Aligning the economic capital of model risk with the strategic objectives of an enterprise

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It all starts here ™

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EXECUTIVE SUMMARY

Enterprise risk management is a method for managing risks associated with strategic objectives of an organisation. Enterprise risk management is designed to identify potential risks affecting the organisation and to manage risks within the organisation's risk appetite. In the financial industry, there exist relationships between setting objectives, using models to set the desired risk appetite threshold, setting aside capital, and complying with the law.

Financial service providers rely constantly on financial models due to the products and services that they provide to their customers. Relying constantly on models may present model risk which may have a negative impact on the daily operations of a financial service provider. Financial crises may as well increase model risk because many models stop to function as usual after a financial crisis; and the model outputs become unreliable. Model developers often change the parameters of the model after the financial crisis without following the entire model development process. This behaviour may escalate model risk.

In this study, we argue that to manage the model risk effectively, complete model development and validation processes should be followed when redeveloping the existing model or when developing a new model. A theoretical framework on model risk management is developed based on a synthesis of both the theoretical and empirical studies conducted.

A financial model performs better if it satisfies all the characteristics of the existing market conditions. For example, during a stable low-volatility market condition a model should incorporate all the factors that are driving the market to be stable; and similarly during a more unstable high-volatility state market condition a model should also incorporate all the factors that are driving the market to be unstable. Markets change all the time and some markets create market cycles in a long run.

To deal with unexpected losses, banks should reserve economic capital, which is defined as the excessive loss level that the enterprise can tolerate to ensure its survival with a certain confidence level. The economic capital should be adjusted to align it with the existing generic strategy of the bank in order to reserve an adequate amount of economic capital and to manage it optimally.

The study attempts to estimate the enterprise's economic capital of a financial model.

In this study, the economic capital is aligned with the enterprise's generic strategy in order to prepare the organisation for unexpected events that may harm the organisation's survival.

KEYWORDS

Uncertainties, enterprise risk management, model risk management, credit risk management, market risk management, operational risk management, regulatory capital, economic capital, value-at-risk, expected shortfall, copula, strategic management.

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DEDICATION AND ACKNOWLEDGEMENTS

This dissertation is dedicated to my son Neo Tumelo Mashele who is my inspiration to work harder and to achieve more.

I would like to express my sincere appreciation to my study leader, Prof James Allison for his support and suggestions throughout this research work. Due to his guidance two papers, which form parts of this dissertation, were submitted for consideration for publication in accredited journals. My deepest gratitude goes to my wife, Mamorena Mashele, for her endless support and understanding during my studies.

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LIST OF ACRONYMS

AIRMIC : Association of Insurance and Risk Managers in Industry and Commerce

BCBS : Basel Committee on Banking Supervision

CASERMC : Casualty Actuarial Society's Enterprise Risk Management Committee

COSO : Committee of Sponsoring Organizations of the Treadway Commission

DICO : Deposit Insurance Corporation of Ontario

ERM : Enterprise Risk Management

IRM : Institute of Risk Management

OCC : Office of the Comptroller of the Currency

OECD : Organisation for Economic Co-operation and Development

SME : Small and medium-sized enterprise

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CHAPTER 1: NATURE AND SCOPE OF THE STUDY

INTRODUCTION

A financial crisis is often a combination of events, including substantial changes in asset prices and credit volume, severe disruptions in financial intermediation particularly the supply of external financing, large scale balance sheet problems, and the need for a large scale of government support (Dewatripont *et al.,* 2010:3). These events may lead to a great recession for many economies in the world. The term financial crisis is commonly used to describe a variety of situations in which investors unexpectedly lose significant amount of their investments, and financial institutions suddenly lose significant proportion of their value (Allen & Snyder, 2009:37). Financial crises include, among others, sovereign defaults, stock market crashes, currency crises, and financial bubbles.

Although one factor may not be singled out as being the source of a financial crisis, the main cause of a financial crisis may be attributed to careless lending practices often adopted by some big financial institutions which are driven by an appetite for higher returns and greed. These unethical behaviours ignore the higher risk involved and the damaging consequences of such practices; and they are facilitated by the absence of an appropriate and adequate regulatory control.

The decade preceding the current financial crisis of 2008-2009 was characterised by high volumes of loans, high loan arrangement fees, flexible short-term lending to increase chances of new mortgage and arrangement fees, and punitive exit fees when borrowers wanted to change their mortgage providers before the lapse of the maturity period (Iannuzzi & Berardi, 2010:287). The substantial profits were used to pay bonuses to loan underwriters and their bosses. Those activities were aggravated by securitisation of mortgages where loans were bundled up and sold to Freddie Mac and Fannie Mae. The banks could then free up their capital and increase the mortgage turnover and earn more selling fees. Banks became short-term lenders, broke long-term relationship with borrowers and ultimately adopted reckless lending (Prasch, 2010:195). Reckless lending was the primary cause of the current financial crisis.

To this end, reckless lending culminated into two practices that precipitated the financial crisis: the use of exotic and complex financial instruments and *over-reliance on financial models*. Several ways of managing risk include risk avoidance, risk retention, risk transfer, and risk reduction. Credit derivative instruments such as credit default swaps (CDS) and collateralised debt obligations (CDO) focus on risk transfer. Over-reliance on financial models made risk quantification easy but lead to illusion of flawlessness, precision and a false sense of security among top managers and regulators. The value-at-risk (VaR) model, which measures the maximum loss a firm may suffer on a daily basis, was widely and blindly used to the extent that the regulators required all financial institutions to disclose their risks to investors using VaR in the absence of any other model that could summarise all the risks the institutions faced (Taleb & Martin, 2012:54).

Over-reliance on financial models by financial institutions may lead to *model risk*. This study pays more attention to model risk management at an enterprise level, and suggests a framework which may help management to deal with this type of risk and to eventually avoid another financial crisis due to model risk. Thus, for model risk to be managed effectively, governance and control should be at the centre of the model risk management framework.

BACKGROUND

An event can have a negative or positive impact, or both. According to Passenheim (2013:14), an event with a negative impact represents a risk, which can destroy existing value or prevent value adding; and an event with a positive impact may offset a negative impact or represent an opportunity. Risks or threats are events that may cause harm, loss or danger (Kotler & Armstrong, 2014:78); whereas opportunities are events that may positively assist to achieve the desired objectives, and preserve or create value (Kotler & Armstrong, 2014:77). In layman's terms, risk is the likelihood that a certain event will unfavourably affect the achievement of objectives, and opportunity is the likelihood that an event will favourably affect the achievement of objectives (Dafikpaku, 2011:3).

Threats and opportunities are external factors created by the operating environment of the organisation and they have the potential to destroy or enhance the organisation's value. A combination of external factors provides uncertainties for the organisation, that is,

$$\text{Uncertainties} = \text{Risks} + \text{Opportunities.}$$

In accordance with Dafikpaku (2011:1), the sources of uncertainties with unfavourable outcomes (that is, risks) are due to the complexity or unpredictability of risks, the response to external events such as compliance to new policies/regulations/standards, economic slowdown, distribution or supply chain failure, damage to reputation, increasing competition, and the behaviour of employees including senior executives.

In order to successfully manage the organisation's risks, and to channel opportunities to its strategy or objective-setting processes, the organisation depends on its internal competencies. The organisation must use its strengths to reduce the likelihood and the impacts of threats, and to take advantage of opportunities (Kotler & Armstrong, 2014:78). Strengths are the internal competencies that an organisation possesses, and represent the organisation's good management, distribution channels, leading brands, scare skills, customer loyalty and technological skills (Kotler & Armstrong, 2014:77). Weaknesses are the internal competencies that an organisation lacks, and represent the organisation's poor management, poor access to distribution, weak brands, the absence of important skills and low customer retention (Kotler & Armstrong, 2014:77). A combination of internal factors provides competencies for the organisation, that is,

$$\text{Competencies} = \text{Strengths} + \text{Weaknesses.}$$

The organisation must address its weaknesses that will make threats a reality, and it must be capable of overcoming the weaknesses that prevent it from taking advantage of opportunities (Kotler & Armstrong, 2014:63).

Future events can affect the value of financial and tangible physical assets as well as the value of key intangible assets such as supplier/employee assets, customer assets, and organisational assets such as the organisation's proprietary systems, innovative processes and brand (Protiviti, 2006:5). Alarm, the public risk management association, in collaboration with AIRMIC and IRM, define risk management as the process whereby the organisation methodically understands, evaluates and addresses the risks attached to its activities in order to maximise the chances of achieving the objectives (AIRMIC, Alarm & IRM, 2002:2). According to Protiviti (2006:5), traditional risk management approaches are focused on protecting the tangible assets reported on an organisation's balance sheet and the related contractual rights and obligations; whereas enterprise risk management (ERM) approach is focused on enhancing, as well as protecting, the unique combination of tangible and intangible assets comprising the organisation's business model. The emphasis of ERM is to enhance the business's strategy (Protiviti, 2006:5).

LITERATURE REVIEW

In the literature review, the study will focus on gaining information on the following keywords: enterprise risk management, economic capital, and model risk management.

Enterprise risk management

According to Protiviti (2006:3), the prime objective for implementing ERM is to provide reasonable assurance to the board and management of the organisation that organisation's business objectives are achieved. "ERM assists management with aligning organisation's risk appetite and strategy, enhancing risk response decisions, reducing operational surprises and losses, identifying and managing cross-enterprise risks, providing integrated responses to multiple risks, seizing opportunities and improving deployment of capital" (Protiviti, 2006:3).

Enterprise risk management is a process of systematic and integrated identification, analysis, evaluation, treatment and monitoring of the entity's risks with the purpose of achieving organisational strategic objectives (Terzi & Posta, 2010:4). ERM is concerned with the establishment of control, oversight and discipline (Protiviti, 2006:3). In order to provide assurance of achieving the organisational objectives, ERM is designed to identify potential risks affecting the organisation and to manage risks within the organisation's risk appetite (Protiviti, 2006:3).

ERM is a cyclical and continuous process whose main objective is to minimise the worst effect of a possible financial loss by

- setting strategic objectives: Enterprise risk management ensures that management has in place a reliable process to set strategic objectives and that the chosen objectives are consistent with the organisation's risk appetite and align with the organisation's mission. (COSO, 2004:3);
- identifying potential risks: The organisation must identify internal and external events that affect the achievement of an organisation's objectives, and it must distinguish between opportunities and risks (COSO, 2004:4);
- assessing the risks: Risks should be analysed and assessed on a residual and an inherent basis (COSO, 2004:4);
- responding to the risks: Risk responses such as acceptance, reduction, avoidance or transference should be developed by a set of actions to align risks with the organisation's risk tolerances and risk appetite (COSO, 2004:4);
- using controls to minimise the risks: The organisation should establish and implement procedures and policies to ensure that the risk responses are effectively implemented. (COSO, 2004:4); and
- monitoring the risks: For the risk to remain within acceptable risk levels, risks and risk response activities should be monitored; and this will assist in identifying emerging risks and gaps and to ensure that risk response and control activities are appropriate and adequate (DICO, 2011:10).

According to DICO (2011:9), to be able to identify the risk, risks should be considered within the following main risk categories: *Strategic risks* which include risks from reputational damage caused by, amongst other factors, fraud, unfavourable publicity and brand erosion (CASERMC, 2003:10); *operational risks* which include risks from business operations (e.g., product development, human resources, capacity, and supply chain management), empowerment (e.g., leadership and change readiness), information technology (e.g., availability and relevance); and information reporting (e.g., accounting information, taxation, budgeting and planning) (CASERMC, 2003:10); and *financial risks* which are reliability of reporting and they include market risk (e.g., asset value), credit risk (e.g., default and downgrade), liquidity risk (e.g., cash flow and opportunity cost), and basis risk (CASERMC, 2003:10).

Economic capital

The two most important concepts of capital within the banking industry are:

Regulatory capital is the amount that the bank must have in order to meet the capital adequacy requirements, based on regulations established by the banking supervisory authorities (Van Mullem, 2004:34). It is the minimum capital requirements which banks are required to hold in order to ensure their ongoing viability and to safeguard the security of the banking institutions (Mausser & Rosen, 2008:682). Elizaldea and Repullo (2007:88) define regulatory capital as the minimum capital set by the regulator of the industry where the enterprise operates its main businesses. Therefore, regulatory capital is the minimum amount that the bank must have in order to have a licence and the bank must comply with regulations to operate its business (Chorafas, 2004a:107). The Basel Accord is the framework created by the BCBS to provide regulations for internationally active banks.

Economic capital is the amount that is required to cover for unexpected losses within a certain confidence level and a certain time period (Van Mullem, 2004:34). Elizaldea and Repullo (2007:88) define economic capital as the excessive loss level that the enterprise can tolerate to ensure its survival with a certain confidence level. It is actually the amount of capital that an organisation must set aside to cover potential losses over a specified time horizon, at a given risk tolerance level (Society of Actuaries, 2004:5). It covers all the risks that may force the bank into insolvency (Mausser & Rosen, 2008:682). It can be considered as the internal equivalent of solvency[1] (Van Mullem, 2004:34). It is the *risk capital*, the amount set aside to absorb all risks, even during bearish market periods (Chorafas, 2004a:111). According to Chorafas (2004a:113), the risk capital serves three primary purposes: it protects against adverse financial results; it funds ongoing operations; and it establishes an operational base. Therefore, unlike regulatory capital, economic

[1] *A financial institution is considered to be solvent if its assets exceed its liabilities (Chorafas, 2004a:314).*

capital requirement is not an issue of compliance with regulations but it is a management requirement (Chorafas, 2004a:107).

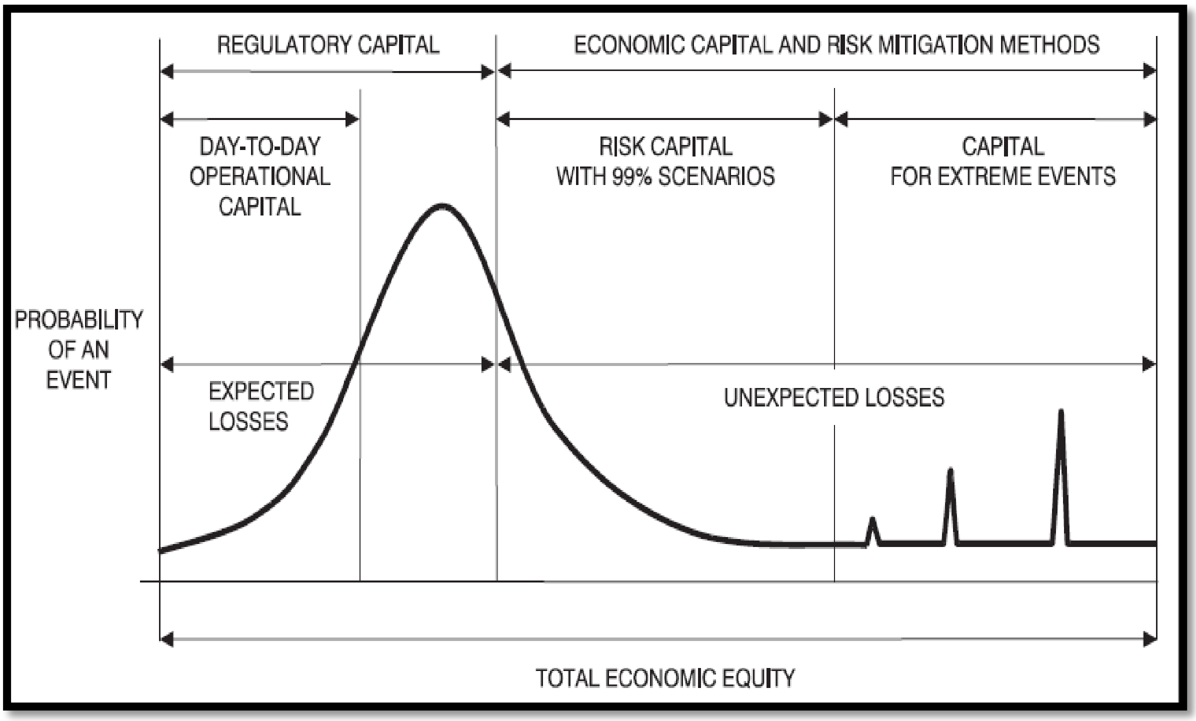

Figure 1: Classification of a bank's capital requirements according to risk (Chorafas, 2004a:107)

In order to estimate population parameters, two types of sample statistics are used, namely, point estimates and interval estimates. A *point estimate* is the value of a single sample statistic while a *confidence interval estimate* is an interval constructed around the point estimate, constructed such that the probability that the population parameter located somewhere within the interval is known (Levin *et al.,* 2014:300).

The capital and risks of the financial institution are related in many forms and one of these forms is the level of confidence (Chorafas, 2004a:115). As shown in Figure 1, to enhance its survival and to promote its long-term market appeal, if the economic capital corresponds with the 99% level of confidence, then the bank should reserve financial resources beyond this level to deal with adverse events at the tail of the distribution (Chorafas, 2004a:115).

Model risk management

OCC (2011:3) defines a *financial model* as a quantitative method or approach that applies mathematical or economic theories, and assumptions to process input data into statistical estimates; and it consists of three components: an information input component, which serves to deliver data and assumptions to the model; a processing component, which serves to transform input data into statistical estimates; and a reporting component, which translates the statistical estimates into useful business information.

Relying constantly on financial models may present *model risk*, which is the potential for unfavourable consequences from decisions that are based on misused or incorrect model outputs which can lead to poor decision making, financial loss or reputational risk (OCC, 2011:3). Model risk is part of the operational risk. “Model risk increases with greater model complexity, higher uncertainty about inputs and assumptions, broader use, and larger potential impact” (OCC, 2011:4). Model risk management should be treated in the same manner as other risks; the sources of model risk should be identified and the magnitude of model risk should be assessed (OCC, 2011:4).

In accordance with OCC (2011:3), model risk occurs because either the model may be used incorrectly; or the model may have fundamental errors which can occur at any point from design through implementation and may produce inaccurate outputs when viewed against the design objective and intended business uses (OCC, 2011:3). According to Derman (1996:6), there are seven types of model risk:

- Inappropriateness of modelling: A model which is not capable to solve the problem at hand.
- Incorrect model: The risk of using a model that is inappropriate under current market conditions.
- Incorrect solutions: The risk of making a technical mistake in finding the analytical solution to a model.
- Inappropriate use: The risk related to an inaccurate numerical solution of an otherwise correct model.

- Badly approximated solutions: The risk appears when there are errors in the numerical solution of a problem, or when there are natural limits to the accuracy of some approximation scheme.
- Software and hardware bugs: When implementing the model, there may be programming mistakes.
- Unstable data: Historical data used by many models may not provide good estimates of future values, and historical values may themselves be unstable and vary strongly with the sampling period.

Model risk increases with higher uncertainty about assumptions and inputs, greater model complexity, larger potential impact, and broader use; and it cannot be eliminated but it can be managed effectively by constantly monitoring the performance of the model, revising or adjusting the model over time, complementing the results of the model with other analysis, and generating limits on model use (OCC, 2011:4).

Model risk management should include knowledgeable and disciplined development and implementation processes that are consistent with the goals of the model user and the situation, and with the bank policy (OCC, 2011:5).

According to OCC (2011:5), in order to reduce model risk, model developers should adhere to the following terms:

- The theory, design, and logic underlying the model should be supported by sound industry practice and published research, and every aspect should be documented.
- The model methodologies that implement the theory should be explained in detail with particular attention to limitations and merits.
- The model components should work as intended for an intended business purpose,
- The model components should be checked if they are statistically correct and conceptually sound by comparing with alternative approaches and theories.

Sound model risk management depends on extensive investment in supporting systems to ensure the integrity of the data and reporting processes, together with testing and controls to ensure proper implementation of models, appropriate use and effective systems integration (OCC, 2011:7).

PROBLEM STATEMENT

On a daily basis, the financial decision making processes of banks rely heavily on models; and banks normally use models for a broad range of activities such as measuring risk, underwriting credits, determining capital and reserve adequacy, valuing exposures, instruments and positions, and managing and safeguarding client assets (OCC, 2011:1). A number of risk types are covered under the ERM framework. Limited research has however been done on model risk as part of the ERM framework.

As a primary objective, the study focuses mainly on aggregating the economic capitals from the credit risk and market risk business lines of the bank. Within credit risk, separate economic capital processes are usually used by banks because retail credit portfolio and commercial credit portfolio require different modelling techniques since they display different risk behaviours (Yang, 2012:2). Within market risk, a multi-factor modelling approach is used to determine the market factors such as volatilities and interest rate which drive assets' prices (Yang, 2012:2).

