THE EVALUATION OF CREDIT RISK IN STRUCTURED FINANCE LENDING TRANSACTIONS IN AGRICULTURE

RESEARCH THESIS

BY

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ABSTRACT

The study focuses on the evaluation of credit risk in Structured Finance lending transactions in agriculture. The secondary motivation of the study is that Structured Finance lending techniques have the potential of increasing access to credit for farmers, especially smallholder farmers, in the agricultural sectors of developing and emerging countries. Recent studies, in agriculture finance, done by the World Bank, Food and Agriculture Organization (FAO) and the United Nations Conference on Trade and Development (UNCTAD), highlights that application of Structured Finance lending techniques such as warehouse receipts, agricultural value chain financing and securitization, *inter alia*, has the potential of deepening credit services in agricultural sectors, especially in developing countries. Access to credit services, among other things, has the ability to unlock the potential for agriculture in developing and emerging countries.

The primary motivation of the study is the observation that most of the studies that have been done so far, with regard to the application of Structured Finance in agriculture, have primarily focused on the principles underlying Structured Finance lending techniques in agriculture and not on the fundamental question that is of importance to a lending institution, in any lending transaction, namely: how to evaluate or measure the credit risk associated with Structured Finance lending transactions in agriculture. Therefore, the study contributes to the body of literature on Structured Finance in agriculture finance by developing a model or tool that can be used to measure credit risk in agricultural based Structured Finance lending transactions.

Therefore, the primary objective of the study is to develop a credit risk model for agricultural-based Structured Finance lending transactions. To develop the credit risk model, the study conceptualizes theoretical framework of modelling credit risk as proposed by Merton (1974) as well as the principles underlying Structured Finance lending techniques in agriculture. Time series econometric forecasting techniques and risk simulation techniques are used to achieve the primary objective of the study. The developed model measures credit risk as the Probability of Default (PD).

To demonstrate the application of the developed credit risk model, the study uses a conceptualized example, where the production of white and yellow maize in the Free State province of South Africa, during the 2009/2010 production season, is financed by Structured Finance loans. Using the developed model, the study shows that the probability of a farmer in the Free State province, defaulting on a

Structured Finance white maize production loan with a face value of R3783/ha (for instance) is 0.0347 or 3.47%.

The output of the developed model, which is the probability of default (PD), can be used by agricultural financial institutions (or agricultural lenders in general) to appraise Structured Finance loans; appropriately price Structured Finance loans and determine the amount of capital to hold against credit risk, *inter alia*. In other words, the developed credit risk model is a tool that can help financial institutions to manage credit risk in agricultural based Structured Finance lending transactions.

***Key words**: Structured Finance in Agriculture; Credit Risk Evaluation; Time Series forecasting; Simulation.*

UITTREKSEL

Die hoofoogmerk van hierdie studie is die evaluering van kredietrisiko by Gestruktureerde Finansiering wanneer leningstransaksies in die landbousektor ter sprake kom. ‘n Sekondêre motivering is dat Gestruktureerde Finansiering se leningsmetodes die potensiaal bevat om meer geredelik en makliker toegang tot kredietfinansiering aan boere te verseker, veral die kleinboere in die landbousektore van ontwikkelende lande. Onlangse navorsing oor landboufinansiering wat deur die Wêreldbank se Voedsel- en Landbou-organisasie (FAO), asook die Verenigde Nasies se Konferensie oor Handel en Ontwikkeling (UNCTAD) gedoen is, beklemtoon dat die aanwending van Gestruktureerde Finansiering se leningsmetodes, soos byvoorbeeld pakhuiskwitansies, landbou waardeketting-finansiering en versekerde dekking, onder andere, die moontlikheid van uitgebreide kredietlewering in die landbousektor, veral in ontwikkelende lande, inhou. Toegang tot geredelik-beskikbare krediet, kan onder andere, help om die moontlikhede vir landbou in ontwikkelende en ontluikende lande te ontsluit.

Die hoofdoel en motivering vir hierdie studie is die feit dat meeste van die studies wat tot dusver op die gebied van Gestruktureerde Finansiering in die landbou gedoen is, hoofsaaklik gefokus het op die onderliggende beginsels van Gestruktureerde Finansiering se leningstegnieke in die landbou en nie op die basiese kwessie van belang vir enige leningsinstelling, te wete, hoe om die kredietrisiko wat met leningstransaksies deur Gestruktureerde Finansiering in die landbou gepaard gaan, te meet of te bepaal nie. Hierdie studie kan dus bydra tot die bestaande literatuur oor Gestruktureerde Finansiering in landboufinansiering deur middel van die ontwikkeling van ‘n model of instrument wat gebruik kan word wanneer kredietrisiko in landbou-verwante transaksies bepaal moet word.

Aangesien die hoofdoel van die studie is om ‘n kredietrisikomodel vir landbou-verwante Gestruktureerde Finansiering leningstransaksies te ontwikkel, het die studie vir hierdie doel ‘n teoretiese raamwerk of model vir kredietrisiko, soos voorgestel deur Merton (1974), sowel as die beginsels onderliggend tot die leningstegnieke van Gestruktureerde Finansiering in die landbou, voorgestel. ‘n dinamiese model vir ekonometriese voorspellingstegnieke en risiko-nabootsingstegnieke word gebruik om die primêre oogmerke van hierdie studie te bereik. Die model wat sodoende ontwikkel is, meet kredietrisiko as ‘n Moontlikheid van Wanbetaling [PD – Probability of Default].

Ten einde die aanwending van die ontwikkelde kredietrisikomodel te demonstreer, word ‘n gekonsepsualiseerde voorbeeld gebruik; waar byvoorbeeld, by die produksie van wit- en geelmielies geproduseer gedurende die 2009/2010 seisoen in die Vrystaatprovinsie, Suid-Afrika, van Gestruktureerde Finansieringslenings gebruik gemaak is. Indien van genoemde ontwikkelde model gebruik gemaak word, dui die studie daarop dat die moontlikheid dat ‘n Vrystaatse boer, aan wie ‘n Gestruktureerde Finansiering witmielie-produksielening ter waarde van R3,783/ha toegestaan is, se wanbetalingspersentasie byvoorbeeld 0.0347 (3,57%) sal beloop.

Die ontwikkelde model beskik oor die vermoë om die moontlikheid van wanbetaling [PD] te voorspel en kan met groot vrug deur landbou-finansieringsinstellings of enige landboukrediteure aangewend word om ‘n bepaling van Gestruktureerde Finansieringslenings, veral prys-gestruktureerde finansieringslenings, se risiko te skat en sodoende die kapitaalbedrag ten opsigte van, onder andere krediet, te bepaal. Met ander woorde, bogenoemde kredietrisikomodel is ‘n instrument wat finansieringsinstellings kan help om kredietrisiko by landbou-gebaseerde Gestruktureerde Finansiering leningstransaksies te bestuur.

Sleutelwoorde: *Gestruktureerde Finansiering in die landbou; kredietrisiko-evaluering; tyd-skaal voorspelling; nabootsing.*

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Mwala Lubinda

Bloemfontein

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CHAPTER ONE

1.0 INTRODUCTION

1. 1 Background to the Research

Several studies, in agricultural finance, have documented the challenges of financing agriculture in developing and emerging economies[1]. In many developing countries, risk management techniques are underdeveloped or insufficient for institutions to efficiently lend to activities in the agricultural sector. Information on borrowers' credit histories is rarely available, resulting in information asymmetries that make accurate credit risk assessment difficult. In addition, while agricultural borrower's major assets are production and land, it is often difficult for banks to use these as collateral and particularly difficult to foreclose on land in case of default (World Bank, 2005).

Compounding this lack of traditional collateral is the presence of a high degree of covariate risk, in particular market price risk and weather risk. Banks lending to agriculture know that agricultural revenues easily drop below break-even levels due to extreme weather events and price falls, which result in defaults and higher loan loss provisions, thereby making lending to agribusiness unprofitable (Langenbucher, 2005; World Bank, 2005a).

The other major constraints in agricultural lending are high transaction and supervisory costs. High levels of transaction and supervisory costs contribute to the absence of functioning rural financial markets and institutions in many developing countries. This lack of adequate financial services can also be partially attributed to the rapid disengagement of governments as the primary source of agricultural lending in many post-liberalization economies. When public sector banking institutions began pulling out of lending or changing their nature of operations, the private sector was expected to take over and offer credit in the agricultural sector. But in many developing countries this space has not yet been filled adequately by the private sector (Langenbucher, 2005; World Bank, 2005a).

Table 1 below illustrates a summary of the limitations in extending agricultural finance from the supply (financiers – mainly banks) and demand (agricultural enterprises) perspective.

[1] For the studies on the Challenges of financing agriculture see: UNCTAD (2004); Siebel (2003); Yaron *et al*. (2001); FAO/ GTZ (1998); and Yaron and Benjamin (1997), *inter alia*.

Table 1: Limitations in Extending Agricultural Finance from the Supply and Demand Perspective

Demand side: Agricultural Enterprises	Supply side: Financiers
• Agribusinesses suffer from poor, insufficient collateral and non enforceability of security due to lack of land and property rights, high costs, and lengthy or lacking registration and foreclosure processes.	• Small size average farm, low population density, higher loan servicing costs due to limited volumes and high information costs.
• Low affordability for farmers of market interest rates and higher margins (up to 2% higher than standard SME loans) that reflect the risk adequately.	• Lack of collateral or adequate security
• Insufficient cash flow planning; farms are not obliged to keep accounts or financial statements; cash flows are hard to assess when clients sell directly to consumers.	• Lack of technical knowledge at the bank level to evaluate and analyze the creditworthiness of agribusinesses.
• Repayment schedules are often difficult for the clients to meet-standard repayment schedules are not adapted to seasonality of the business.	• No specialized product offered by the financial intermediaries to better meet the financing need of the agricultural sector: rural sector requires pre-harvest financing to buy inputs that can only be repaid after harvest and show much more uneven cash flows than urban borrowers, leading to repayment in less frequent instalments, which increases the risk and monitoring costs for financiers.
• Lack of legal education at the farmers' level.	• No branches or limited network in rural areas, thus difficulties to reach and market to farms.
• Farms are often successors of cooperatives, which are rather complex to deal with.	• Risk correlation when lending to farms: all borrowers are affected by the same risk, such as low market prices and reduced yield due to weather.
• Lack of initiative and articulated demand for finance by agribusinesses, especially in primary agriculture.	• Underdeveloped communication and transportation infrastructure.

(Source: Langenbucher 2005, and World Bank, 2005a)

These factors combine to limit the supply of rural financial service in general and agricultural credit in particular. Agricultural borrowers adjust by resorting to informal credit, reduction of farm inputs, suboptimal production techniques, and borrowing from family and friends. This limits the investment in farm equipment and capital as well as other agricultural assets such as oxen. In addition, producers concentrate on low-risk low-return activities because they cannot access the start-up capital required and cannot transfer systemic risks. The combined effect is to push producers (farmers) into poverty (World Bank, 2005; UNCTAD, 2004).

Therefore the challenge for Agricultural Financial Institutions, Governments, Bilateral Organizations and Non-Governmental Organizations (NGOs) with interest in agriculture, *inter alia;* has been to develop low-cost ways of reaching and financing farmers (especially smallholders). In other words, to develop financing models that will deepen credit services (financial services in general) in the agricultural sectors of developing and emerging countries. The other challenge has been to develop tools or techniques of managing the risks associated with agricultural lending (World Bank, 2005; UNCTAD, 2004).

On both fronts innovative ways or techniques of financing agriculture are emerging. The emerging agricultural financing techniques include Collateralized and Securitization Lending Mechanisms and Agricultural Value Chain Financing (also known as Supply Chain Financing)[2], *inter alia* (Langenbucher, 2005; World Bank, 2005; and UNCTAD, 2004). In financial economics, these emerging agricultural financing models and their financial products can be collectively and generally referred to as Structured Finance (SF) Lending Techniques (Michael *et al.*, 2009; and UNCTAD, 2004).

It is important to note that the term Structured Finance is not a concise term. Rather it is a term that is defined and applied differently according to the industry or sector. Even in financial and capital markets, where it is extensively used, there are several definitions of Structured Finance (Ian & Joanne, 2007).

However, the common denominators of all the definitions are: firstly, the concept of using existing assets and commodities and/or future cash flows as security for financing (Michael *et al.,* 2009); and secondly, in Structured Finance the creditworthiness of the borrower (i.e., the ability or capacity of the borrower to repay the loan) is a function of the profitability of the underlying transaction being

[2] These agricultural finance innovations are discussed in detail in Chapter two (2) – literature review.

financed[3] (UNCTAD, 2001). These two denominators differentiate SF lending techniques from conventional lending techniques (i.e., the normal Bank lending techniques).

In financial and capital markets, where it is extensively used, the definition of SF is associated with an advanced form of financial assets securitization which involves pooling and repacking of financial assets and the conversion of future cash flows into marketable securities. Examples of Structured Finance instruments in financial markets includes Collateralized Debt Obligations (CDOs), Asset Backed Securities (ABSs) and Mortgage Backed Securities (MBSs), *inter alia*, (Michael *et al.,* 2009; Laura, 2008; Andreas, 2005; Ingo & Janet, 2005; and Lakshman, 2001).

Structured Finance techniques are used by financial and non-financial institutions in both the banking and capital markets if the established forms of external finance are either (i) unavailable (or depleted) for a particular financing need, or (ii) traditional sources of funds are too expensive for the financial institution to mobilize sufficient funds for what would otherwise be an unattractive investment based on the financial institution's desired cost of capital.

The other common use of Structured Finance techniques in financial and capital markets is market based credit risk transfer, where a financial institution (for instance a bank) transfers the credit risk on its books to another party in the market who is willing to bear the risk[4]. The financial institution achieves market-based credit risk transfer by selling the financial asset to a Special Purpose Vehicle. By selling the financial asset, the financial institution transfers future receivables from the sold assets to the SPV, in return for immediate capital as well as transfer to credit risk (Andreas, 2005).

In commodity trade and finance, Structured Finance is commonly referred to as Structured Commodity Financing (SCF). It is defined as the art of transferring risks (credit risk mainly) in trade financing from parties less able to bear those risks to those more equipped to bear them in a manner that ensures automatic reimbursement of the advances from the underlying assets. Such assets include inventory and export receivables (UNCTAD, 2001). David (2000) adopted the UNCTAD definition and defines SCF as *a technique* whereby certain assets with *more or less predictable cash flows* can be *isolated from the originator, and used to mitigate risks* (foreign exchange, contract performance and credit risks) and thus secure a credit. It is important to highlight and explain some of the key terms in the definition:

[3] In traditional (or conventional) bank based lending, the creditworthiness of the borrower is a function of the borrower's balance sheet status.

[4] For details on how Structured Finance techniques and Instruments are used in market base credit risk-transfer, see: Ingo and Janet (2005); and Andreas (2005).

- "A technique….." suggests that structured finance methodology requires certain skills and knowledge, usually about the governance structure of commodity production and trade;
- "More or less predictable cash flow….." suggests that SF is based on future receivables which are identified and are more or less assured;
- "Isolated from the originator and used to mitigate risks…." suggests that assets to support financing must be available, isolated, and used to mitigate risks.

Therefore SCF has two key characteristics, namely: (1) arrangements which ensure that if the transaction proceeds normally, the financier (bank or financial institution) is automatically reimbursed, hence the loan is self-liquidating; (2) arrangements which further ensures that if anything goes wrong, the financier has recourse to some assets as collateral (usually the underlying asset of the financial transaction). Overall this form of financing (SF) allows for wider possibilities than the other form of short-term financing, which are normally limited to the companies' acceptable credit risk or conditional upon onerous security and gives access to financing on better terms.

Structured Commodity Finance is particularly relevant for commodity companies in countries that are considered as risky by financiers. There are many cases where relatively well-run resource-rich companies do not have access to funds for a number of reasons, including historical ones and including the perception of risk of their country. Structured finance allows many of these companies to obtain finance at reasonable terms. Sound companies in countries considered as risky by financiers can actually often get credit at lower rates than those paid by their countries' Governments, simply by using structured finance solutions (UNCTAD, 2001).

The value of Structured Commodity Finance in commodity trade and finance is that it is very relevant for new companies or agribusiness without a credit profile or track record. One of the first things that a bank will usually ask for in normal balance-sheet-backed, working-capital-type finance is the prospective borrower's track record (usually current and historical financial statements). In a Structured Commodity Finance transaction, such requirements count much less: what matters, is the profitability of the transaction being financed and the ability of the prospective borrower to perform its obligations.

Another important aspect of Structured Commodity Finance is that it converts wealth into ready capital – wealth in the sense of having oil in the ground, plantations to produce cocoa or coffee, even fields to produce annual crops such as cotton. Structuring techniques make it possible to raise funds on the basis of this wealth, funds that can then be used to access and exploit this wealth and convert it into ready money (UNCTAD, 2001).

Michael et al.(2009) gives a descriptive definition of Structured Finance in agricultural production, namely: *"Structured Finance for agriculture and agribusiness is the advance of funds to enterprises (farms) to finance inputs, production and the accompanying support operations, using certain types of security that are not normally accepted by banks or investors and which are more dependent on the structure and performance of the transaction, rather than the characteristics (e.g. creditworthiness) of the borrower."*

The value of Structured Finance in agriculture lies in the fact that many farmers, traders or agribusinesses in developing countries find themselves without the necessary physical collateral or credit rating to attract conventional bank finance. Therefore, by introducing security elements that de-emphasize the individual credit standing of the farm or agribusiness, the banks may be prepared to advance funds which they otherwise would not (Michael *et al.*, 2009). In Structured Finance, some of the risks in a loan transaction, which would normally rest solely with the borrower, are transferred to other parties in the transaction, so that an assessment of the likely performance of the whole transaction becomes more important than a standard credit assessment of the borrower.

Structured Finance can be used as a credit enhancement tool. SF as a credit enhancement tool involves the use of non-traditional collateral (for instance, the commodities underlying the loan transaction) and traditional collateral (building or land) so as to increase the prospective borrower's loan security. For example, a lender may take the assignment of export receivables together with the pledge of farming equipment as a security, with the receivables providing a bridge between the value of the equipment and the value of the loan. Thus, Structured Finance can be very effective in 'stretching' traditional physical collateral (Michael *et al.*, 2009).

In conclusion, Structured Finance provides avenues of deepening credit services in the agricultural sectors of developing and emerging economies. Many researchers have shown and empirically demonstrated the link between financial deepening[5] and economic development (Ross, 1997). The deepening of credit services will help to break the vicious poverty circle (in which most of the commodity producers in developing and countries in transition find themselves in) and turn it into a

[5] Financial deepening here refers to increase, in terms of access, of credit services in agricultural sectors.

virtuous circle of growth. Access to credit enables commodity producers to invest in production assets that will allow them to effectively participate in Agricultural Value Chains.

It must be understood that better access to finance or credit is not, by itself, enough for farmers to escape the circle of poverty. Farmers also need access to improved seed as well as better cultivation techniques, inputs, extension services and market access. However, solving the problem of agricultural finance is crucial to unlocking the growth potential of farmers.

1. 2 Research Focus

The primary focus of this study is on the evaluation of credit risk in Structured Finance lending transactions in agriculture. In order to put everything into perspective, the title of the research can be decomposed into two main parts, namely: (i) Evaluation of credit risk; and (ii) Structured Finance lending transactions in agriculture. In Section 1.1 (previous section), Structured Finance was briefly discussed. Therefore this section will primarily focus on the evaluation of credit risk within the context of Structured Finance lending transactions in agriculture.

