the event space Ω_2 is the uncertain costs of liquid assets. The liquid asset return and cost of liquid asset event spaces probability must satisfy the following conditions; $\sum_{j\in J} p_{\omega_j^1} = 1$ and $\sum_{k\in K} p_{\omega_k^2} = 1$, respectively. Once the cost of liquid assets event space $\omega_k^2 \in \Omega_2$ in stage 2 has been observed, the liquidity buffer $F_2(\omega_k^2)$ is computed by the model as the final decision bank liquidity buffer. It should be noted that the unconditional probability of each node in the scenario is computed as the product of probability of the arcs from the root node to termination node and is given by $p_{s_n} = p_{\omega_j^1} p_{\omega_k^2}$. Each root-leaf path from the scenario tree defines

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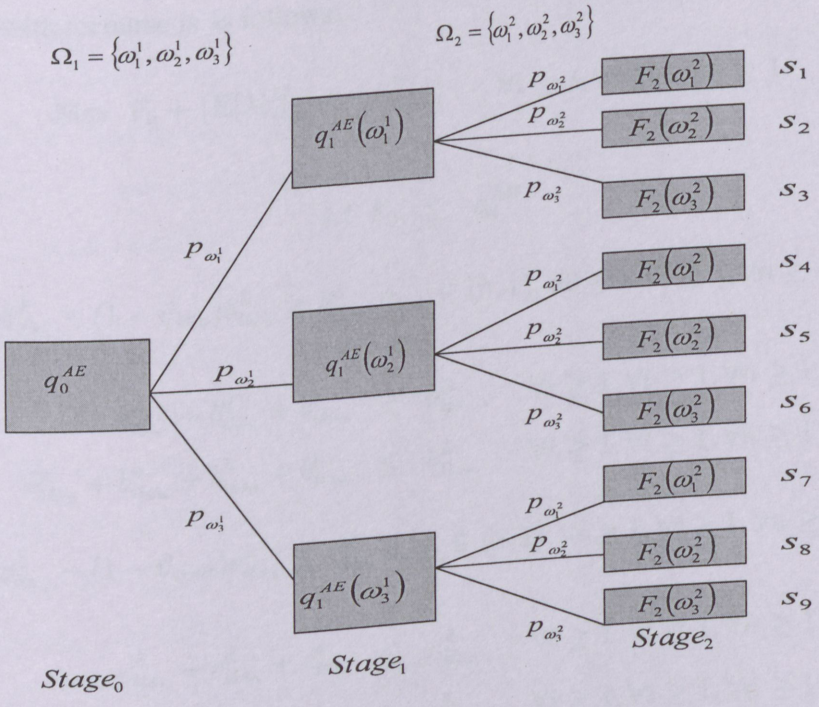
Figure 5.2: Liquidity Buffer Level Scenario Tree



scenario s_n, induced by a sequence of all random events. There is a one-to-one correspondence between the scenarios and the leaf-nodes in our tree.

5.3.2 Core Liquidity Stochastic Programming Model

The advantage of stochastic programming models is that they provide a generic framework to model uncertainties and enables sound decisions that will perform well in the general case. In this model, we need to maximise liquidity buffer requirement. According to the Committee of European Banking Supervisors (2009) and Chagwiza *et al* (2015b), we define liquidity buffer as a subset of counterbalancing capacity. The counterbalancing capacity is partitioned into business-as-usual view, planned stress view and protracted stress view. So in this case, liquid-

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ity buffer is planned stress view. Therefore, the two-stage stochastic programming model with recourse is as follows;

$$\text{Max } F_0 + \{\mathbb{E}[\lambda b^G_{itsn} + \psi f^D_{itsn}]\} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.3}$$

$$s.t \; F_0 \leq q_0^{AB} \tag{5.4}$$

$$\vartheta_{bau} b^A_{itsn} - (1 - \vartheta_{bau}) b^L_{itsn} \geq b^G_{itsn} \; \vartheta_{bau} \in (0,1), \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.5}$$

$$b^z_{itsn} + b^d_{itsn} + b^a_{itsn} \geq b^A_{itsn} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.6}$$

$$b^e_{itsn} + b^v_{itsn} + b^h_{itsn} + b^l_{itsn} \leq b^L_{itsn} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.7}$$

$$\vartheta_{cont} c^A_{itsn} - (1 - \vartheta_{cont}) c^L_{itsn} \leq c^M_{itsn} \; \vartheta_{cont} \in (0,1), \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.8}$$

$$c^z_{itsn} + c^d_{itsn} + c^a_{itsn} \leq c^A_{itsn} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.9}$$

$$c^e_{itsn} + c^v_{itsn} + c^h_{itsn} + c^l_{itsn} \geq c^L_{itsn} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.10}$$

$$(1 + \beta_{b_i^A}) b^A_{itsn} - (1 + \beta_{b_i^L}) b^L_{itsn} - c^M_{itsn} \geq f^D_{itsn} \; \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.11}$$

$$\sum_{i \in I} q^{AE}_{itsn} \leq Q \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.12}$$

$$(1 + r_{itsn}) q^{AB}_{itsn} + q^{AE}_{itsn} - \psi f^D_{itsn} \geq b^G_{itsn} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{5.13}$$

$$F_0 \geq 0, b^A_{itsn} \geq 0, b^L_{itsn} \geq 0, b^z_{itsn} \geq 0, b^d_{itsn} \geq 0, b^a_{itsn} \geq 0, b^G_{itsn} \geq 0, f^D_{itsn} \geq 0 \tag{5.14}$$

$$b^e_{itsn} \geq 0, b^v_{itsn} \geq 0, b^h_{itsn} \geq 0, b^l_{itsn} \geq 0, c^A_{itsn} \geq 0, c^L_{itsn} \geq 0, c^M_{itsn} \geq 0, q^{AB}_{itsn} \geq 0$$

$$c^e_{itsn} \geq 0, c^v_{itsn} \geq 0, c^h_{itsn} \geq 0, c^l_{itsn} \geq 0, c^z_{itsn} \geq 0, c^d_{itsn} \geq 0, c^a_{itsn} \geq 0, q^{AE}_{itsn} \geq 0$$

The objective (5.3) is to maximise liquidity buffer and is computed based on the clean market to market value of the securities. We need to note that $q_0^{AB} = r_0 + x_0 + y_0$ since the initial liquidity buffer includes eligible securities especially

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designated money market funds and central bank reserves and deposits, which are liquid assets. The first stage constraint is denoted by constraint (5.4), where the initial liquid assets held is the initial buffer. The constraint (5.5) is the business-as-usual net funding gap as the difference between the business-as-usual assets and liabilities. The constraints (5.6) and (5.7) are business-as-usual assets and liabilities, respectively.

The net contractual maturity is denoted by constraint (5.8). The contractual maturity of assets and liabilities are denoted by constraints (5.9) and (5.10), respectively. The constraint (5.11) denotes the planned additional funds model which is defined as the difference between an anticipated increase in business-as-usual assets $(1 + \beta_{b_i^A}) b^A_{its_n}$ and the anticipated increase in business-as-usual liabilities $(1 + \beta_{b_i^L}) b^L_{its_n}$ and deducting the net contractual maturity. We need to note that $\beta_{b_i^A} \in (0, 1)$ and $\beta_{b_i^L} \in (0, 1)$. The constraint in (5.12) is the total value of liquid assets the bank is able to buy to meet the liquidity shortfall. The re-balancing constraint is constraint (5.13) that shows the relationship between the additional funds needed and the business-as-usual net funding gap. Finally, the constraint (5.14) denotes the non-negativity constraints.

5.4 Statistical Characteristics of Historical Data

We calibrate our two-stage stochastic programming model using the following data; actual liquid assets held and cash reserves requirement readily available at South African Reserve Bank. The considered data is from year January 1988 to year April 2014. We do not explicitly assume a specific stochastic process for the liquid asset return but viewed it as an independent and identically distributed random variable; and we rely on empirical data distributions. The Lingo 14 software was used to solve the constructed two-stage stochastic programming model with

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recourse. The constructed two-stage stochastic model is assessed for its viability and performance using the South African Reserve Bank. The statistical characteristics of historical data are represented in Table 5.1 below. From Table 5.1, the

Table 5.1: Statistical Characteristics of Historical Data

Statistical Measure	Liquid Assets Held	Cash Reserves	Liquid Asset Returns
Average	1.39788×10^{5}	3.5344×10^{4}	4.01228×10^{-2}
Standard Deviation	9.7145×10^{4}	1.9785×10^{4}	2.842×10^{-3}
Kurtosis	-1.0294046	-1.411302186	-1.269907032
Skewness	$6.87005958 \times 10^{-1}$	$1.41679602 \times 10^{-1}$	$-4.0141792 \times 10^{-2}$
Minimum	3.6634×10^{4}	6.311×10^{3}	-1.269907032
Maximum	3.27016×10^{5}	7.0161×10^{4}	4.6264502×10^{-2}

historical liquid assets and cash reserve requirement data exhibit skewed distributions. Comparing the standard deviation with mean, we can see that they exhibit considerable variance. The random variable liquid asset returns exhibit platykurtic, implying less peaked than the normal distribution. Thus, we need to generate scenarios for liquid asset returns that comply with historical observations, without relying on the normality assumption. We rely solely on the observed actual liquid asset held, cash reserve requirement and liquid asset returns in the market. The estimated first four moments are presented in Table 5.1 and we generate scenarios based on these statistical characteristics. The scenarios generated should replicate their historical values for the scenario generation model to be useful.

5.5 Empirical Analysis

In this section, we present and discuss the performance of our model. We start by analysing the stochastic programming solution status by observing the global optimal status. In this case, solution status is globally optimal implying that the

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results are valid. Now we turn to Table 5.2 where results of different components are shown. Of prime importance, are the stochastic objective values, which are the expected objective values over all different cases and scenarios. We assume that

Table 5.2: Stochastic Programming Solution when $\vartheta_{bau} = 15\%$ and $\vartheta_{cont} = 20\%$

Value	Obj (10^8)	Inf	EV (10^8)	EWS (10^8)	EVPI (10^{-8})	EM (10^8)	EVMU (10^{-8})
$\beta_1 = 0.2$ $\beta_2 = 0.2$	3.6061	0	3.6061	3.6061	5.9605	3.6061	11.921
$\beta_1 = 0.3$ $\beta_2 = 0.2$	3.6061	0	3.6061	3.6061	5.9605	3.6061	5.9605
$\beta_1 = 0.5$ $\beta_2 = 0.4$	3.6061	0	3.6061	3.6061	0	3.6061	5.9605
$\beta_1 = 0.5$ $\beta_2 = 0.5$	3.6061	0	3.6061	3.6061	0	3.6061	5.9605
$\beta_1 = 0.5$ $\beta_2 = 0.6$	3.6061	0	3.6061	3.6061	0	3.6061	5.9605
$\beta_1 = 0.6$ $\beta_2 = 0.4$	3.6061	0	3.6061	3.6061	0	3.6061	5.9605
$\beta_1 = 0.6$ $\beta_2 = 0.5$	3.6061	0	3.6061	3.6061	0	3.6061	5.9605

as β_1 changes regardless of whether β_2 is changing or not and when all other parameters are constant, the overall optimal liquidity buffer should at least change. However from Table 5.2, this is not the case and the liquidity buffer is constant throughout. Similarly the EV of liquidity buffer, EWS of liquidity buffer and EM of liquidity buffer are constant regardless whether β_1 and β_2 change. The basic facts and notations of stochastic programming are explained in Appendix.

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We check whether the model is feasible and in our case, the infeasibility value is zero in all cases implying that no constraints were violated in the deterministic equivalent model. The EV of liquidity buffer is the same as the reported optimal liquidity buffer for the model, further giving weight to the results. The EWS liquidity buffer reports the expected value of the liquidity buffer if we could wait-and-see the outcomes of all liquid asset returns and uncertain costs of liquid assets borrowed to cover the liquidity gap before making decisions. However, in reality it is not possible to wait. Comparing the values of EWS and EV, we expect $EWS \geq EV$ since we are maximising liquidity buffer.

The EVPI is the expected increase in liquidity buffer if we know the future outcome in advance. Thus EVPI is used to compare EWS and EV and measures the maximum amount the decision maker should be willing to pay in return for complete and accurate information regarding the future outcomes of the underlying liquid asset returns. EVPI is the difference between EV and EWS. From Table 5.2, when $\beta_1 = 20\%$ and $\beta_2 = 20\%$, and $\beta_1 = 20\%$ and $\beta_2 = 30\%$ the EVPI is non-zero. However for all other values of β_1 and β_2, the EVPI is zero. Therefore in all cases, the average ratio of total EVPI to total optimal liquidity buffer value is very small and close to zero implying that the decision maker is willing to pay nothing per given period. According to Kall and Wallace (2003), small EVPI shows that randomness plays a minor role in the model. The EM is slightly different from the expected true liquidity buffer as evidenced by EVMU. The EVMU also known as the value of stochastic solution (VSS), is the expected decrease in liquidity buffer if we replaced each stochastic parameter by a single estimate and act as if this value is certain. The $EVMU = EV - EM$ is non-zero in all cases but very small indicating that we gained little by taking into account uncertainty in our model analysis.

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In other words, EVMU measures how good or bad a decision obtained by EV is. In this case, $EV \geq EM$, implying that the model is good since there is a very small difference between EV and EM, and there is no potential for improvement. Therefore, we can observe that $EV \leq EM \leq EWS$, $EVPI \geq 0$ and $EVMU \geq 0$ which are consistent with Barbaro and Bagajewicz (2004) and Birge (1997) conditions. Therefore, at this level, we can infer that the scenarios generated are reliable and valid. We need to note that in some circumstances, there are explicit tradeoffs based on processing all relevant information. We do have situations which are not consistent with Birge (2013) conditions where both EVPI and EVMU are non-zero.

Turning to Table 5.3, when $\beta_1 = 20\%$ and $\beta_2 = 20\%$, the bank has to buy liquid assets in all bands except band 2 to meet the required liquidity buffer. However, when β_1 and β_2 take any other value, the bank has to buy liquid assets in bands 1, 2 and 4.

The change in risk aversion coefficient and other variables remains the same and will only change the stage 0 solution. Here, the value of recourse decision changes as risk aversion coefficients change. However, the stochastic programming solution such as objective value, EV, WS, EVPI, EM, EVMU and random distribution will remain the same in all cases. Table 5.4 shows the liquid assets bought under different values of risk aversion coefficient. When ($\vartheta_{bau} = 4\%$ and $\vartheta_{cont} = 9\%$), and ($\vartheta_{bau} = 10\%$ and $\vartheta_{cont} = 10\%$), the bank should be prepared to purchase liquid assets in all bands. However, when $\vartheta_{bau} = 40\%$ and $\vartheta_{cont} = 20\%$ the bank should buy liquid assets in bands 2 and 5 only.

With reference to Table 5.5, the random distribution of liquid asset return is constant regardless of the values of (β_1 and β_2), and (ϑ_{bau} and ϑ_{cont}). Applying

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Table 5.3: Liquid Assets Bought - Stage 0 Solution

Bands	$\beta_1 = 0.2$ $\beta_2 = 0.2$	$\beta_1 = 0.3$ $\beta_2 = 0.2$	$\beta_1 = 0.5$ $\beta_2 = 0.4$	$\beta_1 = 0.6$ $\beta_2 = 0.5$
1	2.9565 x 10^7	3.5763 x 10^7	1.1495 x 10^8	9.9442 x 10^7
2	0	1.2093 x 10^8	1.0726 x 10^7	1.0726 x 10^7
3	2.4534 x 10^7	0	0	0
4	1.9890x 10^7	2.0128 x 10^8	2.3230 x 10^8	2.4781 x 10^8
5	1.5420 x 10^7	0	0	0
6	2.6779 x 10^7	0	0	0
7	4.4377 x 10^7	0	0	0
8	1.9741 x 10^8	0	0	0

Table 5.4: Changes in Risk Aversion Coefficient - Liquid Asset Bought

Bands	$\vartheta_{bau} = 0.04$ $\vartheta_{cont} = 0.09$	$\vartheta_{bau} = 0.1$ $\vartheta_{cont} = 0.1$	$\vartheta_{bau} = 0.4$ $\vartheta_{cont} = 0.2$
1	7.6437 x 10^6	1.9601 x 10^7	0
2	1.3825 x 10^8	7.0254 x 10^7	2.9155 x 10^7
3	6.3011 x 10^6	1.6246 x 10^7	6.5974 x 10^7
4	5.0557 x 10^6	1.3147 x 10^7	6.9941 x 10^7
5	3.8677 x 10^6	1.0169 x 10^7	1.9291 x 10^8
6	6.8998 x 10^6	1.7743 x 10^7	0
7	1.1597 x 10^7	2.9477 x 10^7	0
8	1.7835 x 10^8	1.8134 x 10^8	0

scenario generation method in equation (5.3), we obtain scenarios for the liquid asset return. The resulting scenarios are equiprobable in our tests, but generally they do not have to be.