Risk Aggregation is the incorporation of multiple types of risks into a single appropriate risk aggregation framework, and this risk aggregation framework is vital for adequate enterprise risk management (Yang, 2012:2). Risk aggregation models are very important in the decision-making processes such as capital allocation and solvency; and they are used for risk management functions such as risk identification, monitoring and mitigation (Aas & Puccetti, 2014:694).

The loss distributions from the credit and market risks will be integrated to form a joint distribution. Then the economic capital of the joint distribution will be calculated in the same manner as the economic capital of the individual distributions and this will be referred to as the model risk economic capital for the enterprise. The measuring instrument to be used to integrate the distributions is a copula. A *copula* is a joint distribution function with uniform [0,1] distributed marginals (McNeil *et al.,* 2005:185).

The new supervisory guidance on model risk requires banks to identify the sources of model risk, assess its magnitude, and establish a framework for managing it (Dil, 2012:47). According to Dil (2012:47), the new framework identifies three elements of a strong process for managing model risk:

- Robust model development, implementation, and use.
- Sound model validation practices.
- A solid governance framework.

As secondary objectives, this study focuses on the above mentioned elements of the model risk framework. The last two elements will be discussed extensively in the next chapter.

RESEARCH QUESTIONS

This study aims to address and explore the following questions:

- What is an optimal revision time to redevelop or replace a model?
- What is an ideal model risk management framework that can be incorporated to the enterprise risk management framework by the board and senior management?
- How to help management to allocate the enterprise's economic capital strategically?

MOTIVATION OF TOPIC ACTUALITY

Financial models are used by banks to allocate capital to different business lines and to determine operational decisions. ERM is about establishing the oversight, control and discipline to drive continuous improvement of an organisation's risk management capabilities. There exist relationships between strategic risk (setting objectives), operational risk (using models to set the desired risk appetite threshold), financial risk (setting aside capital), and litigation risk (complying with the law).

"Even with skilled modelling and robust model validation, model risk cannot be eliminated, so other tools should be used to manage model risk effectively" (OCC, 2011:4). This study suggests that model risk management should be treated as one of the variables in the ERM framework in order for model risk management to become a continuous process whose main objective is to optimise the economic capital of the entire bank. Moreover, under the ERM framework, models can properly be validated and controlled; and model developers and validators are forced to comply with new and existing regulations.

OBJECTIVES OF THE STUDY

The research objectives are divided into a primary objective and secondary objectives.

Primary objective

The primary objective of this research is to determine the enterprise economic capital and to align it with the organisation's strategic objectives in order to manage the enterprise model risk effectively.

Secondary objectives

The secondary objectives of this research are:

- To determine an optimal revision time to redevelop or replace a model.
- To create an ideal model risk management framework that can be incorporated to the enterprise risk management framework by the board and senior management.
- To identify ways that can help management to strategically allocate the enterprise's economic capital.

RESEARCH DESIGN

Research Approach

The nature of this study will be theoretical, analytical and quantitative. According to Whitley (2002:34), quantitative research focuses on identifying the relationship between independent and dependent variables; and these variables are defined in advance by theories. Statistical quantitative data analysis technique will be used to analyse the data. To form a joint distribution between credit risk and market risk loss distributions, a copula will be fitted.

Research methodology

Literature/theoretical study

The sources that will be consulted in this study include:

- Accredited journals
- Relevant books
- Reliable internet education websites
- Financial regulators' websites

The literature review will focus on gaining information on the following keywords: enterprise risk management, economic capital, and model risk management. An extensive scientific research will be used to conduct the literature review. Sources of information will include library resources such as databases, relevant textbooks and accredited articles. Computer search engines such as Google, GoogleScholar, EbscoHost and ScienceDirect will be used to search and download relevant literature.

Empirical study

The historical price data of the JSE All-Share Index will be used to determine the market risk, and the data for the credit portfolio will be simulated. The statistical analysis will be carried out on SPSS and with Excel VBA. Descriptive statistics will be utilized to summarise the samples and to give an idea of the form of the loss distributions.

Research participants

For credit risk business line, the sample of the portfolio of borrowers in the banking institution will be studied, and for the market risk business line, the JSE All-Share Index will be used as a proxy for a portfolio of asset prices. To determine the enterprise economic capital, only the loss distributions from both these portfolios will be considered in the study.

Measuring instrument(s)

Monte-Carlo simulation method will be used to generate a sample comprising of 10,000 observations for each credit risk and market risk portfolio. The loss distributions from the credit and market risks will be integrated to form a joint distribution. The economic capital of the joint distribution will then be calculated to determine the aggregated economic capital. In order to estimate the joint distribution, a parametric copula will be fitted to the bivariate data. Details of this can be found in Chapter 4.

Research procedure

The historical monthly data of the JSE All-Share Index will be downloaded from INET BFA data source. The loss data of the credit portfolio will be simulated. Using the historical volatility and average return of the market portfolio, the loss data of the market portfolio will as well be simulated.

CONTRIBUTION OF THE STUDY

Contribution to the individual

This study will make individuals, especially top managers, aware of the benefits of incorporating model risk in their strategic plans. Top managers will be able to put enough capital in their reserves to deal with unexpected losses created by model risk. Chief risk officers will benefit from the model risk framework that will be suggested by this study.

Contribution to the organisation

This study will help the organisation to manage the enterprise risk effectively, to produce policies that comply with new and existing regulations. An organisation will manage the model risk effectively by setting an acceptable model risk threshold; properly back-testing and validating its models; integrating all model risks from different functions of the business; and reserving the economic capital in line with the generic strategy of the organisation.

Contribution to the literature

Incorporating model risk management to the enterprise risk management is a fairly new concept and limited research is available on this subject, and this study will contribute and add to the literature of enterprise risk management.

LIMITATIONS OF THE STUDY

All risks, including credit, market and operational risks should be included in the calculation of the enterprise's economic capital (Yang, 2012:2). Because of the complexity and lack of adequate data for the operational risk, operational risk will be excluded from the study and the enterprise's economic capital will be assumed to involve the economic capital from the credit and market risks.

ETHICAL CONSIDERATIONS

If the credit data becomes available for this research, the data will consist of personal information of the bank's customers. To ensure that the research project remains ethical, the data will only be available to a researcher once the confidential agreement has been signed by a researcher. The information relating to the bank's customers will remain anonymous throughout the research. Also the name of the bank will remain anonymous throughout the research.

The research proposal was submitted to the ethical committee of the North-West University to be checked for ethical compliance.

LAYOUT OF THE MINI-DISSERTATION

The mini-dissertation is divided into the following chapters: Chapter 1 outlines the problem statement, the research objectives and the literature review. In the literature review, essential keywords are discussed in details. In Chapter 2, model risk governance and model validation practices are discussed; and then suggestions are made with respect to an optimal revision time for model redevelopment or replacement. In this chapter, the model risk management framework is proposed based on the synthesis of the theoretical research and the research findings from the study.

Chapter 3 outlines a detailed overview on the measurement and modelling of the credit risk, market risk and operational risk. In this chapter, models and capital adequacy for each risk category are discussed in details. In Chapter 4, the loss distributions of credit and market risks are integrated using a copula function, and then the economic capital based on this joint distribution is determined. With reference to the generic strategy of the enterprise, the scheme of adjusting the enterprise's economic capital is proposed. Finally, Chapter 5 outlines both the conclusions and recommendations based on the findings from the study.

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CHAPTER 2: MODEL RISK GOVERNANCE AND MODEL VALIDATION PRACTICES

In this chapter, the model risk governance and model validation practices are discussed. Optimal revision time for model redevelopment or replacement, and a model risk management framework based on a synthesis of both the theoretical and empirical studies is proposed.

2.1 Model risk governance

According to OCC (2011:2), model risk management involves control and governance mechanisms such as oversight, an appropriate incentive and organisational structure, compliance and controls, and policies.

Corporate governance is defined as processes and procedures according to which an organisation is managed and controlled (OECD, 2007:151). In accordance with BCBS (2010:5), "effective corporate governance practices are essential to achieving and maintaining public trust and confidence in the banking system, which are critical to the proper functioning of the banking sector and economy as a whole. Poor corporate governance can contribute to bank failures, which can in turn pose significant public costs and consequences due to their potential impact on any applicable deposit insurance system and the possibility of broader macroeconomic implications, such as contagion risk[2] and impact on payment systems".

Poor corporate governance can lead to poor policies, lack of control and non-compliance; and as a result, poor model risk management. From the development to the implementation of the model, correct procedures are ignored or not known. The study proposes a model risk framework that can be used as a guideline within the ERM setup by the board and senior management.

According to OCC (2011:17), the board of directors and senior management should provide model risk governance that fits well into the enterprise risk management

[2] *Contagion risk is the systematic risk due to the failure of an individual or small number of financial institutions causing a widespread disruption in financial markets or significant difficulty at otherwise viable institutions (Furfine, 1999:1).*

framework which provides a structure to risk management functions through policies, which include standards for model development, validation, implementation, use, controls and governance over model risk management process. "Policies should emphasize testing and analysis, and promote the development of targets for model accuracy, standards for acceptable levels of discrepancies, and procedures for review of and response to unacceptable discrepancies" (OCC, 2011:17).

The board of directors should ensure that the level of model risk is within the organisation's accepted level of risk tolerance; and senior management should ensure compliance, oversee model development and implementation, evaluate model results, review model validation, and report regularly to the board of directors on compliance with policy and significant model risk (OCC, 2011:17). Model developers and users should ensure that models are properly developed, implemented and used (OCC, 2011:18); and internal auditors should assess the effectiveness of the model risk framework (OCC, 2011:19). The effectiveness of the model risk framework depends strongly on model development and good model risk governance, acceptable controls and compliance with suitable policies (OCC, 2011:16).

2.2 Model validation practices

OCC (2011:9) defines model validation as "the set of processes and activities intended to verify that models are performing as expected, in line with their design objectives and business uses. Effective validation helps to ensure that models are sound. It also identifies potential limitations and assumptions, and assesses their possible impact".

Prior to implementation, a model must be validated by a suitably, independent qualified validation team, with periodic reviews to ensure that the model remains suitable for its use, and to minimise the model risk (BCBS, 2009a:6). Generally, to avoid biased review of the model and hence decreasing model risk, the model validation team should not be the model development team. In addition to independence, banks should compensate and evaluate the performance of model validations based on the quality of the model validations (OCC, 2011:9).

In accordance with BCBS (2009a:6), model validation processes should be systematically applied to both internally generated and vendor provided models, and the process should include evaluations of:

- the appropriateness of model assumptions, including consistency with relevant predetermined terms of transactions and consistency with market practices;
- the model's mathematical integrity and theoretical soundness;
- benchmarking[3] of the valuation result with the observed market price at the time of valuation or independent benchmark model; and
- sensitivity analyses performed to assess the impact of variations in model parameters on fair value, including under stress conditions.

If any significant deficiencies are found as a result of the validation process, the use of the model should not be permitted until those deficiencies are dealt with, and if the deficiencies are too severe to be addressed within the model's framework, the model should be rejected (OCC, 2011:10).

An effective validation framework should include three core elements:

- *Evaluation of conceptual soundness:* All key assumptions, mathematical formulas and calculations, theoretical construction, and model limitations should be documented; and variables, qualitative information, and the relevance of the data used to develop the model should be evaluated to establish the conceptual soundness of the model (OCC, 2011:11).
- *Outcomes analysis:* This is a comparison of the outputs of the model with the corresponding actual outcomes with the intension of assessing the accuracy of estimates to evaluate the performance of the model, that is, whether the model performs in line with the objectives of its design, and determining the magnitude of the deviation of the model outputs from the actual outcomes (OCC, 2011:13). According to OCC (2011:14), "back-testing is one form of outcomes analysis which involves the comparison of actual outcomes with

[3] *Benchmarking is the comparison of the inputs and outputs of a given model with the estimates from alternative models or internal or external data (Office of the Comptroller of the Currency, 2011:13).*

model forecasts during a sample time period not used in the model development and at an observation frequency that matches the forecast horizon or performance window of the model".

- *Continuous monitoring:* This element involves evaluation of market conditions, products, clients, and activities to determine whether changes in any of these components necessitate model redevelopment or replacement; and it also involves benchmarking and the necessity for overrides[4] with appropriate documentation (OCC, 2011:11). Process verification is part of continuous monitoring which checks for the quality of the model, the code used to program the model, and the entire computer systems of the organisation (OCC, 2011:12).

2.3 Optimal revision time for model redevelopment or model replacement

In this section, the research focuses on techniques or schemes that are used to detect change-points in the time series dataset, namely, the statistical *control schemes (charts)*; and models that are used to deal with nonlinear features in the dataset, the so-called *regime switching models (Markov switching models)*. There is a strong relationship between the functionality of a financial model and the market condition prevailing in the markets where the model operates. In this study, a CUSUM scheme and regime switching models are studied and applied to a two-regime situation to detect a change-point with the intention of revising the model optimally prior to the change-point.

2.3.1 CUSUM control charts

Let $X_1, X_2, ...$ be a sequence of observations related to a certain process, which may represent, for example, sample means, sample standard deviations, investment returns, sample proportions of errors found in successive data sets or successive discrepancies (residuals) between values predicted by some model and the observed values. According to Yashchin (1989:321), a *control scheme* associated with this sequence represents a set of criteria that enables one to judge, at any given

[4] *Overrides are an indication that the model is not performing according to design objectives or model limitations (Office of the Comptroller of the Currency, 2011:13).*

moment of time, whether the process generating the observations is within acceptable variation, that is, it is under control.

According to Mei (2006:883), a process is initially under control if the X's have some distribution f. If at some unknown time *T*, the process goes out of control, when the distribution of the observations changes abruptly to another distribution g, an alarm should be raised as soon as the abrupt change occurs so that an appropriate action can be quickly taken. When the process is either above the upper control limit (UCL) or below the lower control limit (LCL), then the sequence is out of control, otherwise it is under control. The out-of-control signal may occur either because of the change in the underlying parameter or because of randomness inherently present in the data, in which case the signal is referred to as a *false alarm* (Yashchin, 1993:42).

Run Length (RL) is defined as the number of observations taken before a signal is triggered.. The criteria of performance of a control scheme are usually related to the behaviour of some characteristics of its distribution, most typically the Average Run Length (ARL). The ARL of a control chart is the average number of points before the chart indicates a shift in the process level. The ARL should be large when there has been no change in the process, and it should be small when the process has undergone a change.

A control scheme needs to be designed to ensure both a good sensitivity with respect to undesirable patterns of incoming observations and a reasonable degree of protection against false alarms.

Sequential change-point detection problems have many important applications, including financial decision making, industrial quality control, epidemiology, fault detection, reliability, signal detection, security systems and surveillance (Mei, 2006:883).

In the situation where the observations $\{X_n\}$ are independent and both the pre-change distribution f_0 and the post-change distribution f_1 are completely specified, the *cumulative sum* (CUSUM) procedure is one of the efficient detection schemes that can be used to detect the change-point (Mei, 2006:883); and according to

Yashchin (1989:321-324) and Yashchin (1993:44-45), CUSUM is described as follows:

Let $X_1, X_2, \cdots$ be a sequence of independent observations related to a certain process, with n_t observations and γ incidence rate at time *t*. Assume that the incidence rate γ changes from γ_0 to another value γ_1 at some unknown time *T.* The objective is to detect the change as soon as it occurs. The CUSUM procedure is formulated as a sequential hypothesis testing procedure for the change-point from a known in-control density f_0 to another known alternative density f_1. For the sequence $\{C_t\}$, the CUSUM chart has the basic form

$$C_t = \max\{0, C_{t-1} + L_t\},$$

where $C_0 = 0$ and L_t is the score statistic measuring the deviation from the null distribution to the alternative distribution, and it is given by the log-likelihood ratio

$$L_t = \log \frac{f_1(X_t)}{f_0(X_t)},$$

which represents the increment contributed by the *t*-th observation. Given the size of the data n_t, the counts X_t's are conditionally independent. The score statistic for the *t*-th observation reduces to

$$L_t = -n_t(\gamma_1 - \gamma_0) + X_t \log \frac{\gamma_1}{\gamma_0},$$

Therefore, L_t is not only affected by the difference between γ_0 and γ_1, but also by the size of the data. If L_t is substituted into the above equation, then the CUSUM statistic is given by

$$C_t = \max\left\{0, C_{t-1} + \log\left(\frac{\gamma_1}{\gamma_0}\right)\left(X_t - \frac{n_t(\gamma_1 - \gamma_0)}{\log\left(\frac{\gamma_1}{\gamma_0}\right)}\right)\right\}.$$

An out-of-control signal is triggered if $C_t > h_1$, where $h_1 > 0$ is the threshold chosen to achieve a desired in-control ARL

Instead of accumulating X_t in the CUSUM scheme, accumulating scores based on the estimated incidence rate X_t / n_t may be considered; and the CUSUM scheme, based on the quasi-likelihood ratio given by the score statistic

$$L_t^R = -(\gamma_1 - \gamma_0) + \frac{X_t}{n_t}\left(\log\frac{\gamma_1}{\gamma_0}\right),$$

is then developed and is given by

$$R_t = \max\left\{0, R_{t-1} + \log\left(\frac{\gamma_1}{\gamma_0}\right)\left(\frac{X_t}{n_t} - \frac{(\gamma_1 - \gamma_0)}{\log\left(\frac{\gamma_1}{\gamma_0}\right)}\right)\right\}.$$

An alarm is signalled on the chart if $R_t > h_2$, where $h_2 > 0$ is the threshold chosen to achieve a desired in-control ARL. The two above mentioned CUSUM schemes are referred to as the cumulative count (CC) and cumulative ratio (CR) charts, respectively; and if $n_t = n$, that is, if the data remains constant over time, then the CC and CR schemes are equivalent, otherwise they are different if $n_t \neq n$.

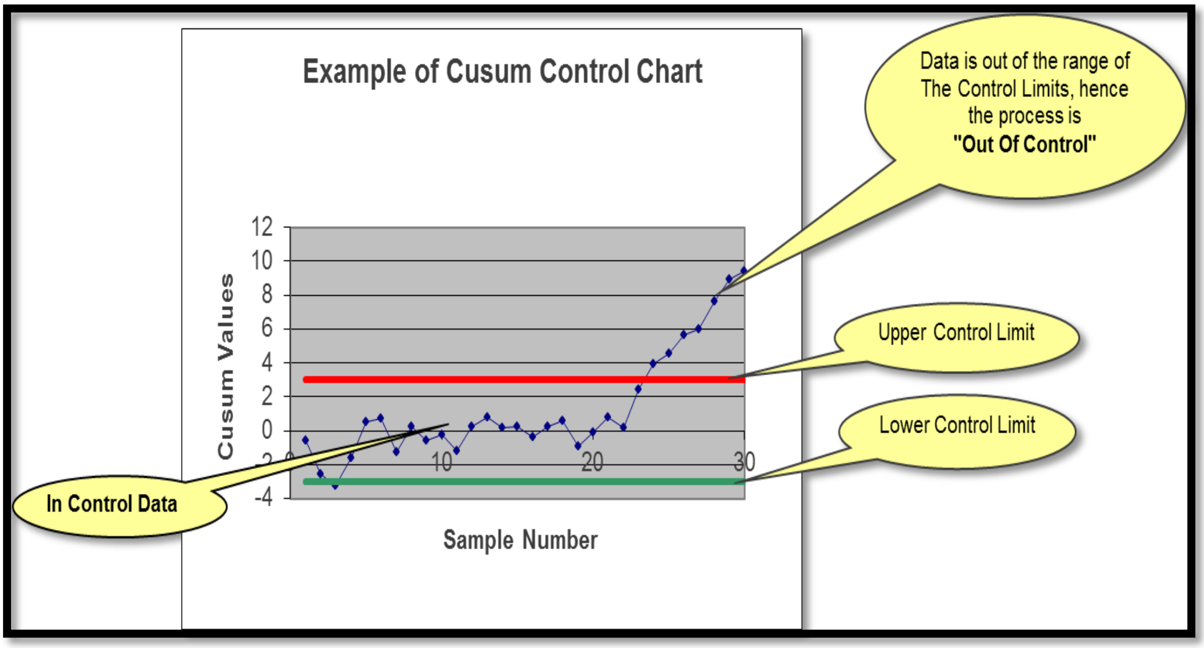

Figure 2: Cusum control chart

Naturally, in practise the assumption of independent observations is not realistic, and thus it has been extended to dependent observations. However, according to Mei (2006:884), it is unclear whether the CUSUM procedure is still efficient in this case.
According to Mei (2006:884), there are two standard formulations for studying the CUSUM procedure:

- *Bayesian formulation*, in which the change-point is assumed to have a known prior distribution.
- *Minimax formulation*, in which the change-point is assumed to be unknown (possibly infinity) but non-random.