The evaluation of credit risk can be defined as a process that is used by financial institutions to measure the credit risk (default risk) associated with any lending transaction. The Basel Committee on Bank Supervision defines credit risk as "the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with the agreed term" (Basel Committee, 2000). When the borrower fails to meet his financial obligations (i.e., when the borrower defaults) the bank incurs a financial loss. Credit risk is mostly associated with loans and securities in a bank's balance sheet and it is the largest risk, from market and operational risks, confronted by financial institutions. Credit risk is regarded as the primary cause of bank failures and it is the most visible risk faced by bank management (Fraser et al., 2001).

Financial institutions have responded (and are still responding) to the adverse effects of credit risk by developing tools (models) that they can use to evaluate or measure credit risk. Credit risk measurement tools are commonly referred to as credit risk models; and credit risk modeling has become a key component in the risk management system of financial institutions (Lopez & Saidenberg, 2000). In literature, the quantitative approaches to credit risk evaluation (i.e., credit risk models) are classified into two families, namely: Traditional credit risk models and Modern credit risk models. The Traditional credit risk models are further classified into three (3) broad classes - Expert Systems and Artificial Neural Networks, Credit Scoring and Credit Rating models. Modern credit risk models are also further classified into three broad classes, namely: (i) Structural credit risk models, (ii) Reduced Form credit risk models, and (iii) Multi-factor Econometric credit risk models (Allen *et al.*, 2004).

Whichever credit risk model (traditional or modern) is used, the primary objectives of evaluating credit risk for a financial institution still remains the same: to enable the financial institution to differentiate good credit from bad credit; evaluate the credit risk associated with individual loans and loan portfolios; forecast possible credit losses over the coming years; to differentiate loan price over borrowers exhibiting different risk; to determine the loan loss reserves and the risk based capital requirements; to evaluate credit concentration and set concentrate limits and to measure risk-adjusted profitability (Lopez & Saidenberg, 2000). Therefore, the evaluation of credit risk is cardinal to the success and profitability of any financial institution.

In financial and capital markets credit risk models, mainly modern credit risk models, are extensively used in the evaluation of credit risk in Structured Finance instruments such as Collateralized Debt Obligations (CDOs). In fact, Structured Finance markets in financial and capital markets are referred to as “Rated Markets” (Ian & Joanne, 2007). The study by Roberto (2004) gives the different types of credit rating models that are used by Rating Agencies to measure or quantify credit risk in Structured Finance instruments.

There is a gap that exists in agriculture finance research, with regards to models (tools) that can be used to evaluate credit risk in Structured Finance lending transactions in agriculture (World Bank, 2005). In fact, from the literature reviewed by researcher, there has not been a study done that focuses on developing a credit risk evaluation model (or tool) for agricultural based Structured Finance Lending transactions. This gap can be attributed to the fact that the application of Structured Finance lending techniques in agricultural finance is still in its infancy; and hence most of the studies that have been done so far have focused on explaining the principles, theories and the operational frameworks that govern Structured Finance lending techniques. This study seeks to address this gap in agriculture finance, by developing a credit risk model that can be used to measure credit risk Structured Finance lending transactions.

The credit risk model that is developed in this study takes into consideration the principles underlying Structured Finance lending techniques in agriculture and credit risk modelling techniques. The developed credit risk model is easy to implement and the model’s data inputs are readily available.

1. 3 Statement of the Problem/ Motivation of the Research

1. 3. 1 Motivation of the Research

The primary motivation of this study is the observation that most of the studies that have been done so far, with regard to the application of Structured Finance lending techniques in agriculture, have primarily focused on the principles or theories underlying SF lending techniques in agriculture. There has not been a study done, from the literature reviewed by the researcher, which addresses the fundamental issue that is of interest to any lending institution, namely: how to evaluate or measure credit risk in agricultural based SF lending transactions. Therefore, this study contributes to the body of literature on the application and use of SF lending techniques in agriculture, by developing a tool (model) that can be used to measure credit risk in Structured Finance lending transactions in agriculture.

The broader motivation of the research study is that the application of Structured Finance techniques in agriculture can help address the challenge of access to capital or credit for commodity producers, processors and agribusinesses, in developing and emerging economies. Access to investment capital, in turn, can help to unlock the potential of commodity producers (especially smallholders), processors and agribusinesses in developing and emerging economies. This is not a conjecture, but a deduction that is arrived at from experiences, of the application of Structured Finance techniques in agriculture, which have been documented by Michael et al. (2009); World Bank (2005); and UNCTAD (2004 &2001). As already stated, access to credit by itself, is not enough to solve all the problems faced by players in the agriculture sector; however, access to capital can help to turn the vicious circle of poverty the agricultural sector entities are locked in, into a virtuous cycle of growth.

1. 3. 2 The Statement of the Problem

The application and use of Structured Finance Lending techniques (especially by formal financial institutions – i.e., banks), in agriculture is constrained by, among other things, the lack of tools or models that can be used to evaluate the credit risk inherent in such lending transactions (Michael *et al.,* 2009; World Bank, 2005; UNCTAD, 2001 & 2004). Therefore, this research seeks to address this challenge by developing a credit risk model that can be used as a tool, by lenders (both formal and informal financial institutions), when evaluating the credit risk in SF lending transactions (or SF instruments) in agriculture.

1. 4 Research Objectives

In an effort to promote the use of Structured Finance lending techniques by lenders, especially formal financial institutions (banks), this study has the following three (3) objectives:

1. To develop a credit risk model that can be used to measure the credit risk in Structured Finance lending transactions in agriculture.
2. To develop a framework that acts as a guide, when using the developed credit risk model to measure credit risk in Structured Finance lending transactions in agriculture.
3. To demonstrate the application of the developed credit risk model.

1. 5 Methodology

To achieve the first and second objectives, the study reviews: literature on the Structured Finance lending techniques in agriculture and also literature on credit risk modelling (i.e., credit risk evaluation or measurement techniques). The principles and theories underlying both the SF lending techniques and credit risk modelling are used to develop the credit risk model and its implementation framework. Therefore, the study does not propose new theories or principles, but rather uses the already existing principles and theories of SF and credit risk evaluation, to develop the credit risk model.

The third objective involves the empirical parameterization of the developed credit risk model. A '*conceptualized example of Structured Finance lending transaction in agriculture*' is used to illustrate or demonstrate the practical application of the developed credit risk model in the measurement of credit risk. In the 'conceptualized example[6]' it is assumed that an Agricultural Lending Institution extended Structured Finance Production Loans to farmers, in the Free States province – South Africa, for the production of white and yellow maize, during the 2009/2010 production season. The developed credit risk model is used to measure or evaluate the credit risk in SF production loans and hence help the Agricultural Lending Institution in its credit risk management.

1. 6 Research Outline

The dissertation proceeds as follows. First, it presents a literature review in Chapter 2. The Chapter is divided into two sections. The first section (2.1) reviews literature on the concepts and theories underlying Structured Finance lending techniques and the different types of Structured Finance

[6] The conceptualized example is explained in details in Chapter four (4).

instruments that are used in agriculture. The second section (2.2) reviews literature on the different types of credit risk models that are used in the evaluation of credit risk. In other words, the section reviews literature on credit risk modelling techniques.

Chapter three (3) addresses the first and second objective of the study. This chapter is divided into four (4) sections. Section 3.1 highlights the theories that are used to develop the credit risk model. The data inputs requirements of the developed credit risk model are also highlighted in this section. The general framework of implementing the credit risk model is developed and illustrated in Section 3.2. Section 3.3 illustrates the application of the developed credit risk model in the measurement of credit risk in different types of SF lending instruments, which were highlighted in Chapter 2. The chapter is concluded in Section 3.4.

Chapter four (4) illustrates or demonstrates the practical application of the credit risk model in a conceptualized example of Structured Financing lending transaction, where the production of white and yellow maize is financed by SF loans from an Agricultural Lending Institution. In the chapter, the developed credit risk model is empirically parameterized to estimate or evaluate the credit risk in the Structured Finance loans, as the Probability of Default. Chapter 5 highlights the conclusions and recommendations of the research.

CHAPTER TWO

2.0 LITERATURE REVIEW

This Chapter is divided into two major sections: Section 2.1, reviews literature on Structured Finance techniques and Structured Finance instruments in agriculture. The second major section, Section 2.2, reviews literature on the different types of quantitative approaches to credit risk modelling (i.e., credit risk models) in agriculture finance.

2. 1 Structured Finance in Agriculture

Literature sources on Structured Finance in agriculture are limited. Michael et al. (2009); World Bank (2005); and the UNCTAD, through its various publications, provide comprehensive literature on the application and use of SF techniques and SF instruments in agriculture. These are the primary sources of literature that are used in this study.

2. 1. 1 Definition of Structured Finance in agriculture

Michael et al. (2009) gives a descriptive definition of Structured Finance, namely: "…*Structured Finance for agriculture and agribusiness is the advance of funds to enterprises to finance inputs, production and the accompanying support operations, using certain types of security that are not normally accepted by banks and which are more dependent on the structure and performance of the transaction, rather than the characteristics (e.g. creditworthiness) of the borrower.*" The definition highlights two fundamental characteristics of Structured Finance.

The first fundamental characteristic of SF is associated with the first part of the definition, namely: *"....the advance of funds to enterprises….using certain types of security that are not normally accepted by banks…."* This implies that, in SF the assets or commodity underlying the loan transaction is or can be used as loan collateral or part of the loan collateral. This is one of the advantages of SF, especially in developing and emerging economies where commodity producers' access to credit, from formal financial institutions, is constrained by lack of traditional loan collateral (i.e., fixed assets such as land and buildings).

The second fundamental characteristic of SF is associated with the second part of the definition, namely: *"….advance of funds to enterprises….and which are more dependent on the structure and performance* *of the transaction, rather than the characteristics (e.g. balance sheet determined creditworthiness) of the borrower.*" This implies that in Structured Finance, the financial institution's decision to lend is based on the profitability of the underlying transaction being financed and not on the prospective borrower's balance sheet determining financial status. Therefore, Structured Finance lending techniques provide avenues of financing enterprises and commodity producers beyond the balance sheet.

Structured Finance, as defined above, excludes straightforward bank finance, based on balance sheet analysis or the use of conventional collateral, such as land or buildings. Instead, it relies on collateral that is inherent in the transaction itself, such as future receivables. Structured Finance is a broad term encompassing many possible financial instruments, any of which may be used individually or combined with conventional finance and/or other SF instruments. It moves the opportunities for financing beyond companies with acceptable credit risks and offers lower costs for financing. Structured Finance relies on the strength of the value chain rather than the typical focus on the security of the borrower.

2. 1. 2 The *k*ey *c*haracteristics of Structured Finance

Structured Finance mainly focuses on the transaction to be financed and thus on performance risk, not on the credit standing of the borrower as in conventional banking or financing. Instead of the traditional credit appraisal (such as the five "Cs" of character, capacity, capital, collateral and conditions), in Structured Finance, the lender assesses the performance (i.e., risks, profitability and cash flow) of the underlying transactions to be financed.

Structured Finance does not rely primarily on conventional loan collateral such as real estate and other fixed assets owned by the borrower. This may be applicable in cases where (a) the entrepreneur doesn't want to put at risk her/his private assets, or (b) where such is insufficient to cover the proposed loan value. Only balance sheet items which are inherent in the transaction, such as flows or stocks of agricultural commodities, are used to secure lending.

Whereas traditional bank lending is based on a direct relationship between the bank and the borrower, several parties are normally involved in SF lending transactions. Depending on the type of transactions, these may be different actors in agricultural value chains (input suppliers, traders, processors, exporters, warehouses, transporters) or specialized financial services providers (factoring, guarantee or leasing companies). A key strength is the familiarity of the players in a specific chain with each other and this factor supports the promotion and development of effective arrangements to facilitate financing. The main purpose is sharing risks among various actors and transferring defined risks to those parties that are best equipped to manage them.

Structured Finance is closely embedded in the underlying commodity transactions. It can be applied at specific stages of the value chain (production, storage, marketing, processing, export, distribution, or the production/import of inputs), but also be extended over various stages (from production to export). Entry and exit points for finance are identified based on the underlying commodity transactions. Disbursement and repayments can be made by any actor in the value chain (not only by banks).

Many SF arrangements have built-in mechanisms for self-liquidation (automatic repayment through deductions at source) at some stage of the value chain. This applies particularly to SF arrangements based on commodity flows and assignment of receivables.

A well-functioning, efficient value chain is a precondition for use of many SF instruments. On the other hand, asset-backed SF instruments such as warehouse receipts financing and repurchase agreements (repos), which are lent against stocks of storable commodities, do not require vertical coordination but well-functioning daily 'spot' markets.

2. 1. 3 Structured Finance Techniques and instruments in agriculture

Structured Finance techniques in agriculture can be classified into two (2) major groups, namely: Collateralized Lending Mechanisms and Agricultural Value Chain Financing Mechanisms. Figure 1 below depicts the classification of SF lending techniques in Agriculture. As shown in Figure 1, each class has different types of instruments.

In collateralized lending mechanisms, already existing (inventory) assets (or commodities) or future receivables are used as loan security (loan collateral). Instruments in this class include warehouse receipts system, repurchase agreements, forfeiting, factoring, securitization, export receivable financing and project financing, *inter alia*.

Agricultural Value Chain financing mechanisms are by far the most widely used SF techniques; they involve the use of the Agricultural Value Chain (AVC) as a conduit for financing. There are several instruments that are used in this class; however, the instruments are general classified into two (2) subclasses, namely: (a) direct value chain finance instruments (internal AVC financing); and (b) indirect value chain financing instruments (external AVC financing). The two (2) classes of Structured Finance techniques and their respective instruments are discussed below.

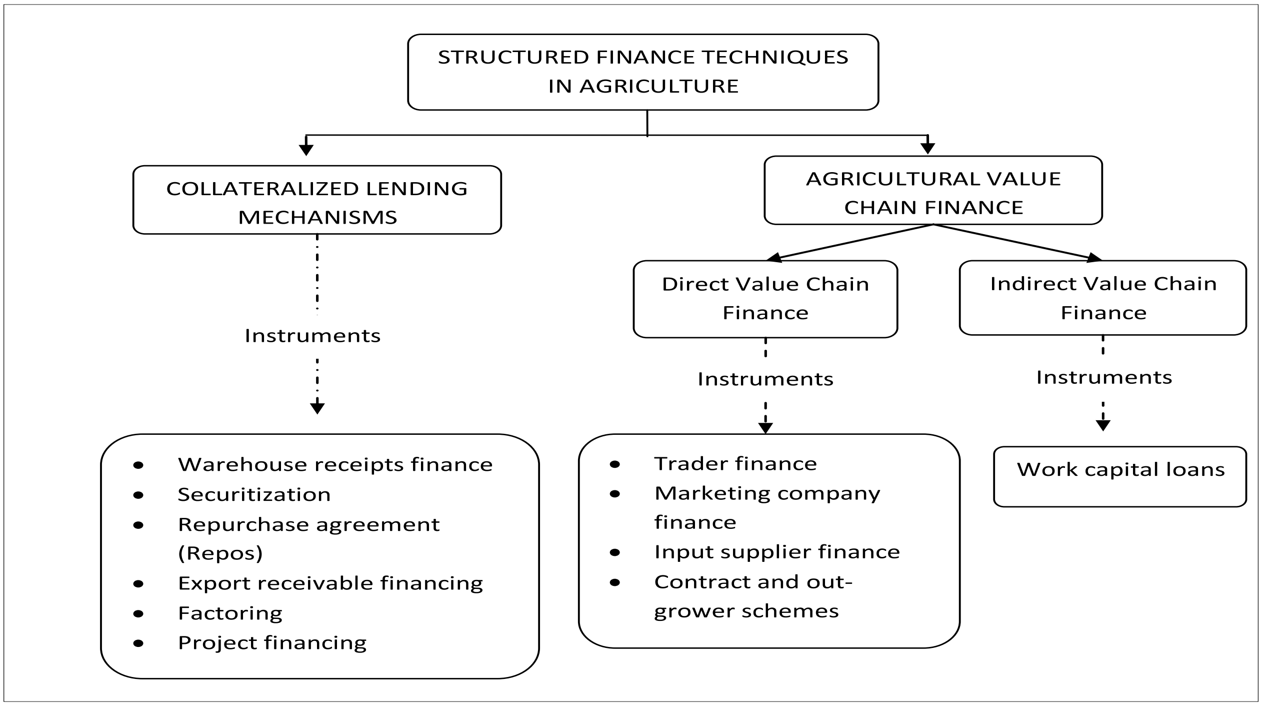

Figure 1: Classification of Structured Finance Instruments in Agriculture (Own figure)

2. 1. 3. 1 Collateralized lending mechanisms

International trade in agricultural goods continues to expand, while at the same time traditional and innovative collateral securitization mechanisms develop to finance these trade flows. Developing countries, however, have not benefited as much from the increase in trade flows and alternative financing mechanisms as developed countries. Warehouse receipt financing and other related collateralized lending mechanisms can provide an alternative to traditional lending requirements of banks and other financiers and are particularly relevant for emerging economies.

The basic rationale behind any collateralized commodity transaction is a structural risk change for the lender: instead of lending money based on the strength of a firm's balance sheet when issuing a corporate loan and hence taking credit risk, the lender now takes performance risk. But through warehouse receipts, even performance risk is minimized because the lender has the ability to sell off the asset in case of nonperformance. In traditional secured lending, the underlying collateral is the second source of repayment that needs to be mobilized when something goes wrong; in collateralized commodity lending, it is the first source of repayment. Rather than relying on the borrower's willingness to repay the loan and his existence as a going concern, the lender relies on the borrower's ability to conduct the underlying commodity transaction and has the possibility to sell off a very liquid asset, namely the commodities, as soon as the loan is in default.

The concept of collateralized lending is not new and on the face may not be viewed as an innovation. However, what is innovative is the use of warehouse receipts as a catalyst to extend financing in markets where other attempts have failed, as well as the creative use of the basic principle collateralized lending in order to design new financing instruments. This section briefly discusses the instruments under the collateralized lending mechanisms – thus: warehouse receipt financing and the other alternative collateralized lending techniques.

2.1.3.1.1 Warehouse receipts financing

In warehouse receipt financing, in the agricultural, the underlying collateral is soft commodities such as grain, cotton, coffee or cocoa. Figure 2 below, displays the basic mechanism of the financing cycle.