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Table 5.5: Liquid Asset Return Distribution Report

Bands	Sample Mean	Sample Standard Deviation
1	4.01562×10^{-2}	1.5040×10^{-5}
2	4.01457×10^{-2}	1.81231×10^{-5}
3	4.0162×10^{-2}	1.2942×10^{-5}
4	4.0140×10^{-2}	1.51683×10^{-5}
5	4.0143×10^{-2}	1.5890×10^{-5}
6	4.01463×10^{-2}	1.5189×10^{-5}
7	4.01478×10^{-2}	1.70903×10^{-5}
8	4.01515×10^{-2}	1.56129×10^{-5}

5.6 Conclusion

The general practice of the banking industry is to hold a unitary liquidity portfolio, not necessarily a segmented one to focus on banks specific liquidity needs. A bank needs to establish a core liquidity portfolio that ensures adequately resourced liquidity buffer. Liquidity buffer is liquidity that is readily available to be used in liquidity stress situations within a given short-term period. The size of liquidity buffer should be determined according to the funding gap under stress conditions over specified time. The assets chosen for the core of the buffer need to be liquidable with a greater degree of confidence. A two-stage stochastic programming model with recourse to maximize liquidity buffer was constructed. A scenario generation model to generate liquid asset return scenarios is developed. The liquid asset return is stochastic and therefore, we represent it on a scenario tree. From Lingo solution output, we observed that the model is feasible. We further analysed whether the scenarios are reliable and valid. After assessing the value of stochastic solution, we inferred that the scenarios generated and results computed are reliable and valid. In addition, the expected value of modelling uncertainty is

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non-zero in all cases. This implies that we really benefited by taking into account the liquid asset return randomness. We need to note that stochastic programming provides important information that can be made under risk. The models assist us in finding the relationship of the optimal liquidity buffer to stochastic models and deterministic models when expected outcomes are derived from a situation of random nature. In designing the portfolio, liquid asset returns are uncertain, and to avoid liquidity problems that may arise, we need to include randomness of asset returns. Taking into consideration liquid asset return ensures the readiness of the bank is preparing for the worst-case scenarios. Understanding the behaviour of liquid asset returns processes studied by deterministic models with regard to creation of liquidity buffers compared to those processes investigated by SP reveals some general aspects of underlying liquidity problems. Those are, clearly, better predicted by the stochastic model. The model performed as expected. Ignoring uncertainty when making decisions may have serious consequences to the bank. By taking into account randomness, the bank is self-insuring against adverse asset price movements. Research can be done on how to compute appropriate liquidity buffer and balance between the broad liquid assets and narrow assets. In addition, tentative research can be done on other methods that can be used to determine the optimal liquidity buffer and compare it with the stochastic programming solution.

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CHAPTER 6

6 CASH CUSHION MANAGEMENT STOCHASTIC PROGRAMMING MODELS

6.1 Introduction

In the growing and profitable market of money lending business, liquidity risk often becomes a secondary concern for the managers of banks. The aggressive expansion of lending operations that became possible through securitisation of loan portfolios helped the banks to further ignore liquidity risk and expand the asset portfolio even on thin capital base. Anticipated expenses are typically paid for with cash that is reserved in some portion in the operational cash portfolio. Anticipated liquidity activites such as home purchases need to be planned for from a liquidity perspective. Positive liquidity events such as inheritance or other anticipated cash inflows can be covered in the liquidity section. However unanticipated cash needs can be met by a cash cushion portfolio, the amount of which is client-specific. For unanticipated expenses, cash cushion portfolio is crucial. The portfolio helps the bank to avoid selling assets to raise money to meet obligations. The cash quota of the overall liquidity portfolio has the function of both enabling flexibility and limiting risk. The portfolio offers the advantage of not having to touch existing positions in cash of liquidity outflows. We need to note that day-to-day price of an asset is not very important but what is important is the price of the asset on the day the bank needs to sell it. This is the reason the bank should have a cash cushion portfolio that will cover bank's nasty surprises. Therefore, banks need a cash cushion portfolio to sustain itself and manage liquidity and in our research, the crucial aspect of the portfolio is the interest rate spread earned.

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Literature on the subject of interest rate spreads is diverse in its approaches and applications. The researches predominantly focus on the determinants of interest rate spread, see Afzal and Mirza (2010), Dumičić and Ridzak (2013), Kit (1997), Männosoo (2012), Perez (2011), Raharjo *et al* (2014), Romero and Rodriguez (2011) and Siddiqui (2012). Lartey *et al* (2013) researched on the trends of the net interest margin and return on assets and their relationship. The investigation by Afroze (2013) focused on the overall idea on trend on the movement and trends of interest rate spread in Bangladesh. The methods on how banks manage net interest margin is explained by Memmel and Schertler (2011) and decomposed the change in banks' net interest margin into change in market-wide rates and a change in the balance sheet composition. Urgur and Erkus (2010) investigate the determinants of the net interest margins of domestic and foreign banks in Turkey. Kit (1997) findings confirm that the optimal interest margin has a positive relation with the bank's market power, with the operating costs, with the degree of interest rate risk and the degree of credit risk.

While research has so far focused on the determinants of interest rate spread and levels of interest spread, less has been said on interest rate spread as a strategy to manage liquidity. Banks are exposed to interest rate risk which has a direct effect on liquidity and they prefer to hold cash to cushion themselves against price volatility and uncertain demand deposits. However, holding money market instruments is a more desirable strategy than cash since money market instruments earn interest. Staying away from loans may have an effect on bank's profitability and therefore, borrowing and lending is part of the game. Therefore, the bank needs to set up a sub-portfolio which will specifically focus on holding cash in transit, and earn interest on those short-term instruments. Thus the main purpose of the research is to investigate the importance of the cash cushion portfolio in

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enhancing proper liquidity management. We construct the two-stage stochastic programming model with recourse to maximise interest spread earned to achieve bank's liquidity management objectives, which best to our knowledge has not been researched and published in internationally recognised journals. The Asian Development Bank (2013) partitioned the overall liquidity portfolio to have a cash cushion sub-portfolio which contains proceeds of the bank's borrowing transactions pending disbursements of these funds. To achieve our objectives, the chapter is structured as follows. The first part envisages the empirical interest rates. Secondly, we present a scenario generation model to compute loan return and leads to a construction of a two-stage stochastic programming model with recourse. Further, we describe the statistical characteristics of historical data. Finally, the analytical results from a two-stage stochastic programming model with recourse are presented and the chapter is concluded.

6.2 Interest Rates Spread

Banks charge a fee which is the spread for the provision of immediacy in offering loan and deposit service to their customers. The definition of interest rate spread varies among authors and there is no consensus on the best measure for interest rate spread. Here we define interest rate spread according to Afroze (2013) as the difference between interest charged on borrowers and interest paid by the bank to lenders. Sensarma and Ghosh (2004) pointed out that higher net interest spread signifies the lack of competition in the industry while, lower net interest spread put stress on the profitability of banks. Interest rate play a key role in amplifying or reducing the losses of banks enduring liquidity shocks. It influences the banks' portfolio decision for holding short-term liquid assets and long-term illiquid assets. There are two approaches for measuring interest rate spreads which are the ex-ante and the ex-post. The ex-ante interest rate spread is the difference between

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the contractual rates charged on loans and the rates paid on deposits. The average rate charged on loans and average rate paid on deposits is the ex-post interest rate spread (Lartey *et al*, 2013). The fee constitutes a cost to the non-financial sector and income for the banks. However, according to Maännasoo (2012), affordable lending rates are a critical factor in enhancing credit access, but at the same time the interest spreads have to cover the banks' costs and risks arising from the funds intermediation. The strong impact of interest spreads on the economic environment is well substantiated and widely recognised. Bank pure spreads are mainly determined by the risk aversion and the market structure of the banking sector, therefore spreads are an important source for the build up of cash cushion portfolio for covering potential losses. Freixas *et al* (2010) develop a model of the interbank market and show that the central bank's interest rate policy can directly improve liquidity conditions in the interbank lending market during a financial crisis.

Lower interest spreads facilitate the access of entrepreneurs and households to credit and enhance economic growth. The arrival of loan requests and deposit supplies is random and exogenous to the bank. The only possible way for the bank to influence the balance between the supply of deposits and demand for loans is to impose a fee over the expected risk-free interest rate. Cash cushion portfolio is the intermediate portfolio of bank's liquidity portfolio. This enhanced cash cushion portfolio acts as a cushion in the event of unforeseen cash needs. The portfolio is expected to provide a higher return than the core liquidity portfolio over a market cycle. Interest expense is payable on deposits, interbank funding and wholesale funding. Wholesale funding consists of debt maturing within one year and longer debt maturing more than one year. Interest income is generated by interbank claims, net loans and investments. The strong liquidity position en-

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ables the banks to offer more favourable rates to their customers. During times of financial market turmoil, the banks with higher liquidity buffers have been able to exert more control over the upward trend in spreads. Therefore bank spread is influenced by credit risk, interest rate risk, market risk, degree of risk aversion and liquidity. There is a trade-off between liquidity and interest rate margins, banks with a higher proportion of liquid assets are likely to generate lower spreads.

6.3 Model Formulation

In our research, the cash cushion portfolio is initially funded by bank's capital and invested in short term investments. In any given period, the portfolio enjoys interest spread as income and it sustains itself. The portfolio does not earn high supplemental income, and therefore is subject to high risk. In other words, the portfolio begins to replicate itself through reinvestment of interest spread earned from short term assets. The cash held should be kept to the minimum needed to meet the above requirements and facilitate smooth operations. Thus the interest spread has to cover the banks' costs and risks arising from the funds intermediation process. The arrival of loan requests and deposit supplies, according to Männosoo (2012), is random and exogenous to the bank such that the only way to influence the balance between the supplies of deposits and demand for loans is to impose a fee. We assume that the institutions distinguish between general debt and funding for liquidity purposes. We further assume that the cost of general borrowing is distinct from cost of funding liquidity under financial stress. We define the notations used in our model.

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Definitions of Sets

T	Set of time space
B	Set horizon bands
G	Set of different types of loans
Q	Set of different types of borrower
s_n	Set of scenarios, for $n \in N$
Ω_1	Set of event space for the unknown loan return
Ω_2	Set of event space for the unknown loan price
$P_{\omega_j^1}$	Set of probabilities of event space for the unknown loan return, where $j \in J$
$P_{\omega_k^2}$	Set of probabilities of event space for the unknown loan price, where $k \in K$
P_{s_n}	Set of scenario probabilities, for $s_n \in S$

Deterministic Data

β	The proportion of deposit the bank must provide as reserve to central bank
x_0	Initial interest spread earned
W^ϕ	Total amount readily available for bank to borrow
V	Amount of initial spread earned
α_C	The risk aversion coefficient
ψ	The recovery rate
r_b^L	Interest rate charged on loans, for $b \in B$
r_b^D	Interest rate paid on deposits, for $b \in B$

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Random Data

$l^{m}_{bts_n}$ Mortgage loans, for $b \in B$, $t \in T$, and $s_n \in S$

$l^{a}_{bts_n}$ Consumer credit loans, for $b \in B$, $t \in T$, and $s_n \in S$

$l^{ch}_{bts_n}$ Corporate short-term loans, for $b \in B$, $t \in T$, and $s_n \in S$

$l^{cg}_{bts_n}$ Corporate long-term loans, for $b \in B$, $t \in T$, and $s_n \in S$

x_{bts_n} Interest spread earned, for $b \in B$, $t \in T$, and $s_n \in S$

$d^{v}_{bts_n}$ Savings deposits, for $b \in B$, $t \in T$, and $s_n \in S$

$d^{a}_{bts_n}$ Call deposits, for $b \in B$, $t \in T$, and $s_n \in S$

$d^{z}_{bts_n}$ Fixed and notice deposits, for $b \in B$, $t \in T$, and $s_n \in S$

$d^{o}_{bts_n}$ Negotiable certificates of deposits, for $b \in B$, $t \in T$, and $s_n \in S$

$d^{u}_{bts_n}$ Repurchase deposits, for $b \in B$, $t \in T$, and $s_n \in S$

$y^{L}_{bts_n}$ Loans return, for $b \in B$, $t \in T$, and $s_n \in S$

Decision Variables

f_{bts_n} Provision for loan default, for $b \in B$, $t \in T$, and $s_n \in S$

L_{bts_n} The loan issued, for $b \in B$, $t \in T$, and $s_n \in S$

D_{bts_n} The deposits received, for $b \in B$, $t \in T$, and $s_n \in S$

W_{bts_n} Non-deposit debt, for $b \in B$, $t \in T$, and $s_n \in S$

6.3.1 Interest-Earned Spread Scenario Tree

The scenario generation is a critical step for the entire modelling process. A set of representative scenarios is needed that adequately depicts the anticipated evolution in the values of the random variable loan return and is consistent with market observations and financial theory. The loan return is stochastic and therefore we represent it on a scenario tree. To construct a scenario tree, we consider now the

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case where the random vector S has a discrete and finite distribution, with n scenario set $S = \{s_1, .., s_n, ..., s_N\}$. We assume that $p_{s_n} \geq 0$ for all $s_n \in S$ and that $\sum_{n \in N} p_{s_n} = 1$. We need to note that a scenario is a path from the root of the tree to one of the leaves. The nodes visited by each path correspond to the values assumed by random parameters in the model. Before we define the scenario generation model, we define the model for computing loan return basing on Mencia (2012) model. We consider that the loan portfolio is having g different types of loans according to types of borrowers and the amount q in each borrower type, then the realisation on loan is generated by;

$$\rho_g = (1 + r_g) \sum_{q \in Q} (L^{qg} - F^{qg}) + \sum_{q \in Q} \psi^{qg} F^{qg} \tag{6.1}$$

where r_g is the net interest required by the bank, L^{qg} is volume of loan g from type q. The recovery rate $\psi^{qg} \in (0, 1)$ is stochastic in case of default and is a proportion of amount that is owed. The default is the volume of non-performing loans and is represented by F^{qg}.

Intuitively from equation (6.1), each borrower will either repay the principal plus interest or default, in which case the bank will receive the recovery rate times the outstanding amount. Therefore, the loan return can be computed as follows;

$$\sum_{g \in G} y^g = \frac{\sum_{g \in G} \rho_g - \sum_{g \in G} \sum_{q \in Q} L^{qg}}{\sum_{g \in G} \sum_{q \in Q} L^{qg}} \tag{6.2}$$

where y^g is the loan return of type g. By taking into consideration (6.1), (6.2) becomes

$$\sum_{g \in G} y^g = \frac{\sum_{g \in G} \sum_{q \in Q} r_g L^{qg} + \sum_{g \in G} \sum_{q \in Q} [\psi^{qg} - r_g - 1] F^{qg}}{\sum_{g \in G} \sum_{q \in Q} L^{qg}} \tag{6.3}$$

Therefore, the average loan return can be computed as:

$$\mu_{y^L} = \frac{1}{g} \sum_{g \in G} y^g \tag{6.4}$$

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We assume that the loan return evolves following

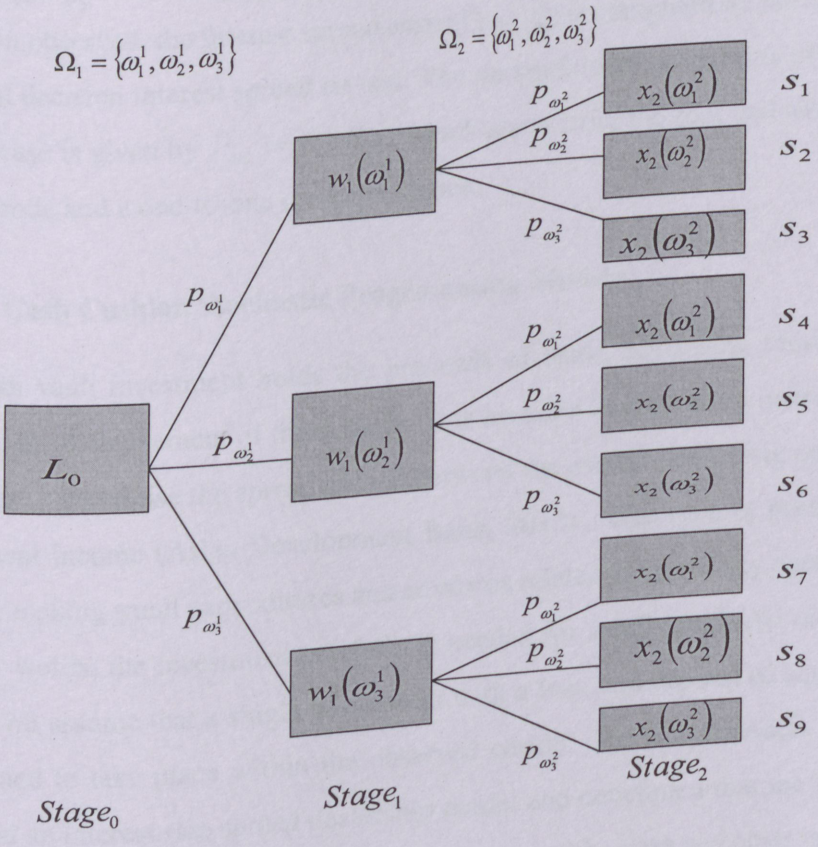
$$y^L = \mu_{y^L} + \gamma_{CI}\delta_{y^L} \tag{6.5}$$

where μ_{y^L} and δ_{y^L} are the loan return mean and variance, respectively. The γ_{CI} is the standard normal value at confidence interval level CI. Therefore, we assume the scenario generation model for loan return is represented by the equation;

$$y^L_{b(t+1)s_n} = \mu_{y^L} + \gamma_{CI}\delta_{y^L}\epsilon_{t+1} \tag{6.6}$$

where ϵ_{t+1} is the random error with mean 0 and variance 1. An illustration of a

Figure 6.1: Interest-Earned Scenario Tree



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scenario tree is provided in Figure 6.1. At stage 0, the loan L_0 issued has to be decided on event space Ω_1 for the unknown loan return y_0^L. The event space have three possibilities $\Omega_1 = \{\omega_1^1, \omega_2^1, \omega_3^1\}$, with corresponding probabilities $P_{\omega_1^1}, P_{\omega_2^1}$ and $P_{\omega_3^1}$. Once the loan return $\omega_j^1 \in \Omega_1$, is observed at the beginning of stage 1, for $j = \{1, 2, 3\}$, a recourse decision $w_1(\omega_j^1)$ is made, at the end of stage 1 based upon which ω_j^1 chose and our previous decision L_0. In this case, the recourse decision is the non-deposit debt under uncertain interest rate. The interest rate is announced at the beginning of stage 2, and its event space is denoted by Ω_2 if the bank borrows. The event space on interest rate has three different outcomes denoted by $\Omega_2 = \{\omega_1^2, \omega_2^2, \omega_3^2\}$ with corresponding probabilities $P_{\omega_1^2}, P_{\omega_2^2}$ and $P_{\omega_3^2}$. We need to note that $\sum_{j \in J} P_{\omega_j^1} = 1$ and $\sum_{k \in K} P_{\omega_k^2} = 1$. After the loan interest $\omega_k^2 \in \Omega_2$ in stage 2 has been observed, the interest spread earned $x_2(\omega_k^2)$ is computed by the model as the final decision interest spread earned. The unconditional probability of a node, in this case is given by $P_{s_n} = P_{\omega_j^1} P_{\omega_k^2}$, which starts from the root and terminates at that node and a one-to-one correspondence.