2.3.2 Markov switching models

The behaviour of many financial time series cannot be modelled solely by linear time series models because linear models fail to capture occurrences such as mean reversion, volatility of stock markets and structural breaks (Ismail & Isa, 2006:55). Linear time series models may be too restrictive to capture empirically observed nonlinear dynamics and economically interesting asymmetries; and as a result, models that are capable of capturing such features while remaining analytically tractable are required (Gonzalo & Pitarakis, 2012:1). According to Ismail and Isa (2006:55), a recent nonlinear model that is getting a lot of attention is the regime switching model or Markov switching model that models parameter changes via the use of an unobservable discrete time Markov process.

A potentially useful approach to model nonlinearities in time series is to assume different behaviour (structural break) in one regime to another. Assume that the time series is divided into two or more regimes. If the date for one regime to switch to another is known, modelling can be done with dummy variables, but if the date for regimes to switch is not known, then the switching point of regimes should be detected or estimated. A regime change or regime switching is defined as the change of parameters of a model due to the occurrence of a particular policy, episode or event; for example, periods of low/high interest rates, low/high stock market valuations or recessions/expansions (Gonzalo & Pitarakis, 2012:1). Frühwirth-Schnatter (2006:314) defines a Markov switching model mathematically as follows:

Let $\{x_1, x_2, \cdots, x_T\}$ be a time series which is observed as a single realisation of a stochastic process $\{X_1, X_2, \cdots, X_T\}$. In the basic Markov switching model the time series $\{x_1, x_2, \cdots, x_T\}$ is assumed to be a realisation of a stochastic process X_t generated by a finite Markov mixture from a specific distribution family

$$X_t \left| s_t \sim \pi\left(s_t\right),\right.$$

where s_t is an unobservable (hidden) *k* state Markov chain, and the variables $X_1, \cdots, X_T$ are stochastically independent on condition that $s_1, \cdots, s_T$ are known .

"Regime switching models are designed to capture discrete changes in the series that generate the data; and they can be used as an intuitive way of capturing policy shifts in macro-economic models as well as numerous other contexts such as forecasting economic growth and dating business cycles" (Ismail & Isa, 2006:56). There are numerous types of Markov switching models; but for the purpose of this research we will consider the following three models: the *Markov switching lognormal model*, the *self-exciting threshold autoregressive model*, and the *Markov switching autoregressive model*. For more orientation and other types of Markov switching models the interested reader is referred to Frühwirth-Schnatter (2006).

I. Markov switching lognormal (MSLN) model

According to Hardy (2001:42), under the regime-switching lognormal model, an asset return process is assumed to lie in one of *k* regimes. Hardy (2001:43) describes the regime-switching lognormal model as follows: Let $\rho_t = \rho(t)$ be the regime in the interval [*t* - 1, *t*), and s_t be an asset price at time *t.* Then r_t denotes the log-return of an asset which is defined as

$$r_t = \ln \frac{s_t}{s_{t-1}}.$$

We assume that the process ρ_t is a Markov chain. A Markov chain is a process $\rho = \{\rho_t : t \in [0, T]\}$ defined on a countable set I which satisfies the Markov property

$$\Pr\left[\rho(t_n) = j \left| \rho(t_1) = i_1, ..., \rho(t_{n-1}) = i_{n-1}\right.\right] = \Pr\left[\rho(t_n) = j \left| \rho(t_{n-1}) = i_{n-1}\right.\right],$$

for all $j, i_1, ..., i_{n-1} \in I$ and any sequence $t_1 < t_2 < \cdots < t_n$ of times. In the MSLN model, the price process $S = \{s_t, t \in [0,T]\}$ of an asset satisfies

$$\frac{dS(t)}{S(t)} = \mu(\rho(t))dt + \sigma(\rho(t))dW, \ \forall t \in [0,T],$$

where, the parameters $\mu(\rho(t))$ and $\sigma(\rho(t))$ are mean rate of return and the volatility of returns for asset prices in regime $\rho(t)$, respectively; and W is a standard Brownian motion.

According to Hardy (2001:43), for a two-regime model, the transition matrix *P* denotes the probabilities of moving regimes, that is,

$$p_{ij} = \Pr[\rho_t = j | \rho_{t-1} = i], \ i, j = 1, 2.$$

Hardy (2001:43) suggests that for the two-regime conditionally independent lognormal model, six parameters have to be estimated:

$$\Theta = \{\mu_1, \mu_2, \sigma_1, \sigma_2, p_{1,2}, p_{2,1}\},$$

where, for $i = 1, 2,$ the parameters μ_i and σ_i are mean rate of return and the volatility of returns for asset prices, respectively. The parameters μ_i and σ_i are assumed to be constant in regime i. The transition probability from regime 1 to regime 2 is denoted by $p_{1,2}$, and $p_{2,1}$ denotes the transition probability from regime 2 to regime 1.

II. Self-exciting threshold autoregressive (SETAR) model

A frequently used linear time series model to capture autocorrelation is the autoregressive process or AR (*p*) model

$$X_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \varepsilon_t,$$

where *p* is the number of lags (or the order of the process), α_t is a real-valued parameter and $\{\varepsilon_t\}$ is a sequence of independent and identically distributed random variables with $\varepsilon_t \sim N(0, \sigma^2_{\varepsilon_t})$.

The returns of financial data tend to display inconsistent behaviour as a result of large negative returns, and this behaviour occurs more often than expected and in addition, it tends to occur in a cluster. Linear models such as the AR (*p*) model do not to capture this nonlinearity or clustering effects when it used to model financial returns.

The Self-Exciting Threshold Autoregressive model can be defined as a nonlinear autoregressive model with the threshold variable taken to be a lagged value of the time series itself. According to Ismail and Isa (2006:56), for a time series which is assumed to have two regimes, SETAR is given by

$$X_t = \begin{cases} \alpha_0 + \sum_{i=1}^{p} \alpha_i X_{t-i} + \varepsilon_t, \text{ if } X_{t-d} \le T \\ \beta_0 + \sum_{i=1}^{p} \beta_i X_{t-i} + \varepsilon_t, \text{ if } X_{t-d} > T \end{cases},$$

where α_i and β_i, $i = 1,...p$, are coefficients to be estimated, *T* is the value of the threshold, *p* is the order of the SETAR model, X_{t-d} is the threshold variable, *d* is the delay parameter, *d* < *p* and $\{\varepsilon_t\}$ is a sequence of independent and identically distributed random variables with $\varepsilon_t \sim N\left(0, \sigma_{\varepsilon_t}^2\right)$. If *T* is known, the observations can be separated according to whether X_{t-d} is below or above the threshold; and then an AR model for each segment is estimated using ordinary least squares method (OLS). However, in most cases the threshold is unknown and must be estimated along with the other parameters of the SETAR model. After the threshold parameter is estimated, the remaining parameters are estimated using either maximum likelihood estimation (MLE) or nonlinear least squares. For in-depth discussion on nonlinear least squares, the interested reader is referred to Ismail and Isa (2006:57).

III. Markov switching autoregressive (MSAR) model

A drawback of theThe SETAR model is that it considers regime switching as a non-random (deterministic) event. However, regime change can happen very quickly and a more appropriate and realistic way is to use the Markov switching autoregressive model (MSAR). MSAR assumes that the regime switching is exogenous and there is a fixed probability for each regime change (Ismail & Isa, 2006:57).

In the Markov switching autoregressive model, the time series X_t is normally distributed with mean μ_i and variance σ_i^2 in each of *k* possible regimes, where

$i=1,2,\cdots,k;$ and each regime is assumed to follow a Markov process, that is, at time *t* the regime is determined randomly and depends only on regime *t*-1 (Ismail & Isa, 2006:57). A MSAR model of two regimes with an AR process of order *p* is given by

$$X_t = \mu(\rho_t) + \sum_{i=1}^{p} \alpha_i \left[X_{t-i} - \mu(\rho_{t-i}) \right] + \varepsilon_t,$$

where $\{\varepsilon_t\}$ is a sequence of independent and identically distributed random variables with $\varepsilon_t \sim N\left(0, \sigma_{\varepsilon_t}^2\right)$, ρ_t is the unobserved regime that takes the values of 1 (expansion period) or 2 (contraction period), and the transition between regimes is governed by a first order Markov process as follows:

$$\begin{aligned}
\Pr\left(\rho_t = 1 \middle| \rho_{t-1} = 1\right) &= p_{1,1} \\
\Pr\left(\rho_t = 1 \middle| \rho_{t-1} = 2\right) &= p_{1,2} \\
\Pr\left(\rho_t = 2 \middle| \rho_{t-1} = 1\right) &= p_{2,1} \\
\Pr\left(\rho_t = 2 \middle| \rho_{t-1} = 2\right) &= p_{2,2}
\end{aligned}$$

where $p_{i,j},\ i, j \in I,$, denote the transition probabilities defined as above with $p_{1,1} + p_{1,2} + p_{2,1} + p_{2,2} = 1$ (Ismail & Isa, 2006:57). In the MSAR model, after a one-time change from s_{t-1} to $s_t \neq s_{t-1}$, an immediate shift of the mean level from $\mu(\rho_{t-1})$ to $\mu(\rho_t)$ occurs (Frühwirth-Schnatter, 2006:360).

2.3.3 Optimal model revision

For simplicity of use, we define redevelopment or replacement of a financial model simply as model revision. According to Morini (2011:98), the model should be revised *periodically*, at least once a year, to incorporate new information or during *triggered periods* when market conditions, products, clients, or activities change. Under new market conditions a model may become unreliable, and thus redevelopment or replacement of the model may be required (OCC, 2011:11). Revision dates are determined by quantitative triggers on market observable or on product features (Morini, 2011:99).

According to Morini (2011:99), model redevelopment or replacement can be done immediately after the market conditions have changed. Mashele and Allison

(2015a:1) argue that model revisions that are done after the market conditions have changed may escalate model risks due to the fact that there is insufficient time to follow proper development and validation processes before the model is implemented.

From the empirical research, Mashele and Allison (2015a:9) discovered that it can take about 8 to 11 months to develop a sophisticated model from scratch and 4 to 7 months to appropriately redevelop the model. Model redevelopment or replacement should be done when there is a strong signal indicating a possible change in market conditions in the near future which can have a negative impact on the parameters and assumptions of the existing model (Mashele & Allison, 2015b:1).

2.3 Summary

This chapter is summarised with the following model risk management framework:

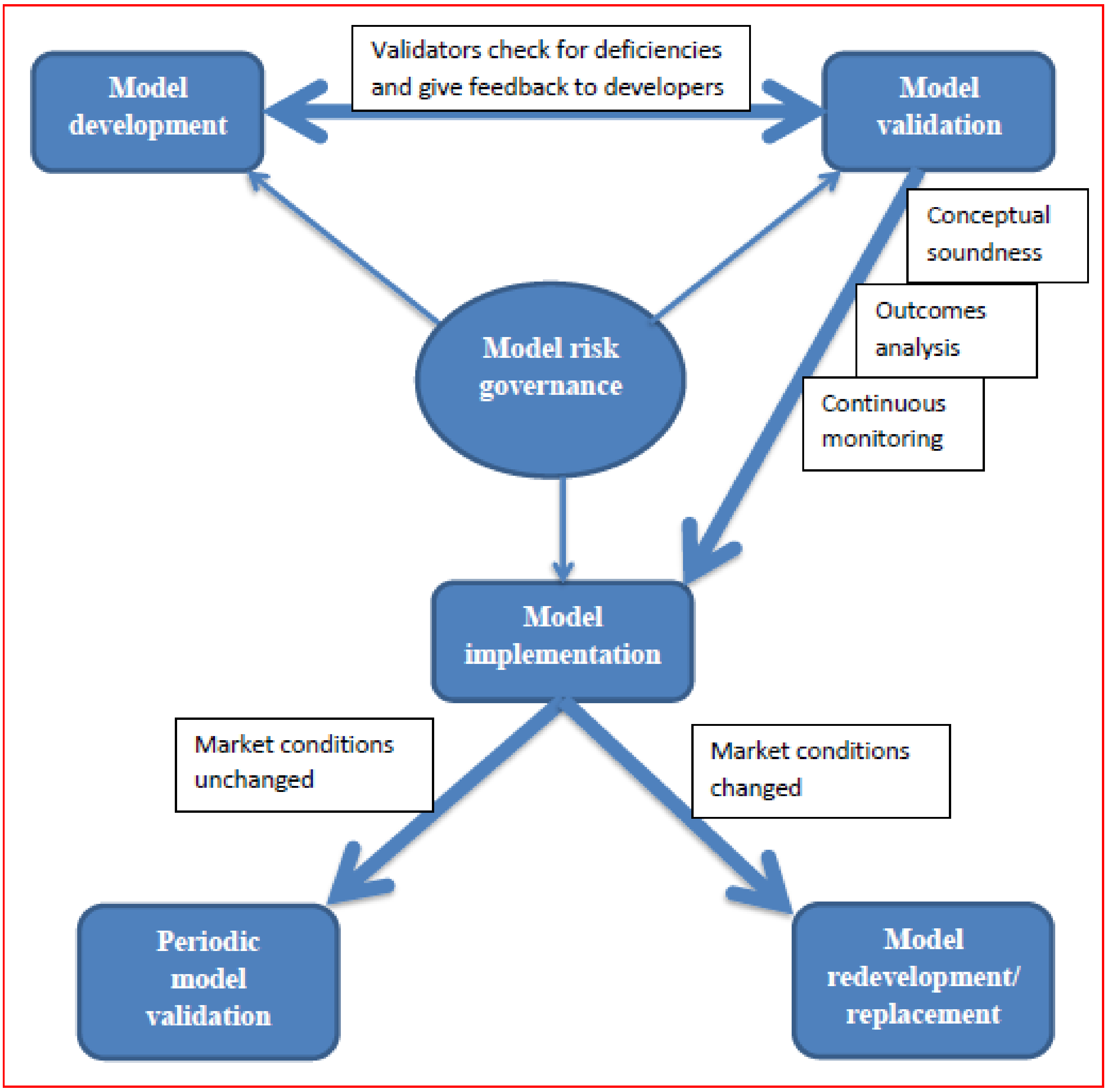

Figure 3: Model risk management framework

With this framework, users are encouraged to continuously monitor the financial model, and the management of the financial entity is encouraged to take a central position and to govern the entire model development and model validation processes. Note that if the model is redeveloped or replaced, then this process starts from the beginning with new model assumptions and inputs.

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CHAPTER 3: THE MEASUREMENT OF CREDIT, MARKET AND OPERATIONAL RISKS

In this chapter, a detailed overview of credit, market and operational risks is given. The approaches for measuring the capital charge for each risk type are discussed; and models associated with these risk types are also discussed. The focus is mainly on these types of risks because they are the most important types of risks in the banking industry. It should be the highest priority of financial industry practitioners to know how to measure, model and manage them.

3.1 Credit risk measurement

Credit risk is defined as the potential for loss due to failure of a borrower to meet its contractual debt obligation in accordance with the agreed terms (BCBS, 2000:1).

Credit risk can be classified under two categories: *issuer risk or default risk;* which is the risk that the issuer/obligor defaults and is unable to fulfil payment obligations; and *credit spread risk*, the risk of a decline in the credit standing of a credit issuer not necessary due to default but because of an increase in the probability of default (Bessis, 2002:13).

According to Brown and Moles (2011:6), a *credit event* is an event that will trigger the default of a bond and includes the following: failure to pay either capital or a coupon; loss event (i.e., when the obligor stops paying); bankruptcy; rating downgrade of the bond by a rating agency such as Moody's or Standard & Poor's.

According to Bluhm *et al.* (2003:11), a *default event* D is an event that an obligor defaults in a certain period of time, and the loss of an obligor is defined by a loss variable

$$\tilde{\mathrm{L}} = \mathrm{EAD} \times \mathrm{LGD} \times \mathrm{L},$$

where EAD (exposure at default) is the expected value of the loan at the time of default; LGD (loss given default) is the amount of the loss if there is a default, expressed as a percentage of the EAD, that is, the expectation of the severity (the frequency of loss); and L is the Bernoulli random variable defined as

$$\mathrm{L} = \begin{cases} 1, \text{ if } \Pr(\mathrm{L}=1) = p \\ 0, \text{ if } \Pr(\mathrm{L}=0) = 1\text{-}p. \end{cases}$$

for some $0 < p < 1$. LGD can as well be defined as 1 – RR (recovery rate) where RR is the proportion of the EAD that the bank recovers in the event of default. According to BCBS (2006:100), a default event on an obligation would occur if one of the following occurs:

- The obligor is unlikely to be able to repay its debt without giving up any pledged collateral[5].
- The obligor has passed more than 90 days without paying a material credit obligation.

3.1.1 Credit capital adequacy

According to BCBS (2006:19), under Basel II, there are two approaches that present a range of possibilities for allocating credit risk capital and for calculating the risk weighted assets (RWA) which is used to calculate the regulatory capital: *Standardised (STD) approach* and *internal ratings-based (IRB)* approach from which two variants exist, a *foundation* approach and an *advanced* IRB approach. A schematic representation of these approaches is given in Figure 4.

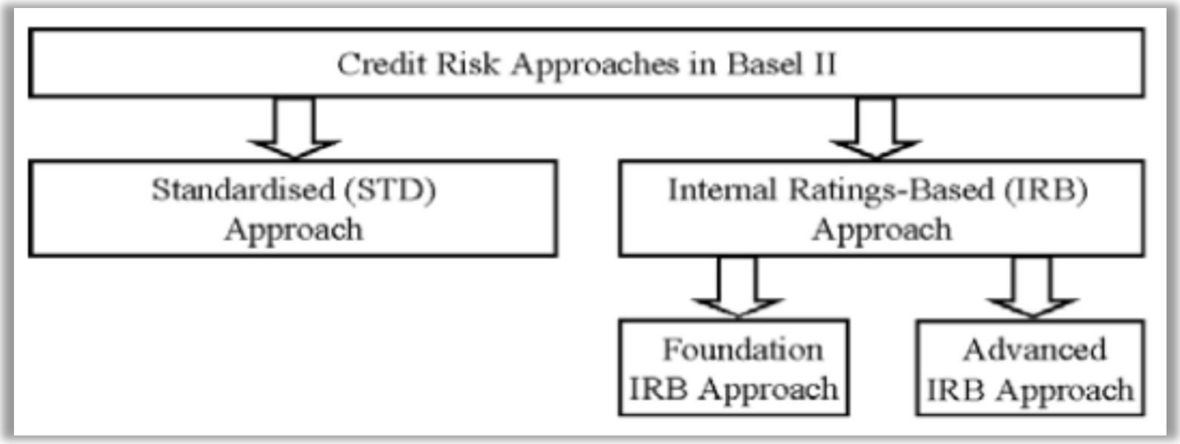

Figure 4: Credit risk measurement

To determine the minimum capital required for credit risk, banks are required to categorise their claims into groups mentioned in regulatory guidelines; and these categories are used to determine their respective risk weights that can either be determined by the regulator or be calculated using credit risk parameters that were

[5] *A collateral is an asset used to secure a loan, e.g., mortgage, bond, guarantee, etc.; and during a credit event (e.g., bankruptcy), the value of the collateral reduces the loss on the defaulted loan. (Bluhm et al., 2003:21).*

estimated using internal models for the purpose of calculating credit capital (BCBS, 2006:12).

The risk weight formulas represent only *unexpected loss (UL)* and do not include *expected loss (EL)*. According to Bluhm *et al.* (2003:12), *EL* is the average loss, i.e., $\mathbb{E}[\tilde{\mathrm{L}}]$, that the bank expects from an exposure over a fixed time period, and is expressed as

$$EL = \mathbb{E}[\tilde{\mathrm{L}}] = \mathrm{PD} \times \mathrm{EAD} \times \mathrm{LGD},$$

where PD is the probability of default, i.e., the likehood that the borrower will fail to make full and timely repayment of its financial obligations.

Since *EL* is an anticipated deterioration in the value of risky assets that the bank has taken into its balance sheet, the bank generally cover its *EL* on a continuous basis through write-offs and provisions; and thus *EL* should be viewed as an anticipated cost of doing business and it should be included in loan pricing and provisioning (Bluhm *et al.*, 2003:12). According to Bluhm *et al.* (2003:23), *UL* is the maximum potential loss at a stated confidence level over a certain time period, and is expressed by

$$UL = \sqrt{\mathrm{Variance}\ [\tilde{\mathrm{L}}]} = \sqrt{\sigma^2[\tilde{\mathrm{L}}]} = \sqrt{\sigma^2[\mathrm{EAD} \times \mathrm{SEV} \times \mathrm{L}]}.$$

UL occurs less frequently and consists of large losses; and thus it is not incorporated into the pricing mechanism, but it requires the bank to hold excess capital reserves so that it can absorb large losses in order to continue to operate (Bluhm *et al.*, 2003:23).