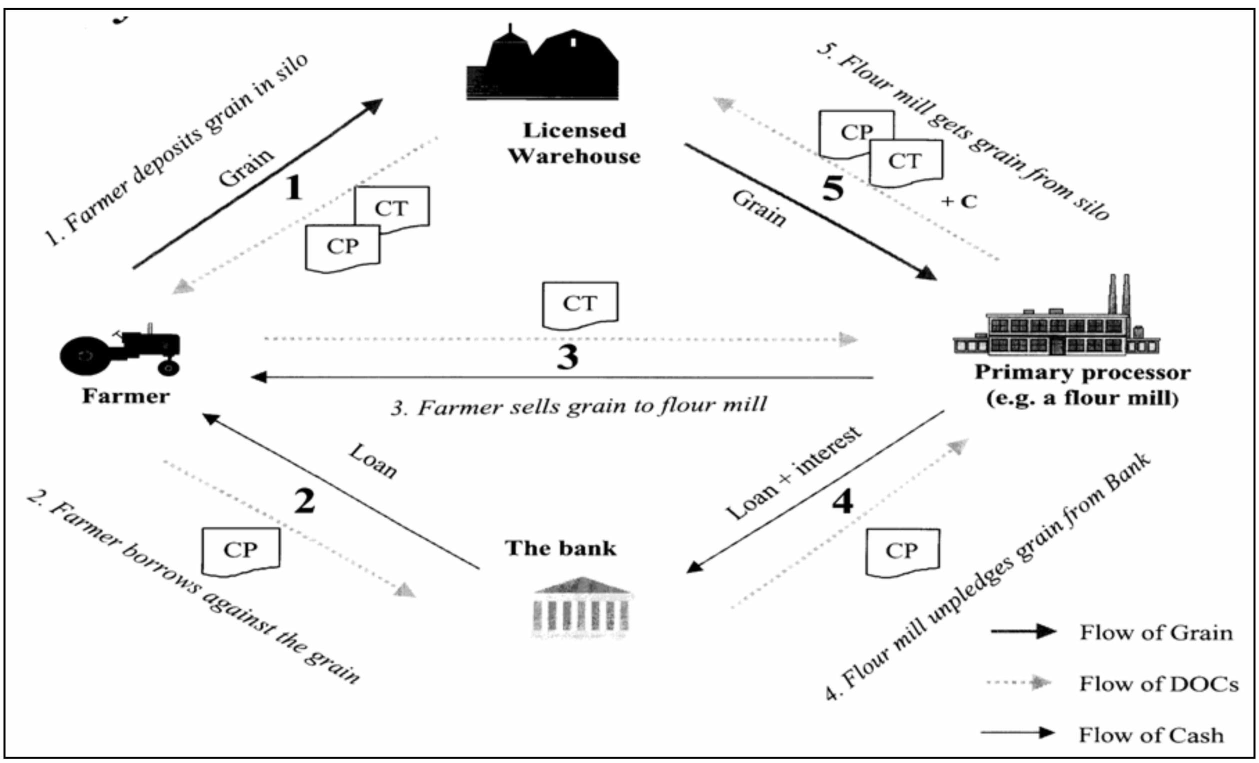

Figure 2: A generic Warehouse Receipts Financing Model [Source: Bryde and Martin, 1999]

A generic warehouse receipt financing cycle starts, after harvest, with the agricultural firm (farmer) depositing the commodities (or grain) into a licensed warehouse. The licensed warehouse issues a receipt proving that the commodities have been received and are physically stored in the warehouse. Ideally, the warehouse receipt consists of two parts: a Certificate of Pledge (CP) and a Certificate of Title (CT)[7]. The CP and CT form the basis of the financing **[Step 1 in Figure 2**].

When issuing the CP to a lender, the farmer, trader, or agricultural company is able to take out a loan: he borrows against the collateral, hence the commodities and hereby covers his working capital needs. Lenders usually advance funds as a specified percentage of the value of the underlying commodities. This percentage needs to account for the costs that lenders have to incur when selling the commodities in case of a loan default, as well as the potential value decrease caused by price volatility in the respective commodity market **[Step 2 in Figure 2]**.

Subsequently the farmer sells his commodities either to a trader or a primary processor; to validate this sale he transfers the CT **[Step 3 in Figure 2]**. The buyer eventually pays back the loan plus interest directly to the lender and receives in exchange the CP that had been deposited with the lender when the loan was issued **[Step 4 in Figure 2]**. Once the buyer has both, the CP and the CT, he can release the commodities from the licensed warehouse **[Step 5 in Figure 2]**.

The advantages and versatility of warehouse receipts make them particularly relevant for emerging economies. In all countries, but particularly in challenging markets, it is easier to handle security given in the form of a possessory pledge, dealing with incontestable identity of collateral, as opposed to disputing ownership or competing over claims. In case of a loan default, the collateral is covered and can be auctioned off and sold at relatively low costs to a liquid market. The holder of the warehouse receipt has a claim against the issuer, hence the warehousing company and the borrower in case of nonexistence or unauthorized release of the collateral. In some countries the existence of competing creditors and unpaid sellers is often difficult to verify, having a document of title to goods in store can cut off claims of such competing creditors.

Because of the easy recourse and the ability to sell a liquid collateral asset in case of default, warehouse receipts-based lending lowers the risk and reduces typical transaction costs of commodity transactions, such as high loan servicing costs due to limited volumes, high information costs, and high supervision costs. Borrowers do not need a balance sheet or long credit history because the lender is not relying on

[7] The legal form of the warehouse receipt depends on the countries' respective regulatory environment.

the company as a going concern, but on the value of the commodity. Thereby, lending costs for financiers are reduced, which, as a result, brings down interest rates for borrowers in sectors that are seen as high risk in any economy - commodity production, processing and trade - but which are of great importance for an emerging or transition country. A warehouse receipt-backed transaction allows a financier to shift his risk away from the borrower to a liquid asset and in some cases, to even enhance it further through the creditworthiness of a strong off-taker.

From a lender's perspective, warehouse receipts allow the type of asset pledged – agricultural commodities - to match the type of financing offered - working capital financing. In those cases where banks take fixed assets as collateral for the production of agricultural commodities, there is a mismatch between the loan and the underlying asset. Fixed assets are more appropriate collateral for long-term financing, where lending maturities would match asset type. In the absence of warehouse receipts, the farmer will pledge fixed assets, such as land, house, and equipment, or whatever he has to offer to obtain production finance. This leaves the farmers without any assets to pledge and unable to access long-term financing when they want to make a capital expenditure investment as their fixed assets are already being pledged for working capital purposes. Hence, the farmers are confined to their current production volumes and cannot grow.

The study done by the World Bank (2005b) highlights the prerequisites and challenges of warehouse receipts as well as other collateralized lending techniques in agriculture. Warehouse receipts are the basis for collateralized commodity transactions. More complicated structures can be observed in developed markets, such as Special Purpose Vehicles (SPV) that issue commodity backed securities, which are then credit enhanced by a financial institution to achieve investment grade rating. The following overview of some other forms of collateral-financing schemes indicates that there are many ways to deepen collateralized agricultural finance structures alongside the development of more sophisticated financial markets.

2. 1. 3. 1. 2 Securitization

Securitization is a financing technique where individual streams of expected future cash flow from an agricultural commodity are bundled and sold on capital markets to investors –mainly pension funds and managed funds, financial intermediaries and the general public. Securitization is extensively used in the financing of residential housing, automobiles, accounts receivable, commercial properties and other types of assets. Securitization provides a lower cost of financing compared to other unstructured sources because of the potential of the pool of assets to have a higher rating than the originator (Andreas, 2005 and Rosenthal & Ocampo, 1989).

The essence of the securitization process is that bilateral financial relationships – such as a bank lending money to its clients – are converted into capital market transactions by means of selling future receivables from these loan assets to a Special Purpose Vehicle (SPV), which is set up to administer the transaction. By placing the assets in a separate SPV, they are protected from any wider difficulties that may be experienced by the original lender (i.e. they become 'bankruptcy remote'). The SPV takes ownership of specified streams of receivables and issues securities into the market, usually in the form of fixed coupon bonds as illustrated in the Figure 3 below:

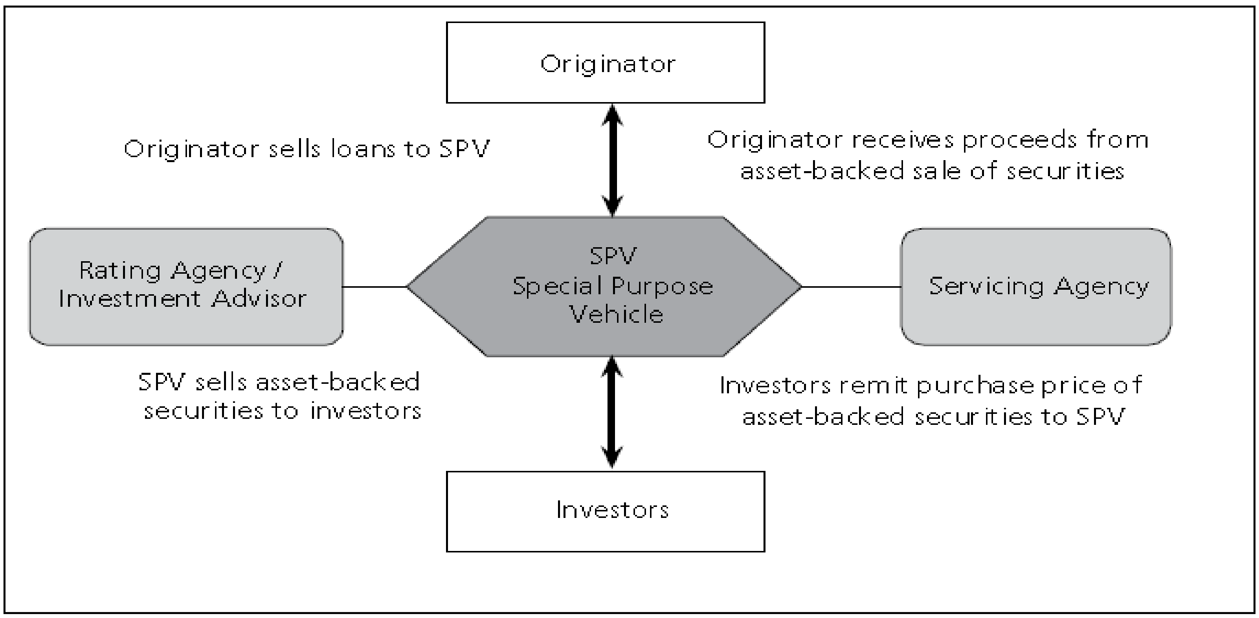

Figure 3: A generic securitization financing mechanism [Source: Michael *et al.,* 2009]

Traditional bank lending comprises four basic activities: originating, funding, servicing and monitoring. Originating means making the loan, funding implies that the loan is held on the balance sheet, servicing means collecting the payments of interest and principal and monitoring refers to conducting regular or periodic surveillance to ensure that the borrower has maintained the financial ability to service the loan. Securitized lending introduces the possibility of selling assets on a bigger scale and eliminating the need for funding and monitoring.

The securitized lending function has only three steps: originate, sell, and service. This change from a four-step process to a three-step one has been described as the fragmentation or separation of traditional lending and should lead to reduced costs, as the monitoring function is removed from the transaction. Securities in the SPV, backed by a credit rating to give investors information on the quality of the loan portfolio, are sold into the market to finance the purchase of the loan portfolio, or other cash flow generating asset portfolio.

The SPV may separate its income stream into different sets of assets, which may be assigned different credit ratings, allowing investors to choose their own risk/reward profile. Securitization techniques can thus be seen to be another form of SF, as risks are spread from the original lender/borrower relationship, by means of assets being bundled into a vehicle with a clear profile of risk and return.

Securitization has, so far, not been widely used in agricultural finance as a result of the perceived higher risk of agricultural loans and the expense of setting up a securitization vehicle, which usually makes the technique suitable only for large transactions. Another important constraint for its use in agricultural finance is the difficulty of obtaining a solid credit rating for the underlying activities. This has become even more difficult because of the failure of many securitized securities since the 2008 financial crisis.

One difficulty lies in the actual structuring of such a transaction: by definition, the transaction has not been done yet – each deal is unique, so lawyers will need to do a good deal of original work. Then securities issues need to be rated and rating firms - for example, Moody's, Standard & Poors - rely to a large extent on hard information to arrive at one rating level or another. In particular, the rating firms will try to identify the risks of the future payment flows from the assets which underlie the securities issue and whether they will be sufficient to serve the financial obligations under the securities issue.

Such ratings are essential, as they replace the credit procedures that a bank would undertake in a bilateral loan and they represent the only information available on the quality of the asset to the typical investor. However, it can be difficult to determine the expected cash flow from certain transactions, e.g. a series of warehouse receipt-based loans. The rating firm will need exact information on the quality of the controls over the warehouse receipts in the different locations involved. It will need to obtain some long-term information on the experience with such loans.

However, one commentator notes: "There is no apparent 'in principle' difficulty to securitizing rural output as a means of obtaining finance"[8]. Of course, this was written prior to the events of 2007-2008

[8] Dwyer, T. M., Lim, R.K.H. & Murphy, T. 2004. *Advancing the Securitization of Australian Agriculture: Hybrid Equity*. Rural Industries Research and Development Corporation, Kingston, Australia, p. 9. The report offers a clear overview of the development of Securitization techniques.

in the capital markets[9]. It is still not clear what the long-term effects of the credit crisis will be, but it is clear that banks have already examined their portfolios very carefully and it is unlikely that elaborate and innovative schemes using securitization will be pursued in the near future. In addition, public confidence in rating agencies has drastically declined, and there is a widespread view that these need to be placed under more thorough operational checks and supervision than before. Finally, it should be acknowledged that the rating business is quite complex, not least in the agricultural and agribusiness sectors.

Nevertheless, these structures are available in the market and will continue to be used selectively. It is considered that the sub-prime crisis related more to a specific class of securities – mainly those backed by residential mortgages – rather than any generic flaws in the securitization process itself. The types of securitization structures which defaulted in the market usually comprised the bundling of several payments streams, from borrowers with different risk profiles. However, the defaults are spreading to structures which were previously thought to be very safe since they had high ratings. With greater attention paid to the quality of the underlying assets, there seems to be room in the market for the application of securitization type structures to specific circumstances, two of which are given as examples in the boxes below.

Some indication of the potential for the use of securitization in agriculture is provided by the case of fattening cattle in Colombia (UNCTAD, 2002). The livestock sector in Colombia performs below its potential considering the productive capacity of its land for cattle fattening, as a result of the high cost and processes behind commercial credit. Another example of the use of securitization financing mechanisms is in Brazil, where the Government created a Cedula de Producto Rural (CPR) bond to raise capital, from the main stream financial and capital markets, which was later used to finance the production of agricultural commodities (UNCTAD, 2002).

Securitization is one of the most sophisticated SF instrument and as such, it is hardly found in developing countries. The presence of a sophisticated financial market, with experienced investors, is a prerequisite. Also, as mentioned, a rating is essential as well as enterprises and many of the developing countries lack quality information which credit agencies require to do their job properly. However, globalization and the integration of financial systems at global level will provide opportunities in the

[9] It can only be assumed that the 2008 turmoil in the Securitization markets and the criticisms being levelled at the rating agencies for poor judgment in assessing risk will have a negative effect on further development of the Securitization instrument in agriculture finance.

future; thus, allowing agribusinesses in developing countries to raise funds from the capital and financial markets in developed countries.

2. 1. 3. 1. 3 Repurchase agreements (Repos)

Repurchase agreements ("repos") are simple forms of commodity finance: the bank, rather than taking a pledge over the goods being stored or shipped, actually *buys* the goods and simultaneously signs a contract for resale at a certain point in time and at a price that reflects the cost of funds from the original time of sale to the resale. Repo finance for agricultural commodities has spread to over a dozen countries in recent years and is particularly popular in jurisdictions that do not allow for adequate laws and regulations regarding the registration of pledges, as well as enforcement and foreclosure mechanisms (World Bank, 2005b).

2. 1. 3. 1. 4 Export receivables financing

In export receivables financing, a loan is made to the exporter on the back of assigned export contracts either already executed or to be executed with the funds of the loan. Such assignment would normally be acknowledged by the buyer with payments made directly to the lender. Where an export receivables facility is granted post shipment, it is regarded as re-financing to keep the exporter in funds, enabling him to continue operations without having to wait for the buyer's payment (UNCTAD, 2001).

2. 1. 3. 1. 5 Factoring

Factoring is the assignment by a supplier of receivables arising from contracts of sale of goods made between the supplier and its customers (debtors) to a factor, in which the factor is to perform *at least two* of the following functions: (i) finance for the supplier, including loans and advance payments; (ii) maintenance of accounts (ledgering) relating to the receivables; (iii) collection of receivables, and (iv) protection against default in payment by debtors (UNCTAD, 2001).

2. 1. 3. 1. 6 Project financing

Project Financing is a form of financing in which lenders look solely or primarily to the cash flows of a project to repay debt service and to all of the underlying project assets (including all physical and contractual assets) as collateral for the loan. Project finance is a technique that is used to repackage financing risks in such a way that they become acceptable to the financiers and therefore, the actual structure of the financing is closely adapted to the conditions of the project and the country in which it is to be executed. For example, taking the underlying assets as collateral may be difficult under local law; then, the project finance has to be structured in such a way that sufficient comfort can be attained even without such collateral (UNCTAD, 2001).

2. 1. 3. 1. 7 Islamic financing

Trade finance structures in accordance with Islamic banking standards have been growing considerably in importance over the last few years and are expected to become even more critical in the future. With Islamic banking, banks need to earn their profit not simply because they make money available, but because they take a production or trade-related risk; that is, the lender must share in the profits and losses arising out of the enterprise for which the money was lent. The so called *Murabaha* is a technique widely used for commodity transactions. Under this structure, an Islamic bank would purchase the commodities in its own name and then sell them on to the end buyer at an agreed mark-up.

2. 1. 3. 2 Agricultural value chain finance

An Agricultural Value Chain or Supply Chain is often defined as the sequence of value-adding activities, from production to consumption, through processing and commercialization. Value chains, or supply chains, in agriculture can be thought of as a "farm to fork" set of processes and flows – from the inputs to production to processing, marketing and the consumer. Each segment of a chain has one or more backward and forward linkages (Miller & da Silva, 2007). When credit or other financial services flows through the actors along the chains, it (credit) appropriately called Value Chain Finance.

Agricultural value chains may be highly integrated or fragmented depending on the sector and country. Vertical coordination of the farmers, processors, marketing companies and others is important to the viability of using SF lending techniques. Such coordination, and often mutual dependence, reduces risks and transaction costs of individual actors within agricultural value chains. A marketing or food processing company has better knowledge of the industry, of its products and its constraints and risks than would a bank itself, even a specialized agricultural bank. Lack of familiarity with a sector almost automatically means that a bank will not offer finance (Michael *et al.,* 2009).

On the other hand, a comprehensive value chain linking the farm, the bank and the off-taker (purchaser or recipient of good or commodity), helps to identify the point or points at which finance might be applied, while minimizing the risk to the bank or investor. In other words, it then becomes feasible to *structure finance* according to the value chain, often building the finance around the strength of the stronger and more bankable participants in the chain, who tend to be the export or marketing companies that have a much stronger financial history and position than, for example, farmers (Michael *et al.,* 2009).

Value chain linkages often involve contractual commitments to ensure compliance. The combination of knowledge and compliance are important for financiers since SF does not have the reliance of traditional collateral to cover for risk, but rather relies upon collateral substitutes and future income flows. Figure 4 below, illustrates the main components of the value chain and how finance flows both through the chain and can come in to it at many levels (Miller & da Silva, 2007). As shown in Figure 4, commodities or products typically flow from stage to stage along a chain in one direction, while financial resources mostly flow in another. Funds can also flow into the chain at any stage.