6.3.2 Cash Cushion Stochastic Programming Models

The cash vault investment holds the proceeds of banks borrowing transactions pending the disbursement of these funds. It is invested in short-term instruments, and aims to maximise the spread earned between the overall borrowing costs and investment income (Asian Development Bank, 2013). This type of portfolio is used for making small expenditures and advances related to day to day operations. In other words, the investment portfolio is needed for small incidental disbursements. We assume that a single transaction with a loan and deposit of equal size is assumed to take place within the observed period. Ho and Saunders (1981) proposed an interest rate spread dealership model and concluded that the interest spread is an intrinsic part of banks'risk buffer covering the risks and costs incurred

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in providing the intermediation service. However in our model, we tend to use actual data and Ho and Saunders (1981) dealership model is used to estimate future interest rate spread earned. In their dealership model, Ho and Saunders considered the following factors; the degree of bank market power, bank risk aversion, interest rate volatility and transaction size. Now we construct the two-stage stochastic programming model with recourse as follows.

$$\text{Max} \qquad [x_0 + [\mathbb{E}[\max[\max[\alpha_c r_b^L L_{bts_n} - (1-\alpha_c) r_b^D D_{bts_n}, 0]]]] \tag{6.7}$$

$$s.t. \qquad x_0 \leq V \tag{6.8}$$

$$l^m_{bts_n} + l^a_{bts_n} + l^{ch}_{bts_n} + l^{cg}_{bts_n} \geq L_{bts_n} \; \forall b \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{6.9}$$

$$d^v_{bts_n} + d^a_{bts_n} + d^z_{bts_n} + d^o_{bts_n} + d^u_{bts_n} \geq D_{bts_n} \; \forall b \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{6.10}$$

$$\frac{1}{\beta}[y^L_{bts_n} L_{bts_n} + (\psi - y^L_{bts_n} - 1) f_{bts_n} + W_{bts_n}] \geq D_{bts_n} \; \forall b \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{6.11}$$

$$\sum_{t \in T} W_{bts_n} \leq W^{\phi} \; \forall b \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{6.12}$$

$$L_0 \geq 0, D_0 \geq 0, r_0^L \geq 0, r_0^D \geq 0, r^L_{bts_n} \geq 0, r^D_{bts_n} \geq 0, L_{bts_n} \geq 0, D_{bts_n} \geq 0 \tag{6.13}$$

$$l^m_{bts_n} \geq 0, l^a_{bts_n} \geq 0, d^v_{bts_n} \geq 0, d^a_{bts_n} \geq 0, d^z_{bts_n} \geq 0, d^o_{bts_n} \geq 0, d^u_{bts_n} \geq 0$$

$$E_{bts_n} \geq 0, l^{ch}_{bts_n} \geq 0, l^{bts_n}, W_{bts_n} \geq 0 \; \forall b \geq 1, \forall t \geq 1, \forall n \geq 1$$

The objective function (6.7) aims at maximising the interest spread earned. The loan value is subject to interest rate on loans r_b^L. It is assumed that r_b^L is computed by imposing a fee τ_b^L over the expected risk-free interest rate r_f, such that $r_b^L = r_f + \tau_b^L$. The τ_b^L is the risk premium charged by the bank to bear refinancing risk. More so, the interest on deposit r_b^D is reduced by τ_b^D from the current risk free rate r_f, such that $r_b^D = r_f - \tau_b^D$. The τ_b^D is the risk premium charged by the

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bank to bear reinvestment risk. We assume that the interest rates are interdependent and $\tau_b^L \geq \tau_b^D$. We need to note that r_b^L and r_b^D depends only on band type and the rates remain fixed after being sat by the bank at he beginning of the decision period.

The constraints (6.8) is the first stage constraint denoting the initial spread earned, where $x_0 = r_0^L L_0 - r_0^D D_0$. The constraints (6.9) and (6.10) are the loan and and deposit constraints, respectively depending on scenario and band. The constraint (6.11) defines the amount the bank should have at time t to meet its deposit liabilities. The value realised from loans is $(1 - y_{bts_n}^L)(L_{bts_n} - f_{bts_n})$. The recovered loans is denoted by ψf_{bts_n}, where provisional loans are assumed to be greater than the actual loan defaults. The bank's money market position is $(1-\beta)D_{bts_n} - L_{bts_n}$. The recourse decision W_{bts_n} represents the readily available lines of credit to meet deposit withdrawals. Constraint (6.12) represents the total amount of readily available lines of credit to the bank. The bank is guaranteed of securing loans when needed. Finally, constraint (6.13) represents non-negativity constraints.

6.4 Statistical Characteristics of Historical Data

The choice of SP has been made for several reasons. In this research, stochastic programming can accommodate general distributions and dynamic aspects by means of a scenario tree. We do not explicitly assume a specific stochastic process for the loan return but view it as an independent and identically distributed random variable; and we rely on empirical data distributions. The Lingo 14 software was used to solve the constructed two-stage stochastic programming model with recourse. The constructed two-stage stochastic model is assessed for its viability and performance using International Monetary Fund (hereinafter, IMF) and South African Reserve Bank data. The total loans and non-performing loans data are

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readily available at IMF and South African Reserve Bank. We considered monthly total loans data from year January 1988 to year April 2014 and non-performing loans data from January 2009 to November 2013. The statistical characteristics of historical data used are as shown in the following Table 6.1 below. The histor-

Table 6.1: Statistical Characteristics of Historical Data

Statistical Measure	Total Loans	Non-performing Loans	Loans Return
Average	2.487×10^{6}	1.229×10^{5}	5.7946425×10^{-2}
Standard Deviation	2.269×10^{5}	1.0637×10^{4}	5.070854×10^{-3}
Kurtosis	$-9.2688011 \times 10^{-1}$	-1.256267606	-1.535792909
Skewness	$7.51102869 \times 10^{-1}$	$-1.1327942 \times 10^{-1}$	2.0827009×10^{-1}
Minimum	2.2569×10^{6}	9.7972×10^{4}	5.070854×10^{-3}
Maximum	2.9581×10^{6}	1.3801×10^{5}	6.6654434×10^{-2}

ical total loans and non-performing loans data exhibit skewed distributions; they also exhibit considerable variance in comparison to their mean. Total loans and loan return exhibit positive skewness while non-performing loans exhibit negative skewness. In addition, the random variable loan return exhibit platykurtic, implying less peaked than the normal distribution. Thus, we need to generate scenarios for loan return that comply with historical observations, without relying on the normality assumption. We rely solely on the observed total loans and non-performing loans in the market. We estimate the first four moments and we generate scenarios based on these statistical characteristics. The scenarios are generated so that the first four marginal moments of the random variables match their historical values.

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6.5 Empirical Analysis

In this section, we present and discuss the performance of our model. We start by analysing the stochastic programming solution status by observing the global optimal status. In this case, solution status is globally optimal implying that the results are valid. Now we turn to Table 6.2 where results of different components are shown. Of prime importance are the stochastic objective values, which are the expected interest spread earned over all different cases and scenarios. If we

Table 6.2: Interest Spread Earned Stochastic Programming Solutions

Interest	Obj (10^5)	Inf	Iter	EV (10^5)	EWS (10^5)	EVPI	EM (10^5)
$r^L_{btsn} = 9\%$ $r^D_{btsn} = 4\%$	5.8785	0	223	5.8785	5.8801	150.1601	5.8785
$r^L_{btsn} = 12\%$ $r^D_{btsn} = 4\%$	7.8381	0	122	7.8381	7.8401	200.2134	7.8381
$r^L_{btsn} = 13\%$ $r^D_{btsn} = 4\%$	8.4913	0	119	8.4913	8.4935	216.8979	8.4913

change the value of r^L_{btsn} and holding all other variables constant, the stochastic solution changes. Thus increasing the value of interest rate on loans, increases the optimal interest spread earned and vice versa. Interestingly, changing the value of interest rate paid on deposits r^D_{btsn} does not have an effect on optimal interest spread earned. Either increasing or decreasing the r^D_{btsn}, the stochastic solution is constant.

As evidenced by the values in Table 6.2, there is a positive correlation between the optimal interest spread earned, and the interest rate on loans r^L_{btsn}. We need to note that changing the risk aversion coefficient α_c leads to change in stochastic interest spread earned solution. The infeasibility value is zero implying that no

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constraints were violated in the deterministic equivalent model. The stochastic programming output notations and facts that followed are explained in Appendix.

The EV of the interest spread earned are the same as the reported optimal interest spread earned for the model, further giving weight to the results. The EWS interest spread earned reports the expected value of the interest spread earnings if we could wait and see the outcomes of all unknown loan return and uncertain interest rate before making decisions. However, in reality it is not possible to wait. Comparing the values of EWS and EV, we expect $EWS \geq EV$ since we are maximising interest spread earned.

The EVPI is used to compare EWS and EV and measures the maximum amount the decision maker should be willing to pay in return for complete and accurate information regarding the future outcomes of loan return and interest rate. It can be computed as follows; $EVPI = |EV - EWS|$. In all cases, the ratio of total EVPI to total interest spread earned of stochastic value is 2.5544 x $10^{-4}\%$ implying that the decision maker is willing to pay an average of 2.5544 x $10^{-4}\%$ per given period. The EVPI is the expected increase in optimal interest spread earned if we know the future in advance. The EM is the same as the expected true objective value since we have assumed that all returns always take on exactly their mean values. According to Birge (2013) conditions, if $EVPI > 0$, the EVMU is zero implying that it cost nothing to the decision maker if uncertainty was not accounted for. The Birge (2013) conditions implies that we had a situation where no single optimal interest spread earned existed for $\forall s_n \in S$ and therefore we expect and found that $EVPI > 0$. EVMU can be computed as; $EVMU = EV - EM$ and in all cases, $EV = EM$. The EVMU measures how good or bad a decision obtained by EV and in our case the decision is good. Therefore, we can observe

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that $EV \leq EM \leq EWS$, $EVPI \geq 0$ and $EVMU \geq 0$ which are consistent with Barbaro and Bagajewicz (2004) and Birge (1997) conditions. Therefore, at this level, we can infer that the scenarios generated are reliable and valid. Since $EVMU = 0$ it means that we did not gain by taking into account uncertainty in our stochastic programming model.

Table 6.3: Loan Return Distribution

Loan Return Bands	Sample Mean	Sample Standard Deviation
Band 1	5.7999×10^{-2}	2.5482×10^{-5}
Band 2	5.7986×10^{-2}	3.2483×10^{-5}
Band 3	5.8015×10^{-2}	2.3007×10^{-5}
Band 4	5.7976×10^{-2}	2.7129×10^{-5}
Band 5	5.7982×10^{-2}	2.8195×10^{-5}
Band 6	5.7987×10^{-2}	2.7231×10^{-5}
Band 7	5.7990×10^{-2}	3.0532×10^{-5}
Band 8	5.7996×10^{-2}	2.7686×10^{-5}

With reference to Table 6.3, the random distribution of loan return is constant regardless of change of the values of interest rate on loans and interest rate paid on deposits. Applying scenario generation method in equation (6.6) on historical values of the random variables, we obtain scenarios for the return on loans $y^L_{b(t+1)s_n}$. The resulting scenarios are equiprobable in our tests, but generally they do not have to be.

6.6 Conclusion

A cash cushion portfolio is maintained through reinvesting interest rate spread earned. The interest rate spread earned is defined as the positive difference between interest received and interest payable. A two-stage stochastic programming

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model with recourse to maximize interest spread was constructed. A scenario generation model to generate loan return scenarios is developed. The loan return is stochastic and therefore we represent it on a scenario tree. From Lingo solution output, we observed that the model is feasible. We further analysed whether the scenarios are reliable and valid. After assessing the value of stochastic solution, we inferred that the scenarios generated and results computed are reliable and valid. However, the expected value of modelling uncertainty is zero in all cases. This might be due to the size of the scenario tree and data used. The change in interest rate on loans has an effect on the level of interest spread earned. However, in this model the change in interest rate paid on deposits does not have an effect on interest spread earned. The changes in interest rates could impact bank liquidity. Thus bank clients are sensitive to interest rate movement. If savings rates are lowered, clients might withdraw their funds and cause a liquidity shortfall. Also higher rates on loans could make it difficult for some clients to meet interest payments, causing a fall in liquidity levels. We need to note that interest rate spread is hypothetical and earn if all assets are borrowed and invest at the going rates. In reality some assets are kept in non-interest bearing accounts and therefore incur borrowing costs without earning any interest. We conclude that the greater interest spread earned implies more profitable to the bank, and less interest spread earned means less profitable. We strongly recommend that banks should design a cash cushion portfolio which is a sub-portfolio of the liquidity portfolio, which will specifically focus on holding cash in transit. However, bank interest spread earned is restricted by capital adequacy, required reserves and deposit insurance defined by the central bank. Of importance, we need to note that the stronger the monopoly power of the bank, the more volatile the interest rates, the higher the spread charged by the bank is.

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Deeper understanding of the relationship between the optimal interest spread earned to stochastic and deterministic models can also be useful in order to understand what to do when a situation is random but the actual numbers and distributions are not known. This applies to algorithmic developments as well as practical use of models in industry. A qualitative understanding of the behaviour of the deterministic solution relative to the stochastic one could be very useful because it could reveal some general properties of the underlying problem and help us to predict how the stochastic model will perform. Solving stochastic programming models help decision makers to measure the expected gain from solving a stochastic model rather than its deterministic counterpart, where all random variables are replaced by their means. The output values are mostly used to argue that stochastic programming models are necessary despite the efforts involved. Further research can be done on appropriate interest rate spread earned model that captures the dynamics of the economy and identifying specific money market instruments that can be included in the portfolio. Improvements can be done on appropriate scenario generation model.

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CHAPTER 7

7 OPERATIONAL CASH MANAGEMENT STOCHASTIC PROGRAMMING MODELS

7.1 Introduction

Banks usually face challenges on determining the future specific cash needs and when they will be due. The cash needs may be deterministic but are subject to cash flow shocks. Liquidity management is used in combination with cash management. Cash management is key to business success and is the single most important element of survival for small business. However, uncertainty of cash flow and the risk of adverse cash flow shocks are central concerns in corporate finance. Good cash management enhances liquidity management. Cornett *et al* (2011) pointed out that banks hold cash and other liquid assets as part of their overall strategy to manage liquidity risks. Cash management is concerned with minimising unproductive balances and investing the cash temporarily advantageous. Its aim is to minimise costs of interest on borrowings, and earning maximum interest from surplus funds. Therefore, cash management must be thought in terms of the overall liquidity needs of the bank, and specifically focusing on the current assets and current liabilities.

Recent work related to bank liquidity management focused primarily on cash related management, see Ferstl and Weissensteiner (2008), O'Leary and O'Leary (1981), Michalski (2009) and Yilmaz (2011). A model strategy that can be applied to short- or medium-term cash management was proposed by Ferstl and Weissensteiner (2008). A goal programming formulation for cash management was constructed by O'Leary and O'Leary (1981) and used multiple objectives.

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Michalski (2009) presented a model to determine cash management that avoids manager's intuition and is based on calculation. Banks may hold cash for, according to Da Costa Moraes and Naganoj (2012), transaction, precaution, speculation and bank reciprocity purposes. Moyer *et al* (1995) explains the cash management function as determining the optimal size of a firm's liquid asset balance.

The aim of the chapter is to construct a net cash flow-based sub-portfolio designed to meet short to middle-term cash requirements over a short-term horizon. The difference between the cash inflow and the cash outflow is termed the net cash flow. In our research, net cash is a countable set of increments. We segment the liquidity portfolio and construct an operational cash portfolio. A two stage stochastic programming model with recourse is constructed to maximise net cash flow. Realising positive net cash flow minimises costs of interest on borrowings and earning maximum interest from surplus funds. Thus positive net cash flow avoids or at least reduces uncertainties of surplus or short funds so that need of borrowings to meet emergencies is avoided. Therefore, net cash flow is crucial to ensuring that a bank remains liquid and able to meet its payment obligations.

7.2 Cash Flow Management as a Part of Liquidity Management

Cash management is defined as part of liquidity and treasury management, and Lee (2001) defines cash management as the administration of liquid assets and liabilities, and raising of funds to finance a bank. Cash management is closely related to the concepts of liquidity problem. Efficient liquidity management includes a cash management system. In cash management process, we zero in on net cash flow and is the amount of cash-on-hand claimed on financial statements after subtracting current liabilities. Net cash flow as shown in Figure 7.1 is typically an

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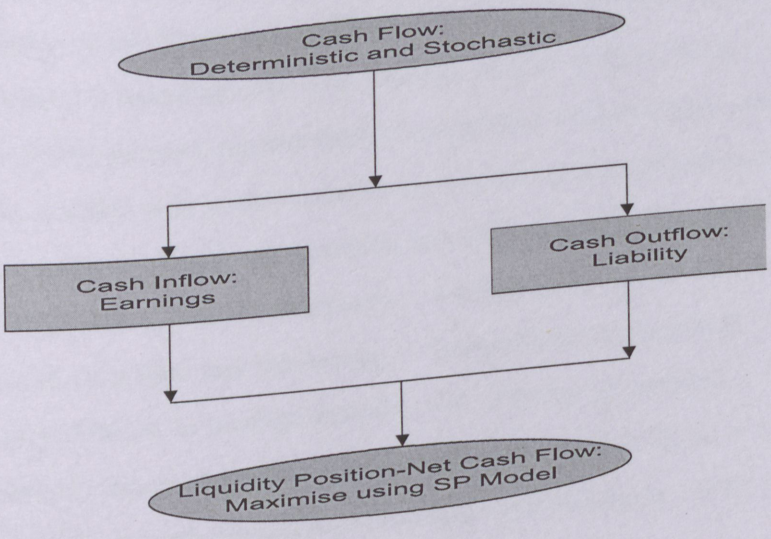
Figure 7.1: Net Cash Flow



indicator of a bank's cash flow position at the end of a reporting period. Thus cash flow is crucial to an entity survival and important liquidity management component that can be defined as the actual movement of money in and out of the bank. Cash flow is a revenue or expense stream that changes cash account over a given period. Therefore cash flow control is crucial to ensuring that a bank remains liquid and able to meet payment obligations. This is carried out through effective management of cash receipts and payments, cash balances and cash transfers between the different parts of a bank.