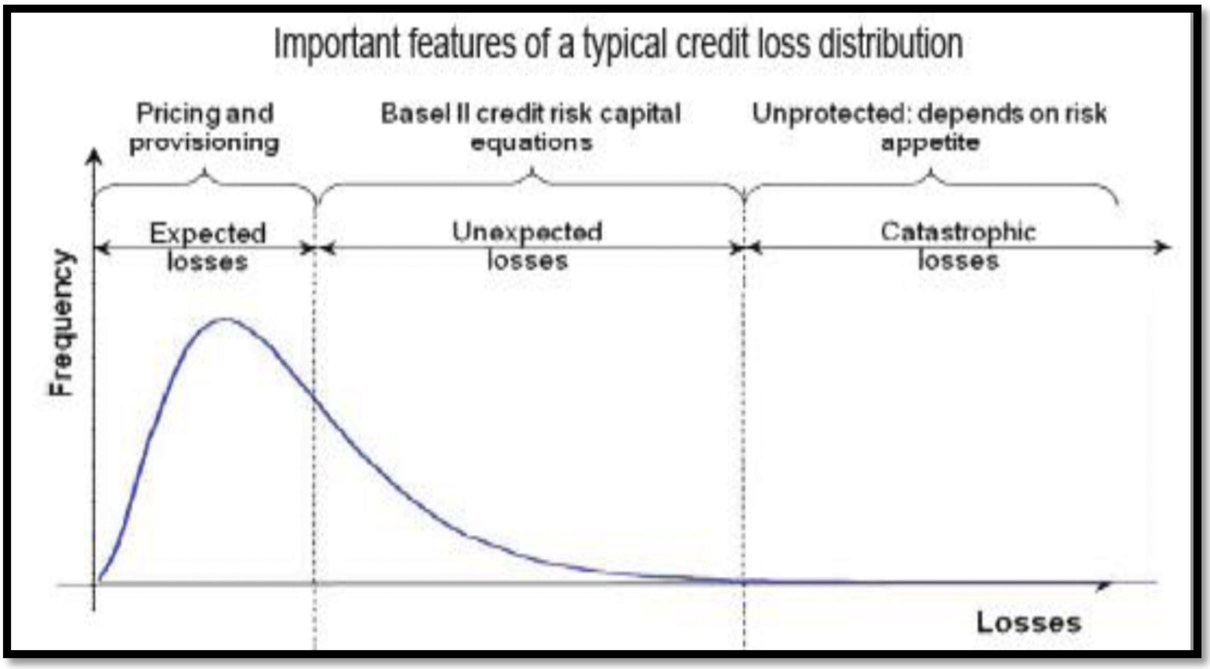

Figure 5: Expected and unexpected credit losses

The excess capital needed to match the bank's estimate of unexpected loss is referred to as *economic capital*.

3.1.1.1 Standardised approach

Using credit ratings, under standardised approach, also known as the *basic indicator approach*, the obligors are categorised without considering their actual credit risks; and categorisations are used to determine risk weights prescribed by the regulator (Fabozzi *et al*., 2006:290). In determining the risk weights in the standardised approach, banks may use assessments by qualified external credit rating agencies recognised by national supervisors (BCBS, 2006:19).

3.1.1.2 Internal ratings-based (IRB) approaches

As Basel II guidelines suggest, before using these approaches, banks that wish to implement the internal ratings-based approaches must first apply to the regulators for accreditation; and the banks that meet certain minimum requirements are then allowed to use their own estimated risk parameters to calculate regulatory capital required for credit risk using their internal models (BCBS, 2006:52).

According to BCBS (2006:52), under the IRB approach, banks must categorise banking-book exposures into the following broad classes of assets with different underlying risk characteristics: (a) corporate – with five sub-classes of specialised lending separately identified; (b) retail – with three sub-classes separately identified; (c) bank; (d) sovereign; (e) equity.

According to BCBS (2006:59), for each asset class, there are three key elements:

- *Risk components*: Estimates of risk parameters provided by banks and some by the supervisors.
- *Risk-weight functions*: The means by which risk components are transformed into risk-weighted assets and therefore capital requirements.
- *Minimum requirements*: The minimum standards that must be met in order for a bank to use the IRB approach for a given asset class.

Moreover, to be allowed to use IRB approaches by the regulators, the bank's internal estimation techniques should meet the following quantitative and qualitative requirements: The internal model is expected to be risk-sensitive to the bank's portfolio and be able to capture obligor characteristics, and should have sufficient information to estimate the key risk parameters within statistical confidence levels; the modelling and capital estimation framework should be linked to the day-to-day operations of the bank; proper corporate governance and internal controls should be set up; and to ensure accurate estimation of required capital for credit risk, and risk components LGD, PD and EAD, an appropriate validation and testing process should be followed (BCBS, 2001:2-3). The following internal ratings-based approaches can be followed:

I. *Foundation internal ratings-based (FIRB) approach*: Banks are allowed to calculate the probability of default (PD) for each asset class; while the regulator determines the LGD and the EAD, and the maturity (M) can be assigned by either (BCBS, 2006:59).

II. *Advanced internal ratings-based (AIRB) approach*: Banks are allowed to use their internal models to calculate PD, LGD, EAD and M (BCBS, 2006:59).

3.1.2 Credit risk models

Given the constraints or requirements, PD can be estimated for a single obligor or a group of obligors with similar credit risk features; and estimation of PD can be done by the underwriting variables, type of borrower, loan size, payment frequency, maturity, and many other variables dependent on either the macroeconomic factors or borrower's attributes (Featherstone *et al.*, 2006:7).

Any of the following three modelling techniques can be used to estimate PD:

I. *Statistical credit scoring models:* Estimated using statistical techniques through macroeconomic and borrower-specific data.

The basic idea under credit scoring models is to assign scores to loan applicants based upon their attributes and credit history, and such scoring systems are called *scorecards* (Lai & Wong, 2008:4). In accordance with Lai and Wong (2008:4), the training sample for building a credit scorecard consists of $(x_i, I_i),\ 1 \le i \le n,$ from *n* loans, where x_i is a *d*-dimensional vector of attributes of the ith loan, and the binary response variable is given by

$$I_k = \begin{cases} 0, & \text{if no default} \\ 1, & \text{if defaulted} \end{cases}.$$

The idea is to regard $(x_i, I_i),\ 1 \le i \le n;$ as a training sample of independent replicates of (X, I) and then to estimate the probability of default $P(I = 1 | X = x)$. The methods that are normally used in credit scoring for this purpose include neural networks, logistic or probit regression, linear or quadratic discriminant analysis, decision trees, and support vector machines (Lai & Wong, 2008:4).

According to Frade (2008:7), the most recommended statistical technique to estimate PD is logistic regression, and it takes the form

$$\ln\left(\frac{\text{PD}}{1-\text{PD}}\right) = \sum_{i=1}^{n} \hat{\beta}_i x_i,$$

where

$$\hat{\beta}_i = \text{ Parameter estimates}$$
$$x_i = \text{Independent variables;}$$

and transformation of this equation gives the probability of default

$$\text{PD} = \frac{\exp\left(\sum_{i=1}^{n}\sum_{i=1}^{n} \hat{\beta}_i x_i\right)}{1+\exp\left(\sum_{i=1}^{n} \hat{\beta}_i x_i\right)}.$$

Logistic regression is a widely used technique for estimating PD for retail, SME and wholesale obligors.

II. *Structural models:* Estimated using company level information.

Structural models link default events explicitly to the fortunes of the company issuing the bond because they focus on the financial structure, that is, debt and equity of the company; and they give an insight into the nature of default and the interaction between shareholders and bondholders (Wang, 2009:30). An example of a structural model is the *Merton model*.

The Merton model assumes that a corporate entity has issued both non-dividend paying equity and a zero-coupon bond such that its total value at time t is $F(t)$ which varies over time as a result of the actions of the company (Wang, 2009:30). Therefore, part of the company's value is a zero-coupon bond with a promised repayment amount of L at a future time T, and the remainder of the value of the company is distributed to the shareholders (Wang, 2009:30).

Therefore, if the company has sufficient funds to pay the debt, the shareholders will receive $F(T) - L$ (Wang, 2009:30). The company will default if the total value of its assets $F(T)$ is less than the promised debt repayment at time T, i.e., $F(T) < L$; and in this case, the bondholders will receive $F(T)$ instead of L and the shareholders will receive nothing (Wang, 2009:30). Combining these two scenarios, we see that the shareholders will receive a payoff of $\max\{F(T) - L, 0\}$ at time T (Wang, 2009:30). This can be regarded as treating the shareholders of the company as having a *European call option*[6] on the assets of the company with maturity T and a strike price equal to the value of the bond L (Wang, 2009:30).

[6] *A European call option is a contract that gives an option holder the right but not an obligation to buy an underlying asset by a certain price on a future date (Hull, 2009:6).*

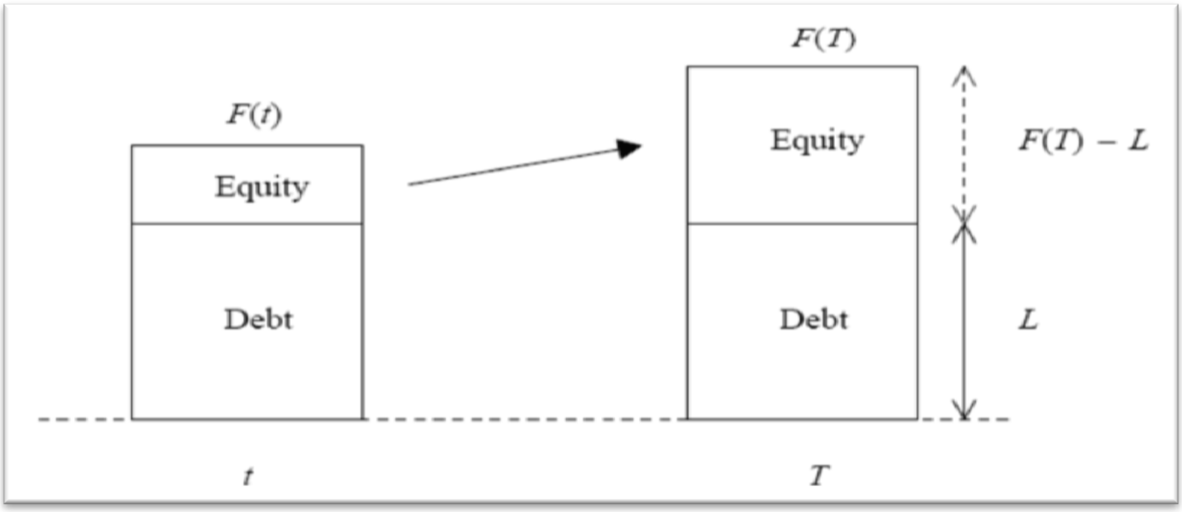

Figure 6: Merton model

III. *Reduced-form models:* Estimated from the observable prices of credit default swaps[7], bonds, and equity options.

Reduced-form models, also known as *default intensity models*, are statistical models which use observed market data along with data on the default-free market to model the movement of the credit rating of the bonds issued by a corporate entity over time; and unlike structural models, default is not directly related with the variability in a firm´s asset value, instead, they model the different levels of creditworthiness and how companies move from one status to another (Pereira, 2013:18). The market statistics usually used in reduced-form models are the credit ratings issued by credit rating agencies such as Moody's and Standard & Poor's (Pereira, 2013:18).

According to Jarrow and Protter (2004:4), the simplest structure of the reduced-form model is the *no-default/default model* which models the movement from no default state *N* to a default state *D*: If $X(t)$ is the state (i.e., credit rating) at time *t,* then the *transition intensity* $\lambda(t)$ can be interpreted in terms of the transition probabilities over the infinitesimal time period [*t, t + dt*], that is,

$$P\left[X(t+dt)=N \middle| X(t)=N\right]=1-\lambda(t)dt+o(dt)$$

and

[7] *Credit default swap (CDS) is a contract that gives the default protection buyer the right to sell bonds (issued by the bond issuer known as the reference entity) to the default protection seller for its face value when a credit event occurs (Hull, 2009:518).*

$$P\left[X(t+dt)=D \middle| X(t)=N\right]=\lambda(t)dt+o(dt),$$

where $o(dt)$ is a smaller order quantity that disappears as the length of the time interval dt tends to zero; and this model can be represented as follows:

$$\textbf{\textit{N} (No default)} \xrightarrow{\lambda(t)} \textbf{\textit{D} (Default)}$$

A more general and more realistic model, with multiple credit ratings rather than the simplistic no-default/default model used above is the *Jarrow-Lando-Turnbull (JLT) model*. In this model there are *n* - 1 credit ratings plus default; for example, for the Standard & Poor's rating system, companies that have already defaulted are in State D; and companies that have not defaulted are rated in one of the seven states: AAA, AA, A, BBB, BB, B, CCC, and for *n* = 8, this would give *n* – 1 = 7 credit ratings, from AAA (= State 1) down to CCC (= State 7), for companies that are not already in default, and the *n*th state (= State 8) would be for companies that are already in default, which are assumed to stay in default forever (Standard & Poor's, 2009:10).

Under the objective probability measure P, the transition intensities from State *i* to State *j* are defined as $\lambda_{ij}(t)$, and they are assumed to be deterministic[8] across time (Hilscher *et al*., 2008:64). The JLT model assumes a constant per period empirical transition matrix or Markov chain which can be represented by the following diagram:

$$Q=\begin{pmatrix} \lambda_{11} & \lambda_{12} & \cdots & \lambda_{1n} \\ \lambda_{21} & \lambda_{22} & \cdots & \lambda_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_{n-1,1} & \lambda_{n-1,2} & \cdots & \lambda_{n-1,n} \\ 0 & 0 & \cdots & 1 \end{pmatrix}$$

[8] *A process is called deterministic if its value as a function of time can be pre-determined.*

Figure 7: Transition matrix under Jarrow-Lando-Turnbull model

On a finite state space $S=\{1,2,\ldots,n\}$, transfer is possible between all states except for the default State *n*, which is absorbing (Hilscher *et al*., 2008:62). If $X(t)$ is the credit rating at time *t,* then the transition probabilities over the short time period [*t, t* + *dt*] are

$$P\left[X(t+dt)=j \middle| X(t)=i\right]=\begin{cases}1-\lambda_{ii}(t)dt+o(dt), & i=j\\ \lambda_{ij}(t)dt+o(dt), & i\neq j\end{cases},$$

for $i=1,2,\cdots,n-1$ (Jarrow & Protter, 2004:6).

3.2 Market risk measurement

Market risk is the loss of value of the financial instrument due to the significant changes in market prices, irrespective of whether these changes are caused by factors related to the individual instrument, its issuer or by factors pertaining to all the instruments traded on the market (Milanova, 2010:395). According to Milanova (2010:395), the most common factors connected to market risk are currency exchange rates, interest rates, prices of commodities and equities, and costs of investments in trade portfolio.

BCBS (2006:157) defines market risk as the risk of losses in on- and off-balance sheet positions arising from market price movements; and it is related to equities and interest rate risk for instruments in the trading book, and foreign exchange risk and commodities risk throughout the bank.

There are positions in commodities and financial instruments in the trading book which should be managed actively and should be valued accurately and frequently (BCBS, 2006:158). These positions are held either with trade intent or for hedging[9] purpose with other elements of the trading book.. Positions held with trading intent are those held with the intent for short-term resale and/or to benefit from the expected or actual short-term movements, or to gain arbitrage profits (BCBS, 2006:158).

[9] *Hedging involves reducing or eliminating financial risk by passing that risk on to someone else (Hull, 2009:10).*

Financial instruments[10] include both cash and financial derivative[11] instruments (BCBS, 2006:158). A *financial asset* is any asset that is cash, the right to receive cash or another financial asset; or the contractual right to exchange financial assets on potentially favourable terms, or an equity instrument. A *financial liability* is the contractual obligation to deliver cash or another financial asset or to exchange financial liabilities under conditions that are potentially unfavourable

3.2.1 Market capital adequacy

Under Basel II, there are two approaches that present a range of possibilities for allocating market risk capital and for calculating the risk weighted assets (RWA): *Standardised (STD) approach* and *internal model-based (IM) approach.* Banks are expected to monitor and report the level of market risk against which a capital requirement is to be applied; and the minimum capital requirement for market risk must be computed as the sum of the capital charges for market risks as determined using the standardised approach or the measure of market risk derived from an internal model-based approach, or a combination of the two approaches (BCBS, 2006:163).

3.2.1.1 Standardised approach

The minimum capital requirement is expressed in terms of two separately calculated capital charges: The capital charge for the specific risk[12] of each security[13], whether it is a long or a short position; and the capital charge for the general market risk (i.e., interest rate risk in the portfolio) to offset long and short positions in different instruments or securities (BCBS, 2009b:4).

The capital charge for specific risk is designed to protect against adverse price movements of a security owing to factors related to the individual issuer (BCBS, 2006:167); the capital charges for equities and interest rate risks apply to items valued by the bank in the trading book; while the capital charges for commodities risk

[10] *A financial instrument is any contract giving rise to both a financial asset of one entity and a financial liability or equity instrument of another entity (BCBS, 2006:158).*
[11] *A financial derivative is a financial instrument whose value is derived from the values of underlying variables (Hull, 2009:1).*
[12] *Specific risk is defined as the risk of loss caused by an adverse price movement of a debt instrument or security due to factors related to the issuer, i.e., exposures to specific issuers of debt securities or equities (BCBS, 2006:163).*
[13] *Security in this instance is a financial asset.*

and foreign exchange risk apply to the bank's commodity positions and total currency, respectively (BCBS, 2006:157).

According to BCBS (2009b:4), the specific risk capital charge for the correlation trading portfolio should be the determined as follows by banks: (i) determine the total specific risk capital charges applicable to the net long positions from the net long correlation trading; (ii) determine the total specific risk capital charges applicable to the net short positions from the net short correlation trading exposures combined; and the larger of these total amounts is then the specific risk capital charge for the correlation trading portfolio

3.2.1.2 Internal model-based approach

The internal model-based approach allows banks to use risk measures derived from their internal risk management models on condition that (i) there are guidelines for stress testing[14] and for specifying an appropriate set of market risk factors; (ii) there exist qualitative standards for internal oversight of the use of models and quantitative standards setting out the use of common statistical parameters for measuring risk; (iii) there exist proper validation procedures for external oversight of the use of models; (iv) certain general criteria concerning the adequacy of risk management are in place; (v) the bank comply with all the rules for banks using a mixture of models and the standardised approach (BCBS, 2006:162).

Banks use sophisticated statistical and mathematical models in the attempt to measure and manage market risk; and the most widely used models are the value-at-risk (VaR) models. A value-at-risk model produces an estimate of the maximum amount that the bank can lose on a particular portfolio over a given holding period with a certain degree of confidence level (Hendricks & Hirtle, 1997:3). The following are value-at-risk models for market risk:

I. Normal VaR model:

According to BCBS (2009b:13), banks are allowed to devise the nature of their internal models; however, to be able to calculate their capital charge properly, they should compute the value-at-risk on a daily basis, using a 99th percentile, one-tailed

[14] *Stress testing (also known as worst case scenarios) is a practice used to address highly unlikely events in order to measure uncertainty (Bessis, 2002:78).*

confidence interval, and an instantaneous price shock equivalent to a 10-day movement in prices, with a minimum of one year of a sample period; updating a dataset at least once a month and reassessing it whenever market prices are subject to material changes; recognising empirical correlations within broad risk categories; and using any model (e.g., historical simulations, variance-covariance matrices or Monte-Carlo simulations).

II. *Stressed VaR model:*

Banks should meet the following minimum standards when calculating the capital charge in order to replicate a VaR calculation that would be generated on the bank's current portfolio if the relevant market factors are experiencing a stress period: The bank should calculate the stressed value-at-risk at least on a weekly basis, using a 99th percentile, one-tailed confidence interval, and an instantaneous price shock equivalent to a 10-day movement in prices, with model inputs calibrated to historical data from a continuous 12-month period of significant financial stress relevant to the bank's portfolio (e.g., for many portfolios a 12-month period relating to significant losses in 2007-2008 would adequately reflect a period of such stress; although other periods relevant to the current portfolio must be considered by the bank); and the period used must be approved by the regulator and be reviewed regularly (BCBS, 2009b:14).

In accordance with BCBS (2009b:15), on a daily basis, the bank must meet a capital requirement for market risk which is calculated according to the following formula:

$$K = \max\left\{VaR_{t-1}, \left(m_c + p_c\right) \times VaR_{avg}\right\} + \max\left\{sVaR_{t-1}, \left(m_s + p_s\right) \times sVaR_{avg}\right\},$$

where

$K =$ Capital charge under VaR and $sVaR$ approaches

$VaR_{t-1} =$ Previous day's value-at-risk

$VaR_{avg} =$ Average of the daily value-at-risk measures on each of the preceding sixty business days

$sVaR_{t-1} =$ Latest available stressed value-at-risk, calculated according to the above instructions

$sVaR_{avg} =$ Average of the stressed value-at-risk measures on each of the preceding sixty business days.