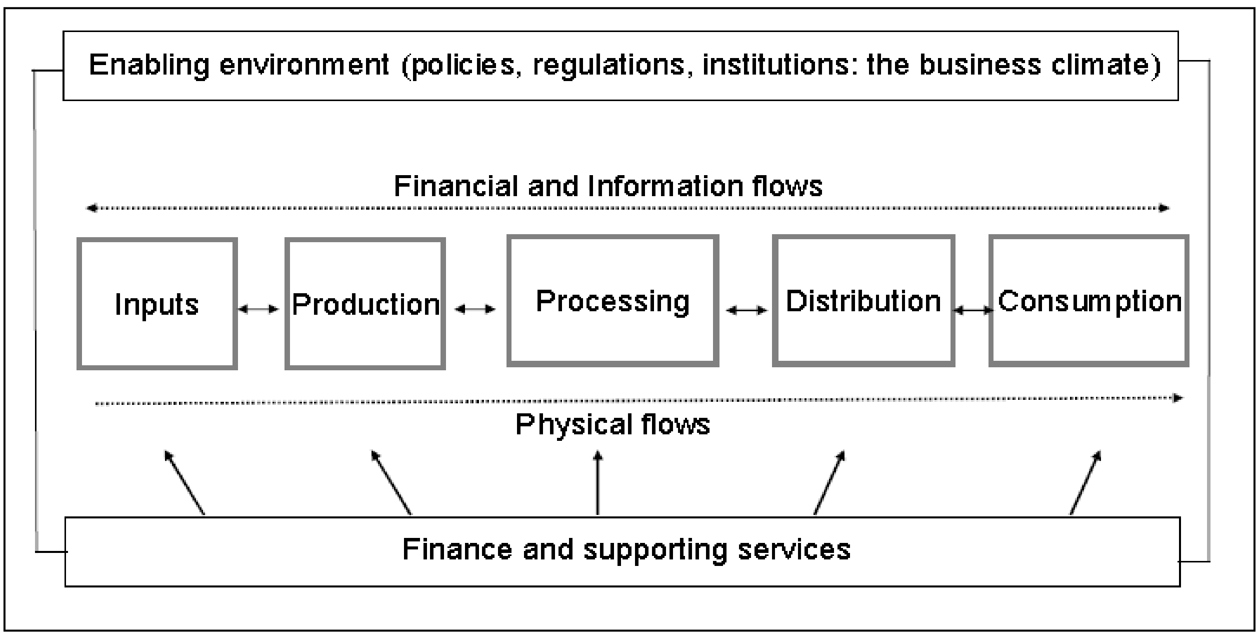

Figure 4: Flow of financial services in an agricultural value chain [Source: Silva and Batalha, 2000]

Successful value chains, whether or not integrated, are rooted in a long-term, shared vision for the success of the chain. Integrating the chain and optimizing links between the components often falls on the actors in the later stages, the exporters, or the food processing and retail groups such as supermarkets, which are most directly driven by consumer demand. However, the finance provider must understand and assess the strength of the relationships since the health of the chain is only as strong as its weakest link. Rabobank, for example, employs many sector specialists to analyze value chains to support its lending operations. They provide an understanding of the trends, the potential and risks and the relationships, and strength of the partners. This information is important for knowing where and how to structure its lending and investments (Michael *et al.,* 2009).

The characteristics of the various chains can have a profound effect on the availability of finance. Some chains, such as those of perishable products which cannot be stored, are not suitable as collateral. Therefore, most banks simply find it easier to focus on the more commoditized products, such as grain, which are easier to use as collateral and have fewer quality issues. As an example of the benefits for finance that participation in a value chain can bring to agriculture, a survey by FAO (2007) in Latin America demonstrated that half of the regulated financial institutions sampled required their agricultural clients to have formal sales contracts and 39 percent requested clients to be part of a value chain. Strong chains, with clearly defined linkages between the parties, represent a powerful framework for structuring finance. Moreover, as agricultural chain relationships strengthen and trust between those involved increases, more sophisticated financial products and measures can be introduced (Michael *et al.,* 2009).

The rise of supermarket shopping in developing countries has created large players at the processing, marketing and retail end of the food chain, which exert a dominant influence all the way up the chain. Moreover, supermarkets have become adept at monitoring the buying patterns of their customers and using the information in dealing with and offering advice to their suppliers. This information is also important to banks and other financiers. Sometimes the interaction includes financial support in the form of prepayment for future deliveries, although it must be emphasized that most supermarket chains, in view of their enormous buying power, seek delayed payment terms from their suppliers, which causes difficulties, particularly for small-scale farmers, who must seek funding elsewhere but who can use their market linkages and sales contracts as support to attract funding (Michael et al., 2009).

The effect of market competitiveness and market risk on the value chain has been noted in a study by Miller and Da Silva (2007), and the conclusion has been drawn that the discipline exerted by market forces, acting from the consumer end of the chain, contributes to a tightening of the linkages. Put simply, the quality and price driven demands of the market are forcing improvements in the agricultural value chain and these improvements are crucial in promoting access to finance (Michael et al., 2009).

As illustrated in Figure 1, Agriculture Value Chain Finance can be classified into two groups, namely: Direct Value Chain Finance (DVCF) and Indirect Value Chain Finance (IVCF). Direct Value Chain Finance is when the source of the credit or financial services is within the value chain; while Indirect Value Chain

Finance is when the source of the credit or financial services is external or outside the value chain – for instance: a bank providing credit services to the value chain. The instruments in each of the groups of AVCF are briefly discussed below.

2. 1. 3. 2. 1 Direct *v*alue *chain f*inancing *i*nstruments

To address the shortage of financial services from banks and other financial institutions, agribusiness often construct quite extensive systems of direct value chain finance: a buyer advancing credit to commodity producers, producer organizations providing inputs on credit to members, an agro-processor advancing credit to its clients and input suppliers providing inputs on credit to commodity producers, *inter alia*. These financial flows between value chain actors often take the form of 'in-kind' transfers, thus, the lender advances inputs such as seed or fertilizers for payment at a later date. Frequently the lender takes payments in the form of produce. In most cases cash does not change hands.

As illustrated in Figure 1, Direct Value Chain Finance instruments includes: Trader Finance, Input Supplier Finance, Marketing or Processing Company Finance and Contract Farming and Out-grower schemes financing. These instruments are briefly discussed below as follows.

2. 1. 3. 2. 1. 1 Trader finance

With Trader Finance**,** the trader is able to advance funds with the guarantee of a crop to be harvested, or in some cases a crop or product to be grown or produced. The price is normally fixed at the time of financing but in the many countries without functioning commodity exchanges, this price-setting is often set by the trader on speculation without knowing what the market price or the quality will be at the time of delivery. In order to reduce trader risk, the prices offered tend to be low and therefore a disadvantage to the farmer.

2. 1. 3. 2. 1. 2 Input supplier finance

The goal of input supplier finance is to facilitate and increase sales, not finance. Finance may be given directly by advancing products on consignment or commission. For proven clients this can work well but for others can be problematic. Supply finance can also be done indirectly through a triangular relationship in which the supplier facilitates finance through a financial organization so the buyers can pay the input suppliers. This has the advantage of letting financial entities handle the financing, using their expertise and systems in place to do so.

2. 1. 3. 2. 1. 3 Marketing or processing company finance

Marketing company finance works in a similar way but whereas traders tend to be smaller and normally operate as intermediaries between producers and processors and marketing companies, the marketing financing is normally driven by the interest of the company to secure products to meet their marketing goals and commitments. They may or may not directly manage the funding since they may choose to involve a bank or other financial institution to directly manage disbursements and collections are managed through receipt of the product. There is often an established relationship between the company and the producers or producer groups.

Marketing companies may have more options to secure advance prices for their commodities and therefore have a more secure basis for setting prices of the products they procure through advancing funds to traders and producers. Marketing finance is often the primary source of funding for commodities even though the relative roles of each varies by region and by commodity. As shown in Figure 5 below for rice, millers and wholesalers often are the pivotal actors in financing, advancing money "down the stream" to local buyers and traders and providing products on consignment or delayed payment to wholesalers or retailers.

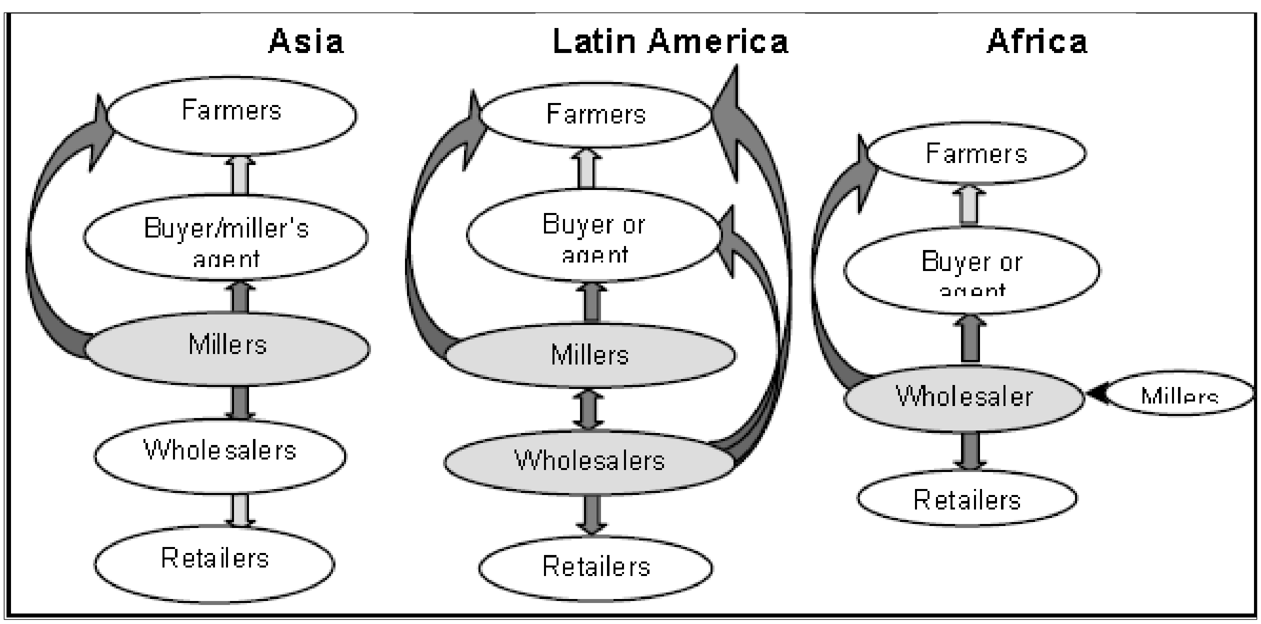

Figure 5: Financial flows in the rice value chains [Source: Miller & da Silva, 2007]

2. 1. 3. 2. 1. 4 Contract farming and out-grower schemes

Contract farming financing has some of the characteristics of marketing company finance but has strict contractual relationships that specify the type of production, quality, quantity and timing of the production to be delivered. Finance and technical assistance provision, if needed, is written in to the binding contract. Contract farming can be defined as an agreement between farmers and processing and/or marketing firms for products under forward agreements and frequently at pre-determined prices. The contractual commitments provide bankers with a signal of security and seriousness as well as a potential for ensuring repayment through discounting from sales income.

Contracts can be formal or informal, even verbal when there is a sufficient level of trust and mutual interest. Less formal and less rigid forms of commitment between producers and buyers are called out-grower schemes which can function similarly to that described above. Out-grower or contract farming schemes generally involves the development of mutually beneficial relationships between parties who need and depend on each other such as with export crops and dairy.

2. 1. 3. 2. 2 Indirect Value Chain Financing Instruments

As already mentioned above, Indirect Value Chain Finance, occurs when a financial institution is linked to value chain. For instance, a bank can lend to a commodity producer based on the relationship between the commodity producer and the commodity off-taker (trader, processor, etc). When a buyer with a sufficiently strong reputation as a reliable purchaser is willing to ‘vouch for’ its producers, even small producers become more attractive clients to financial institutions. Indirect Value Chain Financing instruments are mainly loans from a financial institution (e.g. credit union or bank) to an actor in the value chain (e.g. a farmer).

2. 1. 3. 2. 3 Opportunities and Challenges of Agricultural Value Chain Finance

Agricultural Value Chain Finance (AVCF) can provide many opportunities. However, in order for the financial industry to be able to take full advantage of its opportunities there are many challenges to address, especially in serving smallholders in less developed countries. As shown in Table 2, most of the challenges are due to the lack of capacity, both human and physical. For example, for small producers to be able to integrate into value chains, they require organization to have the economies of scale required. They require technical and management training and they must have roads and communications systems that are adequate to compete in the marketplace. Similarly banks and

Microfinance Institutions (MFIs) need increased understanding on market assessment and need to gain experience in working with the various traders and agribusinesses in the value chains in order to structure their financial products and services to the precise needs of value chain actors, in a way that can maximize the benefits of value chain finance.

Table 2: Opportunities and Challenges of AVC financing

Opportunities	Challenges
Value chain financing (VCF) linkages offer increased financial access: • Lower transaction costs to banks and producers • Reduces financial risks to lenders • Tailored to fit specific chain needs	Required bundle of services for investment in value chains is lacking: • Small, unorganized productive capacity of many producers • Missing physical and financial infrastructure
VCF concept provides increased understanding of agricultural and agribusiness finance: • Better understanding, coordination and control of the marketplace • Improved long-term horizon for financial entities • Adaptation to future market trends	Capacity, understanding and hence commitment are missing: • Small farmers lack capacity and often production competitiveness • Agribusiness and finance institutions lack experience and tools • Governments lack understanding and supporting policies
Increases opportunities for equity finance and capital market interventions: • Increased chain competitiveness • Improved understanding and risk mitigation for investors • Structured finance opportunities and new products	Required investment and support services are not available: • Risk reducing services not universally available (e.g. Commodity exchanges) • Enabling policies and conditions not in place in many countries • Fear of unknown for long-term investment
VCF is not socially exclusive (in principle, small farmers can benefit): • Leading NGOs in sector able to facilitate small farmer inclusion • New technologies open new frontiers	Livelihoods are at risk for those excluded: • Social exclusion of small producers • VCF benefits for actors integrated into chains; but many are not in chains

(Source: Miller & Da Silva, 2007)

2. 1. 3. 2. 3. 1 Value chain risk mitigation products

Value chain management concerns itself in large part with the management of risks incurred within chains and the sale or transfer of some risks which cannot be effectively managed within chains outside chains to third party risk arbitrageurs. Typically, leveraging the strongest balance sheets available within chains assures that the cost of capital for the entire chain as a whole remains as low as possible. Three primary areas of risk in agricultural finance are: (a) production risk; (b) market risk and (c) credit risk. Each of these risks includes factors which may be assessed and those which are unpredictable.

2. 1. 3. 2. 3. 1. 1 Weather and catastrophe insurance

In production risk, management capacity, production practices and diversification of income, natural resource quality and production efficiency can be measured but droughts, floods and other catastrophes occur without warning, often shifting incomes of producers, buyers and financiers from profit to despair. For these, insurance can be used to mitigate risks. A key issue of insurance is cost and even though insurance cost reduction is improving significantly for crop and livestock insurance with index-based insurances which do not require on-site inspection and control, they nevertheless, are not widely used except when subsidized by governments or donors. Partial insurance coverage for those sectors where costs are not prohibitive and production risks impede access to finance or income security is important to consider. Catastrophe insurance for assets and inventories and health insurance are widely used and are important for almost all persons and businesses (Miller & da Silva*,* 2007).

2. 1. 3. 2. 3. 1. 2 Forward contracts

The situation for market and supply chain risks has significantly changed during recent time. For price risks there are both cyclical and seasonal price fluctuations of agricultural products throughout the value chain, not only due to local production variation but also affected by "outside forces." These forces include prices fixed for political reasons, import or export restrictions, exchange controls, subsidies and globalization. With globalization, the risk of the effects of such outside influences has become more pronounced, but fortunately the tools and alternatives for dealing with such risks have also become more readily available throughout the world (FAO, 2007).

These risk mitigation tools can help stabilize income and hence improve borrowing access and conditions. Forward contracts provide an avenue to sell a product for future delivery at a specified price. This price risk tool used widely in developed countries is growing rapidly in lesser developed ones as well, even with smallholders. By "locking in" sales or purchase prices for delivery at a future date forward contracts serve not only to reduce the risks of price changes, but also the futures contract can be used as collateral upon which one can borrow money. This is being used by small farmers in India and a few other countries, but widespread use directly by smaller farmers will be difficult in many developing countries for some time to come.

However, if millers and wholesalers use forward contracts, they can pass on this stability from the pre-agreed prices and offer farmers prices with less risk and ostensibly with a higher price due to the reduction in uncertainty. Furthermore, they can access funding more easily due to the security of such contracts, thus providing more capital and potentially more competition and higher prices to producers.

2. 1. 3. 2. 3. 1. 3 Hedging

A hedge applies a counter force to balance the potential effects of one force with another. Various hedging products are being used in developed economies to allow farmers, millers, traders and others the option of reducing risk by purchasing options and derivatives which can limit future price drops. The concept of a hedge is to reduce or cancel an unwanted business risk such as a product's market price fluctuation, while still allowing the agribusiness to profit from the investment activity. These require commodity exchanges which are becoming more available at least for certain commodities and require careful understanding before using. Even more so than with a forward contract; hedging requires a careful understanding of how the market works. For this reason, hedging is best handled by trade or marketing companies or persons who understand its use (FAO, 2007).

There are various derivatives, options and other ways to hedge that can be quite complicated as well as specific issues related to each value chain or sector. These include: (i) futures – agreements to exchange or sell a commodity (also a currency) at an agreed price in the future such as at harvest time; (ii) swaps – agreements to simultaneously exchange or sell an amount of commodity or currency now and resell or repurchase that it in the future; and (iii) options – instruments that provide the option but not the obligation to buy or sell the commodity or currency in the future once the value of that product reaches a previously agreed price. It must also be noted that since the mechanisms used to hedge incurred costs to cover the transaction and the hedge cost for mitigating the risk, their use and expected benefit must be carefully considered. In any case, since value chain finance works within the chain and hence has a deeper understanding of the market risks, it is easier to apply hedge mechanisms correctly (FAO, 2007).

2. 1. 3. 2. 3. 1. 4 Credit risk management

Credit risk is well-known in the financial industry. Yet, many institutions remain wary of agricultural and agribusiness credit risk as they do not know how to assess it and price it correctly for their loans. This "risk of the unknown" coupled with the lack of the traditional mortgage or other forms of commonly used collateral simply cause them to severely restrict agricultural and rural financing. As stated by the leaders in Rabobank, the largest agricultural lender in the world which is the only commercial bank with a Triple A rating, "Agriculture is no more risky than that of any other sector." Three things must be noted – firstly, the usual credit risk analysis such as the five “C’s”: Character, Capacity, Capital base, Collateral and Conditions, are as important as ever (Bakx*,* 2005).

Secondly, the credit risk assessment must go beyond the client and look at the whole value chain. The health of the value chain and competency within the value chain must be assessed for its trends, the short and long-term position of clients and countries within the competitive agribusiness chain and the expected levels of risk of the value chain and the segments within it. The success of Rabobank mentioned above depends to a large extent on their careful analysis of both each value chain and industry as well as each client. Furthermore, it is able to use that knowledge to know at what levels finance is most needed and effective and to work with the farmers, agribusinesses and/or national and export marketing companies to structure their financial products and services to meet the risk profiles and cash flows of those clients (Miller *et al.,* 2007 and Bakx*,* 2005).