On the other hand, cash flow plays an important role in determining a bank's ability to access external sources of funds. So liquidity relates to flows of cash only. Cash is a characteristic of liquidity that it has to be available all the time and not on average or most of the time. To effectively manage liquidity, banks should differentiate between deterministic cash flow and stochastic cash flow. According

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to Holmström and Tirole (1998), liquidity risk arises because inflows and outlays are not synchronised. Vento and La Ganga (2009) modelled cash flow uncertainty and their model is based on cash flow maturity ladder. In their model, Vento and La Ganga (2009) pointed out that banks are exposed to unexpected cash inflows and outflows, which may occur in the future because of unusual deviations in the timing or magnitude. Banks try to match cash expected and unexpected outflows in each time bucket against a combination of contractual cash inflows. However, the amount of cash flow and the timing is deterministic or stochastic. Thus this makes it very difficult to manage liquidity risk. Timing of cash inflows and outflows is a crucial driver of funding liquidity risk and a bank is liquid if it is able to settle all obligations with immediacy (Drehmann and Nikolaou, 2009).

Cash flow models are used for measuring funding liquidity risk and its management. Banks with positive cash flow are able to raise their capital and borrow from the capital market, while banks with insufficient cash flow are unable to borrow, therefore face the risk of default. Current cash flows are able to predict corporate financial status, then past and present cash flows should be able to determine and predict corporate default (Zeitun *et al*, 2007). Assessing funding liquidity risk through a cash flow constraint is common in practice and it is the basis of Basel 3. Contractual maturities are the ultimate drivers of funding liquidity risk in crises while behavioural maturities are constraints appropriate in normal times. The approach most banks use according to Sigauke *et al* (2012), is the cash flow based approach which compares expected cash inflows and outflows, grouping them in homogeneous maturity buckets and checking that cash inflows are large enough to cover cash outflows. In this case, cash flows are sorted across the different maturities based on contractual maturities, bank's expectations and past experience. Banks may use ladder asset maturities to closely match liability maturities

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and expected payments or gap analysis. The gap is the difference between interest sensitive assets and liabilities for a given time interval. According to Bessis (2002), the gap can be incremental and cumulative. Incremental gap can be defined as earning assets less funding sources in each time bucket; while cumulative gaps are the cumulative subtotals of the incremental gaps. In addition, the gap can be positive or negative. Researches consider cash flow as separate entity from liquidity management. Therefore, in this research, we integrate cash flow management as an important part and strategy of bank liquidity management. In this case, cash flow management is defined as an administration of liquid assets and liabilities.

7.3 Model Formulation

We discuss the scenario generation model and represent the future gross income uncertainty on a scenario tree. The scenario tree is a discrete approximation of the joint distribution of random factors associated with maximising net cash flow. Therefore to formulate the operational cash portfolio, we assume that the portfolio is funded by equity and funds invested in individual short-term highly liquid money market instruments, including time deposits, ultra short bond funds and a commercial paper. Thus the net cash flow from money market instruments are maximised to meet the bank's net cash flow requirements. We discuss stochastic programming model features, the parameters and its dynamics together with its constraints. The stochastic programming model is based on a scenario tree of random variable gross income. We first define the variables and parameters used.

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Definitions of Sets

T	Set of time space
I	Set horizon bands
s_n	Set of scenarios, for $n \in N$
Ω_1	Set of event space for the unknown gross income
Ω_2	Set of event space for the unknown liquid asset return
$P_{\omega_j^1}$	Set of probabilities of event space for the unknown gross income, for $j \in J$
$P_{\omega_k^2}$	Set of probabilities of event space for the unknown liquid asset return, for $k \in K$
P_{s_n}	Set of scenario probabilities, for $s_n \in S$

Deterministic Data

a_0	Initial net cash flow
α_O	The risk averse coefficient
Q^A	The total liquid asset redemption
X	Initial amount of net income
γ	The tax rate

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Random Data

$l^{E}_{its_n}$ Loan amortisation, for $i \in T$, $t \in T$, and $s_n \in S$

$l^{R}_{its_n}$ Loan repayment, for $i \in T$, $t \in T$, and $s_n \in S$

$m^{V}_{its_n}$ Maturing investments, for $i \in T$, $t \in T$, and $s_n \in S$

$b^{V}_{its_n}$ Callable investments, for $i \in T$, $t \in T$, and $s_n \in S$

$l^{O}_{its_n}$ Approved loan pipeline, for $i \in T$, $t \in T$, and $s_n \in S$

$m^{U}_{its_n}$ Maturing advances, for $i \in T$, $t \in T$, and $s_n \in S$

$m^{K}_{its_n}$ Maturing certificates of deposits, for $i \in T$, $t \in T$, and $s_n \in S$

$c^{IFd}_{its_n}$ Cash inflow non-discretionary, for $i \in T$, $t \in T$, and $s_n \in S$

$c^{OFd}_{its_n}$ Cash outflow non-discretionary, for $i \in T$, $t \in T$, and $s_n \in S$

g_{its_n} Gross income from trading activities, for $i \in T$, $t \in T$, and $s_n \in S$

Decision Variables

$c^{y}_{its_n}$ Cash deployment, for $i \in T$, $t \in T$, and $s_n \in S$

$c^{IFD}_{its_n}$ Cash inflow discretionary, for $i \in T$, $t \in T$, and $s_n \in S$

$c^{OFD}_{its_n}$ Cash outflow discretionary, for $i \in T$, $t \in T$, and $s_n \in S$

$c^{IF}_{its_n}$ Cash inflow, for $i \in T$, $t \in T$, and $s_n \in S$

$c^{OF}_{its_n}$ Cash outflow, for $i \in T$, $t \in T$, and $s_n \in S$

$q^{A}_{its_n}$ Cash from sale of liquid assets, for $i \in T$, $t \in T$, and $s_n \in S$

7.3.1 Cash Flow Scenario Tree

To construct a scenario tree, we consider now the case where the random vector S has a discrete and finite distribution, with n scenario set $S = \{s_1, .., s_n, ..., s_N\}$. We assume that $p_{s_n} \geq 0$ for all $s_n \in S$ and that $\sum_{n \in N} p_{s_n} = 1$. We need to note that a scenario is a path from the root of the tree to one of the leaves. The nodes

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visited by each path correspond to the values assumed by random parameters in the model. Before we define the scenario generation model, we define the gross income function and is represented by equation;

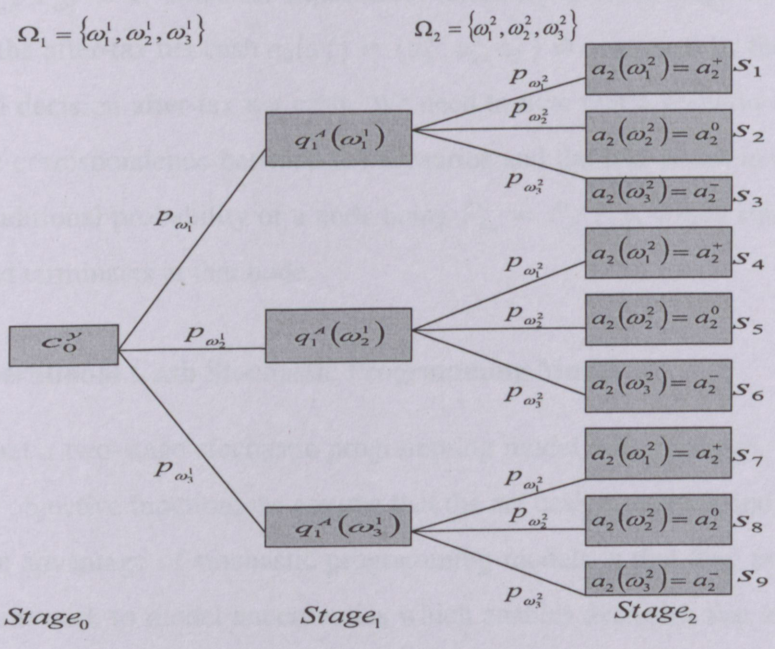
$$g_t = z_t - w_t \tag{7.1}$$

where g_t is the gross income and represent the cash inflow. The y_t and w_t are the cash from the trading activities and cost of sales, respectively. Then we assume that the gross income scenario generation model is represented by the equation;

$$g_{its_n} = \mu_{g_t} + \delta_{g_t}\epsilon_{t+1} \tag{7.2}$$

where μ_{g_t} and δ_{g_t} are mean and standard deviation of gross income, respectively. In the scenario tree in Figure 7.1, at stage 0, the banks decide on cash deployment

Figure 7.2: Cash-Flow Scenario Tree



c_0^y on event space Ω_1 for the unknown gross income. The gross income event

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space have three possibilities $\Omega_1 = \{\omega_1^1, \omega_2^1, \omega_3^1\}$, with associated probabilities $P_{\omega_1^1}, P_{\omega_2^1}$ and $P_{\omega_3^1}$. Once the gross income $\omega_i^1 \in \Omega_1$, is observed at the beginning of stage 1, for $i = \{1, 2, 3\}$, a recourse decision $q_1^A(\omega_j^1)$ is made, at the end of stage 1 based upon which ω_j^1 nature chose and our previous decision c_0^y. In this case, the recourse decision is sale of liquid assets held by the bank under uncertain liquid asset returns. We assume that the assets held by the bank are liquid and enough to cover required cash difference. However, during crisis the liquid asset might become less liquid forcing banks to sale it below its value. The recourse decision is sale of liquid assets held. The liquid asset returns is announced at the beginning of stage 2, and its event space is denoted by Ω_2. The event space on liquid asset return has three different outcomes denoted by $\Omega_2 = \{\omega_1^2, \omega_2^2, \omega_3^2\}$ with associated probabilities $P_{\omega_1^2}, P_{\omega_2^2}$ and, $P_{\omega_3^2}$. We need to note that $\sum_{j \in J} P_{\omega_j^1} = 1$ and $\sum_{k \in K} P_{\omega_k^2} = 1$. Once the liquid asset return $\omega_k^2 \in \Omega_2$ in stage 2 has been observed, the after-tax net cash $a_2(\omega_k^2) = \{a_2^+, a_2^0, a_2^-\}$ is computed by the model as the final decision after-tax net cash. We need to note that a scenario tree is a one-to-one correspondence between the scenarios and the leaf-nodes in our tree with unconditional probability of a node being $P_{s_n} = P_{\omega_j^1} P_{\omega_k^2}$, which starts from the root and terminates at that node.

7.3.2 Operational Cash Stochastic Programming Model

We construct a two-stage stochastic programming model with recourse. To formulate our objective function, we assume that the net cash is positive and subject to tax. The advantage of stochastic programming models is that they provide a generic framework to model uncertainties which enables decisions that will perform well in the general case. In this model, we need to maximise after-tax net cash flow. Therefore, we formulate our model to manage the portfolio as shown

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below.

$$\text{Max} \quad \gamma[a_0 + \mathbb{E}[\max[\max \sum_{i \in I}((1-\alpha_O)c^{IF}_{its_n} - \alpha_O c^{OF}_{its_n}, 0)]]] \tag{7.3}$$

$$s.t. \quad a_0 \leq X \tag{7.4}$$

$$c^{IFd}_{its_n} + c^{IFD}_{its_n} \geq c^{IF}_{its_n} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{7.5}$$

$$c^{OFd}_{its_n} + c^{OFD}_{its_n} \geq c^{OF}_{its_n} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{7.6}$$

$$l^{E}_{its_n} + l^{R}_{its_n} + m^{V}_{its_n} + b^{V}_{its_n} \geq c^{IFd}_{its_n} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{7.7}$$

$$l^{O}_{its_n} + m^{U}_{its_n} + m^{K}_{its_n} \geq c^{OFd}_{its_n} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{7.8}$$

$$c^{OF}_{its_n} + g_{its_n} + q^{A}_{its_n} \leq c^{IF}_{its_n} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{7.9}$$

$$\sum_{i \in I} q^{A}_{its_n} \leq Q^{A} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{7.10}$$

$$c^{IFd}_{its_n} \geq 0, c^{IFD}_{its_n} \geq 0, c^{OFd}_{its_n} \geq 0, c^{OFD}_{its_n} \geq 0 \tag{7.11}$$

$$l^{E}_{its_n} \geq 0, l^{R}_{its_n} \geq 0, c^{IG}_{its_n} \geq 0, m^{V}_{its_n} \geq 0, b^{V}_{its_n} \geq 0$$

$$l^{O}_{its_n} \geq 0, m^{U}_{its_n} \geq 0, m^{K}_{its_n} \geq 0, g_{its_n} \geq 0, q^{A}_{its_n} \geq 0.$$

The objective function (7.3) is the after-tax net cash that is maximised. The initial net cash flow is given by; $a_0 = c^{IF}_0 - c^{OF}_0$, for c^{IF}_0 and c^{OF}_0 are the initial cash inflows and initial cash outflows, respectively. The constraint (7.4) is the first-stage problem. The total cash inflow and cash outflow are represented by constraints (7.5) and (7.6), respectively. The total cash flows include both discretionary and non-discretionary cash flows. The discretionary cash flows are the ones the corporation can control and are bank specific. However, the non-discretionary cash flows are contractual and binding payment flows. The corporation and clients have an obligation to fulfill the contracts when they fall due.

The constraint (7.7) denotes the bank's non-discretionary cash inflow and is a sum

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of loan amortisation, loan repayment, maturing investments and callable investments. The non-discretionary cash outflow is denoted by constraint (7.8) and is the sum of approved loan pipeline, maturing advances and maturing certificates of deposits. The constraint (7.9) represents the relationship between the cash inflow and cash outflow. The cash from sale of liquid assets is the recourse decision depending on the expected gross income. The total cash from liquid assets is denoted by constraint (7.10). Finally, constraint (7.11) are non-negativity constraints.

7.4 Methodology

Evidently, to solve the two-stage stochastic program a complete information on the "underlying" probability measure is necessary. We do not explicitly assume a specific stochastic process for the cash yield but view it as an independent and identically distributed random variable; and we rely on empirical data distributions. To justify our assumption, we analyse the nature of kurtosis. The Lingo 14 software was used to solve the constructed two-stage stochastic programming model with recourse.

7.4.1 Sources of Data

The constructed two-stage stochastic model is assessed for its viability and performance using the International Monetary Fund data. The considered gross income data is from January 2009 to November 2013. The actual liquid assets data is from January 1988 to April 2014.

7.4.2 Statistical Characteristics of Historical Data

We start by computing the statistical characteristics of historical data liquid assets and gross income. The characteristics of data used are as shown in the following Table 7.1 below. Historical liquid assets and gross income exhibit positive skewed

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Table 7.1: Statistical Characteristics of Historical Data

Statistical Measure	Liquid Assets	Gross Income
Average	1.39788×10^5	1.514838×10^4
Standard Deviation	9.7145×10^4	2.34907×10^3
Kurtosis	-1.0294046	$-2.40583632 \times 10^{-1}$
Skewness	$6.87005958 \times 10^{-1}$	$5.00003409 \times 10^{-1}$
Minimum	3.6634×10^4	1.129243×10^4
Maximum	3.27016×10^5	2.206212×10^4

distributions. The difference between the standard deviation and mean is small exhibiting considerable variance. In addition, the random variable gross income exhibit platykurtic, implying less peaked than the normal distribution. Scenarios generated for gross income should imitate the historical observations, without relying on the normality assumption. We solely rely on the observed total gross income data since no other information is available. We estimate the first four moments and we generate scenarios based on these statistical characteristics. The scenarios are generated so that the first four marginal moments of the random variables match their historical values for the model to be appropriate.

7.5 Empirical Analysis

In this section, we present and discuss the performance of our model. We start by analysing the stochastic programming solution status by observing the global optimal status. In this case, solution status is globally optimal implying that the results are valid. Further, we inspect the infeasibility values and in this case they are zero in all cases implying that no constraints were violated in the deterministic equivalent model. Now we turn to Table 7.2 where results of different components are shown. Of prime importance, are the stochastic objective values, which are the

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expected objective values over all different cases and scenarios. In our model, the objective value is the optimal net cash flow. By changing the risk aversion coefficient

Table 7.2: Stochastic Programming Solutions: Changing the Risk Aversion Coefficient

Risk	Obj	Inf	EV	EWS	EVPI	EM
0.08	2.6461 x 10^4	0	2.6461 x 10^4	2.6461 x 10^4	0	2.6461 x 10^4
0.1	2.5886 x 10^4	0	2.5886 x 10^4	2.5886 x 10^4	0	2.5886 x 10^4
0.15	2.4447 x 10^4	0	2.4447 x 10^4	2.4447 x 10^4	0	2.4447 x 10^4
0.2	2.3009 x 10^4	0	2.3009 x 10^4	2.3009 x 10^4	0	2.3009 x 10^4
0.4	1.7257 x 10^4	0	1.7257 x 10^4	1.7257 x 10^4	0	1.7257 x 10^4

cient α_O and holding all other variables constant, the stochastic solution changes. Thus increasing the value of risk averse coefficient, decreases the optimal net cash flow and vice versa. There is a negative correlation between the objective values, and the risk averse coefficient α_O. The EV of the net cash flow are the same as the reported optimal net cash flow for the model, further giving weight to the results. The EWS model's optimal net cash flow reports the expected value of the net cash flow if we could wait and see the outcomes of all unknown gross income and uncertain liquid asset returns before making decisions. However, in reality it is not possible to wait. Comparing the values of EWS and EV, we expect $EWS \geq EV$ since we are maximising after-tax net cash flow.

The EVPI is a measure of opportunities forgone. Thus knowing the true after-tax net cash flow before making decisions allows the decision to make appropriate and informed decisions. EVPI is used to compare EWS and EV and measures the maximum amount the decision maker should be willing to pay in return for complete and accurate information regarding the future outcomes of the underlying

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liquid asset returns. It can be computed as follows; $EVPI = |EV - EWS|$. In all cases, the ratio of total EVPI to total optimal after-tax net cash flow is zero implying that the decision maker is willing to pay nothing per given period. The EM is the same as the expected true optimal net cash flow since we have assumed that all returns always take on exactly their mean values. According to Birge (2013) conditions, if $EVPI > 0$, then EVMU is zero. However from Table 7.2, the EVPI are very small close to zero in all cases, and this means that there is no evidence that we gained by taking into account uncertainty in our model analysis. The formula for computing EVMU is given by; $EV - EM$ and in our case $EV = EM$. We can observe that $EV \leq RP \leq WS$, $EVPI \geq 0$ and $VSS \geq 0$ which are consistent with Barbaro and Bagajewicz (2004) and Birge (1997) conditions. Therefore, at this level, we can infer that the scenarios generated are reliable and valid.