The multiplication factors m_c and m_s are set by individual supervisory authorities on the basis of their assessment of the quality of the bank's risk management system, subject to an absolute minimum of 3 for both m_c and m_s; and p_c and p_s are the 'plus' or 'add on' factors, generally ranging from 0 to 1, to be decided by the bank based only on the results of the back-testing of its value-at-risk model and not stressed value-at-risk model; and they are directly related to the ex-post performance of the model, thereby introducing a built-in positive incentive to maintain the predictive quality of the model; and hence, if the back-testing results are satisfactory and the bank meets all of the qualitative standards set out above, the plus factor could be zero (BCBS, 2009b:15).

3.3 Operational risk measurement

Operational risk is defined as the potential for loss due to inadequate or failed internal processes, systems and people, or due to external events (BCBS, 2006:144). According to Chorafas, (2004b:147), there are seven types of operational risks: Internal fraud; external fraud; employment practices and workplace safety; clients, products and business practices; damage to physical assets; business disruption and system failures; and execution delivery and process management.

3.3.1 Operational capital adequacy

There are three approaches that present a range of possibilities for allocating operational risk capital; and banks are encouraged to move along the spectrum of available approaches as they develop more sophisticated operational risk measurement systems (BCBS, 2006:144).

3.3.1.1 Basic indicator approach (BIA)

According to Chorafas (2004b:129), the basic indicator approach is intended for small, unsophisticated banks; practically, it does not involve measurement of risk; and capital charge is determined using gross income as an indicator which is defined as

Gross income = net interest income + net non-interest income

where

net non-interest income = (fees and commissions receivable) – (fees and commissions payable) + (the net result on financial operations) + (other income).

According to BCBS (2006:144), banks using the basic indicator approach must hold capital for operational risk equal to the average over the previous three years of a fixed percentage denoted by α, that is,

$$K_{BIA} = \frac{1}{n}\sum_{i=1}^{n}\left(GI_i \times \alpha\right),$$

where

$K_{BIA} =$ Capital charge under BIA
$GI =$ Annual gross income, where positive, over the previous three years
$\alpha =$ Constant (fixed percentage) set by Basel
$n =$ Number of the previous three years for which gross income is positive.

The basic indicator approach is easy to implement and universally applicable across banks to arrive at a capital charge for operational risk; however, its shortcoming is that it involves just a generalised, unreliable estimate of operational risk (Chorafas, 2004b:129).

3.3.1.2 Standardised approach (SA)

Banks with substantial operational risk exposures and internationally active banks are expected to upgrade to the standardised approach, which is more sophisticated than the basic indicator approach, and it is suitable for the risk profile of these banks (BCBS, 2006:144).

In the standardised approach, the bank's activities are divided into eight business lines: retail banking, trading and sales, corporate finance, payment and settlement, commercial banking, agency services, retail brokerage, and asset management (BCBS, 2006:146). Both the basic indicator approach and the standardised approach use gross income as a proxy of operational risk exposure (Chorafas, 2004b:145); but with the standardised method, operational risk is measured using an indicator that reflects the volume of the bank's activities with each business line (Chorafas, 2004b:129).

According to BCBS (2001:7), within each business line, the capital charge is calculated by multiplying a bank's broad financial indicator by β, which serves as a rough proxy for the relationship between the industry's operational risk loss experienced for a given business line and the broad financial indicator representing the banks' activity in that business line, calibrated to a desired supervisory soundness standard:

$$K_{SA} = \sum_{i=1}^{n} \left(GI_i \times \beta_i \right),$$

where

$K_{SA} =$ Capital charge under standardised approach
$GI =$ Annual gross income for each business line over the previous three years
$\beta =$ Constant (fixed percentage) for each business line, set by Basel
$n =$ Number of business lines in the bank.

For example, for the corporate finance business line, the regulatory capital charge would be calculated as follows:

$$K_{\text{Corporate Finance}} = \text{Gross Income} \times \beta_{\text{Corporate Finance}},$$

where

$K_{\text{Corporate Finance}} =$ Capital requirement for the corporate finance business line
$GI =$ Gross income for the corporate finance business line
$\beta_{\text{Corporate Finance}} =$ The capital factor to be applied to the corporate finance business line.

3.3.1.3 Advanced measurement approaches (AMA).

Under advanced measurement approaches, the regulatory capital requirement is the same as the risk measure generated by the internal operational risk measurement system of the bank using the quantitative and qualitative criteria (BCBS, 2006:147).

Banks are allowed to develop and use advanced measurement approaches subject to the approval of the relevant supervisors, and the approval is conditional on the bank demonstrating to the satisfaction of the supervisors that the allocation mechanism for internationally active banking subsidiaries is proper and can be supported empirically (BCBS, 2006:147).

"AMA operational risk data can be grouped into the following four categories: (1) *internal loss data*, (2) *external data*, (3) *scenario data and data related to a bank's* *business environment* and (4) *internal controls*; it has multiple functions, including risk quantification, risk management, accounting and other forms of reporting. Some data are suitable for more than one application. To maintain consistency, a bank should develop data policies and procedures that include, for example, guidelines around perimeter of application, minimum observation period, reference date, minimum modelling thresholds, and data treatment" (BCBS, 2011:5).

According to Chorafas (2004b:150), advanced measurement approaches are more advanced than the standardised approach because they are analytical solutions, i.e., they provide clarity on how the concept of *system analysis* works in practice. System analysis lies in the background of all three advanced measurement approaches: the *internal measurement approach (IMA)*, *loss distribution (LD)*, and *scoreboard* (Chorafas, 2004b:150).

I. Internal measurement approach (IMA):

Under IMA, banks are allowed to use internal loss data, and supervisors provide the banks with the method to calculate the required capital and impose quantitative and qualitative standards to ensure the quality of data used, the integrity of the measurement approach, and the adequacy of the internal control environment (BCBS, 2001:8).

According to BCBS (2001:8), under the IMA, a capital charge for the operational risk of a bank would be determined using the following procedures:

- the activities of a bank are categorised into a number of business lines and a broad set of operational loss types within business lines; and within each combination of a business line and a loss type, an *exposure indicator* (*EI*) which is a proxy for the size (or amount of risk) of each business line's operational risk exposure is specified by the supervisor.
- In addition to the exposure indicator, for each combination of a business line and a loss type, a bank measures a parameter representing the *probability of loss event* (*PE*) based on its internal loss data, as well as a parameter representing the *loss given that event* (*LGE*).
- The *expected loss* (*EL*) for each combination of a business line and a loss type is then calculated as

$$EL = EI \times PE \times LGE.$$

- The supervisor supplies γ for each combination of a business line and a loss type, which translates the expected loss into a capital charge, which is expressed with the following formula:

$$K_{IMA} = \sum_{i,j=1}^{n}\left(EI_{ij} \times PE_{ij} \times LGE_{ij} \times \gamma_{ij}\right) = \sum_{i,j=1}^{n}\left(EL_{ij} \times \gamma_{ij}\right),$$

where

$K_{IMA} =$ Capital charge under internal measurement approach
$EI =$ Exposure indicator which represents a proxy for the size of operational risk exposure for the business line i
$PE =$ Probability of occurrence of loss events
$LGE =$ Propostion of transaction or exposure that would be expensed as loss, given the event
$EL =$ Expected loss for each business line/risk type
$\gamma =$ A multiplier translating the estimate of EL into a capital charge per i business line and j type of operational risk event.

- Instead of just supplying the supervisors with the product *EL,* banks provide individual components of the expected loss calculation (i.e. *EI, PE, and LGE*) to facilitate the process of supervisory validation, and the supervisors then use this information to calculate *EL* and then adjust for unexpected loss through a multiplier γ to achieve the desired soundness standard.

The shortcoming of the IMA is that it needs a multiplier γ to move from expected losses to unexpected losses, and γ must be produced by the business line; and this procedure becomes complex if it is done by event type (Chorafas, 2004b:152).

II. Loss distribution approach (LDA):

A more advanced version of IMA is the loss distribution approach (BCBS, 2001:11), which has to be based on sound internal reporting practices (Chorafas, 2004b:152). According to BCBS (2001:11), “under the LDA, a bank, using its internal data, estimates two probability distribution functions for each business line (and risk type); one on single event impact and the other on event frequency for the next (one) year. Based on the two estimated distributions, the bank then computes the probability distribution function of the cumulative operational loss. The capital charge is based on the simple sum of the VaR for each business line (and risk type). The approach adopted by the bank would be subject to supervisory criteria regarding the assumptions used".

Thus, the LDA process involves modelling the frequency distribution and severity distribution independently and then combining the two distributions to form a distribution of total losses (Chorafas, 2004b:154). According to Chorafas (2004b:154), banks that choose a confidence level of 99.9% can obtain much greater assurance that they can withstand extreme events because they have enough operational risk capital reserves to cover themselves against these events.

III. Scoreboard approach:

The scoreboard approach, also known as the *scorecard approach*, is an approach that bases the risk profile on organisational information other than historic loss data (Anders, 2003:223). Since it is sensitive to risk, the scorecard approach provides the following incentive: it reflects a positive change in an organisation; such as an improvement in controls, a change in the risk profile due to an increase in quality or an introduction of a new insurance cover (Anders, 2003:223).

This approach begins with the determination of an initial operational risk capital, either at firm or at business line level, using for example the basic indicator or the standardised approach; and then the initial values are modified on the basis of scorecards, relying on a number of indicators which should be proxies for particular risk types in the business lines (Anders & Sandstedt, 2003:47).

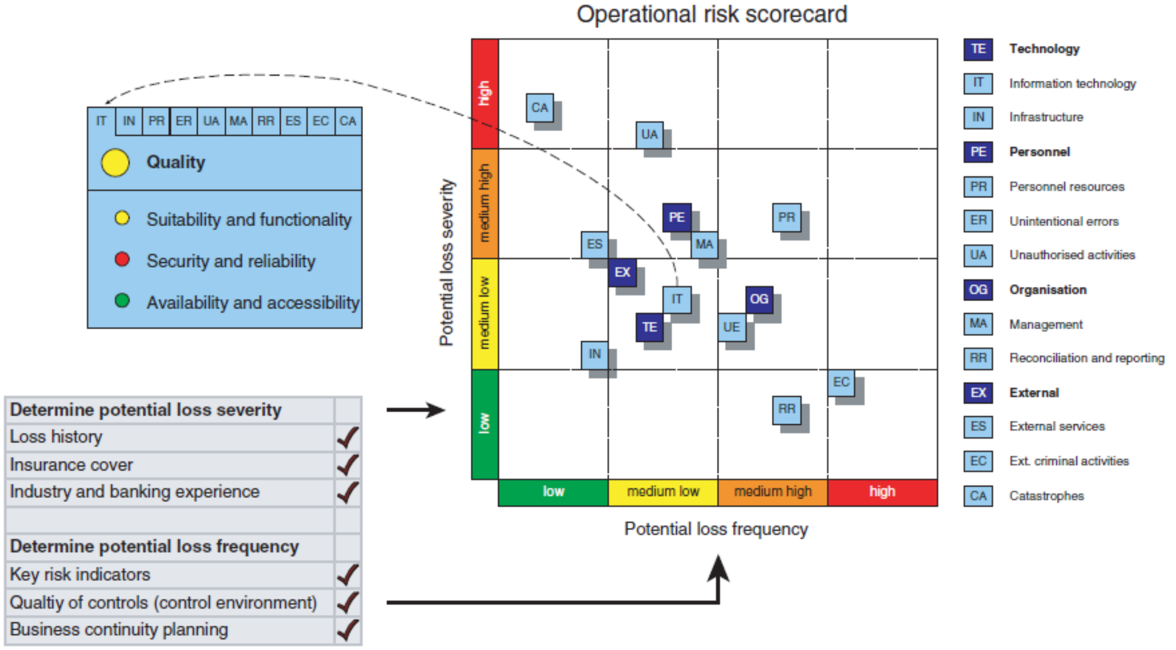

Figure 8: Scorecard report (*Source:* Anders & Sandstedt, 2003:48)

These scorecards are completed regularly, and then the capital charge is computed as

$$K_S = \sum_{j=1}^{8} \left(K_j^0 \times R_j \right),$$

where

$K_S =$ Capital charge under scorecard approach

$R =$ the risk score that rescales the initial capital charge K_j^0 to a new one for the business line j.

Operational risk approaches are summarised in the following diagram:

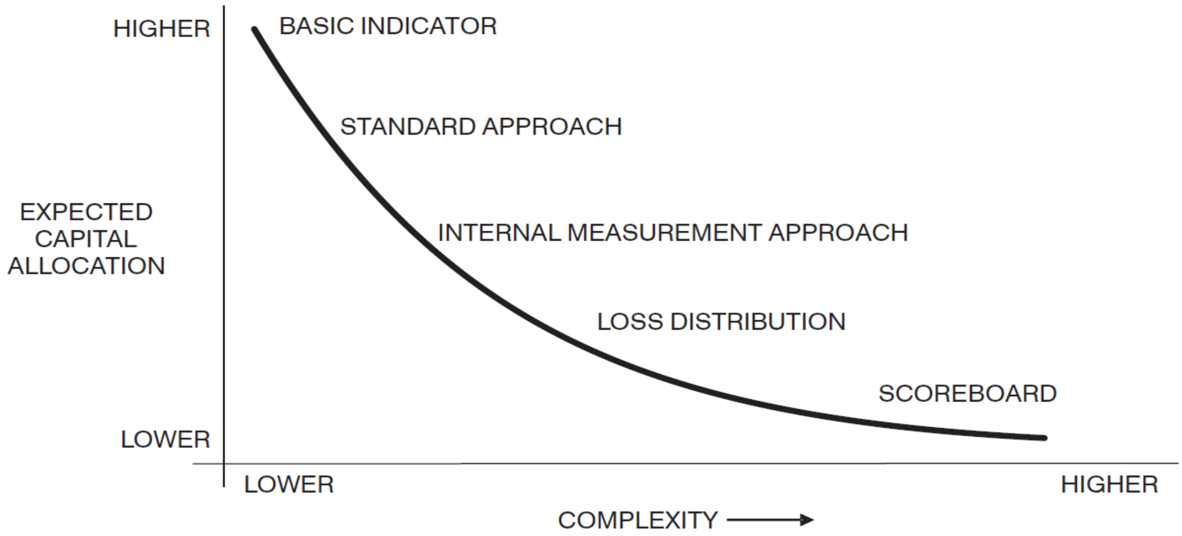

Figure 9: Capital allocation based on operational risk approaches (*Source*: Chorafas, 2004b:141)

As indicated in Figure 9, the amount of capital to be allocated for operational risk depends on the approach used for capital calculation; and the choice of the approach also depends on the complexity of the business, for example, small banks may use basic indicator or standardised approach to allocate capital for its operational risk; but bigger banks with more business lines should choose advanced approaches.

3.4 Summary

To be able to measure and allocate the required capital:

- For the credit risk, standardised approach and/or foundation and advanced internal ratings-based approaches must be used by banks; and banks that wish to implement the internal ratings-based approaches must first apply to the regulators for accreditation;
- For the market risk, standardised approach and/or internal model-based approaches must be used by banks; and banks that wish to implement internally the value-at-risk model should compute the value-at-risk on a daily basis using a 99th percentile, one-tailed confidence interval; and during the stress period, banks should compute stressed value-at-risk at least once a week;

- For the operational risk, banks have the options between the basic indicator and standardised approaches, as well as internal measurement, loss distribution and scoreboard advanced measurement approaches.

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CHAPTER 4: AGGREGATION OF CREDIT AND MARKET RISKS

According to Yang (2012:2), all risks, including credit, market and operational risks should be included in the calculation of the enterprise's economic capital. Because of the complexity and lack of adequate data for the operational risk, operational risk will be excluded from the study and the enterprise's economic capital will be assumed to involve the economic capitals from the credit and market risks. In this chapter, the following three main measures of risk from the credit and market risk loss distributions are analysed and measured: Value-at-risk, expected shortfall and economic capital. Using a copula, the two loss distributions are aggregated in order to calculate the economic capital for the enterprise. The economic capital is then adjusted to suit the enterprise's strategic objectives.

4.1 Loss distributions for credit and market portfolios

According to Hogg and Klugman (1984:1), unexpected events such as death, disability, flood, damage due to fire, car accident, hail, theft, and illness can cause losses that are problematic to individuals and the whole society; and they may be hedged by buying insurance policies. Hogg and Klugman (1984:1) define *frequency of losses* as

$$\frac{\text{number of occurrences}}{\text{exposure (to risk) basis}};$$

and the expected value of the individual loss random variable or *severity of losses* as

$$\frac{\text{total losses from all occurrences}}{\text{number of occurrences}}.$$

The main objective of aggregated risk management is to measure and manage the enterprise's risk and capital from all business units of the financial institution; and this can only be accomplished by integrating different types of risks (Rosenberg & Schuermann, 2004:1).

Irrespective of the sectors were financial institutions operate, all such institutions are subject to three types of risks: *market, credit*, and *operational risks*. The shape of the distribution of each risk type varies substantially; for example, market risk, usually generates portfolio value distributions that are nearly symmetric and often approximated as normal; and operational and credit risks usually generate more skewed distributions because of infrequent extreme losses due to large catastrophes in the case of operational risk or large lending exposures in the case of credit risk (Rosenberg & Schuermann, 2004:1).

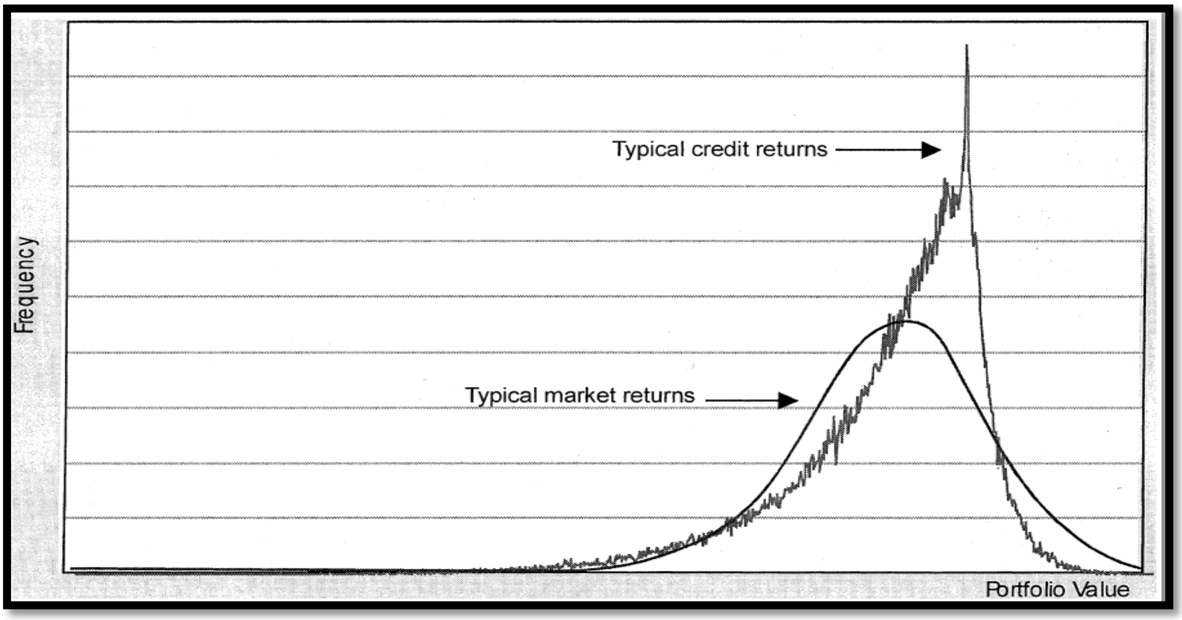

Figure 10: Comparison of the distributions of credit returns and market returns (*source:* Crouhy *et al.*, 2000:64)

In order to have in place good processes and procedures leading towards proper investment decisions, regulatory reporting, calculations and risk management, risk measures are needed to summarise the loss distribution and to highlight one or few aspects of portfolio risk (Van Gestel & Baesens, 2009:278). According to Van Gestel and Baesens (2009:278), a risk measure ρ is said to be *coherent* if it satisfies these four properties:

- *Subadditivity*: A diversified risk is obtained after combining various risks; that is, for bounded random variables *X* and *Y*, $\rho(X+Y) \leq \rho(X)+\rho(Y)$.
- *Monotonicity*: The risk increases with the variables; that is, if $X \leq Y$, then $\rho(X) \leq \rho(Y)$.
- *Positive homogeneity*: The risk scales with the variables; that is, $\rho(\lambda X) = \lambda\rho(X)$, for $\lambda \geq 0$.