Thirdly, value chain financing often combines the provision of business support services with the provision of credit. It is inherently multi-dimensional with multi-stakeholders all interested in each others’ success in order to have efficient and profitable agribusiness chains. Moreover, it is well tailored and more suited to the multiple development requirements of specific farmer groups than, for example, credit only services provided singularly through financial institutions (Bakx*,* 2005).

2. 2 Evaluation of Credit Risk

Credit risk (whose evaluation in SF lending transaction in agriculture is the primary focus of this study) is defined as "*the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms*" (Basel Committee, 2000). It is usually associated with loans and securities, which by generating interest income, are the primary source of revenue for banks or lending institutions. The primary effect of high credit risk on a financial institution (bank) is loss in assets and interest income. This reduces the bank's profit, depletes its capital and might at the extreme, lead to -- bank failure.

Liang (1989) showed empirically that credit risk reduces bank profit because a bank recognizes expected costs associated with high risk, such as higher premiums on uninsured deposits demanded by risk-averse investors. Berger and De Young (1997) examined the inter-temporal relationship between loan quality and cost efficiency using the Granger causality concept. Their empirical results suggest that high levels of problem loans cause banks to increase spending on monitoring, working out, and/or selling off these loans and possibly become more diligent in administering the portion of their existing loan portfolio that is currently performing. Credit risk is regarded as the primary cause of bank failures and it is the most visible risk faced by bank management (Fraser et al., 2001).

During 1980s and 1990s, the banking industry was confronted by the forces of financial deregulation and globalization. Many banks suffered during this period for a multitude of reasons, including the heavy loan losses emerging during late-1980s and early-1990s. There have been other drivers of change the industry, such as a worldwide structural increase in the number of bankruptcies, a trend towards disintermediation by the highest quality and largest borrowers, more competitive margins on loans, a declining value of real assets, and a dramatic growth of off-balance sheet instruments with inherent default risk exposure (Altman and Saunders, 1998). These worldwide phenomena have led to the development of modern credit risk evaluation techniques (Kim, 2006).

Credit risk modelling has been developed rapidly over the past decades to become a key component in the risk management system of the banking industry. Credit risk models help bank management measure the credit risk associated with individual loans as well as their asset portfolio. They enable a bank to forecast possible credit losses over the coming year, to differentiate loan prices over lenders having different risks, to determine the loan loss reserves and risk-based capital requirements, to evaluate credit concentration and set concentrate limits and to measure risk-adjusted profitability (Lopez and Saidenberg, 2000).

The goal of credit risk management (or evaluation) is to maximize a bank's risk-adjusted rate of return by maintaining credit risk exposure within acceptable parameters. Banks need to manage the credit risk inherent in the entire portfolio as well as the risk in individual credits or transactions. Banks should also consider the relationships between credit risk and other risks. The effective management of credit risk is a critical element of a comprehensive approach to risk management and essential to the long-term success of any banking organization (Basel Committee, 2000).

Most credit risk models consider two sources of credit risk: default risk and migration risk. Default risk is the risk that borrowers default, meaning that they fail to meet their debt obligation. Default triggers a total or partial loss of any amount lent to the borrower. Migration risk is the risk that obligors' credit rating goes down into a lower loan classification. The deterioration of credit rating doesn't imply default but it does imply that the probability of default has increased (Bessis, 2002).

There have been various arguments about the definition of default. They vary by models and by banks, and depend on the philosophy and/or data available to each model builder. Liquidation, bankruptcy filing, loan loss (or charge off), non-performing loan, or loan delayed in payment obligation are used at many banks as proxies of loan default. Default risk can be measured at individual loan level, which is called stand-alone credit risk and at portfolio level, which is called portfolio credit risk. The most direct and common measure of default risk is the probability of default (PD), which is the likelihood that a loan falls into default. It captures the volatility of default risk and is usually expressed as a distribution and its parameters, probability density function (PDF) or cumulative distribution function (CDF). It is calculated for an individual borrower as well as for entire bank portfolio.

When calculating default risk at the portfolio level, Value at Risk or simply VaR has become the industry standard measure[10]. It is defined as the loss exceeding expected loss (or unexpected loss) at some given fraction of occurrences (the confidence interval) if a portfolio is held for a particular time (holding period). When estimating credit risk facing a bank, common practice is to employ a long holding period (one year or more) and a small confidence level, usually one percent or less (Jackson & Perraudin, 1999). VaR is a theoretical measure of the potential loss for a portfolio capturing downside risk. Its concept is

[10] VaR was initiated to measure market risk in trading portfolios. It has roots in Modern Portfolio Theory and a crude VaR measure was published by Leavens in 1945. VaR becomes a proprietary risk measure in 1990s after the Basel Committee authorized the utilization of VaR when banks calculate capital requirement (Holton, 2002).

favoured for three major reasons, which are providing a complete view of portfolio risk, measuring economic capital, and assigning a fungible value to risk (Bessis, 2002).

In credit risk literature, models that are used to evaluate or measure default risk (credit risk) are classified in several ways. Allen *et al.* (2004) and Georgakopoulus (2004) also classify credit risk models into two broad families, namely: traditional credit risk models and modern credit risk models. Each family has several classes. Figure 6 below, illustrates the classification of credit risk models according to Allen et al. (2004) and Georgakopoulus (2004). This is the classification of credit risk models that is used in this study.

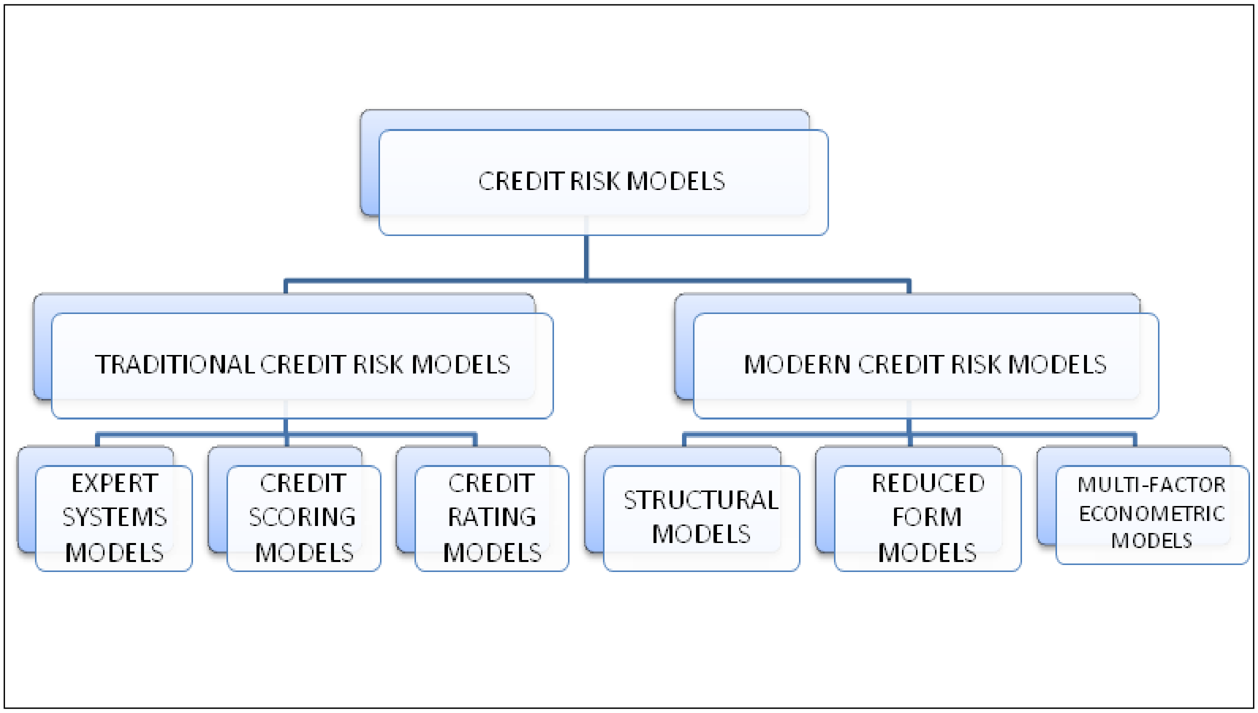

Figure 6: Classification of credit risk models

2. 2. 1 Traditional Credit Risk Models

Traditional credit risk models try to estimate the probability of default (PD), rather than the potential losses in the event of default (LGD). Furthermore, these models typically specify “failure” to be bankruptcy filing, default, or liquidation, thereby ignoring consideration of the downgrades and upgrades in credit quality that are measured in mark to market models. The three (3) broad groups of traditional credit risk models that are used to estimate the Probability of Default are: (i) Expert systems, including artificial neural networks; (ii) Rating systems; and (ii) Credit scoring models (Allen et al., 2004; Georgakopoulus, 2004).

2. 2. 1. 1 Expert Systems Models

Historically, bankers have relied on expert systems to assess credit risk. These are based on, Character (reputation), Capital (leverage), Capacity (earnings volatility), Collateral, and Cycle (macroeconomic) conditions. Evaluation of these variables is performed by human experts, who may be inconsistent and subjective in their assessments. Moreover, traditional expert systems specify no weighting scheme that would order these systems in terms of their relative importance in forecasting the probability of default. Thus, artificial neural networks have been introduced to evaluate expert systems more objectively and consistently.

The neural network is "learning" using historical repayment experience and default data. Structural matches are found that coincide with defaulting firms and then used to determine a weighting scheme to forecast the probability of default. Each time that the neural network evaluates the credit risk of a new loan opportunity, it updates its weighting scheme so that it continually "learns" from experience. Thus, neural networks are flexible, adaptable systems that can incorporate changing conditions into the decision making process.

Empirical tests of the accuracy of neural networks produce mixed results. Kim and Scott (1991) use a supervised artificial neural network to predict bankruptcy in a sample of 190 firms. While the system performs well (87% prediction rate) during the year of bankruptcy, its accuracy declines significantly over time, showing only a 75%, 59%, and 47% prediction accuracy one year prior, two years prior, and three years prior to default, respectively. Altman and Saunders (1998) examine 1,000 Italian industrial firms from 1982-1992 and find that neural networks have about the same level of accuracy as do credit scoring models.

Podding (1994), using data on 300 French firms collected over three years, claims that neural networks outperform credit scoring models in bankruptcy prediction. However, he finds that not all artificial neural systems are equal, noting that the multi-layer perceptron (or back propagation) network is best suited for bankruptcy prediction. Yang *et al.* (1999) use a sample of oil and gas company debt to show that the back propagation neural network obtained the highest classification accuracy overall, when compared to the probabilistic neural network and discriminant analysis. However, discriminant analysis outperforms all models of neural networks in minimizing the type 2 classification errors, which is, misclassifying a good loan as bad (Allen *et al.,* 2004).

During "training" the neural network fits a system of weights to each financial variable included in a database consisting of historical repayment/default experiences. However, the network may be "over fit" to a particular database if excessive training has taken place, thereby resulting in poor out-of-sample estimates. Moreover, neural networks are costly to implement and maintain. Because of the large number of possible connections, the neural network can grow prohibitively large rather quickly. Finally, neural networks suffer from a lack of transparency. Since there is no economic interpretation attached to the hidden intermediate steps, the system cannot be checked for plausibility and accuracy. Structural errors will not be detected until estimates become noticeably inaccurate.

2. 2. 1. 2 Credit Rating Models

External credit ratings provided by firms specializing in credit analysis were first offered in the USA by Moody's in 1909. Agency ratings are opinions based on extensive human analysis of both the quantitative and qualitative performance of a firm. Companies with agency-rated debt tend to be large and publicly traded. Moody's primary business is providing credit opinions on financial obligations for investors. These ratings are well-accepted by the investment community and extend not only to commercial firms but municipal, sovereign and other obligators. These ratings cover approximately 6,500 firms worldwide and 3,000 in the USA (Falkenstein *et al.,* 2000). The credit opinions are statements about loss given default and default probability, specifically expected loss and thus act as combined default prediction and exposure models.

White (2002) identifies 37 credit rating agencies with headquarters outside of the US. These firms offer bond investors access to low cost information about the creditworthiness of bond issuers. The usefulness of this information is not limited to bond investors. The Office of the Comptroller of the Currency (OCC) in the USA has long required banks to use internal ratings systems to rank the credit quality of loans in their portfolios. However, the rating system has been rather crude, with most loans rated as Pass/Performing and only a minority of loans differentiated according to the four non-performing classifications (listed in order of declining credit quality): other assets especially mentioned (OAEM), substandard, doubtful and loss.

Similarly, the National Association of Insurance Commissioners (NAIC), in the USA, requires insurance companies to rank their assets using a rating schedule with six classifications corresponding to the following credit ratings: A and above, BBB, BB, B, below B and default. Many banks have instituted internal ratings systems in preparation for the Bank of International Settlement (BIS) New Capital Accords whose implementation started in 2005. The architecture of the internal rating system can be one-dimensional, in which an overall rating is assigned to each loan based on the probability of default PD; or two-dimensional, in which each borrower's probability of default is assessed separately from the loss severity of the individual loan (LGD).

Treacy and Carey (2000) estimate that 60 percent of the financial institutions in their survey had one-dimensional rating systems, although they recommend a two-dimensional system. Moreover, the Bank of International Settlement (2000) found that banks were better able to assess their borrowers' probability of default than their LGD. Treacy and Carey (2000) in their survey of the 50 largest US bank holding companies and the Bank of International Settlement (2000) in their survey of 30 financial institutions across the G-10 countries found considerable diversity in internal ratings models. Although all used similar financial risk factors, there were differences across financial institutions with regard to the relative importance of each of the factors. Treacy and Carey (2000) found that qualitative factors played more of a role in determining the ratings of loans to small and medium-sized firms, with the loan officer chiefly responsible for the ratings, in contrast with loans to large firms in which the credit staff primarily set the ratings using quantitative methods such as credit scoring models. Typically, ratings were set with a one year time horizon, although loan repayment behaviour data were often available for 3-5 years.

2. 2. 1. 3 Credit Scoring Models

Credit scoring began as a tool for banks to decide whether or not to grant credit to consumers (Thomas, 2000). Durand (1941) was the first paper that employed statistical methods in discriminating good and bad loans. Since then, many researchers have made efforts to develop better theoretical and empirical models. New statistical methodologies have been utilized in this area and remarkable development in computer systems enables banks to apply a variety of new models. Today, many banks are implementing credit scoring models in their credit decision-making. Credit scoring models are widely used in credit card approval, mortgage loans and consumer loans and are increasingly used for business loan applications (Mester, 1997)[11]. When constructing a credit scoring model, banks are confronted by two critical issues, (1) the functional form and (2) choice of explanatory variables.

There is no common consensus on which variables should be included in a credit scoring model because economic theory hardly supports the issue. As a practical matter, the choice of the explanatory variables largely relies on data availability. There are four methodological forms of parametric models in the credit scoring literature: (1) Discriminant Analysis (DA), (2) Linear Probability Models (LPM), (3) Logit models and (4) probit models. DA assumes that there are two groups of loans, good and bad and finds the best linear combination of explanatory variables, thus, characteristics of borrower, that can discriminate each group (Betubiza & Leatham, 1990). There is a great deal of literature on discriminant analysis (DA) in 1970s and 1980s, including studies by Altman et al. (1977), Sexton (1977) and Reichert et al. (1983).

Linear probability models (LPM), logit models and probit models employ standard statistical techniques and provide banks with the probability of default for a borrower. LPM use a least square regression approach, where the dependent variable is 1, if a borrower is in default, or 0, otherwise. The regression equation is expressed as a linear function of explanatory variables (Orgler, 1970). Logit and probit models are different from LPM in that they assume the probability of default is logistic or normal distribution. Application of logit and probit models in credit scoring began in the 1980s under the background development of quantitative choice model in 1970. After Wiginton (1980) and Grablowsky and Talley (1981), numerous papers have been published, and logit and probit analysis became the most preferred models in credit scoring research.

It has been pointed out that a weakness of DA is that the method doesn't produce a probability of default. Furthermore, when DA models are estimated, the OLS estimator used is not efficient because it basically assumes that explanatory variables of two groups are normally distributed and have the same variance-covariance matrix (Turvey, 1991). Since the DA approach exhibited good performance in large samples in spite of statistical problems and because it has the advantage of technical convenience in estimation and maintenance, it was widely used in the 1960s and 1970s.

LPM has similar statistical problems to DA. Its biggest problem is that the estimated probability of default might exist outside the interval (0, 1). LPM has the advantage in that it can suggest default

[11] 97% of banks use credit scoring model to approve credit card applications and 70% of banks use credit scoring in their small business lending (Kim, 2006).

probability and its estimated parameters can be easily interpretable. It also has the advantage of technical convenience. Logit and probit models were developed to solve the statistical problems existing in DA and LPM. Estimators of logit and probit models are efficient and consistent. These methods do not need the strict assumptions on data. Loan officers can conveniently calculate the default probability of a borrower with the logit or probit model, but the parameters estimated are more difficult to understand because of their nonlinear characteristics (Green, 2000; Maddala, 1983).

Since the 1980s, there have been many attempts to use non-parametric statistics or artificial intelligence techniques such as neural networks, recursive partitioning algorithms, expert systems, and nearest neighbour methods. These models are highly flexible in modelling because they do not have distributional assumptions on data and/or do not require pre-specification of the model (Chhikara, 1989). A great deal of attention has been given recently to new methodologies. Some argue that new techniques can improve the predictive accuracy of credit scoring models (Desai et al., 1996; Freed & Glover, 1981; Frydman et al, 1985; Henley & Hand, 1996 and Srinivasan & Kim, 1987).

Many consulting institutions are applying these new statistical techniques. In spite of their statistical advantages and good performance, these models have as many limitations as non-parametric models. Most of all, they cannot provide the probability of default and informative parameters useful in loan pricing, management policy decisions, and portfolio credit risk modelling.

Model accuracy has been a critical argument in research on credit scoring models[12]. There have been many papers arguing a specific model representing the best accuracy, but generally there were no major differences in performance among these models. Thomas (2003) argued that there is no conclusive evidence on model accuracy and there is no agreement on which statistical technique should be preferred. No matter what model banks use, the application of credit scoring can cut operating costs by making the loan process simple, reduce potential loan losses and focus attention more on problem loans. Banks are expending the application of credit scoring over their credit line. For example, recent modifications of credit scoring models have given banks the opportunity to treat small business loans as retail credit (Allen et al., 2004; Longenecker et al., 1997; Mester, 1997).

[12] Type I error and type II error are used for statistical measure of model accuracy that represent how well a model can predict good or bad loan. In credit scoring model, type I error, classifying bad loan as good, is more important than type II error, classifying good loan as bad.

2. 2. 2 Modern Credit Risk Models

Modern credit risk models are classified into three (3) groups. The first group is *Options-Theoretic Structural Approach* pioneered by Merton (1974). The second group is the *Reduced form approach* utilizing intensity-based models to estimate stochastic hazard rates, pioneered by Jarrow & Turnbull (1995); Jarrow et al. (1997) and Duffie and Singleton (1998, 1999). The third group is the *Multi-factor Econometric* approach pioneered by Wilson (1997a, 1997b).

The three (3) approaches propose differing methodologies to accomplish the estimation of default probabilities. The structural approach models the economic process of default, whereas reduced form models decompose risky debt prices in order to estimate the random intensity process underlying default. Multi-factor econometric approach uses the intuitive theory that credit cycles closely follows business cycles and hence the approach proposes a methodology of linking macroeconomic factors to the probability of default of a loan.