Table 7.3: Gross Income Distribution

Gross Income Bands	Sample Mean	Sample Standard Deviation
Band 1	1.516170 x 10^4	6.764954
Band 2	1.515960 x 10^4	8.083038
Band 3	1.515708 x 10^4	4.939858
Band 4	1.516291 x 10^4	7.868774
Band 5	1.516130 x 10^4	7.386719
Band 6	1.515892 x 10^4	5.903985
Band 7	1.516147 x 10^4	7.508655
Band 8	1.515714 x 10^4	6.367355

Referring to Table 7.3 the random distribution of gross income is constant regardless of the values of interest rate on loans and interest rate paid on deposits. Applying scenario generation method in equation (7.2) on historical values of the

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gross income, we obtain scenarios for the gross income. The resulting scenarios are equiprobable in our tests, but generally they do not have to be.

7.6 Conclusion

Today's banking industry treats the liquidity portfolio as any other company portfolio and not taking into account bank specific needs embedded in the portfolio. We define a sub-portfolio that mainly focuses on meeting operating activities and referred to as operational cash portfolio. The portfolio is funded by short-term liquid assets. Lingo software is used to solve the stochastic programming model and solution output is observed to ascertain if the model is feasible, and in our case it is feasible. We further analysed whether the scenarios are reliable and valid. After assessing the value of stochastic solution, we inferred that the scenarios generated and results computed are reliable and valid. However, the expected value of modelling uncertainty is zero in all cases. This might be due to the size of the scenario tree and data used. From the results, if the level of risk tolerance level is changed, the value of the after-tax net cash will change in tandem with the tolerance value. If we increase the tolerance level, the after-tax net cash flow level decreases and if we decrease the level, the after-tax net cash flow value increases. We need to note that in all cases, the company benefits by taking into consideration the randomness of outcomes. We conclude by saying that the higher the after-tax net cash level, the higher is the basis liquidity level, and less after-tax net cash means less liquid. We have found that an appropriate net cash flow management enhance effective and efficient liquidity management through stochastic programming model with recourse. Therefore, net cash flow management is an important liquidity management strategy. Hence we strongly recommend that banks should design an operational cash portfolio which is a sub-portfolio of the overall liquidity portfolio, which will specifically focus on meeting operational cash needs. However,

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bank net cash is restricted by tax rate, interest rates, market performance, and operating business strategy. Further research can be done on designing models to compute net cash that incorporate customer behaviour and stochastic cash flows. More research can be done on stochastic cash flow models that appropriately can be used to manage liquidity and compare with deterministic cash models to check the performance.

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CHAPTER 8

8 DISCRETIONARY LIQUIDITY MANAGEMENT STOCHASTIC PROGRAMMING MODELS

8.1 Introduction

Deposit-taking institutions such as banks are subject to uncertain cash flow. Bank clients are frequently depositing and withdrawing money so that the amount of money for the reserve requirement is constantly changing. Therefore, due to the stochastic liability side of the balance sheet and the predetermined stock of bank capital, banks are subject to occasionally binding constraints. The banks may access central bank funds market, but if it is limited, the banking sector ends up holding aggregate excess reserves. The banks' clients deposit and withdraw money randomly so that the amount of money for prescribed reserve requirement is constantly changing. The banks are finding it very difficult to maintain the prescribed reserve requirement. During the 2009 financial crisis, most banks were found holding fewer reserves than the prescribed reserves. The current liquidity risk models do not incorporate excess reserve as a liquidity management strategy. Rather, excess reserve is not explicitly considered in most models as an avenue to accurately and effectively manage liquidity risk. The demand for excess reserves is a crucial part of a bank's liquidity management decision, and it is a significant factor influencing liquidity in the banking system. The uncertainty about liquidity shocks, the volume of payment flows and the inefficiencies in the interbank money market borrowing have effects on the pattern of reserve holdings. Therefore, with the introduction of uncertainty, the research intends to highlight the most signifi-

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cant benefit of excess reserve to mitigate ambiguity of cash flows.

The reserve management problem is interesting because of the inherent asymmetry in costs incurred by the foregone interest when bank meets its reserve requirements, and the penalty costs for having reserves fall below the reserve requirement. There is an extensive literature focusing on bank reserves management and the demand for excess reserves, see Bartolini *et al* (1999), Brown (1970), Coelho and Pinto (2004), Jallath-Coria *et al* (2002), Talasli and Ozyildirim (2013), Talasli (2010). Bartolini *et al* (1999) modelled liquidity role of reserves and defined that when liquidity deviates from target level, a quadratic cost is incurred by the bank. In their research, Bartolini *et al* (1999) found out that banks hold more reserves around end-period, when interests are typically highest. The effects of uncertainty about reserve losses is discussed by Brown (1970) and assumed that credit expansion involves an increase in the deposits of the borrowers. Jallath-Coria *et al* (2002) investigated how banks manage their reserves. The model constructed focuses on overall reserve prediction. Talasli (2010) used autoregressive moving average-based approach to model the pattern of excess reserves within the maintenance period and used quantities of reserve balances.

The stochastic dynamic programming model for demand of reserves in the Brazilian market was constructed by Coelho and Pinto (2004). We can recall the model by Coelho and Pinto (2004) to analyse the behaviour of banks towards the management of their reserves by minimizing deficit costs. Heller and Lengwiler (2003) derived an exact solution to an individual bank's optimisation problem subject to uncertainty and stochastic reserve requirements. Agénor *et al* (2004) proposed a model looking at the case of Thailand during the Asian crises. Saxegaard (2006) extended Agénor *et al* (2004) model and decomposed the evolu-

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tion of free reserves into voluntary and excess reserve factors. Saxegaard (2006) regressed holdings of free reserves to a range of variables thought important in determining the holding of voluntary and excess reserves. Using his model, Saxegaard (2006) found that presence of excess reserves has influence on financial stability objectives and monetary policy. Anderson-Reid (2011) investigates the impact of high levels of excess reserve on price stability. The demand for excess reserves was estimated by Anderson-Reid (2011) using the auto-regressive distributed lag bounds test approach. In her model, Anderson-Reid (2011) found that the determinants of excess reserves of commercial banks in the long-run and short-run are the reserve requirements, fluctuations in the currency-to-deposit ratio, the deviation of income from trend, the volatility of income, the exchange rate and interest rate offered by the central bank's 180-day security.'

Due to non-consideration of significance of excess reserve in current liquidity management models, we construct a discretionary liquidity portfolio to specifically ensure that the prescribed reserve requirement is met to avoid liquidity problems. The discretionary liquidity portfolio is a subset of overall liquidity portfolio, and it is a function of maximised excess reserve. The discretionary liquidity portfolio is used to support medium-term funding needs and is funded by debt to provide flexibility in executing the funding programme over the medium term and to opportunistically permit borrowing ahead of cash flow needs and bolster bank's access to short-term funding through continuous presence in the market. In this paper, the discretionary liquidity is the amount held by the institution above the minimum prescribed by the central bank. Thus the bank reduces costs and where possible, avoids the penalty costs through maximising excess reserves using a two-stage stochastic programming model with recourse. The chapter focuses on the scenario tree, scenario generation model for payment flows are constructed

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and the stochastic programming model to manage discretionary liquidity.

8.2 Bank Reserves for Liquidity Risk Management

According to Olagunju *et al* (2011), bank reserves can be partitioned into primary, secondary or tertiary reserves. The primary liquidity reserves are non-interest reserves, they should be optimised in order not to undermine realisation of the principle of profitability. On the other hand, according to Luckett (1980) secondary liquidity reserves represent the next level of banks' liquidity defence. They present the interest-bearing investments such as short-term government securities, short-term securities issued by central bank or company with a high rating. Secondary liquidity reserves are activated only when the primary liquidity reserves are exhausted. Tertiary liquidity reserves include the bills without the possibility of discounting, unused short-term loans tranches obtained from other banks and bonds. Banks are required to hold a prescribed percentage of their total liabilities in cash on their cash reserve accounts at the central bank. The amount of cash reserves held at the central bank is referred to as the structural liquidity requirement. This is the amount that the liquidity requirement would have been if all the other factors influencing liquidity in the money market had a combined zero balance. Ganley (2003), Kolar *et al* (2011) and Rule (2012) classified bank reserves as cash required reserves imposed by the central bank and excess reserve. The cash reserve requirement with central bank is mandatory and not divertible to other uses.

Three elements of required reserves are the currency magnitude of base liabilities, the required reserve fraction and the currency magnitude of qualifying cash assets. In our thesis, we use the cash reserve ratio which can be defined as the amount of funds that all scheduled commercial banks are required to maintain without any floor or ceiling rate with central bank with reference to their total net

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demand and time liabilities to ensure liquidity and solvency of banks. Reserve requirements are imposed on the deposit liabilities of the commercial banks by the monetary policy, referred to as the reserve base. The monetary policy and Basel 3 spelt out that the banks should hold a proportion of their deposit liabilities at the central bank in either remunerated or unremunerated form. Gray (2011) explains three reasons for the imposition of reserve requirement which are prudential, monetary control and liquidity management. The reserve base comprises of transferable deposits, savings deposits, time deposits and other funds that the public has entrusted to the banks. Banks may use different currencies as reserve requirements and must be maintained in the currency of denomination of the deposit liabilities. The reserve requirements in given foreign currency liabilities are therefore payable in the respective currencies. The reserve ratio varies from country to country, and in our model the ratio is differentiated by the type of deposit liability. However if the bank has foreign currencies liability, the reserve can be differentiated according to currency denomination.

Apart from cash reserve ratio, every bank is required to maintain at the close of the business every day, a minimum proportion of their net demand and time liabilities as liquid assets in the form of cash, gold and unencumbered approved securities. A higher reserve requirement according to Kara (2014) induces a decline in liquid asset holdings lowering the liquidity buffers on the banking systems. Alper *et al* (2014) point that many central banks in emerging economies have used reserve requirements to alleviate the trade-off between financial stability and price stability in recent years. The holdings of reserves over the business cycle, according to Chadha *eta al* (2012), acts as a substitute for more costly provision of commercial bank assets and thus reduces the volatility of interest spreads to shocks. To control liquidity risk, countries such as New Zealand introduced minimum ra-

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tio requirements which are; one-week mismatch ratio, one-month mismatch ratio and one-year funding ratio which are distinguished by market and non-market funding, see Richards (2010). Delfiner *et al* (2006) argue that a bank can store a stock of liquid assets to ensure some liquidity which can be referred to as liquidity warehousing. Therefore liquidity risk is closely linked to other dimensions of the financial structure of the bank.

In our model, the safety reserve can be referred to as voluntary reserves according to Rule (2012) and is defined as additional reserves held by the banks for precautionary motives. We assume that the safety reserves are not more than the bank's own reserve requirement. Therefore, the cash reserve requirement and the safety reserve are contained in the bank's own reserve. Further, we define excess reserve as surplus reserves holdings of bank with the central bank beyond the bank's own reserve requirement. The excess reserve is demanded for precautionary reasons and therefore, it cannot be understood in a certainty model. The excess reserve helps banks to hedge against the possibility of running short of reserves during the maintenance period. The total of safety reserve and excess reserve is the discretionary reserve. Like the excess reserve, the discretionary reserve serves as a buffer against unexpected liquidity shocks which serve as a cushion against overdraft. Figure 8.2 shows the overall categories of bank reserve that have been used in designing our model. The quality of reserves in the system is determined by the elements of the bank's statement of financial position. The safety reserve arises from a desire to self-insure and can vary dependent on the uncertainty of payment flows. However unremunerated required reserves are more costly to the bank. If the central bank decides to pay a rate of return to the bank, we assume that it can be at market or sub-market rate of interest. We need to note that the cost of required reserves depend on their coverage, namely how much of the bank's lia-

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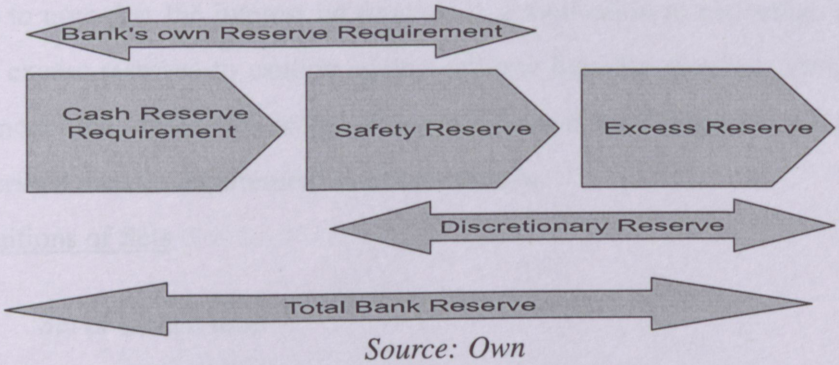
Figure 8.1: Total Bank Reserve



Source: Own

bilities are included. The discretionary reserves are deposits held at the discretion of the banks. In principle, the banking system's demand for reserves increases when the interest rates decline and decrease when they rise. Therefore, this shows the interest rate elasticity of demand for reserves. Calorimis *et al* (2012) show that the role of liquidity requirements should be conceived in a more nuanced way, not just as an insurance policy to deal with liquidity risk that can arise in a financial crisis but as a prudential regulatory tool. The best way to deal with a liquidity crisis is to design a combination of capital and liquidity requirements that prevent liquidity crises by ensuring that banks do not become weak enough so that their default becomes imaginable.

8.3 Model Formulation

Banks voluntarily hold excess reserves but by definition will not want to hold surplus reserve balances. Excess reserves can be easily observed by the central bank, in contrast surplus reserves are harder to observe accurately. To achieve our objective of maximising excess reserve, we assume that the bank is in a position to partition its overall reserve into distinct segments. The reserve segments are the compulsory statutory cash reserve requirement and the discretionary reserve.

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The assumption is that the discretionary reserve level is defined by the bank. We need to note that the interest on reserves is a motivation to encourage banks to have excess reserves to caution against adverse liquidity demand. However, in our model the assumption is that the central bank is not paying interest on either prescribed reserve requirement or excess reserve.

Definitions of Sets

T	Set of instant time
I	Set horizon bands
s_n	Set of scenarios, for $n \in N$
Ω_1	Set of event space for the unknown payment flow
Ω_2	Set of event space for the unknown penalty costs and rates on reserve shortfall
$P_{\omega_j^1}$	Set of probabilities of event space for the unknown payment flow, for $j \in J$
$P_{\omega_k^2}$	Set of probabilities of event space for the unknown penalty costs and rates on reserve for $k \in K$
P_{s_n}	Set of scenario probabilities, for $s_n \in S$

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Deterministic Data

$\beta \in (0,1)$	The statutory reserve proportion
O^R	Total precautionary fund
e_0	The initial excess reserve
$L^{w^{CB}}$	Required reserve ratio for borrowing from central bank's interbank market
L^{d^D}	Required reserve ratio for demand deposits
L^{g^F}	Required reserve ratio for savings and fixed deposits
Q	Total amount of initial excess reserve
$\alpha_D(\gamma, s\overline{e})$	The risk aversion coefficient
ϕ	The proportion of deposit withdrawals

Random Data

$c^D_{its_n}$	The cash deposits with partner banks, for $i \in I$, $t \in T$, and $s_n \in S$
$c^R_{its_n}$	Cash reserve requirement deposited with central bank, for $i \in I$, $t \in T$, and $s_n \in S$
$c^U_{its_n}$	Cash vault, for $i \in I$, $t \in T$, and $s_n \in S$
$f^R_{its_n}$	The bank's discretionary reserves, for $i \in I$, $t \in T$, and $s_n \in S$
$d^D_{its_n}$	The demand deposits, for $i \in I$, $t \in T$, and $s_n \in S$
$g^F_{its_n}$	The savings and fixed deposits
$w^{CB}_{its_n}$	The borrowing from central bank's interbank market, for $i \in I$, $t \in T$, and $s_n \in S$
$v^R_{its_n}$	Bank's safety reserve, for $i \in I$, $t \in T$, and $s_n \in S$
$y^R_{its_n}$	The payment flow, for $i \in I$, $t \in T$, and $s_n \in S$

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Decision Variables

$r^R_{its_n}$ The bank's own reserve requirement, for $i \in I$, $t \in T$, and $s_n \in S$

$b^R_{its_n}$ The total bank reserve decision, for $i \in I$, $t \in T$, and $s_n \in S$

$o^R_{its_n}$ The precautionary reserves, for $i \in I$, $t \in T$, and $s_n \in S$

8.3.1 Bank Reserve Scenario Tree

To construct a scenario tree, we consider now the case where the random vector S has a discrete and finite distribution, with n scenario set $S = \{s_1, .., s_n, ..., s_N\}$. We assume that $p_{s_n} \geq 0$ for all $s_n \in S$ and that $\sum_{n \in N} p_{s_n} = 1$. We need to note that a scenario is a path from the root of the tree to one of the leaves. The nodes visited by each path correspond to the values assumed by random parameters in the model. Before we define the scenario generation model, we define the payment flow function and is represented by equation that follows;

$$y^R_t = \mu_{y^R_t} + \gamma_{CI}\delta_{y^R_t} \tag{8.1}$$

where y^R_t are the payment flows at time t. The $\mu_{y^R_t}$ and $\delta_{y^R_t}$ are the mean and standard deviation of payment flows, respectively. The γ_{CI} is the standard normal value at confidence interval level CI. Then the scenario generation model is represented by equation that follows.

$$y^R_{i(t+1)s_n} = \mu_{y^R_t} + \gamma_{CI}\delta_{y^R_t}\epsilon_{t+1} \tag{8.2}$$

where we assume ϵ_t is the random error with mean 0 and variance 1. The Figure 8.1 is the scenario tree. In the scenario tree, we have two stages and at stage 0, the bank's own initial safety reserve v^R_0 held has to be decided on event space Ω_1 for the unknown payment flow $y^R_{0s_n}$. The event space have three branches to the