- *Translation invariance*: The risk translates down or up by addition or subtraction of a multiple of the risk-free discount factor; that is, $\rho(X \pm \alpha r) = \rho(X) \pm \alpha r,$ for $\alpha \in \mathbb{R}$ and risk-free discount factor r.

According to Van Gestel and Baesens (2009:274), the following measures of risk summarise the loss distribution:

I. *Expected loss:* It can be defined as the anticipated deterioration in the value of a risky asset that the bank has taken onto its balance sheet. It is therefore the mean value of the loss of the loan for a given time horizon; and its value depends on the loss given that the borrower defaults, the exposure at the time of default, and the probability of default, that is,

$$\mathbb{E}(L) = \text{LGD} \times \text{EAD} \times \text{PD},$$

where LGD is the loss given default defined as the percentage of the EAD that is lost in the event of a default. It is a stochastic variable ranging between 0 and 100%, and it represents the severity of the loss in the case of default, that is, LGD is the same as 1 – Recovery Rate; EAD is the exposure at default, which refers to the outstanding amount at the time of default. It can be considered as a deterministic or a stochastic variable, with the stochastic aspect most important for credit cards and liquidity business lines;

PD is the probability of default, also known as default intensity, which may be predicted from the prices of bonds. The likelihood of default is calculated as

$$\text{PD} = \frac{\text{credit spread}}{\text{LGD}} = \frac{\text{risky bond yield } - \text{ risk-free bond yield}}{1 - \text{RR}}.$$

The *expected loss* of the portfolio is the sum of the expected losses of the individual loans,

$$\mathbb{E}(L_P) = \sum_{i=1}^{N} \mathbb{E}(L_i) = \sum_{i=1}^{N} (\text{LGD}_i \times \text{EAD}_i \times \text{PD}_i),$$

which gives an idea on the average loss of the portfolio, and it should be covered by the excess interest rate charged to the obligors (Van Gestel & Baesens, 2009:278). Although it is a coherent measure of risk, the expected loss does not provide information on the shape or dispersion of the loss distribution; nor provide any information into the probability of extremely large losses due to default of a large exposure, economic crises with waves of defaults and reduced recoveries (Van Gestel & Baesens, 2009:278).

II. *Value-at-risk:* It is the loss amount that will only be exceeded with a confidence level of 1 - α on average over a given time horizon, that is, it is the smallest amount l such that the probability that the loss L exceeds l is no larger than 1 – α (Van Gestel & Baesens, 2009:282). Therefore, value-at-risk on the portfolio with the loss distribution L_P is defined as

$$VaR_\alpha = \inf\left\{ l \in \mathbb{R} \middle| P\left(L_P > l\right) \leq 1-\alpha \right\};$$

that is, the VaR is the maximum amount at risk to be lost over the time horizon or holding period given the confidence level; with the time horizon of 10 days for market risk and 1 year for credit risk (Van Gestel & Baesens, 2009:282). According to Van Gestel and Baesens (2009:282), the value-at-risk depends therefore on the time horizon and the confidence level.

According to Frey and McNeil (2002:1319), the definition of VaR coincides with the definition of an α-quantile q_α of the distribution of L_P in terms of a generalised inverse of the distribution function F_{L_P} because, for the random variable *X,* the VaR_α at $100(1-\alpha)\%$ is

$$VaR_\alpha = VaR_\alpha\left(X\right) = \inf\left\{ l \in \mathbb{R} \middle| 1 - F_{L_P}\left(l\right) \leq 1-\alpha \right\} = \inf\left\{ l \in \mathbb{R} \middle| F_{L_P}\left(l\right) \geq \alpha \right\},$$

and if q_α is the 100th α-quantile of the distribution F_{L_P}, then

$$\alpha = F_{L_P}\left(q_\alpha\right) \text{ or } \alpha = P\left(L_P \leq q_\alpha\right).$$

A major drawback of the VaR is that it does not yield information on the shape of the distribution and on the expected loss that can happen in α percentage of the time when the portfolio expected loss *EL* exceeds the VaR. For credit and operational risk, one typically uses very high confidence levels in the deep tail of the distribution. At these levels, all assumptions regarding correlations and distributions may have an important impact on the VaR. The VaR estimate can become unstable at high confidence levels. Moreover, VaR is not a coherent measure of risk because it does not satisfy the subadditivity property.

III. *Expected shortfall: A*lso known as conditional VaR, expected tail loss or worst conditional expectation, expected shortfall measures the expected loss when the portfolio loss exceeds the VaR limit; and for a loss distribution L_P with $\mathbb{E}(|L_P|) < \infty$ and the distribution function F_{L_P}, the expected shortfall at significance level $\alpha \in (0,1)$ is defined as

$$ES_\alpha = \frac{1}{1-\alpha}\int_\alpha^1 VaR_u(L_P)du = \mathbb{E}(L_P | L_P > VaR_\alpha);$$

that is, the expected shortfall gives the expected value by which the VaR will be exceeded in the small number of cases with significance level *α* (Van Gestel & Baesens, 2009:285). It indicates the average loss given a default event, that is, when the economic capital is insufficient to absorb the losses (Van Gestel & Baesens, 2009:285). Even though the VaR and the expected shortfall are complementary risk measures that describe the tail of the loss distribution, the expected shortfall is a more stable estimate than VaR; it is a coherent measure of risk; and it is often preferred over VaR for capital allocation. (Van Gestel & Baesens, 2009:285).

IV. *Economic capital:* It is defined as the difference between the value-at-risk and the expected loss at a given significance level *α*, that is,

$$EC_\alpha = VaR_\alpha - \mathbb{E}(L);$$

and since it is based on the VaR measure, it has the same properties as the VaR, that is, it is not subadditive, it is instable for high confidence measures; however, it can be used to measure the capital required to support the portfolio risk (Van Gestel & Baesens, 2009:284).

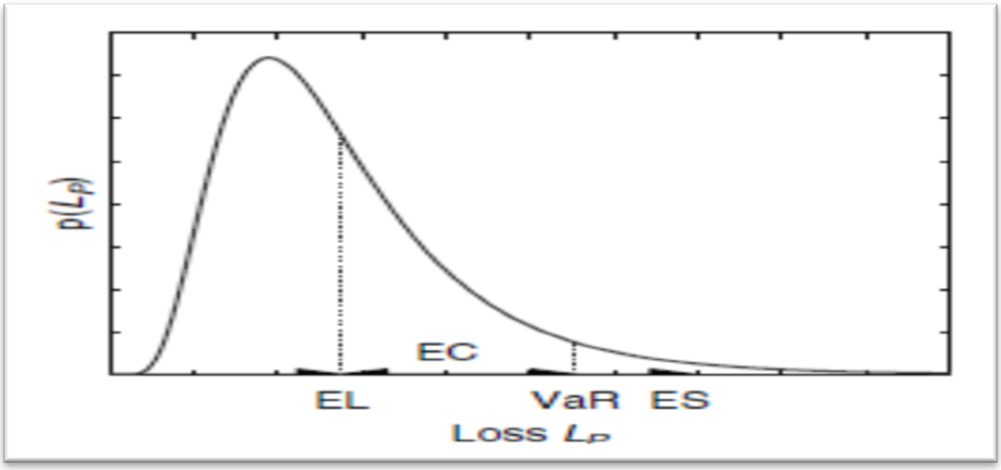

Figure 11: Expected loss, value-at-risk, economic capital and expected shortfall at the 95th percentile

4.2 Copulas

Copula is a Latin word which means connection (Yang, 2012:2). From a mathematical point of view, a copula is used to describe the dependence between random variables (Yang, 2012:2); by combining univariate marginal distributions to construct a joint distribution with a specific dependence structure (Shim *et al.,* 2009:10). According to Yang (2012:2), "technically, a copula is a tool that expresses joint probability function as a function of marginal distributions; and therefore, in the two-dimensional case, a copula between two random variables *X* and *Y* is a function $C(u,v):[0,1]\times[0,1]\rightarrow[0,1]$ such that

$$\text{Prob}\{X < x, Y < y\} = C\big(F(x), G(y)\big),$$

where $F(x) = \text{Prob}\{X < x\}$ and $G(x) = \text{Prob}\{Y < y\}$ are cumulative distribution functions".

In accordance with Yang (2012:2), the usefulness of copulas is summarised by Sklar's theorem which provides a way of analysing the dependence structure of multivariate distributions without studying marginal distributions:

Lemma 4.2.1 (Sklar's Theorem). Let *F* be an *n*-dimensional cumulative distribution function with marginal distributions $F_1,\cdots,F_n$. Then there exists a copula function *C* such that $\text{Prob}\{X_1 < x_1,\cdots,X_n < x_n\} = C\left(F_1(x_1),\cdots,F_n(x_n)\right).$

This theorem is useful because it declares that any relationship between any random variables can be captured by a copula (Yang, 2012:2). According to Shim *et al.* (2009:11), a copula can be viewed as a multivariate function with standard uniform marginal distributions, and it is unique if marginal distributions are continuous:

Lemma 4.2.2. Let u_i be the observed value of $F_i(X_i)$, for $i=1,\cdots,n.$ Then for continuous univariate marginal distributions, the unique copula function is given by

$$C(u_1,\cdots,u_n) = F\left(F_1^{-1}(x_1),\cdots,F_n^{-1}(x_n)\right),$$

where $F_1^{-1},\cdots,F_n^{-1}$ denote the quantile functions of the univariate marginal distributions $F_1,\cdots,F_n$.

Therefore, a copula can be constructed under the assumption that marginal distributions are known and can be consistently estimated from a given data (Shim *et al.,* 2009:11).

4.3 Categories of copulas

Although a wide range of copulas exist, the two most popular categories of copulas are the *elliptical class* and *Archimedean class* (Yang, 2012:2).

4.3.1 Elliptical copulas

Elliptical copulas are suitable in modelling dependence structures with multi-dimensions; and they are flexible since they allow for both positive and negative dependence (Shim *et al.*, 2009:11). Flexibility in terms of simulation procedures and structure's shape is due to the introduction of a correlation matrix as a multidimensional parameter (Shim *et al.*, 2009:11).

According to Yang (2012:2), "an *n*-dimensional elliptical distribution ***X*** is of the following form:

$$\boldsymbol{X} = \mu + RAU,$$

where μ is an *n*-dimensional mean vector, *A* is an *n* × *k* matrix, *U* is a *k*-dimensional random vector uniformly distributed on the unit hypersphere and $R \geq 0$ is a one-dimensional random variable independent of *U*. Here $k \leq n$ is any dimension and R can be arbitrary. The copula determined by the joint distribution function of *X* is an elliptical copula".

Gaussian, *Student's t*, and *Cauchy* copulas are different types of elliptical copulas (Shim *et al.*, 2009:11).

A. Gaussian copula

According to Shim *et al.* (2009:12), the Gaussian copula is derived from the multivariate Gaussian distribution; and the dependence structure among the marginal distributions is described by a copula *C* such that

$$C_R^G(\boldsymbol{u}) = C_R^G(u_1, \cdots, u_n) = G\left(\phi_1^{-1}(u_1), \cdots, \phi_n^{-1}(u_n)\right),$$

where ϕ^{-1} is the inverse of the univariate standard normal distribution function; *G* denotes the joint distribution function of the multivariate standard normal distribution function with linear correlation matrix *R*, and $\boldsymbol{u} = (u_1, \cdots, u_n) \in \mathbb{R}^n$. In the case of bivariate distribution, a Gaussian copula can be written as

$$C_R^G(u_1, u_2) = \int_{-\infty}^{\phi^{-1}(u_1)} \int_{-\infty}^{\phi^{-1}(u_2)} \frac{1}{2\pi\left(1 - R_{12}^2\right)^{1/2}} \exp\left(-\frac{s_1^2 - 2R_{12}s_1s_2 + s_2^2}{2\left(1 - R_{12}^2\right)}\right) ds_1 ds_2,$$

where R_{12} is the linear correlation coefficient of the corresponding bivariate normal distribution, and $s_1, s_2 \in [0,1]$ (Shim *et al.*, 2009:12).

In accordance with Shim *et al.* (2009:12), in the case of tail dependence, the Gaussian copula does not allow for extreme events to be dependent, and this is illustrated with the bivariate distribution: let bivariate variables X_1 and X_2 be continuous random variables with marginal distribution functions F_1 and F_2; then the coefficients of tail dependence are asymptotic measures of the tail dependence of the bivariate distribution of X_1 and X_2, with the coefficients of lower and upper tail dependences of X_1 and X_2 defined as

$$\lambda_L = \lim_{u \downarrow 0} P\left(X_2 < F_2^{-1}(u) \middle| X_1 < F_1^{-1}(u)\right),$$
$$\lambda_U = \lim_{u \uparrow 1} P\left(X_2 > F_2^{-1}(u) \middle| X_1 > F_1^{-1}(u)\right),$$

respectively, provided that the limit exists in the interval [0,1]; and hence the tail dependence states the probabilities of having a low (high) extreme value of X_2 given that a low (high) extreme value of X_1 occurs. According to Shim *et al.* (2009:13), the dependence structures are of a great variety from one copula to another: for example, random variables X_1 and X_2 are said to be asymptotically independent in the lower (upper) tail, that is, no tail dependence if $\lambda_L = 0$ $(\lambda_U = 0)$, which is the case of the Gaussian copula; and on the contrary, X_1 and X_2 are asymptotically dependent in the lower (upper) tail if $\lambda_L \in (0,1]$ $(\lambda_U \in (0,1])$.

According to Shim *et al.* (2009:13), to simulate the random vector $\boldsymbol{X} = (X_1, \cdots, X_n)^T$ from the Gaussian copula C_R^G, where $\boldsymbol{X} = \mu + AZ$ is a normal distribution with mean μ and covariance $\sum$, the following algorithm can be used:

a) Construct the lower triangular matrix *A* using Cholesky decomposition so that the covariance matrix $\sum = AA^T$, for some *n* x *n* matrix *A*.
b) Simulate *n* independent standard normal random variables $Z = (Z_1, \cdots, Z_n)^T$ from *N*(0,1).
c) Take the matrix product of *A* and *Z*, i.e., *Y* = *AZ*.
d) Set $U_i = \phi(Y_i),\ i = 1, \cdots, n,$ where ϕ is the distribution function of the standard normal distribution.
e) Set $X_i = F_i^{-1}(U_i),\ i = 1, \cdots, n.$
f) $(X_1, \cdots, X_n)^T$ is the random vector with marginal distributions $F_1, \cdots, F_n$ and Gaussian copula C_R^G.

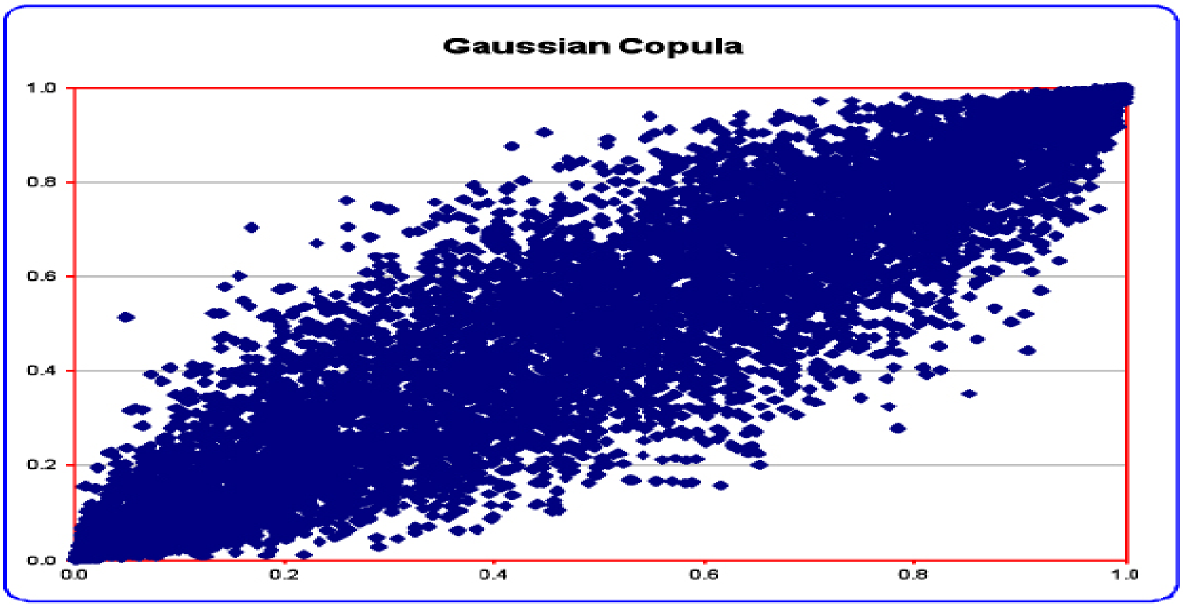

Figure 12: The Gaussian copula (*Source:* Yang, 2012:3)

B. Student's *t*-copula

According to Shim *et al.* (2009:14), Student's *t*-copula (or simply *t*-copula) is derived from the multivariate Student's *t* distribution; and the dependence structure among the marginal distributions is described by a copula *C* such that

$$C_{v,R}^{t}\left(u_1,\cdots,u_n\right)=t_{v,R}\left(t_v^{-1}\left(u_1\right),\cdots,t_v^{-1}\left(u_n\right)\right),$$

where v is the degree of freedom, $t_{v,R}$ denotes the multivariate *t*-distribution function, and t_v^{-1} is the inverse of the univariate *t*-distribution function. In the case of bivariate distribution, a *t*-copula can be written as

$$C_{v,R}^{t}\left(u_1,u_2\right)=\int_{-\infty}^{t_v^{-1}(u_1)}\int_{-\infty}^{t_v^{-1}(u_2)}\frac{1}{2\pi\left(1-R_{12}^2\right)^{1/2}}\left(-\frac{s_1^2-2R_{12}s_1s_2+s_2^2}{v\left(1-R_{12}^2\right)}\right)^{-(v+2)/2}ds_1ds_2,$$

where R_{12} is the linear correlation coefficient of the corresponding bivariate t_v distribution if $v>2$, and $s_1,s_2\in[0,1]$ (Shim *et al.*, 2009:14).

In accordance with Shim *et al.* (2009:14), in the case of tail dependence, "unlike the Gaussian copula, *t*-copula generates joint extreme movements regardless of the marginal behaviour of random variables. The *t*-copula has both lower and upper tail dependence, expressing dependence between extreme events. The coefficient of the upper tail dependence (λ_U) is increasing in R_{12} and decreasing in v. Thus, a *t*-copula is more appropriate than a Gaussian copula to model the case where extreme events occur simultaneously. Furthermore, the coefficient of the upper tail dependence tends to zero as degrees of freedom v tend to infinity for $R_{12} < 1$, implying that a *t*-copula converges to a Gaussian copula as v tends to infinity".

According to Shim *et al.* (2009:15), to generate the random vector $\boldsymbol{X} = \left(X_1, \cdots, X_n\right)^T$ from the *t*-copula $C_{v,R}^t$, where $\boldsymbol{X} = \mu + AZ$ is a *t*-distribution with mean μ and covariance $\sum$, the following algorithm can be used:

a) Construct the lower triangular matrix *A* using Cholesky decomposition so that the covariance matrix $\sum = AA^T$.
b) Simulate *n* independent standard normal random variables $Z = \left(Z_1, \cdots, Z_n\right)^T$ from *N*(0,1).
c) Simulate a chi-squared random variables *S* with v degrees of freedom, independent of $Z = \left(Z_1, \cdots, Z_n\right)^T$.
d) Take the matrix product of *A* and *Z*, i.e., *Y* = *AZ*.
e) Set $T_i = \sqrt{\frac{v}{S}} Y_i,\ i = 1, \cdots, n.$
f) Set $U_i = t_v\left(T_i\right),\ i = 1, \cdots, n.$
g) Set $X_i = F_i^{-1}\left(U_i\right),\ i = 1, \cdots, n.$
h) $\left(X_1, \cdots, X_n\right)^T$ is the random vector with marginal distributions $F_1, \cdots, F_n$ and *t*-copula $C_{v,R}^t$.