2. 2. 2. 1 Structural Credit Risk Models

Structural credit risk models use the option pricing theory in valuation of loans, as first proposed by Merton (1974). In fact, Merton's (1974) model is regarded as the classical structural credit risk model. There is an assumption that borrowers have an incentive to repay the loan if the firm's assets exceed the amount borrowed and default on the loan otherwise[13]. According to Merton's (1974) theory, if a loan is repaid, the lender will earn a fixed return on the loan. If a loan is in default, the lender can suffer large losses that may exceed the outstanding principal and interest. This behaviour makes loan payoff to the lender analogous to writing a *Put Option* on the assets of the borrowing firm.

The value of a risky loan is dependent on the variables used in calculating the value of the option: the short-term risk-free interest rate, the loan time horizon, the amount borrowed, the market value of the assets of a firm and the volatility of asset value. The last two variables are usually not directly observable. Proprietary credit risk models such as KMV solves this problem for corporate borrowers by using a firm's stock price to estimate market value of its assets and volatility of the firm's equity to estimate volatility of assets. KMV offers a "Private Firm Model" for non-traded firms and approximates their asset value and asset volatility by those of publicly-traded firms with similar characteristics. It would not be appropriate for agricultural lenders to use the Private Firm Model since there are no

[13] This assumption holds for agricultural borrowers as well. Babetskaya (2000) shows that debt-to-asset ratio is the major consistent predictor of borrower's repayment capacity.

publicly traded firms with similar characteristics: agricultural firms (farms) are in general a lot smaller than even smallest of publicly-traded firms.

Lyubov (2003) proposes an approach of directly computing the borrower's market value of assets based on balance sheet information and calculate volatility of assets based on historical borrower balance sheet data. This approach was used by Katchova and Barry (2005), who used a borrower's current balance sheet data and historical balance sheet data to determine the borrower's market value of assets and asset volatility respectively.

After all of the five required variables are available, the probability density function (PDF) of the borrower can be determined. The Distance-to-Default is calculated as the difference between the asset value and loan (debt) value, divided by the volatility of asset value. If one makes the assumption that future asset values are normally distributed around the firm's current asset value (projected growth rate can be incorporated in calculating the future asset value distribution), probability of default (PD) can be derived from the Distance-to-Default using a normal distribution. Katchova and Barry (2005) used this procedure to measure the credit risk in the loan portfolio of the Farm Credit System in the US.

For proprietary credit risk model, KMV, the calculate Distance-to-Default is mapped to its historical data base to calculate the probability of default (PD). The KMV model calculates PD as the number of firms that defaulted within a specified time horizon with asset values of given distance from default divided by total number of firms with asset values of given distance from default. The empirical based PD can vary significantly from the PD based on the normal distribution.

2. 2. 2 .2 Reduced Form or Intensity-Based Model of Credit Risk Models

The reduced form model was originally introduced by Jarrow and Turnbull (1992) and subsequent research includes Jarrow and Turnbull (1995), Jarrow et al. (1997) and Duffie and Singleton (1999). Reduced form credit risk models use a mathematical technique common in loss distribution modelling, which was developed in the insurance industry, the so-called actuarial model[14]. Credit Suisse Financial Products developed a commercial reduced form model, which is called Credit Risk Plus.

Credit Risk Plus only models default risk, not migration risk. In other words, it is assumed that at the end of the risk horizon the borrower is in one of two states, namely, default or non-default. Contrary to the option-based structural model, this model does not make any assumptions on timing and causality

[14] It is also called as intensity model or mortality models of default.

between default and other variables. The influence of systematic factors on the default rate is supposed to be captured through default rate volatilities instead of default correlation between borrowers. It further assumes that the probability of default for a loan is constant over time.

Credit Risk Plus first assigns each loan to a credit rating category (or segment) and calculates key inputs for each loan: (1) credit exposure, (2) obligor default rate, and (3) obligor default rate volatilities. Default rates for each loan are usually estimated by mapping of default rate to its credit rating[15]. Default rate volatility is defined as the historical standard deviation of the default rate. Loans are assumed to be mutually independent of each other and each rating category consists of homogeneous loans with identical credit risk characteristics such as default rate and volatility. If there are a large number of loans in a portfolio, the effect of a loan exposure on the probability of default to the portfolio is very small and the default frequency in any given period is independent of default frequency in any other period. Under those conditions, the probability distribution for the number of defaults at the portfolio level during a given period of time can be represented by the following Poisson distribution:

$$P(n) = \frac{\mu^n e^{-\mu}}{n!} \dots \dots (2.1)$$

Where: n is average number of defaults per year and μ stands for the expected number of defaults in the portfolio.

To estimate the loss distribution for a loan portfolio, the joint default behaviour of loans is captured by treating the default rate of a portfolio as a continuous random variable with volatility, which incorporates uncertainty about the future state of loans. The default rate for each segment (i.e., X) is supposed to follow a gamma distribution and can be expressed as:

$$X_k \sim \Gamma(\alpha_k, \beta_k), \text{where: } \alpha_k = \frac{\mu_k^2}{\sigma_k^2}; \text{and } \beta_k = \frac{\sigma_k^2}{\mu_k} \dots \dots (2.2)$$

The default rate at the portfolio level is calculated by a probability generating function of a gamma distribution and a probability generating function for the entire portfolio derived by the multiplication of probability generating function for each segment. Finally, the distribution of the credit loss is estimated by the probability generating function and depends on distributional assumptions, the default rate for each loan, the standard deviation of the default rate, and weight of each loan.

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[15] This implies that banks already have rating system or can use agency ratings. Banks also should have historical default rates by rating category.

2. 2. 2. 3 Multi-factor Econometric Credit Risk Models

The multi-factor econometric credit risk models evaluate systemic credit risk of a country, an industry or a portfolio segment as opposed to an individual exposure. This model assumes a homogenous credit standing for firms within a portfolio segment and the existence of causal relationship between credit risk of a portfolio segment and economic conditions associated with the loan portfolio (Bessis, 2002). The econometric model begins with the intuitive theory that credit cycles follow business cycle closely, but its behaviour is different from industries. Since the state of nature is, to a large extent, driven by macroeconomic factors, the econometric approach proposes a methodology to link the macroeconomic factors to the probability of default of a loan.

CreditPortfolio View (CPV), which was the first multi-factor econometric model, was developed by Wilson (1997a, 1997b) of McKinsey Group. It focuses on the default rate and the migration rate. CPV consists of two model blocks: (1) the default block and (2) the time series block. In default block, default rate for a portfolio is formulated as a logit specification. The index variable (or default rate) is expressed as a linear function of macroeconomic variables (multi-factor model) and is assumed to follow logistic distribution as shown below:

$$\mathrm{Y_{it}} = \frac{1}{1 + \exp(\mathrm{Z_{it}})} \dots \dots (2.3)$$

$$\mathrm{Z_{it}} = \alpha_0 + \sum_{j=1}^{n} \alpha_i \mathrm{X_{jt}} + \mathrm{e_t} \dots \dots (2.4)$$

Where Y_{it} is conditional probability of default in period t for i^{th}loan or segment, Z_{it} is the index value from the multi-factor model, X_{jt} macroeconomic variables, αs are unknown parameters and e_t is an error term. Each macroeconomic variable is supposed to follow a univariate autoregressive process of order 2, or:

$$\mathrm{X_{jt}} = \gamma_{j0} + \sum_{k=1}^{2} \alpha_{jk} \mathrm{X_{j,t-k}} + \mathrm{v_t} \dots \dots (2.5)$$

This model simulates the joint distribution of the default rate conditional on the macroeconomic factors like unemployment rate, rate of economic growth, government expenditure and aggregate savings rate.

To estimate the distribution of default probabilities for a loan portfolio, the model first determines the stochastic macroeconomic state. This is accomplished by simulating the relevant macroeconomic variables over several years more than 1,000 times. The conditional defaults probability is then estimated by country or by industry segment. It is also assumed that all default correlations are caused by the correlated segment-specific default. This means there is no further information beyond country, industry, the state of nature and the state of economy used for predicting the default correlation between borrowers. Finally the model estimates the default distribution for a portfolio from the relevant segment default distributions.

2. 3 Credit Risk Models in Agriculture Finance

Traditional credit risk models (especially credit scoring models) are extensively used in agriculture finance. Credit scoring models (in agriculture finance) have been used in the following studies to measure credit risk: Allen *et al.* (2006); and Novak and la Due (1994), *inter alia*. The study by Odeh (2005) examined the performance of logistic regression (i.e., credit scoring model), artificial neural networks (i.e., expert system) and adaptive neuro-fuzzy inference system (i.e., expert system), to predict credit risk using data from Farm Credit System, in the USA.

Research on the application of modern credit risk models in agricultural finance is in its infancy. Lyubov (2003) developed the first modern credit risk model applied to agricultural lending; it is actually a portfolio credit risk model. The model is a reduced form model rooted along the lines of Credit Risk Plus, but addresses a disadvantage of this approach by incorporating recent research on sector relationships using a more stable algorithm. The model was applied to a representative Farm Credit System association in Minnesota, AgStar Financial Services. The model output is a loan loss distribution (i.e., the probability of default), which is used to calculate the expected and unexpected loan losses for the overall portfolio and to estimate required capital.

Katchova and Barry (2005) specify an option based structural model much like the CreditMetrics® and Portfolio Manager Models. This represents the first attempt at applying the theories of Structural Credit Risk Models to agricultural loans. Yan et al. (2009) addressed the problems of measuring credit risk under the structure model; their study proposed the use of unrelated regression model (SUR) to predict a farm's ability in meeting its current and anticipated obligations in the next 12 months.

Kim (2006) developed a multi-factor econometric model much like CreditPortfolio® View. The model was used to evaluate credit risk (i.e., determine the probability of default) in the Farm Credit System's loan portfolio, in the USA. In the model it was assumed that creditworthiness is a function of Net Farm Income.

When modelling credit risk in agricultural loans, one must account for the attributes of the agricultural sector and its borrowers, which is substantially different from the credit risk exposures in the other sectors of the economy. Agriculture is a capital-intensive sector with investment in farm land, buildings, machinery and breeding stocks dominating the asset structure of most types of farms (Barry *et al.,* 2003). The agricultural sector has liquidity problems; it experiences chronic cash-flow pressures resulting from relatively low but volatile returns to production assets. These characteristics contribute to the aggregate debt-servicing capacity and creditworthiness of farms (Barry et al., 2002).

Credit risk in agricultural loans is closely tied to a farm's net cash flow just as it is for other retail loan categories[16]. Net cash flows in agriculture are volatile mainly due to the fluctuations in commodity prices and weather conditions. However, the expected net cash flow is a good leading indicator for the eventual creditworthiness of an agricultural borrower. Economic performance in the agricultural sector is also widely influenced by events in both the domestic and international economy. Capturing the state of these economies may be in some cases critical when credit risk modelling for the agricultural sector.

[16] Most Financial Institutions classify agricultural loans as retail loans (Burns, 2002)

2. 4 Conclusion

The first part of the chapter (Section 2.1) provided extensive literature on Structured Finance lending techniques and their respective instruments, in agricultural finance. Although different in structure and organization, there are two fundamental concepts underlying any Structured Finance lending transaction. The first fundamental concept is the use of existing assets and commodities and/or future cash flows as security for financing (Michael *et al.*, 2009). In other words, in Structured Finance lending techniques assets other than fixed assets such as buildings and land can be used for a loan.

The second fundamental concept underlying any SF lending transactions is that the creditworthiness of the borrower is a function of the profitability of the underlying transaction being financed and not a function of the borrower's balance sheet standing. For instance, in the Structured Financing of maize production, the creditworthiness of the maize producer is a function of the profitability of the maize production activity and not a function of the balance sheet standing of the maize producer (Winn *et al.,* 2009; UNCTAD, 2001). Therefore although sometimes simple or complex in terms of structural arrangements, Structured Finance techniques are basically and broadly defined as Expected Cash Flow based lending techniques.

The second part of the chapter (Section 2.2) provided extensive literature on the different types of models that are used to measure credit risk. The credit risk models were classified into two broad families, namely: Traditional credit risk models and Modern credit risk models. In agriculture finance, traditional credit risk models (especially credit scoring models) are the most widely used models in quantitative evaluation of credit risk in loans. The use of modern credit risk models in agricultural finance is still in its infancy, with studies done by Yan *et al.* (2009), Kim (2006), Katchova and Barry (2005) and Luybov (2003) leading the way.

The information highlighted in this chapter is used to achieve the primary objective of this study, namely, to develop a credit risk model that can be used to measure or evaluate credit risk in SF lending transactions in agriculture. The building blocks of the Credit Risk Model are Structured Finance and Credit Risk Modeling principles. Both the credit risk model and its implementation framework are developed in the next chapter.

CHAPTER THREE

3.0 METHODOLOGY

This Chapter address the first and second objectives of the study. Therefore in this Chapter, the Credit Risk Model and its implementation framework are developed and illustrated respectively. The Chapter is divided into four (4) major sections. Section 3.1 highlights the theories that are used to develop the credit risk model. The implementation framework of the developed Credit Risk Model is illustrated in Section 3.2. Section 3.3 highlights the data requirements of the developed Credit Risk Model. The Chapter is concluded in Section 3.4.

3. 1 The Theoretical Framework of the developed Credit Risk Model

In Chapter two (2) – literature review, it was concluded that although diverse in terms of structural governance and arrangements, Structured Finance techniques are basically Cash Flow based lending techniques, where the creditworthiness of the borrower is a function of profitability of the underlying transaction, being financed, and not a function of the balance sheet status of the borrower. Therefore, this means that when modelling credit risk in Structured Finance balance sheet variables (such as Liquidity, Solvency and Leverage ratios, *inter alia*) cannot be used. Hence Traditional Credit Risk Models that are popularly used in agriculture cannot be adapted and applied to measure credit risk in agricultural based SF lending transactions.

Therefore given the above challenge, there was need to think-out-of-box, and explore the entire universe of credit risk modelling techniques. The researcher identifies the credit risk modelling techniques, as first proposed by Merton (1974) as the possible and appropriate credit risk modelling technique in agricultural based Structured Finance transactions. The theories proposed by Merton (1974) are extensive used in modelling credit risk in cash flow based lending techniques, especially in corporate finance.

Hence, theories that are used to develop the Credit Risk Model are derived from Merton's Option Pricing Approach or rather Merton's (1974) model – which is regarded as the Classical Structural Credit Risk Model (Giesecke, 2004). The credit risk modelling technique proposed by Merton is extensively used and applied in credit risk modelling studies in financial economics, for instance: proprietary credit risk model such as KMV Portfolio Manager®[17] and CreditMetrics®[18] are developed using the theories proposed by Merton. In agriculture finance, Yan et al. (2009) and Barry and Katchova (2005) used Merton's credit risk modelling approach to develop credit risk models, that they subsequently used to measure the credit risk in agriculture loan portfolios. The following are the assumptions of the developed credit risk model.

3. 1. 1 First Assumption: what drives credit risk?

Under the Merton's credit risk modelling approach, credit risk is driven by the uncertainty associated with the market value of the firm (farm) at debt maturity. The market value of the firm at debt maturity is equivalent to the total market value of the firm's assets.

3. 1. 2 Second Assumption: the evolution of the Firm's Asset Value over time.

Following Merton (1974); Yan et al. (2009); Katchova and Barry (2005); Stokes and Brinch (2001) and many finance studies, the study assumes that the market value of the firm's assets (**V**) follows a standard Geometric Brownian Motion (GBM)[19]. Therefore, the market value of the firm's assets, at any time T in the future (V_T), can be mathematically expressed as follows:

$$V_T = V_0 \exp\left\{\left(\mu - \frac{\sigma^2}{2}\right)T + \sigma\sqrt{T}Z_T\right\} \ldots\ldots (3.1)$$

Where: μ and σ^2 are the mean and variance, respectively, of the instantaneous rate of return on the assets of the firm, $(\partial V_T/V_T)$; Z_T is the standard normal distribution variable ($Z_T \sim N[0,1]$) with zero (0) mean and unitary (1) variance. Note that V_T is lognormally distributed with the expected value at time T, $E(V) = V_0 \exp\{\mu T\}$ (Katchova and Barry, 2005; Crouhy *et al.,* 2000).

Equation 3.1 is a mathematical representation of a GBM model. The equation can be simplified by 'natural logging' it. Therefore, using the natural log operation, Equation 3.1 can be expressed as follows:

$$\ln V_T = \ln V_0 + \left(\mu - \frac{\sigma^2}{2}\right)T + \sigma\sqrt{T}Z_T \ldots\ldots (3.2)$$

---

[17] KMV Portfolio Manager is a proprietary credit risk model developed by KMV Corporation, in 1993. KMV Corporation merged with Moody's Corporation in 2002, to form one of the world's largest credit-rating agency. For details about the model see www.moody'skmv.com

[18] CreditMetrics® is a proprietary model developed by JP Morgan (a Credit Rating Agency); it was released in 1997. For details about the CreditMetrics® see www.creditmetrics.com

[19] The GBM model is also popularly called the Random Walk Model in finance studies.

Where $\ln V_T$ is the natural-log of the market value the firm's assets, at time T, $\ln V_0$ is the natural log of the initial market value of the firm's assets; μ is the mean rate of return on the farm's assets; σ is the volatility of the farm's asset value; T is time period; and Z_T is the standard normal distribution variable, with zero mean and variance equal to one (i.e., $Z_T \sim N(0,1)$).

3. 1. 3 Third Assumption: Firm Default Specification

Again following Merton (1974) and many other finance studies, the study assumes that a firm defaults at debt maturity (i.e., time T), when the market value of the firm's assets (**V_T**) is less than the face value of firm's debt (**D**). Therefore, probability of default (PD), which is the measure of credit risk, is defined as the likelihood that the market value of the firm's assets (V_T) will be less than the face value of the firm's debt (D), at time T – when the debt matures (Merton, 1974; Yan *et al.,* 2009; Katchova and Barry, 2005 and other finance studies). The probability of default (PD) can be expressed as follows:

$$\mathrm{PD} = \Pr[\mathrm{V_T} < D] \ldots \ldots (3.3)$$

Equation 3.3 is the theoretical specification of the Credit Risk Model under the Merton (1974) framework. The probability of default (PD) is determined by substituting Equation 3.2 into Equation 3.3 and simplifying – thus:

$$\mathrm{PD} = \Pr\left[\mathrm{Z_T} \leq -\frac{\ln[\mathrm{V_0/D}] + \left(\mu - \frac{\sigma^2}{2}\right)\mathrm{T}}{\sigma\sqrt{\mathrm{T}}}\right] \ldots \ldots (3.4)$$

$$\therefore \mathrm{PD} \equiv \mathrm{N(-DD)};\ \text{where } \mathrm{DD} = -\frac{\ln[\mathrm{V_0/D}] + \left(\mu - \frac{\sigma^2}{2}\right)\mathrm{T}}{\sigma\sqrt{\mathrm{T}}}$$

DD is called the Distance-to-Default and $N(\cdot)$ is the standard normal cumulative density function (Katchova and Barry, 2005; Crouhy *et al.,* 2000). Figure 7 below, illustrates the graphical representation of Equation 3.4.

Figure 7 shows how the stochastic firm assets value (**V**) and deterministic debt (**D**) evolve over time, with default occurring when the value of assets (**V**) falls below the value of debt (**D**). The figure also illustrates the distribution of the value of farm assets relative to debt obligations, the Distance-to-Default, and the probability of default (PD). The DD depends on the difference between asset value (**V**) and debt value (**D**) as well as the expected growth (**μ**) and variance (**σ**) of asset returns. The shaded area is the probability of default (i.e., the probability that the value of assets will be less than the value of debt), which is a function of the DD.