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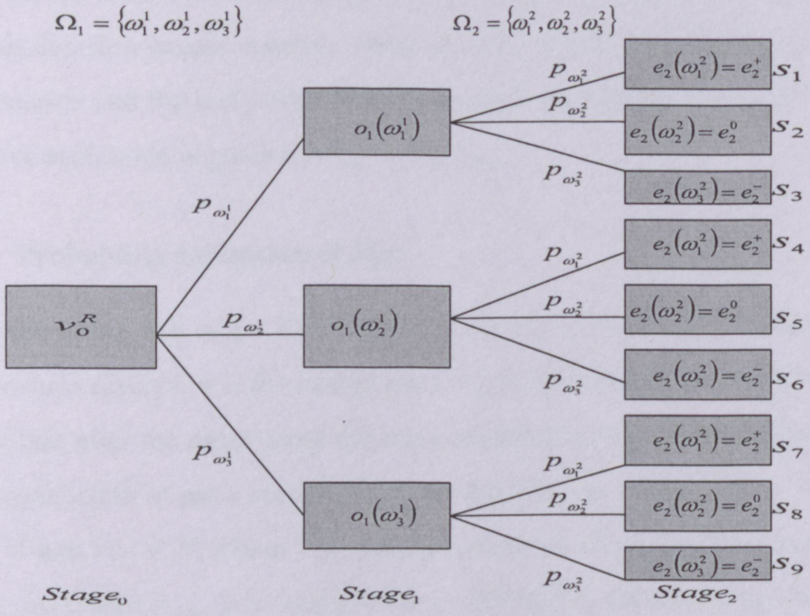
Figure 8.2: Bank Reserve Scenario Tree



next stage which denote three possibilities $\Omega_1 = \{\omega_1^1, \omega_2^1, \omega_3^1\}$, with corresponding probabilities $P_{\omega_1^1}, P_{\omega_2^1}$ and $P_{\omega_3^1}$ for the next stage. Once the payment flow $\omega_j^1 \in \Omega_1$, is observed at the beginning of stage 1, for $j = \{1, 2, 3\}$, a recourse decision $o_1^R(\omega_j^1)$ is made, at the end of stage 1 based upon which ω_j^1 nature chose and our previous decision v_0^R. In this case, the recourse decision is borrowing from the interbank market under uncertain penalty costs and rates. The bank may borrow from the central bank or other banks to maintain its own reserve requirement. The recourse decision is the precautionary fund. The penalty costs and rates are revealed at the beginning of stage 2, and its event space is denoted by Ω_2 if the bank borrows. The event space on penalty costs and rates in this case has three different outcomes denoted by $\Omega_2 = \{\omega_1^2, \omega_2^2, \omega_3^2\}$ with associated probabilities $P_{\omega_1^2}, P_{\omega_2^2}$ and $P_{\omega_3^2}$, respectively. We need to note that $\sum_{j \in J} P_{\omega_j^1} = 1$ and

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$\sum_{k\in K} P_{\omega_k^2} = 1$. Once the penalty costs and rates $\omega_k^2 \in \Omega_2$ in stage 2 have been observed, the excess reserve $e_2(\omega_k^2) = \{e_2^+, e_2^0, e_2^-\}$ is computed by the model as the final decision excess reserve. There is a one-to-one correspondence between the scenarios and the leaf-nodes in our tree and therefore the unconditional probability of each node is given by $P_{s_n} = P_{\omega_j^1} P_{\omega_k^2}$.

8.3.2 Probability Definition of Risk

We compute our risk $\alpha_D(\gamma, \overline{e}) = \mathbb{P}[e(\gamma) < \overline{e}]$, where $\alpha_D(\gamma, \overline{e})$ is the risk, $\overline{e}$ is the target excess reserve, γ is the design and $e(\gamma)$ is the actual reserve. Then we need to note that after the uncertainty has been unveiled, excess reserve corresponding to the realisation of each scenario is given by; $e_{its_n}(\gamma) = \psi_{its_n}\overline{b_{its_n}^R} - r^R(\gamma)$, for $\forall n \geq N$ and $\forall s_n \in S$, where $r^R(\gamma)$ is the optimal total bank reserve second-stage for scenarios and ψ_{its_n} is a constant value. Therefore, the risk of not meeting the target excess reserve in each individual scenario realisation is given by;

$$\alpha_D(\gamma, \overline{e}) = \sum_{n\in N} \mathbb{P}[e_{its_n}(\gamma) < \overline{e}] \tag{8.3}$$

$$= \sum_{n\in N} \mathbb{P}[\psi_{its_n}\overline{b_{its_n}^R} - r^R(\gamma)] \tag{8.4}$$

Therefore, we use our risk as the risk aversion coefficient in our model.

8.3.3 A Discretionary Liquidity Stochastic Programming Model

We formulate a two-stage stochastic programming model with recourse to manage discretionary liquidity portfolio. The advantage of stochastic programming models is that they provide a generic framework to model uncertainties and enable decisions that will perform well in the general case. The reserve maintenance period lasts one week and at every t^{th} day, we assume that the required reserves are calculated based on the four weeks moving average of the reserves. Further,

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we assume that banks that fail to meet the reserve requirements in domestic currency are subject to financial penalty. The penalty includes interest payment over the period of the shortfall. The interest charges are calculated using the highest lending rate of the relevant bank plus certain basis points and are prohibitively large, abstracting the bank's ability to roll over a fraction of their reserve imbalances to future periods, or to borrow from central bank at penalty rates. In the event of a liquidity shortage, we assume that the bank has recourse to the credit facility of the central bank, which is referred to as the discount window. However, we assume that there is no penalty if a bank fails to hold sufficient reserve balances in foreign currency. We further assume that a bank is permitted to utilise a certain part of their required reserves to lend, for example, private residential construction. In this case, the bank can lend up to a maximum percentage ($\alpha\%$)of the reserve base. We assume that the institution defines its own minimum reserve which is above the statutory minimum reserve requirement and is not fixed, and in this case it is the bank's own reserve requirement. Therefore, we maximise a stochastic programming model that follows;

$$\text{Max} \qquad [e_0 + \mathbb{E}[\max[\max \sum_{i \in I}((1-\alpha_D(\gamma,\overline{e}))b^R_{its_n} - \alpha_D(\gamma,\overline{e})r^R_{its_n}, 0)]]] \quad (8.5)$$

$$s.t. \quad e_0 \leq Q \quad (8.6)$$

$$c^R_{its_n} + c^U_{its_n} + c^D_{its_n} \leq b^R_{its_n} \qquad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \quad (8.7)$$

$$(L^{d^D} - \phi)d^D_{its_n} + (L^{g^F} - \phi)g^F_{its_n} + (L^{w^{CB}} - \phi)w^{CB}_{its_n} + y^R_{its_n} + v^R_{its_n} + o^R_{its_n} + B^R_{its_n} \geq r^R_{its_n} \quad (8.8)$$

$$\forall i \geq 1, \forall t \geq 1, \forall n \geq 1$$

$$L^{d^D} d^D_{its_n} + L^{g^F} g^F_{its_n} + L^{w^{CB}} w^{CB}_{its_n} \geq c^D_{its_n} \qquad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \quad (8.9)$$

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$$v^R_{itsn} + c^D_{itsn} \geq r^R_{itsn} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{8.10}$$

$$c^D_{itsn} + f^R_{itsn} \leq b^R_{itsn} \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{8.11}$$

$$\sum_{i \in I} o^R_{itsn} \leq O^R \quad \forall i \geq 1, \forall t \geq 1, \forall n \geq 1 \tag{8.12}$$

$$e_0 \geq 0, f^R_{itsn} \geq 0, o^R_{itsn} \geq 0, O^R \geq 0 \tag{8.13}$$

$$c^R_{itsn} \geq 0, c^U_{itsn} \geq 0, c^D_{itsn} \geq 0, b^R_{itsn} \geq 0, y^R_{itsn} \geq 0, o^R_{itsn} \geq 0$$

$$v^R_{itsn} \geq 0, d^D_{itsn} \geq 0, g^F_{itsn} \geq 0, w^{CB}_{itsn} \geq 0, r^R_{itsn} \geq 0$$

The objective function (8.5) is the total excess reserves that is maximised. The constraint (8.6) is the first-stage problem and represent the initial excess reserve $e_0 = b^R_0 - r^R_0$, where b^R_0 and r^R_0 are the initial total bank reserve and initial bank's own reserve, respectively. The total bank reserve is represented by constraint (8.7) and includes the cash reserve requirement, safety reserve and the excess reserve as shown in Figure 8.2. The constraint (8.8) denotes the bank's reserve in relation to anticipated deposit withdrawals per given time t. The precautionary fund is the recourse decision depending on the expected payment flow.

The constraint (8.9) is the cash reserve requirement deposited with the central bank. The bank receives demand deposits, savings and fixed deposits from its own clients and can borrow from the central bank at penalty rate. Each type of funding has a distinct reserve liquidity ratio that the bank must transfer to the reserve account. The bank's own reserve requirement is defined by constraint (8.10) which is computed by adding the cash reserve requirement and the safety reserve. We need to note that the bank should define its own reserve requirement higher than the statutory reserve as a precautionary measure. Therefore, constraint (8.11) denotes the total bank reserve that is computed by adding the cash reserve requirement and the discretionary reserve. The discretionary reserve is the total of safety

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reserve and excess reserve. The total precautionary fund is denoted by constraint (8.12). Finally, constraint (8.13) is non-negativity constraints.

8.4 Statistical Characteristics of Historical Data

Our model constructed is validated using data obtained from the International Monetary Fund through the South Africa Reserve Bank form January 1988 to April 2014. The statistical characteristics of historical cash reserve requirement and payment flow data are computed to define the nature of the data. We need to note that the values in this research are denoted in South African Rand. The results are presented in tabular form. The Lingo 14.0 software package is used to solve the stochastic programming model. We compare results based on different values of the risk aversion coefficient $\alpha_D(\gamma, \overline{e})$. We start by computing the statistical characteristics of historical data, which are the cash reserve requirement and payment flow as shown below. The cash reserves requirement and payment flow

Table 8.1: Statistical Characteristics of Historical Data

Statistical Measure	Cash Reserves	Payment Flow
Average	3.5344×10^4	1.7369×10^3
Standard Deviation	1.9785×10^4	4.7336×10^2
Kurtosis	-1.411302186	-4.2×10^{-1}
Skewness	$1.41679602 \times 10^{-1}$	2.1×10^{-1}
Minimum	6.311×10^3	2.70717×10^3
Maximum	7.0161×10^4	7.01×10^2

evidently exhibit positive skewed distributions. The standard deviation comparing it to historical computed mean shows considerable variance. The payment flow exhibit platykurtic, implying that it is less peaked than the normal distribution. We generate scenarios for payment flows using the proposed scenario generation

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model and should comply with historical observations, without relying on the normality assumption. We rely solely on the observed cash reserves and payment flow in the market. The first four moments computed are used as inputs in our scenario generation model to generate scenarios. The scenarios are generated so that the first four marginal moments of the random variables should match but not exactly as their historical values.

8.5 Empirical Analysis

We present our results in the form of tables and a graph. The first step is to evaluate whether the model is feasible before analyzing other components of the stochastic programming solution. Referring to Table 8.2, the model is feasible in all cases because the value of feasibility is zero. We further check the expected objective value. If we change the value of $\alpha_D(\gamma, a\overline{e})$ and holding all other variables constant, the stochastic solution changes. Thus if we increase the value of risk aversion coefficient, the objective value decreases. In this case, the objective value is the optimal excess reserve. The EV of excess reserve is the same as the reported optimal excess reserve for the model, further giving weight to the results. The EWS excess reserve reports the expected value of the optimal excess reserve

Table 8.2: Stochastic Programming Solutions: The Risk Aversion Coefficient $\alpha_D(\gamma, \overline{e})$ Changing

Risk	Obj (10^9)	Inf	EV (10^9)	EWS (10^9)	EVPI	EM (10^9)s	EVMU (10^{-7})
0.025	1.4786	0	1.4786	1.4786	0	1.4786	2.3841
0.09	1.3800	0	1.3800	1.3800	0	1.3800	2.3841
0.15	1.2890	0	1.2890	1.2890	0	1.2890	2.3841
0.21	1.1981	0	1.1981	1.1981	0	1.1981	2.3841
0.30	1.0616	0	1.0616	1.0616	0	1.0616	2.3841

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if we could wait and see the outcomes of all unknown payment flow and uncertain penalty costs and rates before making decisions. We expect $EWS \geq EV$ since we are maximising excess reserve.

The EVPI is used to compare EWS and EV and measures the maximum amount the decision maker should be willing to pay in return for complete and accurate information regarding the future outcomes of the underlying random variables. It can be computed as follows; $EVPI = |EV - EWS|$. In all cases, the ratio of total EVPI to optimal excess reserve is zero implying that the decision maker is willing to pay nothing per given period. The EM is the same as the expected true optimal excess reserve since we have assumed that all random variables always take on exactly their mean values. The Birge (2013) conditions state that if EVPI is zero, the corresponding EVMU should be non-zero. In our case, all EVMU are non-zeros, implying that we did gain by taking into account uncertainty in our model analysis. In addition, the EVMU is constant regardless of the value of risk aversion coefficient. The formula for computing EVMU is given by; $EV - EM$. Therefore, we can observe that $EV \leq EM \leq EWS$, $EVPI \geq 0$ and $EVMU \geq 0$ which are consistent with Barbaro and Bagajewicz (2004) and Birge (1997) conditions. Therefore, at this level, we can infer that the scenarios generated are reliable and valid.

Referring to Table 8.3, the random distribution of payment flow is constant regardless of change in risk aversion coefficient. Applying scenario generation method represented by equation (8.2) on historical values of the random variables, we obtain scenarios for the payment flows. Figure 8.3 shows the payment flow scenarios per band. The resulting scenarios are equiprobable in our tests, but generally they do not have to be.

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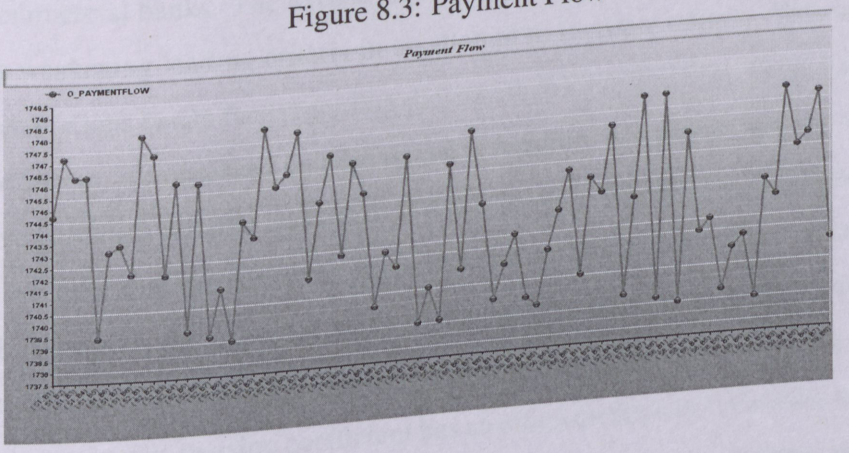
Table 8.3: Payment Flow Distribution

Payment Flow Bands	Sample Mean	Sample Standard Deviation
Band 1	1.743350×10^4	3.589000
Band 2	1.743703×10^4	3.064271
Band 3	1.743431×10^4	1.822321
Band 4	1.744712×10^4	3.296366
Band 5	1.742448×10^4	2.844511
Band 6	1.743002×10^4	2.462562
Band 7	1.744480×10^4	3.122188
Band 8	1.741975×10^4	1.592960

Figure 8.3: Payment Flow



8.6 Conclusions

We partition the bank's unitary liquidity portfolio to have a discretionary liquidity portfolio to focus on meeting the reserve requirements and provide buffer against unexpected liquidity shocks. We need to note that the total demand for bank reserves depends on prescribed reserve ratio by the central bank, the interbank market rate and the central bank policy rate. Thus there is an inverse relationship between the bank reserves and the interest rates, while on the other hand, a direct relationship with the reserve requirement ratio. The level of excess reserve

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is largely determined by the interest rate level paid on the reserve requirement and the excess reserve. Higher interest rate encourages holding of excess reserves and lower rates discourages and thus banks tend to minimise holding non-interest bearing excess reserves. Therefore, central banks should be encouraged to craft regulations to pay interest on reserve requirement and excess reserve. Excess reserves improve country's monetary policy and broaden the scope of the central bank lending programmes to address conditions in credit markets. In addition, paying interest on reserve expand the central bank's balance sheet to provide the liquidity necessary to support financial stability and thus maximise employment and price stability. However, excess liquidity induces asymmetric pricing of loans by commercial banks. The excess reserves may lead banks to loosen credit standards weakening lending criteria in an attempt to increase returns. This is one of the temptations banks face regarding the excess reserve decision. From Lingo solution output, we observed that the model is feasible. We further analyse whether the scenarios are reliable and valid. After assessing the value of stochastic solution, we infer that the scenarios generated and results computed are reliable and valid. However, the expected value of modelling uncertainty is non-zero in all cases. This implies that we benefited by incorporating randomness in our model. The change in risk aversion coefficient has an effect on the level of excess reserves. Increasing the risk aversion factor decreases the optimal excess reserve while decreasing the coefficient leads to increase in optimal excess reserve. Therefore, we strongly recommend banks to create discretionary liquidity with the aim of hedging against unexpected liquidity shocks. However, more research can be done on how to accurately compute future discretionary reserve using historical data and incorporating stochastic elements in the model. In addition, appropriate models that can be used to estimate safety and excess reserves need to be investigated.

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CHAPTER 9

9 INTEGRATED LIQUIDITY MANAGEMENT STOCHASTIC PROGRAMMING MODELS

9.1 Introduction

There has been intense interest on whether the traditional tools that have been at policymakers' disposal remain adequate in the face of modern liquidity crises. The Basel 3 Accord defined liquidity ratios banks should hold at any given time to minimise liquidity risk and looked at liquidity as a unitary portfolio. However, banks suffer from "tunnel vision", which involves determining optimal decisions under a specific circumstance where the management assume perfect foresight. Banks hold cash assets to satisfy four objectives; the first is to meet customers' regular transaction needs to meet legal reserve requirements, to assist in the cheque payment and to purchase corresponding banking services. Generally, banks own four types of liquid assets which are the vault cash, demand deposit balances at the central bank, demand deposit balances at private financial institutions and cash items in the process of collection.