C. Cauchy copula

According to Shim *et al.* (2009:15), the Cauchy copula is a special case of the *t*-copula with the degree of freedom v equals to one; and this copula generated by a multivariate Cauchy distribution is given by

$$C_{1,R}^C\left(u_1, \cdots, u_n\right) = t_{1,R}\left(t_1^{-1}\left(u_1\right), \cdots, t_1^{-1}\left(u_n\right)\right),$$

where $t_{1,R}$ denotes the joint distribution function of a standard Cauchy random vector, and t_1^{-1} is the inverse of the standard Cauchy distribution with the probability density function

$$t_1(x) = \frac{1}{\pi}\frac{1}{1+x^2}, \quad -\infty < x < \infty.$$

In the case of a bivariate distribution, a Cauchy copula can be written as

$$C_{1,R}^{C}(u_1,u_2) = \int_{-\infty}^{t_1^{-1}(u_1)}\int_{-\infty}^{t_1^{-1}(u_2)} \frac{1}{2\pi\left(1-R_{12}^2\right)^{1/2}}\left(-\frac{s_1^2 - 2R_{12}s_1s_2 + s_2^2}{\left(1-R_{12}^2\right)}\right)^{-3/2} ds_1 ds_2,$$

where R_{12} is the linear correlation coefficient of the corresponding bivariate t_1 distribution, and $s_1, s_2 \in [0,1]$ (Shim *et al.*, 2009:15). Due to its relationship with the *t*-copula, the Cauchy copula also yields tail dependence; and lastly, to generate a random vector $\boldsymbol{X} = \left(X_1,\cdots,X_n\right)^T$ from the Cauchy copula $C_{1,R}^{C}$, the *t*-copula algorithm with $v = 1$ is followed (Shim *et al.*, 2009:16).

4.3.2 Archimedean copulas

Because they represent dependence structure with a few parameters, Archimedean copulas limit the complex nature of the dependence structure (Shim *et al.*, 2009:11). According to Nelsen (2006:110), an *n*-dimensional Archimedean copula is defined as follows:

Let $\varphi:[0,1]\to[0,\infty)$ be a continuous, strictly decreasing, convex function such that $\varphi(1)=0,$ and let $\varphi^{[-1]}:[0,\infty)\to \boldsymbol{I}$ be its pseudo-inverse $\varphi,$ where the domain of $\varphi^{[-1]}$ is $[0,\infty)$, the range of $\varphi^{[-1]}$ is the set of integers $\boldsymbol{I}$, and $\varphi^{[-1]} = \varphi^{-1}$ if $\varphi(0)=\infty.$ Then, for the case $\varphi^{[-1]} = \varphi^{-1}$, an *n*-dimensional Archimedean copula is defined by

$$C\left(u_1,\cdots,u_n\right) = \varphi^{-1}\left(\varphi\left(u_1\right)+\cdots+\varphi\left(u_n\right)\right).$$

The function φ is called a generator of the copula. If $\varphi(0)=\infty,$ then φ is called a strict generator and *C* is said to be a strict Archimedean copula. To be precise, φ is an additive generator of the copula *C*. If we set $\lambda(t)=\exp(-\varphi(t))$ and $\lambda^{[-1]}(t)=\varphi^{[-1]}\ln(t)$, then

$$C(u_1,\cdots,u_n)=\lambda^{[-1]}\left[\lambda(u_1)\lambda(u_2)\cdots\lambda(u_n)\right],$$

so that λ is a multiplicative generator (Nelsen, 2006:110). Nelsen (2006:113) highlights the following properties of Archimedean copulas:

Lemma 4.3.1 (Properties of Archimedean copulas). Let *C* be a two-dimensional Archimedean copula with a generator φ. Then

a) C is symmetric, i.e., $C(u,v)=C(v,u)$ for all $u,\ v$ in $\boldsymbol{I}$.

b) C is associative, i.e., $C(C(u,v),w)=C(u,C(v,w))$ for all $u,\ v,\ w$ in $\boldsymbol{I}$.

c) If $c>0$ is any constant, then $c\varphi$ is also a generator of C.

Clayton, *Gumbel* and *Frank* copulas are different types of Archimedean copulas (Shim *et al.*, 2009:11).

A. Clayton copula

According to Nelsen (2006:116), a two-dimensional Clayton copula with a generator φ is represented by

$$C_\phi^C(u_1,u_2)=\left[\max\left(u_1^{-\phi}+u_2^{-\phi}-1,0\right)\right]^{-1/\phi},$$

with a parameter $\phi>1$, and a continuous decreasing convex function $\varphi:[0,1]\to[0,\infty)$ defined by

$$\varphi_\phi(t)=\frac{1}{\phi}\left(t^{-\phi}-1\right).$$

B. Frank copula

According to Nelsen (2006:116), a two-dimensional Frank copula with a generator φ is represented by

$$C_\phi^F(u_1,u_2) = -\frac{1}{\phi}\ln\left[1+\frac{(\exp(-\phi u_1)-1)(\exp(-\phi u_2)-1)}{\exp(-\phi)-1}\right],$$

with

$$\varphi_\phi(t) = -\ln\left(\frac{\exp(-\phi t)-1}{\exp(-\phi)-1}\right).$$

C. Gumbel copula

According to Nelsen (2006:116), a two-dimensional Gumbel copula with a generator φ is represented by

$$C_\phi^G(u_1,u_2) = \exp\left[-\left((-\ln u_1)^\phi + (-\ln u_2)^\phi\right)^{1/\phi}\right],$$

with

$$\varphi_\phi(t) = (-\ln t)^\phi,$$

and it possesses a very desirable feature: heavier losses are associated with higher correlations, which is in contrast to the constant correlation assumption with the Gaussian copula.

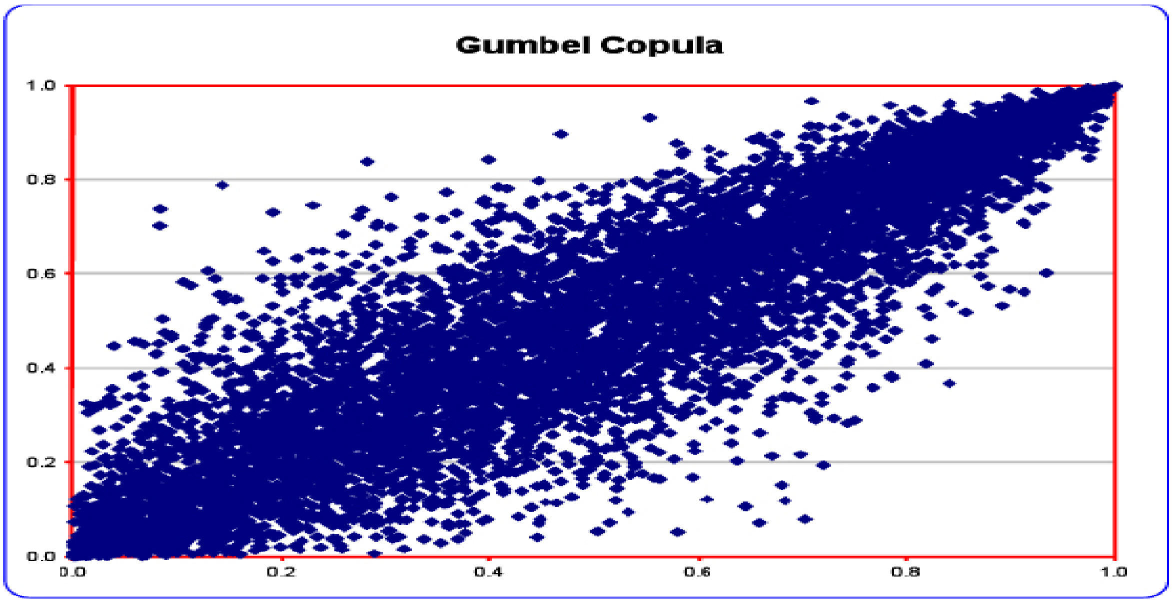

Figure 13: The Gumbel copula (*Source:* Yang, 2012:3)

Note that in all the three cases of Archimedean copulas, the parameter ϕ controls the behaviour of the copula, including the correlation between losses.

4.4 The determination of the economic capital for the model risk of the enterprise

Risk Aggregation is the incorporation of multiple types of risks into a single appropriate risk aggregation framework, and this risk aggregation framework is vital for adequate enterprise risk management (Yang, 2012:2). Risk aggregation models are very important in decision-making processes such as capital allocation and solvency; and they are used for risk management functions such as risk identification, monitoring and mitigation (Aas & Puccetti, 2014:694).

The types of financial models that are considered in this study are *risk-tackling models* which are analytical or statistical methods for valuing instruments, measuring risk and/or attributing regulatory or economic capital; or econometric or advanced statistical methods for parameter estimation or calibration (Wu & Olson, 2010:179).

4.4.1 Integration of loss distributions

The loss distributions from the credit and market risks were integrated to form a joint distribution. The measuring instrument used to model the dependency between the two loss distributions was a copula.

4.4.2 Data and methodology

The historical monthly closing prices of the JSE All-Share Index were downloaded from INET-BFA data source. The price data ranges from June 1995 to June 2015. The log returns and the standard deviation of returns were calculated and annualised. The portfolio with an initial investment of R10 million was constructed; the loss distribution was constructed using negative monthly returns; and the distribution was then normalised and standardised. Using the historical annualised mean return and volatility, a sample with a size of 10,000 was generated. Due to the unavailability of a credit risk portfolio, a sample with a size of 10,000 was generated using Monte-Carlo simulation. The sample was normalised to construct a Pareto distribution. This distribution represents a loss distribution of a credit portfolio.

Assuming the expected loss of R500,000 and the threshold level of R1000,000 for each portfolio; the value-at-risk at 99% confidence interval, the expected shortfall and the economic capital for each loss distribution were determined. The two loss distributions were then aggregated using a copula to determine the aggregated value-at-risk, expected shortfall and economic capital.

4.4.3 Choosing a copula

For the purpose of risk integration, Yang (2012:2) suggests that a copula should meet the following prerequisites to be chosen:

- It should be easy to implement;
- It should be familiar with practitioners and regulators;
- It should be simple and it should robustly estimate parameters;
- It should be compatible with fat-tail distributions; sensitive to large losses, but less sensitive to small losses.

Based on the above prerequisites, a Gumble copula was chosen in the study to integrate the loss distributions of the credit and market portfolios.

4.4.4 Results and discussions

Results:

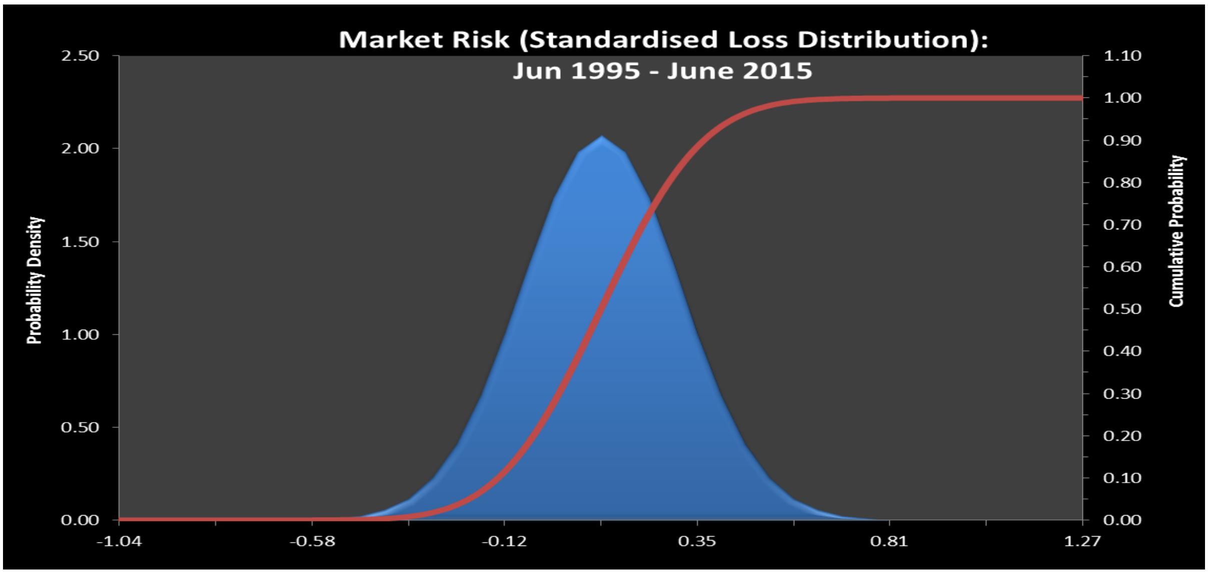

Figure 14: Market risk loss distribution

In Figure 14, the negative returns were standardised and normalised to form a loss distribution for the market risk portfolio. The VaR at 99%, expected shortfall and economic capital for the market risk loss distribution are displayed in Table 1 below.

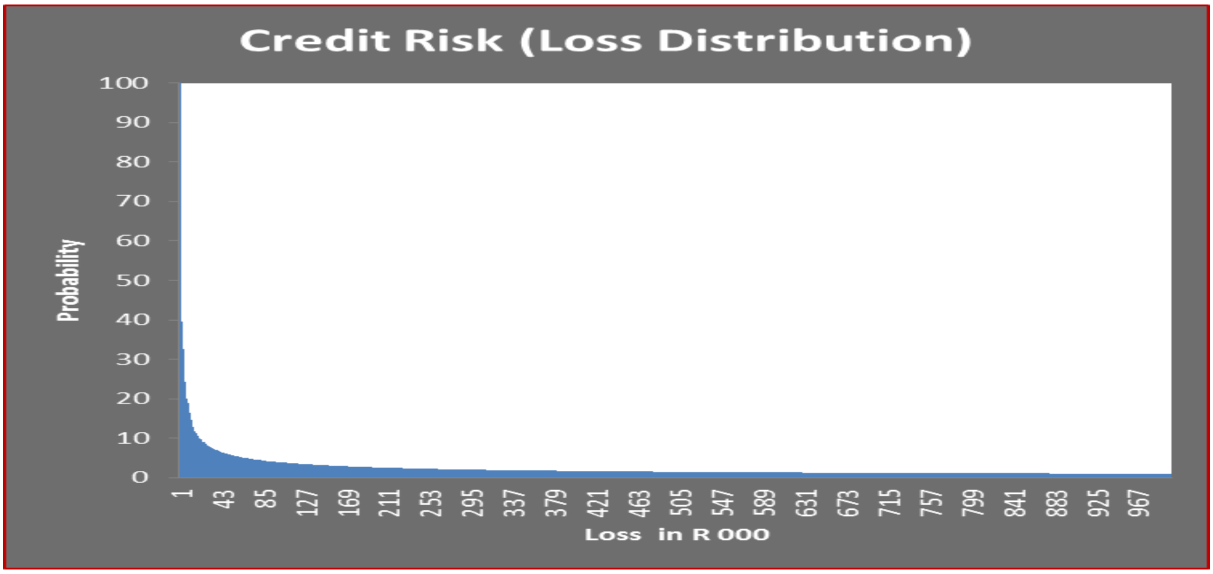

Figure 15: Credit risk loss distribution

In Figure 15, a sample with a size of 10,000 was generated to form a loss distribution for the credit risk portfolio. As expected, the distribution is in the form of a Pareto distribution. The VaR at 99%, expected shortfall and economic capital for the credit risk loss distribution are displayed in Table 1 below.

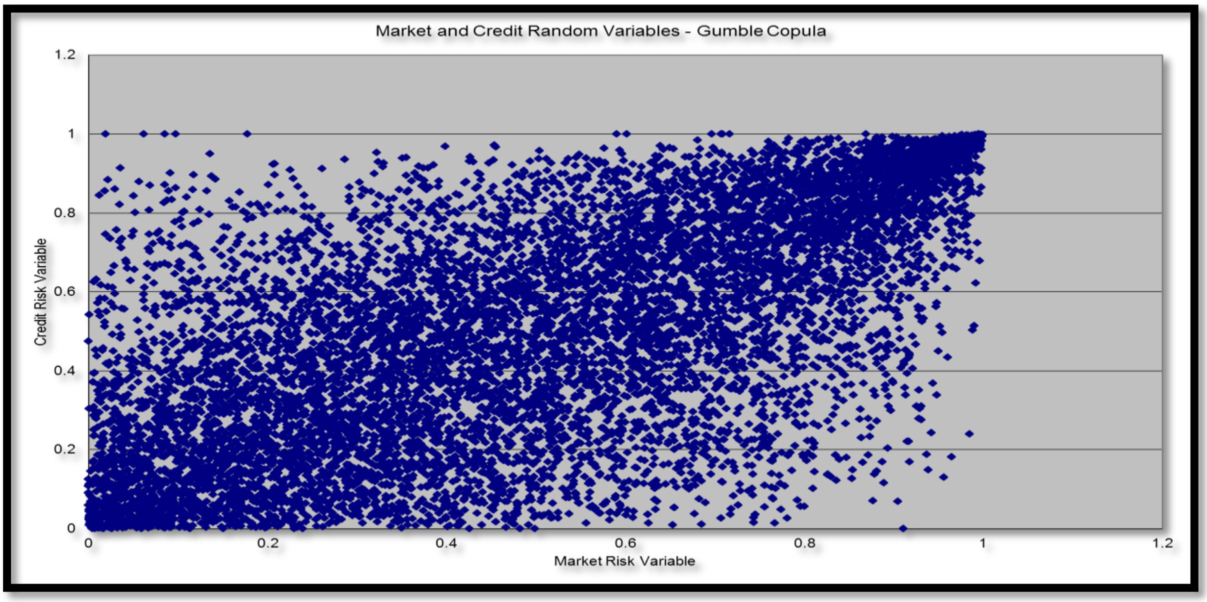

Figure 16: Random variables generated using Gumble copula

In Figure16, a two-dimensional Gumbel copula was fitted to both credit and market loss datasets which were simulated using Monte-Carlo. The parameters of the Gumbel copula were estimated using maximum likelihood in SAS 9.3.

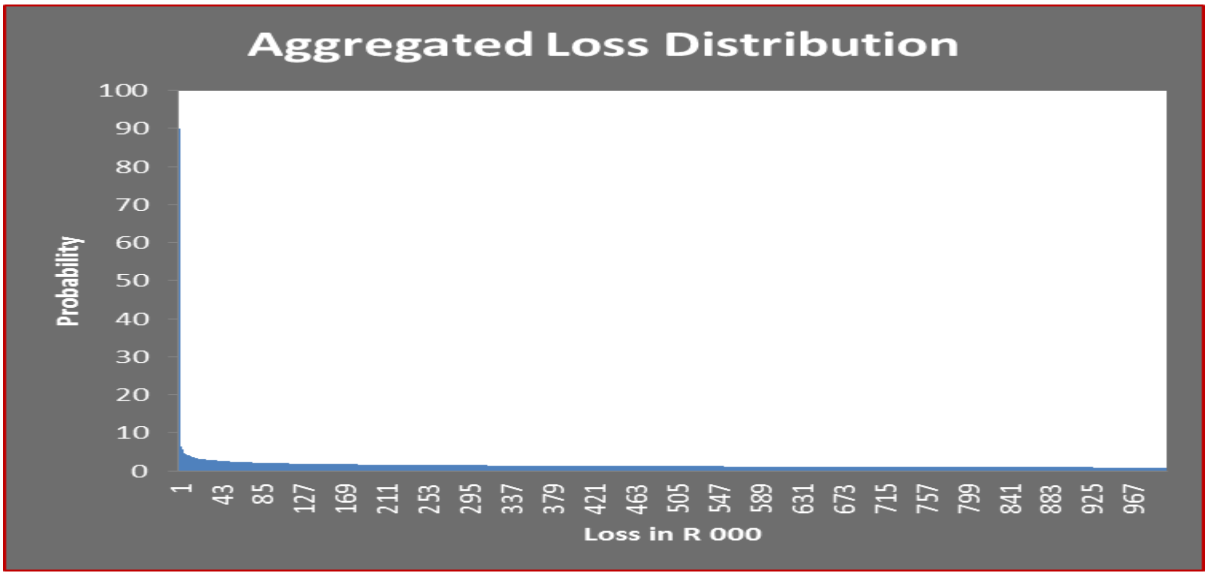

Figure 17: Aggregated loss distribution generated using Gumble copula

Figure17 shows a joint distribution after credit and market loss distributions were aggregated using a two-dimensional Gumbel copula. The resultant distribution is in the form of a Pareto distribution.

Table 1: Value-at-risk, expected shortfall and economic capital

	Market risk	Credit risk	Aggregated risk
Initial investment	R 10 000 000.00	R 10 000 000.00	R 20 000 000.00
Expected loss	R 500 000.00	R 500 000.00	R 500 000.00
Threshold level	R 1 000 000.00	R 1 000 000.00	R 2 000 000.00
Value-at-risk (at 99%)	R 1 503 109.94	R 1 005 771.08	R 2 008 881.03
Expected shortfall	R 1 503 109.94	R 1 000 104.43	R 2 503 214.37
Economic capital	R 1 003 109.94	R 505 771.08	R 1 508 881.03

Discussions:

Given an equally weighted portfolio which consists of market and credit portfolios, the economic capital required to cover for the unexpected losses from the market risk is at most two times than that of the credit risk. Recall that to simulate the returns of the credit portfolio, the average historic volatility was used. The volatility was determined from periods which included higher volatile markets. This explains why measures of risk are higher for the market portfolio. However, if the credit portfolio data was available, the results could have been different due to the 2008-2009 financial crises which affected this portfolio significantly.