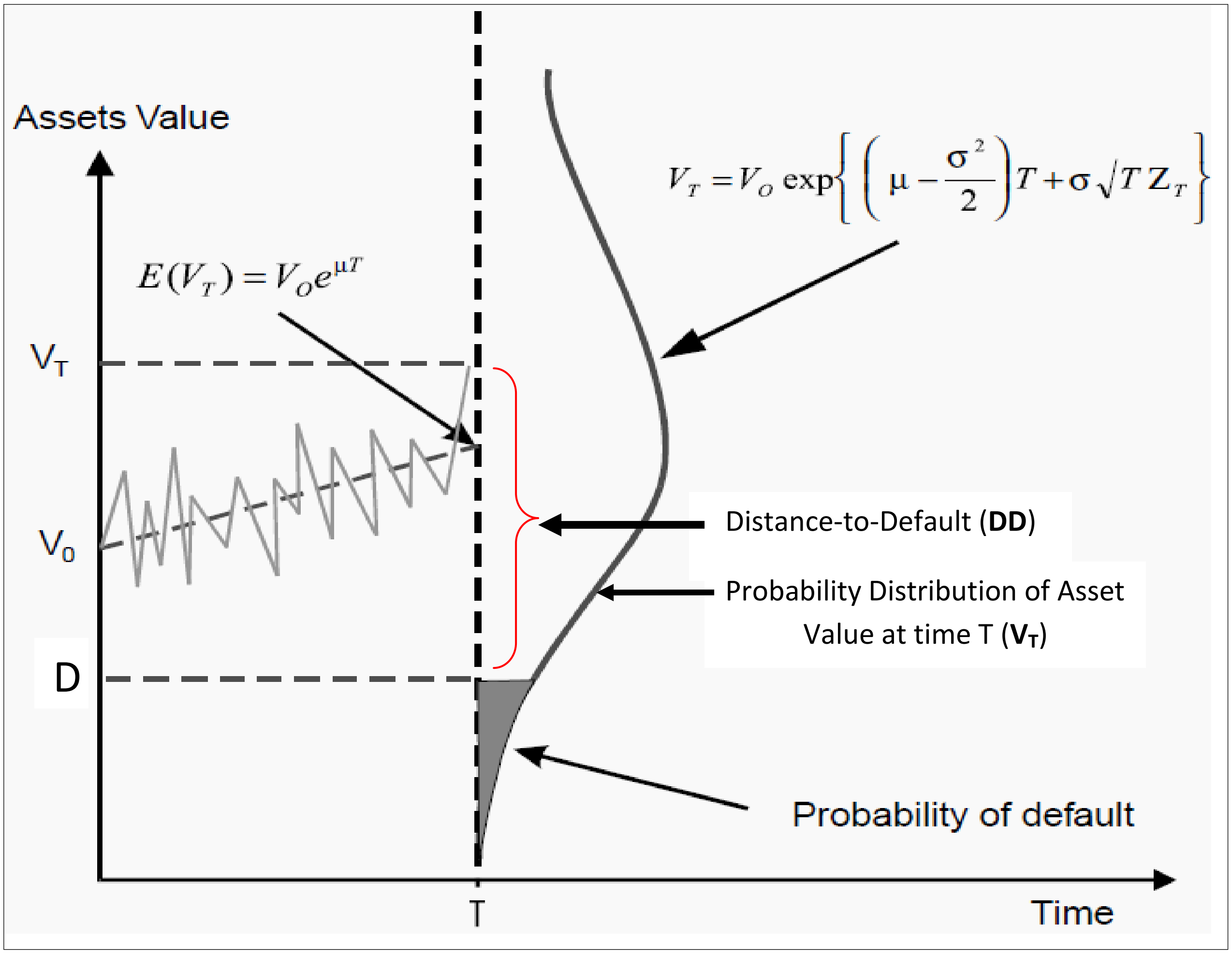

Figure 7: Probability distribution of asset values (VT) and distance-to-default (DD) [Source: Katchova and Barry, 2005; Crouhy et al., 2000]

The statistical probability of default (PD) is calculated using the properties of the standard normal distribution as the probability that assets (V) will fall below debt value (D). The actual procedure involves the calculation of the Distance-to-Default (DD), using Equation 3.4 and then reading the DD value from a normal distribution statistical table to determine the probability of that DD value. The probability of the DD value is the probability of default (PD). In other words, the probability of the DD value is the probability that the value of the farm's assets at time T, will fall within the shaded area in Figure 7.

3. 2 Implementation Framework

In order to use Merton's model, we need to know the market value of the firm (V) and its volatility (σ). The market value of the firm (V) and its volatility (σ) are not observable in the market; but since the equity (share) price of firms can be found in the market, it is possible to iteratively retrieve the market value of the firm (V) and its volatility (σ) from the equity prices and equity price volatility – this can be done using the approaches proposed by Bharath and Shumway (2004), Crosbie and Bohn (2003) and Vassalous and Xing (2001).

The implementation requirements, mentioned in the above paragraph, restricts the use and application of Merton's model to corporate liabilities (i.e., firms whose debt is publicly traded). However in agriculture, Lyubov (2003) proposed the direct calculation of the market value of the farm (i.e., market value of the firm) and its volatility, from the market value of the farm's assets and asset volatility. Katchova and Barry (2005) implemented Merton's model by directly calculating the market value of the farm and its volatility from the farm's current and historical assets values, which were derived from the farms' current and historical balance sheet information. In this study, a different way of determining the market value of the farm and its volatility is proposed and used. The derivation of the market value of the farm in this study is supported by the principles of Structured Finance lending techniques.

According to Giesecke (2004) the market value of the firm (V) in Merton's model, is considered to be the firm's expected future cash-flow. Therefore, it then follows that the market value of the farm (V) is the farm's expected future cash-flow. In agriculture the farm's (or firm's) expected future cash-flow is either from the commodities under production or commodities in the warehouse (inventory). Hence, the market value of the farm (V) is the expected future cash flow from inventory or from commodities under production. This implies that the market value of the farm (V) is basically the market value of the commodities in the warehouse or commodities under production.

As illustrated in Chapter two (2), Structured Finance lending techniques in agriculture are always linked to an underlying commodity, asset or product; whose production, processing or marketing is being financed. Therefore in agricultural based Structured Finance lending techniques, the market value of the farm is basically or equivalent to the market value of the commodity underlying SF lending transaction. For instance, when the production of maize is financed by a Structured Finance loan, the market value of the farm is therefore equivalent to the expected market value of the maize.

The market value of the commodity underlying the SF lending transaction is basically the product of the Price (P) and Quantity (Q) of the commodity. Hence the market value of the farm, in a Structured Finance lending transaction, can be expressed as the product of the price and quantity of the commodity, underlying SF lending transaction, thus:

$$V = P \times Q \ldots \ldots (3.5)$$

In Merton's model or Structural approach, credit risk is driven by the uncertainty associated with value of the farm or farm's assets at debt maturity. Therefore, putting Equation 3.5 into context, market value of the farm at time T, V_T, is a function of the Expected Price (P_T), Expected Price Risk (P_R), Expected Quantity (Q_T) and Expected Quantity Risk (Q_R). Hence, Equation 3.5 can be expressed as follows:

$$V_T = f(P_T, P_R, Q_T, Q_R) \ldots \ldots (3.6)$$

The Expected Price Risk (P_R) and Expected Quantity Risk (Q_R) are the variables that make the Expected Price (P_T) and Expected Quantity (Q_T) of the commodity, respectively, to be uncertain at time T – at debt maturity. In other words, P_R and Q_R make the Price and the Quantity of the commodity at time T (in the future) to be random or stochastic. Therefore, putting Equations 3.5 and 3.6 into consideration, the market value of the farm at time T (V_T) can be expressed as follows:

$$V_T = (P_T + P_R) \times (Q_T + Q_R) \ldots \ldots (3.7)$$

Given the above equation, the study proposes and uses Time Series Forecasting Techniques to estimate the parameters P_T, Q_T, P_R and Q_R. In Time Series Forecasting Techniques, the future value of a time series can be explained and determined from the past (lagged) values of the time series. Therefore, historical commodity price and quantity time series data are used to develop Time Series Forecasting models called Autoregressive Integrated Moving Average (ARIMA) models. The ARIMA models are used to forecast the Expected Price (P_T) and Expected Quantity (Q_T) of the commodity underlying the SF lending transaction (i.e., the market value of farm's assets) at time T – when the SF loan matures. ARIMA models (time series forecasting models) are generally expressed as follows:

$$X_t = \theta + \sum_{i=1}^{p} \alpha_i X_{t-1} + \sum_{i=1}^{q} \beta_i \omega_{t-1} + \varepsilon \ldots \ldots (3.8)$$

The variables highlighted in the above equation will be explained in detail later in this section. However, at this point it is important to note that the variable on the right-hand side of Equation 3.7, X_t denotes the time series value at time T. Therefore in the context of this study, X_t then denotes the commodity price or commodity quantity time series.

The first three (3) terms on the left-hand side of Equation 3.8 (i.e., $\theta + \sum_{i=1}^{p} \alpha_i X_{t-1} + \sum_{i=1}^{q} \beta_i \omega_{t-1}$) denotes the expected value of the time series at time T. Therefore in the context of Equation 3.6, the first three (3) terms of left hand side of the equation above denote the Expected Price (P_T) or Expected Quantity (Q_T) of the commodity at time T.

The last variable on the left hand side of Equation 3.8 (ε) denotes the error term or the unforecastable component of the time series. In time series forecasting models, the error term (ε) is used to account for any observed deviation of the time series value, at time T, from its expected value. In other words, ε accounts for the any observed difference between the actual value and the forecast value (i.e., the expected value). In ARIMA models, ε is assumed to be normally distributed with zero (0) mean and a constant variance (σ^2) − i.e. $\varepsilon \sim N(0, \sigma)$[20]. Therefore in the context of Equation 3.6, ε denotes the commodity Price Risk (P_R) or the commodity Quantity Risk (Q_R).

Putting the above deductions into consideration, Equation 3.6 can be expressed as follows:

$$V_T = \left(P_T + \varepsilon_p\right) \times \left(Q_T + \varepsilon_q\right) \ldots \ldots (3.9)$$

Where ε_p and ε_q denotes the Price Risk (P_R) and the Quantity Risk (Q_R) of the commodity, respectively. Note that ε_p and ε_q (i.e., the error terms) are standard normal distribution variables. The implication of the previous statement is that the Expected Price (P_T) and Expected Quantity (Q_T) of the commodity at time T become stochastic or random. Since ε_p and ε_q are standard normal distribution variables, P_T and Q_T are then stochastic variables that are normally distributed. Therefore, Equation 3.9 can be expressed as follows:

$$V_T = \left(P_T + \varepsilon_p\right) \times \left(Q_T + \varepsilon_q\right)$$

$$V_T = \left(P_T + N\left(0, \sigma_p\right)\right) \times \left(Q_T + N\left(0, \sigma_q\right)\right) \ldots \ldots (3.10)$$

It can be proven empirically that adding a constant (in this case P_T or Q_T) to a standard normal distribution, the mean of the distribution will increase by the size and magnitude of the constant, while the variance of the distribution remains constant. Therefore, Equation 3.10 can be expressed as follows:

[20] See Gujarati (2003) page 838.

$$V_T = N(P_T, \sigma_p) \times N(Q_T, \sigma_q) \ldots\ldots (3.11)$$

Where $N(P_T, \sigma_p)$ and $N(Q_T, \sigma_q)$ denotes the Price and Quantity normal distributions. One of the properties of normal distributions is that the product of two normal distribution variables is also a normal distribution. Therefore, V_T as expressed in Equation 3.11 is then a normal distribution (V_T-normal distribution). The V_T-normal distribution can be converted into a V_T-lognormal distribution by using the natural log operation, so as to make Equation 3.11 consistent with the assumption that the value of the farm (or farm's assets) at time T, V_T, is log-normally distributed.

Therefore, under the implementation framework proposed by this study, the Probability of Default (PD) is defined as the likelihood that the market value of the commodity underlying the SF loan (i.e., market value of the farm or farm's assets), V_T, will be less than the value of the SF-loan – at time T, when the SF-loan matures. Hence Equation 3.3 (in Section 3.1) can be expressed as follows:

$$\mathrm{PD} = \Pr[V_T < D]$$

$$\therefore \mathrm{PD} = \Pr\Big[\big[N(P_T, \sigma_p) \times N(Q_T, \sigma_q)\big] < D\Big] \ldots\ldots (3.12)$$

Note that in Equation 3.10; $N(P_T, \sigma_p) \times N(Q_T, \sigma_q)$ denotes the V_T-normal distribution[21]. Therefore, the Probability of Default (PD) can be defined as the probability of the area on the V_T-normal distribution that is less than D (i.e., the value of the SF-loan). Figure 7 (in Section 3.1) is also a graphical illustration of Equation 3.12.

To estimate the Probability of Default (PD), the study proposes the following methodological framework, which has five (5) main steps:

1. The first step involves the use of Time Series Forecasting techniques to develop Autoregressive Integrated Moving Average (ARIMA) models that will be used to estimate or forecast the Expected Price (P_T) and Expected Quantity (Q_T), at time T, of the commodity underlying the SF-loan. Therefore, the main data inputs in this step are commodity price and quantity time series data. The outputs of this step are P_T, Q_T, ε_p and ε_q.
2. The second step involves the capturing of the residuals from the ARIMA (p, d, q) model that was used to forecast P_T or Q_T and then estimating their mean and standard deviation (volatility). Volatility (standard deviation) is basically the square root of the variance. The main data input

[21] The V_T-normal distribution is actual a V_T normal Probability Density Function (PDF).

in this section or step are the residuals from the ARIMA (p, d, q) models that were used to forecast P_T and Q_T. The outputs for this step are the mean and standard deviation of the residuals.

3. The second step involves the simulation of the Price and Quantity of the commodity, underlying the SF-loan, at time T. The simulation price and quantity is done in two steps: (i) generation of random numbers using the Random Number Generation Function in Microsoft Excel® and (ii) using the generated random numbers to simulate the price and quantity. The simulation procedure yields Commodity Price ($N(P_T, \sigma_p)$) and Commodity Quantity ($N(Q_T, \sigma_q)$) normal distributions. The mean and standard deviation of the price and quantity residuals (estimated in Step 2) are the data inputs in this step. The outputs of this step are the simulated price and quantity values, which are normally distributed. This step generates confidence intervals in which the Price and Quantity of the commodity is expected to fall in.
4. The simulated price and quantity values (i.e., price and quantity normal probability density functions, generated in Step 3) are ranked from the largest to the lowest and then multiplied to generate the V_T-Cumulative Density Function (V_T-CDF). The data inputs in this step are the price and quantity normal distributions. The output of this step is the V_T-CDF. This step generates a confidence interval in which the market value of the *structured finance commodity* is expected to fall in.
5. Estimation the Probability of Default by reading probability of the SF-loan value (D) on the generated V_T-CDF. The data inputs in this step are the V_T-CDF and the SF loan value. The output of this step is the Probability of Default (PD).

Figure 8 below, depicts the chronological steps of the methodology framework. The figure shows that the primary data input in the methodology framework, is the commodity price and quantity time series. In time series modelling techniques (especially when developing ARIMA (p, q, d) models) require that the time series must have at least 40 observations. The steps are explained in details below as follows:

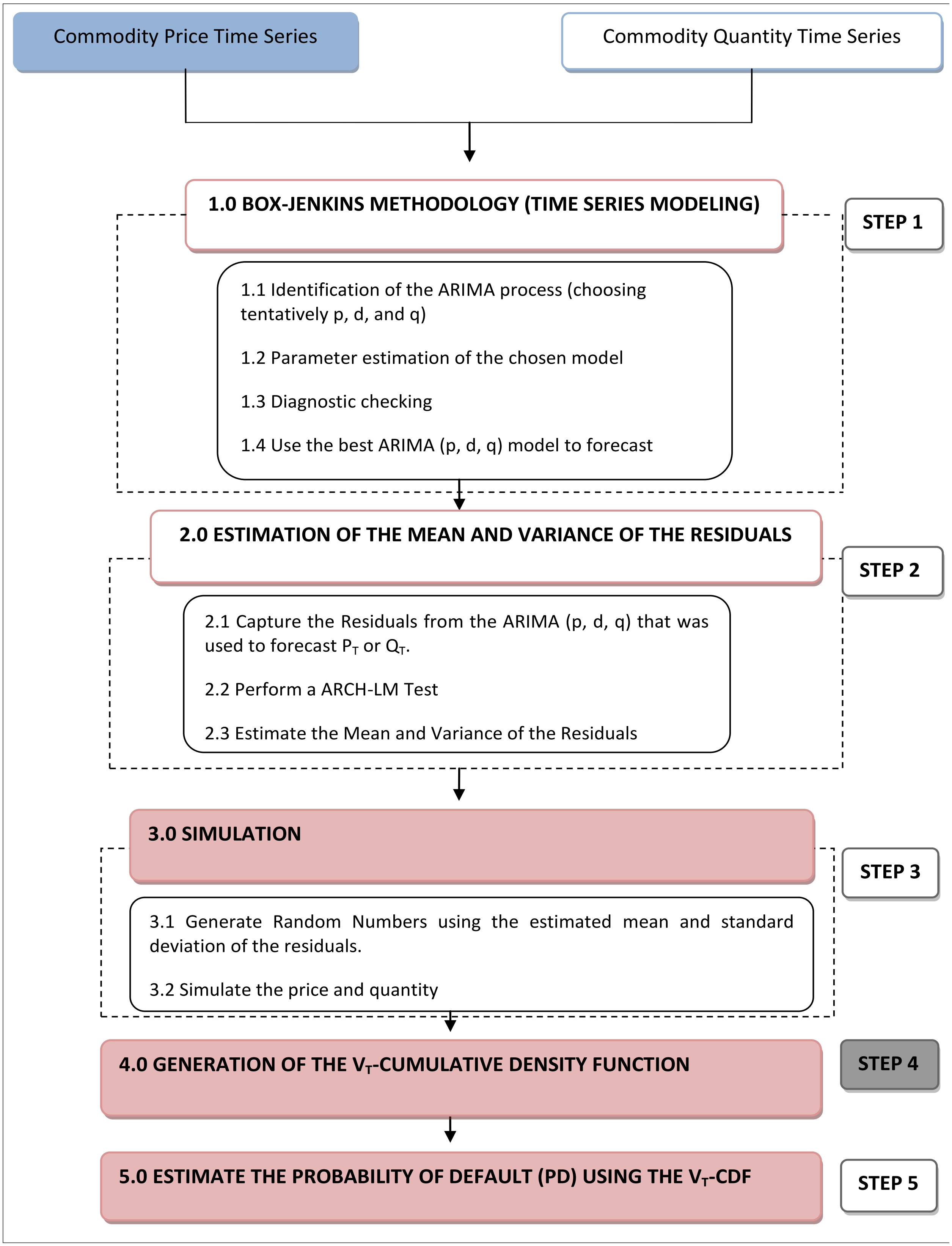

Figure 8: The Methodology framework for estimating the probability of default (PD)

3. 2. 1 Time series forecasting – [STEP 1]

The application of time series modelling techniques in credit risk modelling is not new; time series models are used in Multi-factor Econometric credit risk models such as CreditPortfolio View®, developed by the McKinsey group (Kim, 2006; Wilson, 1997a and 1997b). Therefore the application of time series modelling techniques in this study is consistent with other credit risk modelling studies.