The Basel Committee for Banking Supervision did not specifically define sub-portfolios banks should hold to enhance liquidity management. According to Burucs, liquidity risk arises from many sources which are event-driven sources, transaction-and product-driven sources, and market trend. The event-driven sources include potential damage to a firm's reputation. The transaction-and product-driven sources include specific products and activities and potential changes in the macroeconomic environment. Liquidity risk management modelling here means integrating the four portfolios of future cash flows which rests on a stochastic

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foundation and not only depend on expert judgement. The quality of the model is based on the quality of the model's data input. Liquidity risk is insolvency risk in the narrower sense and is the danger that a bank will be unable to meet its present and future payment obligations completely or on time. There is a connection between liquidity risk and other types of risks. The value of liquid assets and the availability of external refinancing, depend not least on the market situation but on several factors such as public relations with other financial institutions and banks corporate clients. Therefore it is sensible to integrate liquidity risk management with the management of other types of risk such as credit risk, interest rate risk, concentration risk, and operational risk. Thus the banks should implement an integrated stress test covering all types of risk.

Since there is no single model that has successfully separated liquidity according to liquidity needs, in this thesis we integrate the four portfolios and we find the optimal weighted difference between threshold and shortfall. The four segments of the overall liquidity portfolio are the core liquidity, cash cushion, operational cash and discretionary liquidity sub-portfolios. As has been previously explained, the core liquidity portfolio focuses on preserving the liquidity buffer through investing in short-term and high quality liquid assets. The second cash cushion portfolio focuses on holding cash in transit through maximizing interest earned spread. The third operational cash portfolio is designed to meet short to near-term cash requirements over a time horizon of ninety days to one year. It is funded by individual money market securities, including time deposits, ultra short bond funds and commercial paper. Finally, the discretionary liquidity portfolio is used to support medium-term funding needs and is funded by debt to provide flexibility in executing the funding programme over the medium term and to opportunistically permit borrowing ahead of cash flow needs and bolster bank's access to

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short-term funding through continuous presence in the market. We construct a two-stage stochastic programming model to manage the integrated liquidity portfolios. To meet the liquidity requirement, we maximise the difference between the threshold and shortfall. The choice of stochastic programming led to the development of an effective integrated risk management framework and practical decision support tools for total liquidity risk management. The empirical validation of the models is done through extensive numerical tests using real market data.

9.2 Banks Liquidity Risk Management Strategies Framework

Rather than getting mired in the theoretical debate on causes of liquidity crises, we take a more pragmatic approach and outline strategies banks may implement. Gongol and Vodová (2014) point that one of the key characteristics of the global financial crisis was the inaccurate and ineffective liquidity risk management. Different banks are implementing different strategies to curtail liquidity risk. Neu and Vogt (2010) explained that it is appropriate for the bank to segment liquidity risk into three categories. The first category is the maturity mismatch risk. Maturity transformation is one of the primary economic functions and banks manage this risk by holding a reserve of central bank eligible securities. Previously we have defined the portfolio as the core liquidity portfolio. The second category is the contingency liquidity risk and can be defined as the risk of not having sufficient funds to meet sudden and unanticipated short-term obligations. By managing this risk, a bank safeguards its reputation to meet its obligations, especially in times of crisis. Banks need to develop contingency plans, keep a comfortable level of counterbalancing capacity and capital on hand and manage investors' perception by disclosing the bank's liquidity profile and funding needs under different scenarios. The contingency liquidity risk is not different from funding liquidity risk and according to Iqbal (2012), the former relates to the solvency. The final category

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is the market liquidity risk and relates to the financial instruments in the market. The contingency and market liquidity risk are far more difficult to manage and to understand those risks, banks need to anticipate how markets and customers will respond to extreme situations, and how these responses, in turn will affect the bank's funding ability and the saleability of its assets.

To appropriately and efficiently manage liquidity risk, the levels of liquidity risk management should be designed to provide required cash at appropriate time, while at the same time allowing investment policies that maximise returns on investments. In order to achieve the proper balance between cash availability and maximum return, it is necessary for the bank to examine a broad range of economic scenarios and stress events. In this thesis we define four levels. The first level is the day-to-day cash management, which involves controlling day-to-day cash flow variability by balancing cash positions and lines of credit. The first level is mainly managed by cash cushion portfolio. In modern banks, according to Cornett *et al* (2011), liquidity risk stems largely from exposure to undrawn loan commitments, the withdrawal of funds from wholesale deposits and the loss of other sources of short-term financing, rather than from the loss of demand deposits. Therefore as a strategy, a bank holds cash and other liquid assets to manage liquidity risk. Gomes and Khan (2011) explain the new liquidity standards and ratios defined in Basel 3 which are the liquidity coverage ratio and the net stable funding ratio. The second level is the ongoing cash flow management and involves ongoing cash needs and in our thesis, the period is over the next 1 to 3 months. It involves analysis of cash inflows and outflows. If future cash flow needs exceed future available cash, this implies that the bank should plan to restore liquidity through restructuring or fine-tuning the portfolio, selling more or fewer of selected products, diversifying where possible and changing the invest-

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ment strategy if needed. Renegotiating the terms of large liabilities or assets is an important strategy that protects the bank from serious liquidity risk. The third level is the intermediate cash flow management which involves liquidation of secondary reserves and is over 3 to 9 months. The final level is the stress liquidity risk management and it involves the ability of the bank to meet the demands of many customers for cash over a short period of time. Day-to-day and ongoing term cash management plan provides lower levels of adversity and involves cash management and cash lines, while stress liquidity risk management, involves liquidation. Ioan and Dragoş (2009) proposed a strategy of altering the behaviour of assets and liabilities and encourages banks to have liquidity back-up lines. Ibe (2013) points that liquidity management has an effect on the profitability of Nigerian banks.

By law, banks are required to hold liquidity buffers to self-ensure against unexpected cash outflow. Instead of self-insuring, banks could resort to other forms of financing such as accessing interbank markets, central bank liquidity discount window or external credit lines. However asymmetric information may lead to coordination failures on the interbank market and external credit lines may freeze as evidenced by the Lehman case, thus banks hold a buffer of liquid assets as self-insurance. The banks may implement three different regimes; the reserve requirement, exclusively prudential liquidity requirements in the absence of central bank and both reserve requirement and prudential liquidity requirement (Deléchat *et al*, 2014). Liquidity mismatch induces a trade-off between profiting from lending and incurring additional liquidity risk. Banks face a trade-off between the safety of greater liquidity and the expense of obtaining it. This makes it difficult to answer the question of how much liquidity is enough. According to Elliot (2014) banks try to ensure that they have sufficient liquidity to meet all relevant regulatory requirements plus a buffer to reduce the likelihood that liquidity falls

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below these thresholds and triggers a regulatory or market response or creates constraints on the banks' actions. Capital is arguably the most important safety buffer, since it provides the resources to recover from substantial losses of any nature and also gives those dealing with the bank confidence in its safety.

Sound liquidity risk management requires the following elements; well established strategies, policies and procedures for managing both resources and uses. The other element is liquidity risk measurement systems that are appropriate that can range from simple gap derived cash flow measures to very sophisticated cash flow simulation models, and adequate internal and external controls and its processes. Finally, a comprehensive liquidity contingency planning should be in place in case of unexpected cash flow movements. The general procedure in liquidity risk management strategy is that the management board defines the liquidity risk strategy based on recommendations made by capital and risk committee. Periodically management board review and approve the limits which are applied to the group to measure and control liquidity risk as long-term funding and issuance plan. Therefore liquidity risk management framework is designed to identify measure and manage liquidity risk position. The liquidity risk management approach starts at the intra-day level forecasting cash flows and factoring in access to central bank. The approach covers the tactical liquidity risk management dealing with access to secured and unsecured funding sources. The last part of the procedure is the strategic perspective which comprises the maturity profile of all bank assets and liabilities and issuance strategy. We need to note that the funding matrix is important to funding liquidity risk management. Of prime importance is the stress testing and scenario analysis which play central roles in liquidity risk management framework. Thus it is important for each bank to have an approved strategy for the operational management of the liquidity, a strategy that must be communicated

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within the organisation. The liquidity banking strategy has to present specific policies. The strategy should address the bank's goal of protecting financial strength and the ability to withstand stressful events in the market place. A bank's liquidity strategy should enunciate specific policies.

9.3 Model Formulation

The models constructed in Chapters 5 to 8 are integrated to form a single model. We construct a two-stage stochastic programming model to maximize the difference between the threshold and the shortfall subject to a set of constraints. Now we start by defining model notations below.

Definitions of Sets

J	Set of liquidity sub-portfolios
s_n	Set of scenarios, $n \in N$
Ω_1	Set of event space for the unknown portfolio returns
Ω_2	Set of event space for the unknown sub-portfolio return
$P_{\omega_i^1}$	Set of probabilities of event space for the unknown portfolio return, for $i \in I$
$P_{\omega_k^2}$	Set of probabilities of event space for the unknown sub-portfolio return, for $k \in K$
P_{s_n}	Set of scenario probabilities, for $s_n \in S$

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Deterministic Data

$\alpha \in (0,1)$	The probability of the overall portfolio ending value less than or equal to threshold
B	The total budgeted amount
D	The difference between the threshold and shortfall
G	The target expected return
R	Total value of overall liquidity portfolio at the end of stage 1
$r_j^{s_n}$	The sub-portfolio j returns from scenario s

Decision Variables

Z	The value-at-risk threshold at stage 0 decision
x_j	The amount invested in sub-portfolio , a stage 0 decision

9.3.1 Portfolio Return Scenario Tree

We need to generate scenarios for each sub-portfolio returns. Now consider a case where the random vector s_n, has a discrete and finite distribution with $s_n \in S$. We denote p_{s_n} as the probability of realization of scenario s, where $\sum_{s_n \in S} p_{s_n} = 1$ must be satisfied. A scenario is defined as a path from the root of the tree to one of the leaves. The nodes visited by each path correspond to the values assumed by random parameters in the model. The random variable portfolio return scenarios can be computed by equation;

$$r_t = \overline{r} + \delta_r \gamma_{CI} + \epsilon_t \tag{9.1}$$

In the scenario tree at stage 0, the x_j^0 represents the initial amount invested in each sub-portfolio to be decided under event space having three possibilities $\Omega_1 = \{\omega_1^1, \omega_2^1, \omega_3^1\}$, with associated probabilities $p_{\omega_1^1}, p_{\omega_2^1}$ and $p_{\omega_3^1}$. The event space ω_1 represents portfolio returns. At the beginning of stage 1, the sub-portfolio returns

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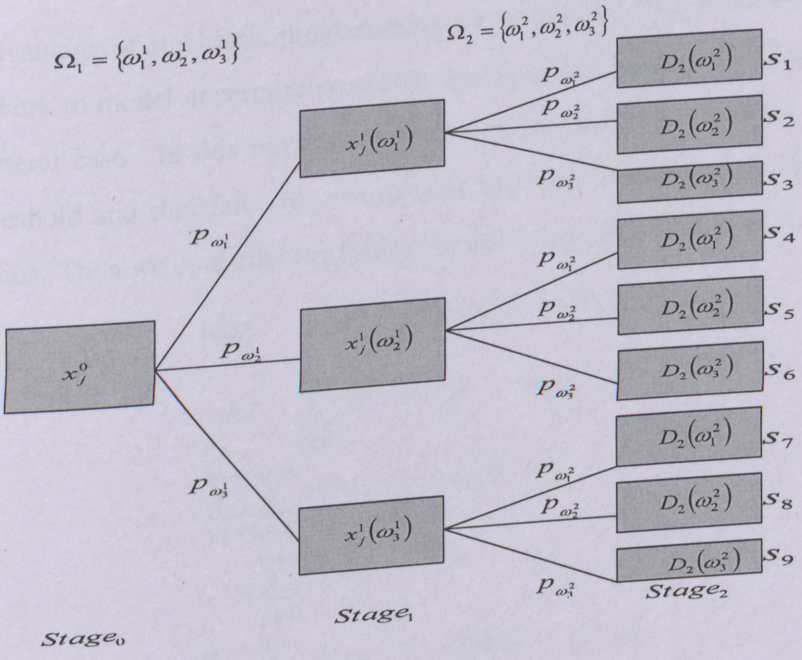
Figure 9.1: Scenario Tree



are revealed and a recourse decision $x_j^1(\omega_i^1)$ is made. An investment decision factoring in the random return is made at the end of stage 1 under event space $\Omega_2 = \{\omega_1^2, \omega_2^2, \omega_3^2\}$ with associated probabilities $p_{\omega_1^2}$, $p_{\omega_2^2}$ and $p_{\omega_3^2}$. At the beginning of stage 2, the difference between threshold and shortfall $D_2(\omega_k^2)$ in computed. We need to note that the event space Ω_2 is the uncertain sub-portfolio return. The sub-portfolio return before first stage and after first stage event spaces probability must satisfy the following conditions; $\sum_{i \in I} p_{\omega_i^1} = 1$ and $\sum_{k \in K} p_{\omega_k^2} = 1$, respectively. The unconditional probability of a node in this case is given by $p_{s_n} = p_{\omega_i^1} p_{\omega_k^2}$, which starts from the root and terminates at that node.

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9.3.2 An Integrated Stochastic Programming Model

The advantage of stochastic programming models is that they provide a generic framework to model uncertainties and enable decisions that will perform well in the general case. In this model, we need to maximise the difference between the threshold and shortfall. We assume that the bank invests in four liquid sub-portfolios. Then we construct the following stochastic programming model.

$$\text{Max} \qquad \alpha Z - \mathbb{E}[\max[Z - r_j^{s_n}, 0]] \tag{9.2}$$

$$s.t. \quad \sum_{j \in J} x_j = B \qquad \forall j \geq 1 \tag{9.3}$$

$$\sum_{j \in J} \sum_{n \in N} r_j^{s_n} x_j \geq s_N G \tag{9.4}$$

$$\sum_{j \in J} r_j^{s_n} x_j = R \tag{9.5}$$

$$Z - \sum_{j \in J} r_j^{s_n} x_j \leq \max[Z - r_j^{s_n}, 0] \tag{9.6}$$

$$x_j \geq 0, r_j^{s_n} \geq 0, Z \geq 0 \tag{9.7}$$

The equation (9.2) denotes the objective function where we maximize the weighted combination of threshold minus shortfall. The function $Z - r_j^{s_n}$ is the amount the portfolio value falls short of threshold, a stage 1 decision. The constraint (9.3) is the stage 0 decision where the bank cannot invest more than the budget. The target expected return is denoted by constraint (9.4).The constraint (9.5) denote the total value of overall liquidity portfolio at the end of stage 1. The constraint (9.6) denotes the amount by which portfolio all short of threshold. The non-negativity constraints are denoted by equation (9.7).

9.4 Methodology

The choice of stochastic programmes has been made for several reasons. In this research, stochastic programming can accommodate general distributions and dy-

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namic aspects by means of a scenario tree. We do not explicitly assume a specific stochastic process for the sub-portfolio return but viewed as an independent and identically distributed random variable; and we rely on empirical data distributions. The Lingo 14 software was used to solve the constructed two-stage stochastic programming model. The monthly data used is from the South African Reserve Bank from year January 2000 to March 2014. We start by computing the statistical characteristics of historical data. The Lingo 14 software was used to analyse the data.

Table 9.1: Statistical Characteristics of Historical Data

Statistical Measure	Prescr Liq Ass	Liq Ass Held	Exc Liq Ass	Total Liab
Average	9.4374×10^{4}	1.39788×10^{5}	4.5413×10^{4}	1.612×10^{6}
Standard Deviation	4.4982×10^{4}	9.7145×10^{4}	5.6658×10^{4}	7.4934×10^{5}
Kurtosis	-1.5283	-1.0294	-6.827×10^{-1}	-1.5388
Skewness	8.919×10^{-2}	6.870×10^{-1}	1.0283	2.922×10^{-2}
Minimum	3.3279×10^{4}	3.6634×10^{4}	-5.1×10^{3}	5.3282×10^{5}
Maximum	1.71446×10^{5}	3.27016×10^{5}	1.6902×10^{5}	2.8524×10^{6}

Table 9.1 above shows the statistical characteristics of liquid assets held, the prescribed liquid assets, excess liquid assets and the total liabilities of all commercial banks. The historical liquid asset held required liquid asset, excess liquid asset and total liability data exhibit skewed distributions; they also exhibit considerable variance in comparison to their mean. In addition, the operation cash and discretionary liquidity sub-portfolio returns exhibit platykurtic, implying less peaked than the normal distribution while the core liquidity and cash cushion sub-portfolios exhibit leptokurtic implying fatter tails. Thus, we need to generate scenarios for sub-portfolio return that comply with historical observations, without relying on the normality assumption. We rely solely on the observed actual liq-

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uid asset held and sub-portfolio returns in the market. We estimate the first four moments and we generate scenarios based on these statistical characteristics. The scenarios are generated so that the first four marginal moments of the random variables match their historical values. Table 9.2 that follows shows the statistical

Table 9.2: Random Sub-Portfolio Return Statistical Characteristics

Statistical Measure	Core Liquid	Cash Cushion	Operat Cash	Discret Liquid
Average	1.02593	1.008743	1.006531	1.01260
Standard Deviation	0.27691	0.140659	0.106185	0.0648885
Kurtosis	5.537219	17.3288	0.669912	1.530876
Skewness	1.35321	2.58914	-0.005345	0.55568
Minimum	0.4	0.588	0.75	0.882353
Maximum	2	1.75	1.25	1.2

characteristics of the four sub-portfolio returns.