A copula is a powerful tool for constructing the multivariate probability distributions (Bee, 2010:3). According to Bee (2010:2), estimating the parameters of the resulting distributions is usually feasible in the univariate case, but it is difficult both computationally and theoretically in a multivariate case. In a multivariate case the complications are mostly related to the large number of parameters. To deal with these complications, one must first choose a univariate model for the marginal distributions and estimate its parameters; and then study the dependence structure and estimate the joint distribution using a copula (Bee, 2010:2).

One has to assume independence of the two distributions if copulas are not used. This could lead to wrong estimations of parameters and incorrect allocation of capital.

4.5 Capital alignment with enterprise's strategic objectives

4.5.1 Strategic management process

An organisation's strategy refers to managers' action plan for running the business and conducting operations which involves competitive moves and business approaches that managers employ to grow the business, to attract and please customers, to compete successfully, and to achieve the targeted levels of organisational performance (Hough, *et al.,* 2011:5). A strategy is an organisation's way of creating unique value for the organisation and its stakeholders (Dobson, *et al.,* 2004:3).

According to Dobson, *et al.* (2004:3), a *strategy* is used to set an agenda for future actions; *strategic goals* state the milestones and target dates to achieve each milestone; *policies* set the guidelines and limits to achieve the strategic goals; and *programmes* provide a step-by-step sequence of actions and the timetable necessary to achieve major objectives. A well-defined strategy incorporates an organisation's objectives, policies, major plans, and programmes; it allocates limited resources optimally, and it is capable of dealing with the potential actions of intelligent opponents (Dobson, *et al.,* 2004:3).

Strategic management enables the organisation to position itself properly in order to survive in a competitive environment (Dobson, *et al.,* 2004:3).

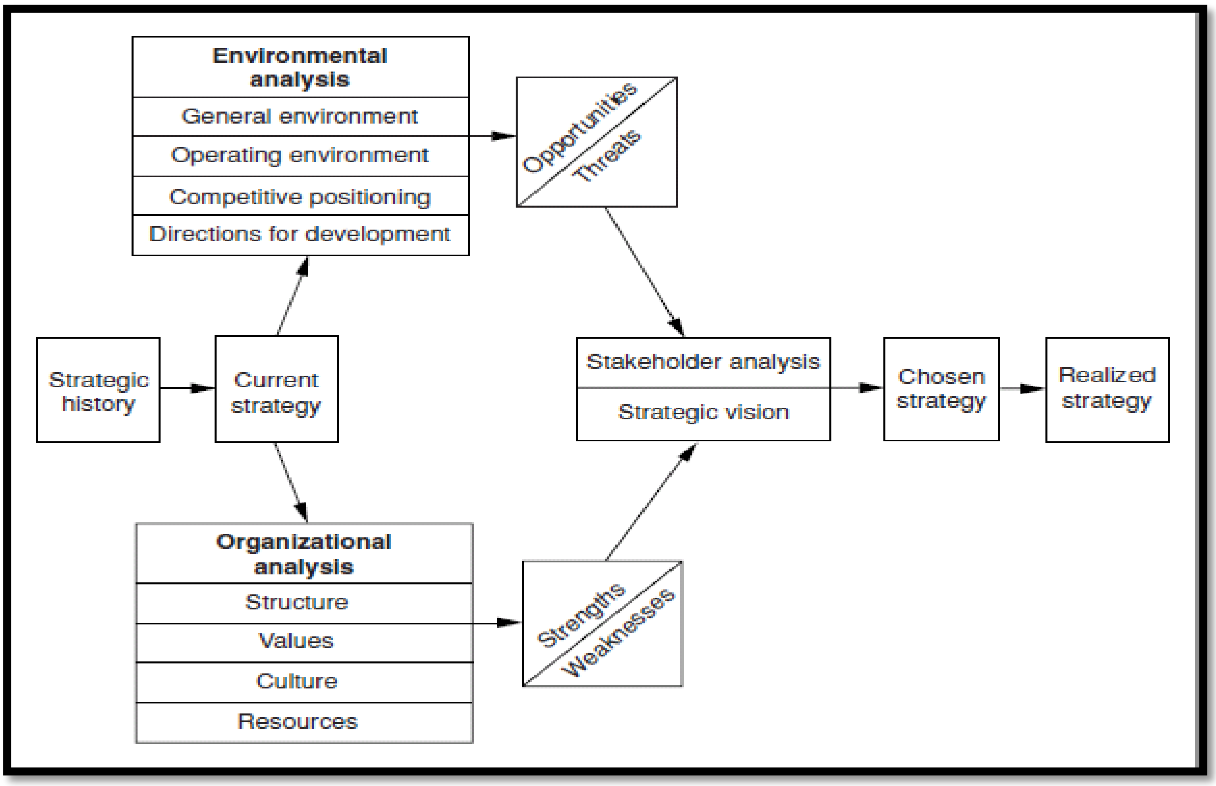

Figure 18: Strategic management process (*Source:* Dobson, *et al.,* 2004:4)

Strategic development and execution process is part of the strategic management process which consists of five interrelated and integrated phases which are displayed in the figure below:

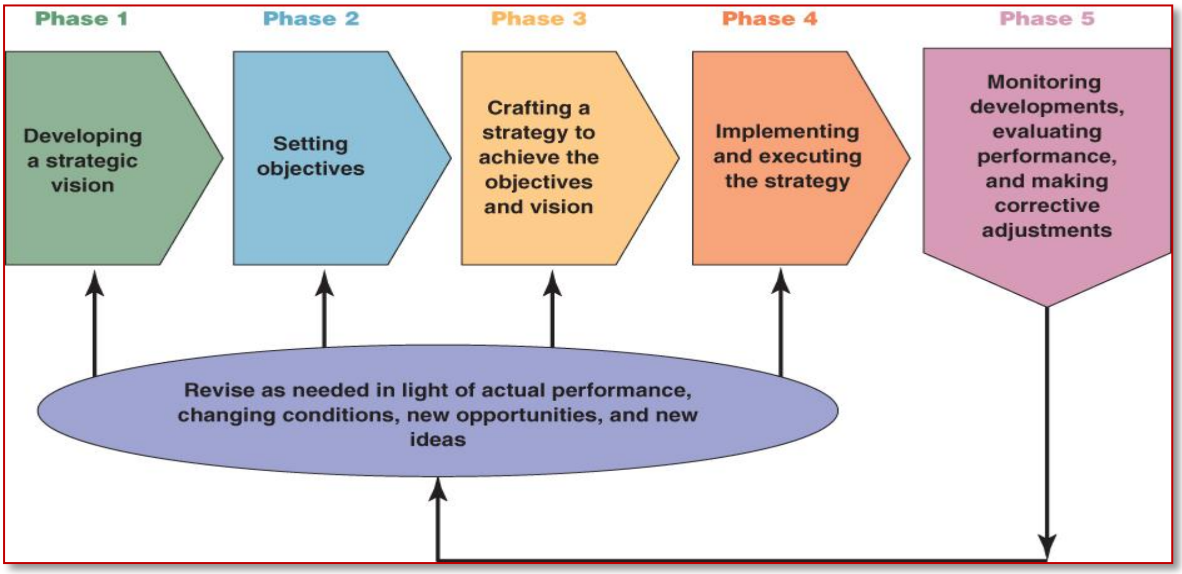

Figure 19: Strategic development and execution process (*Source:* Hough, *et al.*, 2011:19)

4.5.2 Strategic objectives

By setting objectives, the management of the organisation commits to convert the strategic vision into specific outcomes and targeted results; and these well-stated objectives are measurable and have a deadline for achievement (Hough, *et al.,* 2011:34). Two types of objectives are essential: *financial objectives* which relate to the establishment of financial performance targets by managers; and *strategic objectives* which relate to the establishment of targets which are focusing on improving competitive strength and market standing of the organisation (Hough, *et al.,* 2011:35).

Table 2: Examples of financial and strategic objectives (*Source:* Hough, *et al.*, 2011:35)

Financial objectives	Strategic objectives
• Annual revenue growth of X%. • X % increase in after-tax profits annual. • Earnings per share growth of X% annually. • Annual dividend increases of X%. • Profit margins of X%. • X% return on capital employed (ROCE). • Annual stock price increases that average X% over time. • Strong bond and credit ratings. • Sufficient internal cash flows to fund 100% of new capital investment. • Stable earnings during periods of recession.	• Winning an X% market share within 3 years. • Achieving lower overall costs than rivals. • Overtaking key competitors on product performance or quality or customer service within 2 years. • Deriving X% of revenues from sale of new products introduced in past 5 years. • Being the recognized industry leader in product innovation and/or technological know-how. • Having a wider product line than rivals. • Consistently getting new or improved products to market ahead of rivals. • Having stronger national or global sales and distribution capabilities than rivals.

According to Hough, *et al.* (2011:36), the financial performance measures show an entity's current or past financial performance and organisational activities, and thus they are non-reliable lagging indicators; while strategic outcomes are reliable and leading indicators because they show a company's future financial performance and business prospects which indicate the strengths or the weaknesses of a company's market position and its competiveness.

4.5.3 Alignment of the economical capital with strategic objectives

To align the economic capital with strategic objectives, we follow the SOAR process, which comprises of four steps (Monahan, 2008:46):

- ***S****et* metrics for each of the defined strategic objectives.
- ***O****bserve* metric values.
- ***A****nalyse* movements in metric values.
- ***R****eact* to what the analyses reveal.

Monahan (2008:13) defines enterprise risk management as a methodology for managing risks associated with strategic objectives of an organisation. Recall that ERM is concerned with the establishment of control, oversight and discipline with the purpose of achieving the organisational strategic objectives (Protiviti, 2006:3). The most critical element of the SOAR process is the identification and application of controls (Monahan, 2008:7).

Application of the SOAR process highlights poorly defined objectives and associated risks in early stages of the process and may identify a need to review objectives or risks, where the uncertainty associated with achieving an objective or the risk level associated with objectives is unacceptable (Monahan, 2008:39).

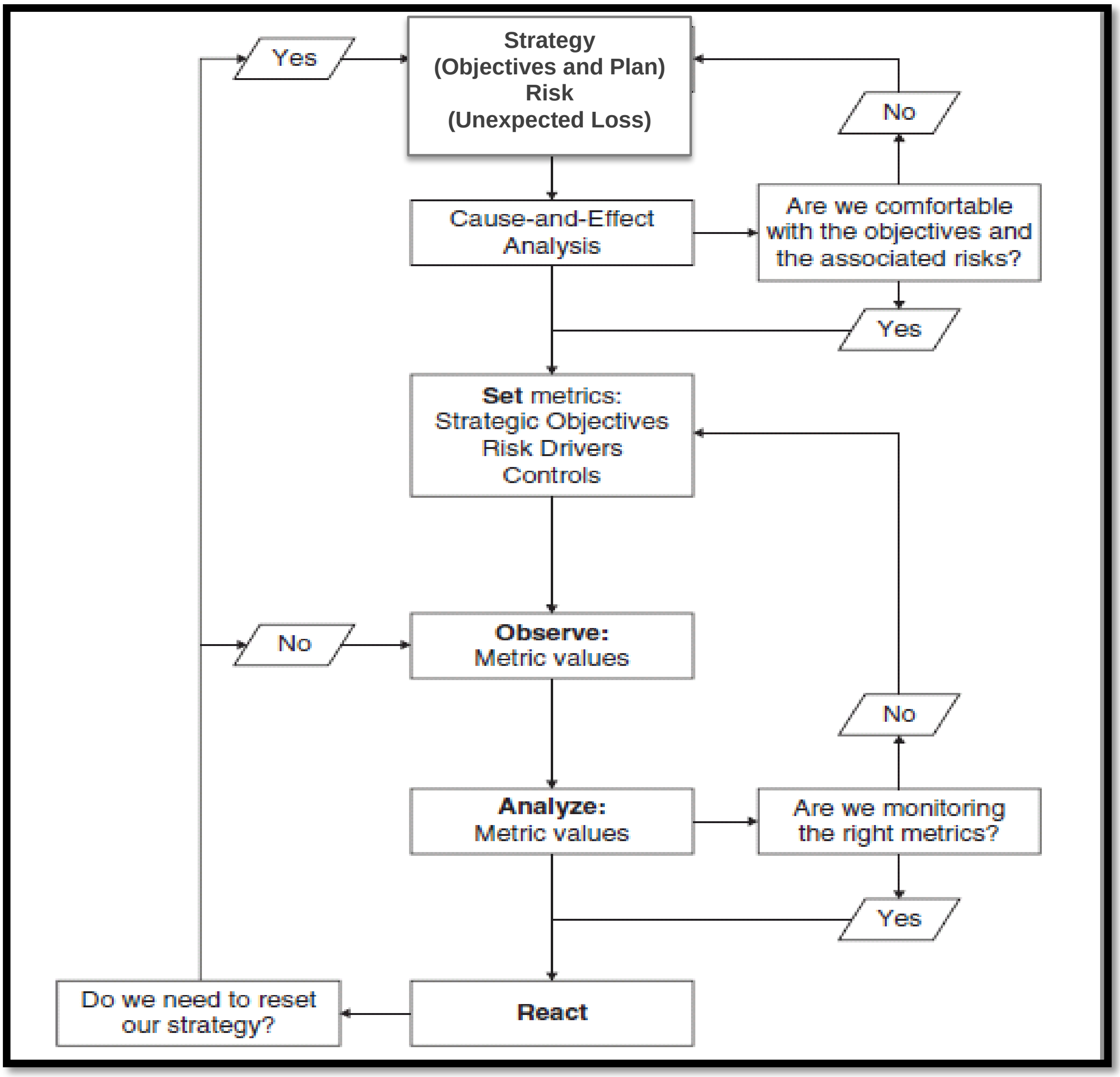

Figure 20: SOAR process (*Source:* Adapted from Monahan, 2008:47)

The SOAR process thus enables the organisation to set objectives that are relevant to the organisation's operations and the competitive environment where it conducts its businesses. However, the process ignores to align the enterprise risk with the acknowledged organisational objectives in order to prepare it for unexpected events. In this study, the economic capital is adjusted to match the strategic objectives and to prepare the organisation for unexpected losses. The study categorises the banking industry in South Africa according to three competitive generic strategies:

- *Low-cost service provider strategy* (e.g., Capitec Bank and African Bank Limited) has the following distinguishing features:

Table 3: Distinguishing features of a low-cost provider strategy (*Source:* Maritz, 2007:141)

Strategic target	A broad cross-section of the market
Basis of competitive advantage	Lower overall costs than competitors
Product line	A good basic product with few frills (acceptable quality and limited selection)
Production emphasis	A continuous search for cost reduction without sacrificing acceptable quality and essential features
Marketing emphasis	Trying to make a virtue out of product features that lead to low cost
Keys to sustaining the strategy	Economical prices/good value; low costs (year after year) in every area of the business

- *Differentiation service provider strategy* (e.g., Standard Bank, Barclays Africa, FNB and Nedbank) has the following distinguishing features:

Table 4: Distinguishing features of a differentiation strategy (*Source:* Maritz, 2007:144)

Strategic target	A broad cross-section of the market
Basis of competitive advantage	Ability to offer buyers something attractively different from competitors
Product line	Many product variations; wide selection; emphasis on differentiating features
Production emphasis	Differentiating features buyers are willing to pay for; product superiority
Marketing emphasis	Flaunting differentiation features; changing a premium price to cover the extra costs of differentiating features
Keys to sustaining the strategy	Constant innovation to stay ahead of imitative competitors; a few key differentiating features

- *Narrow market niche service provider strategy* (e.g., Investec Bank) has the following distinguishing features:

Table 5: Distinguishing features of a narrow market niche strategy (*Source:* Maritz, 2007:146)

	Focus: Low cost	**Focus: Differentiation**
Strategic target	A narrow market niche where buyer needs and preferences are distinctively different	A narrow market niche where buyer needs and preferences are distinctively different
Basis of competitive advantage	Lower overall costs than rivals in serving niche members	Attributes that appeal specifically to niche members
Product line	Features and attributes tailored to the tastes and requirements of niche members	Features and attributes tailored to the tastes and requirements of niche members
Production emphasis	A continuous search for cost reduction while incorporating features and attributes matched to niche member preferences	Custom-made products that match the tastes and requirements of niche members
Marketing emphasis	Communicating attractive features of a budget-priced offering that fits niche buyers' expectations	Communicating how product offering does the best job of meeting niche buyers' expectations
Keys to sustaining the strategy	Constant innovation to stay ahead of imitative competitors; a few key differentiating features	Commitment to serving the niche better than rivals; not blurring the organisation's image by entering other market segments or adding other products to widen market appeal

In this study, allocation of the economical capital, as calculated in Section 4.4, is applicable to a differentiation service provider. Using a differentiation strategy as a benchmark, the economic capitals for the other two generic strategies are adjusted as follows to match the applicable strategy:

- *Low-cost service provider strategy:* A low-cost service provider bank provides services to its customers at a low cost. The bank pursuing this strategy is typically highly concentrated with low-income earners. Because of his/her low income, a borrower does not usually have collateral for the loan and the bank thus provides an unsecured loan to a borrower. The total portfolio of loans is unsecured and less diversified. The disadvantage of this business model is that the bank can seriously be affected by unexpected events. To deal with this problem the bank needs to add an X amount of capital on top of the economic capital calculated in Section 4.4 to survive during unexpected events.

  A good example of this business model failing is what happened to African Bank Limited in 2014 whose business model was based solely on unsecured lending. Due to the aftermath of the 2008-2009 financial crises and long mining strikes in 2014 with a 'no-work-no-pay' statute attached to it, miners who were the majority of borrowers in the African Bank's credit portfolio, failed to pay their loans, and African Bank recorded a loss and needed R8.5 billion to survive.

- *Narrow market niche service provider strategy:* Narrow market niche service provider bank provides a diverse range of financial products and services to a niche client base. Most of the customers are high earners and tycoons. The total portfolio of loans is more diversified and secured because most of the clients have collateral for their loans. The advantage of this business model is that the bank may not seriously be affected by unexpected events. For the effective management of capital, the bank can afford to subtract an X amount of capital from the economic capital calculated in Section 4.4 and still survive during unexpected events.

For example, Investec has a diverse range of financial products and services to a niche client base in three principal markets, the United Kingdom, South Africa and Australia, as well as certain other geographies.

4.6 Summary

A copula was utilised to aggregate the enterprise economic capital. The Gumble copula was chosen as an instrument to aggregate the loss distributions of the market and credit risks. The resultant economic capital was assumed to be the amount of a large bank which pursues a differentiated strategy. To align the economic capital with the generic strategy, the following aligning framework was proposed:

Table 6: Alignment of the economic capital with the generic strategy

Strategy	Credit portfolios	Capital reserved for unexpected losses
Differentiation strategy	Diversified Secured and non-secured	Economic capital
Low-cost strategy	Undiversified Non-secured	Economic capital + X amount
Narrow market niche strategy	Diversified Secured and non-secured	Economic capital - X amount

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CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS

This study suggests that model risk management should form part of the ERM framework in order to minimise the model risk of an entity. To accomplish this task, the study suggests that managers of an entity should govern model development and validation processes for the whole enterprise; and ensure that model developers and model validators comply with new or existing regulations. In order to achieve this, the study suggested that models should be revised in time once the changes in market conditions are detected. This procedure will ensure that the model development and validation processes are completed in time and the business operations of an entity continue without any interruptions that can lead to a significance loss of money.

The study suggested CUSUM control charts and Markov switching models as common techniques that are used to detect the change-point of market conditions. The main objectives of these techniques are to allow complete model development and validation processes to take place prior the change-point and thereby revising the model optimally; to enhance continuity of the model usage; and to minimise the model risk.

A theoretical framework on model risk management was developed for this purpose. The framework encourages model users to monitor the financial model continuously and the management of the enterprise to take a central position in the entire development and validation processes of the model.

Moreover, the study suggested that effective model risk management can also be achieved through the aggregation of models from all business units. Aggregation of models can be done by integrating the economic capitals covering the model risks from business units. This procedure will ensure that there is always adequate capital to cover for unexpected losses; and appropriate allocation of capital across business units will be executed.

In this study, a copula was used as an instrument to integrate the economic capitals from the credit and market portfolios. Because there are dependencies between these two types of portfolios, it is essential that one takes this into account when calculating risk measures. It was discovered that the best copula to fit in order to integrate the loss distributions of the credit and market portfolios was the Gumble copula because of its robustness when estimating parameters, its compatibility with fat-tail distributions, and its sensitivity to large losses but less sensitivity to small losses. The economic capital was then determined and adjusted to match the generic strategy of the bank. The alignment can assist the bank to reserve the optimal economic capital for unexpected losses and to properly manage the economic capital.

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