9.5 Empirical Analysis

In analysing the stochastic programming solution, we start by observing the global optimal status. In this case, solution status is globally optimal implying that the results are valid. Now we turn to Table 9.3 where results of different components are shown. Of prime importance are the optimal weighted combination of threshold minus shortfall, which are the expected objective values over all different cases and scenarios. The probability value is changing and as expected, the objective value should also change. Here the objective value increases as the probability increases. The EV are the same as the reported objectives for the model, further giving weight to the results. The EWS reports are different from the expected value of the objective if we could wait and see the outcomes of all random

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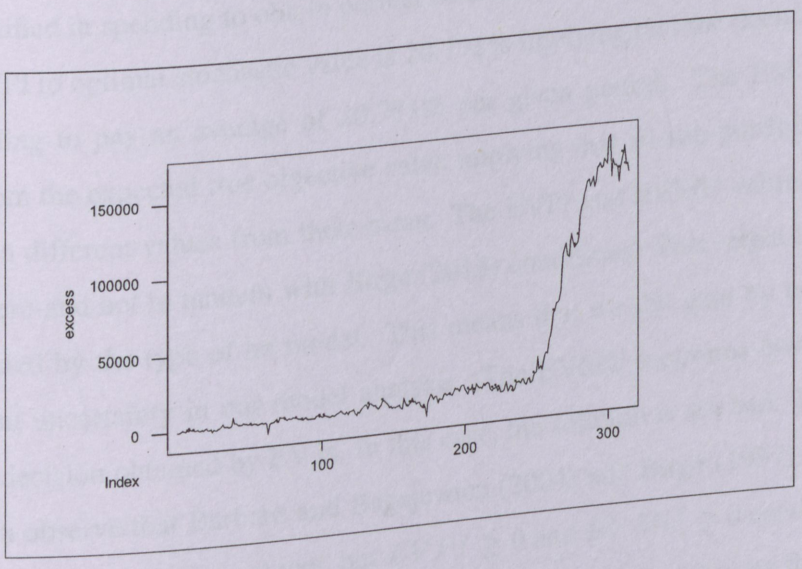
Figure 9.2: Excess Liquidity



variables before making decisions. For further explanation of the stochastic programming notations and facts refer to the Appendix.

Table 9.3: Stochastic Programming Solutions when β is changing

Probability	Obj	Inf	EV	EWS	EVPI	EM	EVMU
$\beta = 0.025$	42.51550	0	42.51550	53.93086	11.41535	-153.8827	196.3982
$\beta = 0.05$	85.03101	0	85.03101	107.8617	22.83071	-102.1269	187.1579
$\beta = 0.14$	238.1424	0	238.1424	302.0128	63.87038	84.19390	153.9485
$\beta = 0.33$	563.1944	0	563.1944	711.8873	148.6929	477.5379	85.65652
$\beta = 0.4$	693.9000	0	693.9000	862.8937	168.9937	622.4541	71.44591

Changing the value of the probability and holding all other probability changes, the threshold changes as well as the amount invested in each sub-portfolio.

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The EVPI is the upper bound on the amount of money the decision maker would be justified in spending to obtain perfect information. In all cases, the ratio of total EVPI to optimal stochastic value is 20.791% implying that the decision maker is willing to pay an average of 20.791% per given period. The EM is different from the expected true objective value implying that all sub-portfolio returns take on different values from their mean. The EVPI and EVMU values are both non-zero and not in tandem with Birge (2013) conditions. This might have been attributed by the type of he model. This means that we did gain by taking into account uncertainty in our model analysis. The EVMU measures how good or bad a decision obtained by EV is. In this case, the solution is not bad. Therefore, we can observe that Barbaro and Bagajewicz (2004) and Birge (1997) condition $EV \leq EM \leq EWS$ is not met, but $EVPI \geq 0$ and $EVMU \geq 0$ conditions are satisfied. Table 9.4 above shows the decisions that should be taken by the bank in

Table 9.4: Stage 0 Solutions

Portfolio	$\beta = 0.025$	$\beta = 0.05$	$\beta = 0.14$	$\beta = 0.33$	$\beta = 0.4$
Threshold	1700.620	1700.620	1704.930	1715.286	1924.015
Core liquidity	0.000000	0.000000	0.000000	0.4624592	620.5734
Cash Cushion	0.000000	0.000000	0.000000	0.000000	0.000000
Operational Cash	1389.937	1389.937	1700.000	1699.538	1079.427
Discretionary Liquidity	310.0629	310.0629	0.000000	0.000000	0.000000

the initial stage per sub-portfolio. The values change as the probability changes. We can observe that the cash cushion portfolio is zero implying that changing the probability value will not have an influence on investing in cash cushion sub-portfolio. Table 9.5 shows the return distribution of each sub-portfolio generated through solving the model. The distribution of random distribution is assumed not

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Table 9.5: Stage 0 Solutions

Return	Mean	Standard Deviation
Core Liquidity	1.217783	0.2502227
Cash Cushion	1.113193	0.1338227
Operational Cash	1.117031	0.1000602
Discretionary Liquidity	1.037102	0.03391588

to follow any process and we assume they are stochastic. The sub-portfolio return values are constant regardless of the probability value. The resulting scenarios are assumed to be equiprobable in our tests, but generally they do not have to be.

9.6 Conclusion

A two-stage stochastic programming model to maximize deviation between threshold and shortfall was constructed. A scenario generation model to generate portfolio return scenarios is developed. The portfolio return is stochastic and therefore we represent it on a scenario tree. From Lingo solution output, we observed that the model is feasible. We further analysed whether the scenarios are reliable and valid. After assessing the value of stochastic solution, we inferred that the scenarios generated and results computed are reliable and valid. Changing the probability value has an effect on the level of difference between threshold and shortfall. In other words, increasing the probability value increases the weighted difference between threshold and shortfall. Therefore we conclude that the greater the difference between the threshold and shortfall, the better the bank liquidity is. So it is worthwhile increasing the threshold as long as the fraction of outcomes is less than the probability. We strongly recommend that banks should design four liquidity sub-portfolios each having specific objectives to be fulfilled. A stochastic programming model may be used to determine the value of each portfolio since

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it has an advantage that the banks are well-hedged against worst-case scenarios. However, bank liquidity is restricted by capital adequacy, required reserves, liability and deposit insurance defined by the central bank. Further research can be done on modelling the banks threshold and shortfall.

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CHAPTER 10

10 SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

10.1 Summary

A number of financial intermediaries in different countries throughout the world faced serious challenges that ranged from chronic liquidity problems, deep-rooted risk management deficiencies and poor corporate governance practices during 2007 to 2009 financial crisis. The liquidity crisis especially in USA was caused by low real interest rates stimulating an asset price bubble fuelled by new financial products that were not stress tested and that failed in the downturn. Large depository institutions face the question of how to optimally allocate and generate liquidity. Thus varying levels of sensitivity of depositors is making it very difficult for institutions to predict volume response and as a measure, most financial intermediaries are focusing on deposit rate and the volume response.

There are three approaches a financial intermediary can adopt to the cost of uncertainty which are; disregarding uncertainty, take uncertainty and prepare for it and finally, eliminate uncertainty. In all our constructed models, we take uncertainty and prepare for it by constructing stochastic programming models with recourse. To be specific, we consider the use of simulation and two-and multi-stage stochastic programming with recourse models in the optimisation of liquid asset portfolios. The stochastic programming is a multi-faceted problem, and even the most focused treatment necessarily incorporates techniques from a wide range of disciplines. Through the development of fully coherent models and a sufficiently robust solution methodology, we provide a thorough overview of the

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problem at hand, discussing approaches in both industry and in academia. We introduce practical and theoretical advances that are to our best knowledge unexplored in the current literature, and document the usefulness of these avenues through a systematic series of increasingly complex applications and experiments. Liquidity management process involves two paradigms relating to the asset-side and liability-side of a bank's financial position statement. The first paradigm is funding liquidity that focuses on maturity transformation. The market liquidity is the second paradigm, which transforms the assets itself from illiquid pools of loans into liquid securities. In making decisions, the bank should consider the following stress scenarios; the idiosyncratic, market-wide and combination of both stresses. Liquidity risks are endemic to banking given the maturity transformation they undertake. The first line of defence should be appropriate liquidity policy on asset and liability side, supported by adequate capital and bank supervision.

Our contribution is fourfold. First we investigate appropriate scenario generation methods and perform a rigorous investigation on how to generate multistage scenario trees. Further, we investigate the inclusion of all qualifying liquid assets instruments into the portfolio optimisations. We propose a novel multistage stochastic programming methodology for liquid asset control. Thus we define how to construct and solving stochastic programming models for liquidity needs-driven sub-portfolios. Our approach is based on scenario trees and makes no assumptions on the distributions of random variables. Finally, we investigate the inclusion of liquidity needs-driven strategies which are core liquidity, cash cushion, operational cash and discretionary liquidity into the overall liquidity portfolio. The stochastic programming explicitly recognises uncertainty by using random variables for some aspects of the problem and defining the sequence of decisions in relation to the realisation of the random variables. Given the sequence, an

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objective function is defined that reflects a rational criterion for evaluating the decisions made before the realisation of randomness may have feasibility consequences after the realisation.

10.2 Conclusion

Cash and liquidity management are core elements of a successful financial intermediary. Appropriate liquidity management should ensure that cash available is enough to meet all expected and unexpected payment needs. However to efficiently and effectively manage liquidity, it involves forecasting, transparency and communication, risk management and bank relationships. Therefore, the optimal liquidity management framework should address the actual and potential cash demands. Today's banking industry are treating the liquidity portfolio as any other company portfolio and not taking into account bank specific needs embedded in the portfolio. Most commercial banks generally hold a unitary liquidity portfolio and not necessarily segmented to focus on bank specific cash and liquidity needs. Banks do have different cash needs at different times. Financial intermediaries to manage liquidity efficiently and effectively, segmenting the optimal liquid asset portfolio is the best management strategy. Liquidity is affected by stochastic deposits and withdrawals. Therefore, factoring in factors that affect bank liquidity is of prime importance.

Bank's liquidity management depends on liquidity buffer, interest rate spread, net cash and the level of excess. The sub-portfolio models constructed assist the decision makers in finding the relationship between the optimal liquid asset to stochastic models and deterministic models when a situation is random. In designing the sub-portfolios, liquidity determinants such as liquid asset returns, loan returns, payment flow and gross income are uncertain, and to avoid liquidity problems in

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the near future, we need to include randomness on these variables. By taking into consideration randomness on liquidity determinants, the bank is preparing for the worst-case scenarios. Understanding the behaviour of the deterministic liquidity variables relative to stochastic reveals some general properties of the underlying problem and help to predict how a stochastic model will perform. However we need to note that if EVPI is large, it should be a signal to the decision maker to seek another alternative. The stochastic programming models with recourse have been considered because of their growing importance in the field of finance than linear programmes. Stochastic programming is decision making under risk and provide a powerful paradigm for decision making under uncertainty. We constructed a multi-stage stochastic programming to control liquid asset portfolio. The bank needs to know how many liquid assets to liquidate to meet its liquidity obligation at the beginning of each instant time. The decision maker's decision depends on the state of liquidity level, liquidity demand, the asset price, holding and maintenance costs and the defined lower and upper liquidity thresholds.

10.3 Findings

The stochastic programming models with recourse are clear, easy to implement, very efficient and provide the optimal solution according to future possible set of scenarios. In defining and constructing stochastic programming models with recourse, sensitivity analysis should be carried out to increase the decision maker's understanding of the problem and to show the effect of different assumptions. Constructing an SP model with more stages provides better approximations compared to a single-period model. The use of the proposed models through segmenting the unitary liquidity portfolio improves the management of liquidity compared to current techniques which are based on simulation, experience and trial-and-error. Thus high quality liquidity buffers insure the bank against any adverse liq-

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uidity risk. We found that liquidity buffer is best modelled as a stochastic process than the deterministic. Incorporating randomness in the model enlighten decision makers to make informed decisions. Solving SP models helps decision makers to measure the expected gain from solving an SP model than its deterministic counterpart, where random variables are placed by their means. Changes in interest rate impact on bank liquidity and we need to note that bank clients are sensitive to interest rate movement. High net cash flow enhances effective and efficient liquidity management. Finally, excess reserves improve country monetary policy and broaden the scope of central bank lending programmes to address conditions in credit markets but on the other hand, may lead banks to loosen standards by weakening lending criteria in an attempt to increase returns. In addition, excess liquidity induces asymmetric pricing of loans by commercial banks.

10.4 Recommendations

To effectively and efficiently manage liquidity, there are key liquidity principles which the bank may be required to follow. The first is that the bank needs to understand and categorise its cash needs into at least four liquidity sub-portfolios as explained in previous chapters. We strongly recommend that banks should design the following sub-portfolios; liquidity buffer, cash cushion, operational cash and discretionary liquidity. The objective and funding of each sub-portfolio should be clearly defined. A stochastic programming model may be used to determine the value of each sub-portfolio since it has an advantage that the banks are well-hedged against worst-case scenarios. Secondly, the bank should establish appropriate investment guidelines in each sub-portfolio focusing on availability and safety. Third, the bank should select investment types within guidelines that are appropriate for each cash category. Then finally, the bank should establish a diversified contingent funding source such as the use of liquidity derivatives.

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However, bank liquidity is restricted by capital adequacy, required reserves, liability and deposit insurance defined by the central bank. Also the changes in interest rates could impact on bank liquidity. Bank clients are sensitive to interest rate movement. If savings rates are lowered, clients might withdraw their funds and cause a liquidity shortfall. On the other hand, higher rates on loans could make it difficult for some clients to meet interest payments, causing a liquidity shortage. The bank net cash is restricted by tax rate, interest rates, market performance, and operating business strategy. The level of excess reserve is largely determined by the interest rate level paid on the reserve requirement and the excess reserve. Therefore higher interest rate encourages holding of excess reserves and lower rates discourage and thus banks tend to minimise holding non-interest bearing excess reserves. So we recommend that it is the duty of the central bank and the government to monitor interest rates movements and keep them at optimal level. In addition, we encourage the central banks to pay interest on excess reserve holdings. Further, banks need to build better information infrastructure that are capable of tracking cash flow mismatches and contingency liquidity outflows and improve on funding mix.

10.5 Further Research

Finally, we highlight areas for further research. Investigations may be carried out on optimal liquidity level that will help to solve the problem of excess liquidity such that it may not reduce bank profits. Cash flow forecasting has always been and will continue to be one of the most important tasks associated with minimising liquidity risk, and therefore it needs further in-depth investigation. Quantitative approaches are critical; however mathematical models cover only some elements that contribute to bank's risk profile and thus robust quantitative techniques for

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forecasting cash outflow need to be developed. The variety of natural and social phenomena which produce risk is infinite while mathematical and statistical techniques for capturing risk are very few. Thus the qualitative connotations of risk are extremely complex and variegated, research regarding robust models that capture behavioural cash flows and related phenomenon need to be carried out. Collapsing of some banks during the financial crisis was due to inappropriate pricing of liquidity risk, and therefore research can be done on appropriate pricing models of liquidity risk. Quest for appropriate models that can accurately estimate the discretionary and excess reserves need to be investigated.

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Appendix

We define the basic facts and notations according to Maggioni and Wallace (2012).

$$\max_{x \in X} \mathbb{E}[z(x, \xi)] = \max_{x \in X} \{f_1(x) + \mathbb{E}_\xi[h_2(x, \xi)]\} \tag{A1}$$

where

x	First-stage decision variable restricted to the set $X \in \mathbb{R}^n$
$\mathbb{E}_\xi$	The expectation with respect to a random vector ξ defined on some probability space $(\Omega, \mathbb{F}, p)$ and given probability distribution p on the algebra $\mathbb{F}$
h_2	The recourse function, the value of another optimisation problem
$\mathbb{E}_\xi[h_2(x, \xi)]$	The expected recourse function

The recourse function is

$$h_2(x, \xi) = \max_{y \in Y(x,\xi)} f_2(y, x, \xi) \tag{A2}$$

The function reflects the costs associated with adopting to information revealed through a realisation ξ of the random vector ξ. The solution x^* obtained by solving A1 is the here-and-now solution and

$$EM = \mathbb{E}_\xi[z(x^*, \xi)] \tag{A3}$$

is the optimal value of the associated objective function. $EVPI = |EV - EWS|$

Replace all random variables by their expected value and solve the deterministic programme - the expected value problem (EV)

$$EV = \max_{x \in X} z(x, \xi) \tag{A4}$$

where $\xi = \mathbb{E}[\xi]$. Let $\overline{x}(\overline{\xi})$ be an optimal solution to A4, called the expected value solution and let EEV be the expected cost when using the solution $\overline{x}(\overline{\xi})$:

$$EEV = \mathbb{E}_\xi[z(\overline{x}(\overline{\xi}), \xi)] \tag{A5}$$

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EVMU can be referred to as the value of the stochastic solution (VSS) is then defined as

$$EMVU = EEV - EM \tag{A6}$$

and measures the expected increase in value from solving the stochastic version of a model rather than the simpler deterministic one.

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tio requirements which are; one-week mismatch ratio, one-month mismatch ratio and one-year funding ratio which are distinguished by market and non-market funding, see Richards (2010). Delfiner *et al* (2006) argue that a bank can store a stock of liquid assets to ensure some liquidity which can be referred to as liquidity warehousing. Therefore liquidity risk is closely linked to other dimensions of the financial structure of the bank.

In our model, the safety reserve can be referred to as voluntary reserves according to Rule (2012) and is defined as additional reserves held by the banks for precautionary motives. We assume that the safety reserves are not more than the bank's own reserve requirement. Therefore, the cash reserve requirement and the safety reserve are contained in the bank's own reserve. Further, we define excess reserve as surplus reserves holdings of bank with the central bank beyond the bank's own reserve requirement. The excess reserve is demanded for precautionary reasons and therefore, it cannot be understood in a certainty model. The excess reserve helps banks to hedge against the possibility of running short of reserves during the maintenance period. The total of safety reserve and excess reserve is the discretionary reserve. Like the excess reserve, the discretionary reserve serves as a buffer against unexpected liquidity shocks which serve as a cushion against overdraft. Figure 8.2 shows the overall categories of bank reserve that have been used in designing our model. The quality of reserves in the system is determined by the elements of the bank's statement of financial position. The safety reserve arises from a desire to self-insure and can vary dependent on the uncertainty of payment flows. However unremunerated required reserves are more costly to the bank. If the central bank decides to pay a rate of return to the bank, we assume that it can be at market or sub-market rate of interest. We need to note that the cost of required reserves depend on their coverage, namely how much of the bank's lia-

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