The publication of the paper by Box and Jenkins (1976) – '*Time Series Analysis: Forecasting and Control*', ushered in a new generation of forecasting tools for economic variables such as commodity prices, gross domestic product (GDP), inflation and exchange rates, *inter alia*. These forecasting tools or approaches are popularly known as the Box-Jenkins (BJ) methodology, but technically known as the Autoregressive Integrated Moving Average (ARIMA) methods and the statistical models that are developed or constructed using these methods are popularly called ARIMA (p, d, q) models.

The emphasis of the Box-Jenkins methodology is not on constructing single-equation or simultaneous-equation models, but on analyzing the probabilistic, or stochastic, properties of the economic time series on their own under the philosophy '*let the data speak for themselves*. Unlike the regression models, in which the dependent variable (Y_t) is explained by k regressors (i.e., X_1, X_2, …, X_n); ARIMA models allows Y_t to be explained by past, or lagged, values of Y itself and stochastic error terms. For this reason, ARIMA models are sometimes called *atheoretic* models as there are not derived from any economic theory (Gujarati, 2003).

The objective of the Box-Jenkins methodology is to identify and estimate a statistical model which can be interpreted as having generated the sample data. The statistical model is called the time series' ARIMA process, which is generally described by parameters **p**, **d** and **q** (i.e., ARIMA (**p**, **d**, **q**)). In the ARIMA (**p, d, q**) process, the parameter **p** denotes for the number of Autoregressive (AR) terms; **q** denotes the number of Moving Average (MA) terms and **d** denotes the time series' order of integration. Therefore tentatively, the objective of the Box-Jenkins methodology is to identify the time series' ARIMA process parameters **p**, **d** and **q**. The ARIMA (p, d, q) processes or models are generally expressed as follows:

$$X_t = \theta + \sum_{i=1}^{p\,max} \alpha_i X_{t-1} + \sum_{i=1}^{qmax} \beta_i \omega_{t-1} + \varepsilon \ldots\ldots (3.13)$$

Where: X_t represents the time series variable, e.g. SF-commodity price or SF-commodity quantity data, θ represents the constant; $\sum_{i=1}^{p\max}\alpha_i X_{t-1}$ represents the Autoregressive (AR) terms: $\sum_{i=1}^{q\max}\beta_i\omega_{t-1}$ represents the Moving Average (MA) terms; α_i and β_i are the coefficients of the AR terms and MA terms, respectively and ε is the error term, which represents the unforecastable component of the time series. It is also standard normal distribution variable, thus, $\varepsilon \sim N(0,1)$.

The Box-Jenkins methodology achieves the objective of determining the parameters of the ARIMA (p, d, q) process, through four (4) chronological steps: (a) identification of the model (i.e., identification **p**, **d** and **q**); (b) parameter estimation of the chosen model; (c) Diagnostic checking and (d) forecasting. The four (4) chronological steps are explained in detail below.

3. 2. 1. 1 Identification of the model

This step involves the identification of the ARIMA process parameters **p**, **d** and **q**. In time series modelling literature, the first ARIMA process parameter that is determined is the time series' order of Integration (**d**). The main statistical tool or test that is popularly used in determining **d**, is the Augmented Dickey Fuller Test (ADF –test), developed by Dickey and Fuller (1981). The Augmented Dickey Fuller (ADF) test will be applied test for the presence of unit root in the time series and to determine the number of times the series needs to be differenced to make it stationary. The ADF test will be performed using Eviews®6 statistical software.

The Null Hypothesis (H_O) in ADF test is that the time series has a Unit Root – meaning that the time series is not stationary. The Alternative Hypothesis (H_A) is that the time series has no Unit Root – meaning that the time series is not stationary. The Null Hypothesis is accepted (rejected) if the ADF-statistic is less (greater) than the Critical Value or if the ADF's Probability value (P-value) is greater (less) than the acceptance probability. In this study the H_0 is accepted (rejected) is the ADF-statistic is less (greater) than the Critical Value at 5% significance level.

Once the presence of the unit root is confirmed, the data needs to be differenced to make it stationary. The ADF test is then applied on the differenced data sets to test whether differencing the data made it stationary. This process is to be repeated until it yields a stationary series that is used further in analysis to determine **p** and **q**. The number of times the series needs to be differenced indicates its order of integration and hence the value of **d** in the ARIMA (p, d, q) process.

After the integration of the time series (i.e., **d**) has been determined and the time series differenced accordingly, the next step is to determine the parameters **p** and **q**. The chief tool that is used in the identification of the p and q parameters are the stationary time series' Autocorrelation Function (ACF); Partial Autocorrelation Function (PACF) and the resulting correlograms, which are simply the plots of ACFs and PACFs against the lag length. The correlograms are used to determine the ARMA pattern of the time series. The time series can follow a pure Autoregressive (AR), pure Moving Average (MA) or a combination of the two (ARMA) processes. Gujarati (2003) gives the general guidelines of that must be followed when using the correlograms to determine the pattern that the time series follows. The general guidelines are given in Table 3 below.

Table 3: Theoretical Patterns of the ACF and PACF

Type of Model	Typical pattern of ACF	Typical pattern of PACF
AR (p)	Decays exponentially or with a damped sine wave pattern or both	Significant spikes through the lags p
MA (q)	Significant spikes through q	Declines exponentially
ARMA (p, q)	Exponential decay	Exponential decay

(Source: Gujarati, 2003 pg 844)

The number of significant lags length on the ACF and PACF correllograms denotes the value of q and p, respectively. The significant lags (spikes) are the lags that enter the ARIMA model, whose coefficients are to be estimated, in the next step. This process of determining the **p** and **q** parameters is repeated over and over until an appropriate ARIMA (p, d, q) model that satisfies the conditions in the diagnostic checking stage is identified.

However Box and Jenkins (1976) developed a systematic methodology of determining the ARIMA process parameters **p** and **q**. The systematic methodology involves the use of the Akaike Information Criterion (AIC) and the Schwartz Information Criterion (SBC). The ARIMA process can be represented by the following equation (Box & Jenkins, 1976):

$$X_t = \theta + \sum_{i=1}^{p\,max} \alpha_i X_{t-1} + \sum_{i=1}^{qmax} \beta_i \omega_{t-1} + \varepsilon \ldots \ldots (3.13)$$

Based on Equation 3.13, forty-nine (49) combinations of (AR 0-6) by (MA 0-6) are estimated. Theoretically the point where the highest value of either AIC or SBC lies is seen to determine the values of **p** and **q** (Pesaran & Pesaran, 1997). In simple terms, an ARIMA (p, d, q) process indicates that the intercept needs to be lagged **p** times, the series is to be differenced *d* times to yield a stationary series, and the error term is to be lagged **q** times to generate the desired results. Note, however, that the highest AIC or SBC value is only a guideline the others include:

- ✓ The coefficients of the chosen ARIMA (p, d, q) process (i.e., α_i and β_i in Equation 3.12) must all be significant.
- ✓ The roots of the AR and MA must be invertible

3. 2. 1. 2 Estimation of the coefficients of the ARIMA (p, d, q) model

Having identified the appropriate p, d and q values; the next step is to estimate the coefficients (i.e., α_i and β_i in Equation 3.13) of the identified ARIMA (p, d, q) processes. The coefficients are estimated using Eviews®6.

3. 2. 1. 3 Diagnostic checking

The objective of this step is to determine how well the selected ARIMA (p, d, q) model fit the time series data. There are three standard tests that are used to achieve the objective of this step, namely: (i) residual Normality Test; (ii) Box-Pierce Test (Q-statistic Test) and (iii) the Roots of AR and MA polynomials.

Residual Normality Test – the principle behind the use of this test is that if the ARIMA model estimated fit the data well, the residuals of that ARIMA model must be white noise or stochastic. The residuals are white noise, if there are normally distributed with zero mean and unitary variance. Therefore, the Jarque-Bera (JB) statistic test is used to determine whether the residuals of the Estimated ARIMA models, in step 2, are normally distributed – white noise. The probability value (P-value) of the JB statistic is used in the decision making, thus, the Null Hypothesis is rejected (accepted) if the JB statistic's P-value is less (greater) than 5%.

Box-Pierce (Q-statistic) Test – the Q-statistic test has a *joint hypothesis* that all the ACF coefficients, up to a certain lag length (ρ_κ) are simultaneously equal to zero. The chi-square distribution is used to make the decision of rejecting or accepting the hypothesis. Thus, if the computed Q-statistic exceeds the critical values from the chi-square distribution, the *joint null hypothesis* is rejected and the residuals are not white noise. The *joint Null hypothesis* is accepted if the computed Q-statistic is less than the critical value (i.e., the residuals are white noise). Equation 3.14 below mathematically expresses the Box-Pierce Test.

$$Q = n\sum_{k=1}^{m} \rho_k^2\,; \rightarrow Q \sim \chi^2_{m\ df} \ldots\ldots (3.14)$$

Where: n = sample size; m = lag length; and $Q \sim \chi^2_{m\ df}$ means that the Q-statistic, in large samples, follow a chi-square distribution with m degrees of freedom (Gujarati, 2003). The Probability value (P-values) of the Q-statistic is used in making the decision of accepting or rejecting the *joint Null hypothesis*. The joint hypothesis is accepted (rejected) if the Q-statistic's P-value is greater (less) than 5%.

The AR and MA Roots – if the estimated ARIMA model fit the time series data well, all its AR and MA roots should lie inside the unit circle. Otherwise, the estimated ARIMA model does not fit the time series data. The test of whether or not the AR and MA roots lie inside the circle is done using Eviews®6.

The ARIMA (p, d, q) processes or models that satisfy all the diagnostic tests above are selected and among the best ARIMA (p, d, q) model is selected. The tools that are used in the selection of the best ARIMA (p, d, q) model are highlighted in the next step (2).

3. 2. 1. 4 Forecasting the Expected Price (P_T) and Expected Quantity (Q_T)

This step involves the selection of the best model among the ARIMA (p, d, q) models that passed the diagnostic test and using the selected ARIMA model to forecast the Expected Commodity Price (**P_T**) or Expected Commodity Quantity (**Q_T**), at time T – when the SF-Loan matures. The ARIMA (p, d, q) model selection process involves the use of the Akaike Information Criterion (AIC) and R – squared (R^2). The ARIMA (p, d, q) model with the smallest AIC and highest R^2 is selected as the best model and used to forecast P_T or Q_T.

For instance, if the best model is ARIMA (1, 1, 1), which implies that the time series is integrated to the order of 1 (i.e., because d = 1 – the time series becomes stationary after being differenced once), has one (1) Autoregressive term (i.e., because p =1) and has one (1) Moving Average term. The ARIMA (1, 1, 1) model can be expressed as follows:

$$\Delta y_t = c + \theta_1 \Delta y_{t-1} + \alpha_1 \varepsilon_{t-1} + \varepsilon_t \;\ldots\ldots (3.15)$$

$$\text{where: } \Delta y_t = y_t - y_{t-1};\; \Delta y_{t-1} = y_{t-1} - y_{t-2}$$

Where: c is the constant, y_t is either the current price or quantity value of the commodity; y_{t-1} is the price or quantity of the commodity in the previous period (i.e., Autoregressive (AR) term); ε_{t-1} is the residual of the price or quantity time series in the previous period (Moving Average (MA) term); ε_t is the error term – the unforecastable component, which is assumed to be normally distributed with zero mean and constant variance (i.e., $\varepsilon_t \sim \mathrm{N}(0, \sigma)$); and the symbol delta(Δ) means that the time series is differenced (i.e., $\Delta y_t = y_t - y_{t-1}$). To forecast the time series variable y_t h periods ahead, the ARIMA (1, 1, 1) model must be transformed to its level form, by integrating the ARIMA (1, 1, 1) model as follows:

$$y_t - y_{t-1} = c + \theta_1(y_{t-1} - y_{t-2}) + \alpha_1\varepsilon_{t-1} + \varepsilon_t$$

$$\therefore y_t = c + (1 + \theta_1)y_{t-1} + \theta_1 y_{t-2} + \alpha_1\varepsilon_{t-1} + \varepsilon_t \;\ldots\ldots (3.16)$$

Equation 3.16 above is the level form (integrated form) of the ARIMA (1, 1, 1), i.e. Equation 3.15, which is a differenced equation. Therefore to forecast for instance, the price of a commodity t + h periods ahead, the coefficients α_1, (1 +θ_1) and θ_1 are used as information weights, thus, to forecast the expected commodity price in the next period, t + 1 (i.e., y_{t+1}), the following equation can be used:

$$y_{t+1} = c + (1 + \theta_1)y_t + \theta_1 y_{t-1} + \alpha_1\varepsilon_t + \varepsilon_{t+1} \;\ldots\ldots (3.17)$$

And to forecast y_{t+2} the following equation can be used:

$$y_{t+2} = c + (1 + \theta_1)y_{t+1} + \theta_1 y_{t-1} + \alpha_1\varepsilon_{t+1} + \varepsilon_t = c + (1 + \theta_1)y_{t+1} + \theta_1 y_{t-1} + \varepsilon_v \;\ldots\ldots (3.18);$$

$$\text{where: } \varepsilon_v = \alpha_1\varepsilon_{t+1} + \varepsilon_t$$

Note that after two periods ahead, the Moving Average term becomes part of the unforecastable component (i.e., the error term). The unforecastable component increases with each h period ahead forecast. It is for this reason that time series forecasting models are not used for long horizon forecasts.

However, forecasting can be done easily using Eviews®. In this Study Eviews®6 will be used to conduct the forecasting. The procedure for performing out-of-sample forecasts, using Eviews®6, is illustrated in the Eviews®6 User Guide II (Chapter 27).

3. 2. 2 Estimation of the Mean and Variance of the Residuals [STEP 2]

This step involves the capturing of the residuals of the ARIMA (p, d, q) model that was used to forecast P_T or Q_T, and estimating their mean and variance. Recall that in Step 1 one of the diagnostic checks was that the residuals of the ARIMA model must be white noise. In other words, the residuals must have a zero (0) mean and constant variance (i.e., the residuals must be homoscedastic). Therefore, the mean of the residuals will be assumed to zero, or statistically not significantly difference from zero (0). Hence, the only residual parameter that needs to be estimated is the variance.

The variance of the residuals (or time series) has two characteristics that affect the way it is estimated. The first characteristic is that the variance of the residuals (or time series) remains constant over time , i.e., the residuals are homoscedastic. In other words, the variance of the residuals is time invariant. The second characteristic is that the variance of the residuals (or time series) does not remain constant over time, i.e., the residuals are heteroscedastic. In other words the variance of the residuals (or time series) is time variant. In time series modelling, the Autoregressive Conditional Heteroscedasticity Lagrange Multiplier (ARCH – LM) Test is used to determine whether the residuals are homoscedastic or heteroscedastic. The ARCH-LM test, in Eviews®6 is used in this study.

3. 2. 2. 1 The ARCH-LM Test

The Null Hypothesis (H_0) in the ARCH-LM test is that there is no ARCH effect, meaning that the variance of the time series is homoscedastic, thus, the variance of the time series is time invariant. The Alternative Hypothesis (H_A) is that there is ARCH effect, meaning that the variance of the time series is heteroscedastic, thus, the variance of the time series is time varying.

The Lagrange Multiplier (LM) and F-tests were used to test the null hypothesis of no ARCH effect. Probability values lower than 0.05 (5%) indicate that the null hypothesis is rejected at 5 percent level of significance, indicating that the variance (in essence the volatility or standard deviation) varies over time (i.e., the variance is heteroscedastic).

Accepting or rejecting the Null Hypothesis has implications on how the variance (in essence, the volatility or standard deviation) of the residuals (or time series) is estimated. The estimation of the variance of the residuals under different states (homoscedastic or heteroscedastic) is illustrated in the two sections below.

3. 2. 2. 2 Estimation of the Residual Variance (when the ARCH-LM Test Null Hypothesis is accepted)

Accepting the Null Hypothesis of No ARCH Effect, as already mentioned, implies that the variance of the residuals is homoscedastic. Therefore, variance of the time series can be directly determined from the residuals of the ARIMA (p, d, q) model that was used to forecast in Step 1. The variance of the residuals (in this case) is calculated by squaring the captured residuals (ε_i^2), and finding the average. Therefore the standard deviation (volatility) of the price (σ_p) or the quantity (σ_q) residual can be estimated using the following equation:

$$\sigma_p \text{or } \sigma_q = \sqrt{\mathrm{Var}(X)} = \sqrt{\frac{1}{n}\sum_{i=n}^{n} \varepsilon_i^2} \ldots \ldots (3.19)$$

3. 2. 2. 3 Estimation of the Residual Variance (when the ARCH-LM Test Null Hypothesis is rejected)

Rejecting the ARCH-LM test's Null Hypothesis of No ARCH Effect, means that the variance of the residuals is Heteroscedastic, thus, the variance is time varying. Therefore, the Autoregressive Conditional Heteroscedasticity (ARCH)/Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are estimated using the captured squared residuals. The ARCH/GARCH[22] models are generally expressed as GARCH (**q, p**); where **q** is the number of Autoregressive terms and **p** is the number of Moving Average terms.

Models of conditional variance, in particular GARCH models, have dominated the time series variance estimation literature (Kroner et al., 1994; and Bollerslev et al., 1992). The GARCH (1, 1) specification has received considerable attention and has often been found to be the best specification for conditional volatility (standard deviation) among alternative and more complex variants of GARCH models (Manfredo *et al.,* 2001). The GARCH (1, 1) estimates the conditional variance at any time t, as a function of the previous periods' squared residual (ε_{t-1}^2) (i.e., the ARCH term, thus, Autoregressive term (**p**)) and the previous period's conditional variance (σ_{t-1}^2) (i.e., the GARCH term, thus, Moving Average term (**q**)). The GARCH (1, 1) model is mathematically expressed as follows:

$$\sigma_t^2 = \gamma_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \ldots \ldots (3.20)$$

Where: σ_t^2 is the conditional variance at time t; ε_{t-1}^2 is the squared residuals in the previous period, σ_{t-1}^2 is the conditional variance in the previous period and γ_0, $\alpha_1$and $\beta_1$are coefficients that are

[22] For detailed theoretical discussion of the ARCH and GARCH type of models see Engle (2004 & 2001) and Bollerslev (1986) respectively.

estimated using the Maximum Likelihood procedure. The coefficient in Equation 3.20 must be greater zero (i.e., $\gamma_0 > 0, \alpha_1 > 0$ and $\beta_1 > 0$); and the sum of α_1 and β_1 must be less 1 (i.e., $\alpha_1 + \beta_1 < 1$)[23].

The equation that is used for developing multi-period GARCH variance estimation or forecasting is (Manfredo *et al.,* 2001):

$$\sigma_{p(t+h)} \text{or } \sigma_{q(t+h)} = \begin{cases} \gamma_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 & \text{if } h = 1 \\ \gamma_0 + (\alpha_1 + \beta_1)^h \sigma_{t+h-1}^2 & \text{if } h \geq 2 \end{cases} \ldots \ldots (3.21)$$

Where: $\sigma_{p(t+h)}$ or $\sigma_{q(t+h)}$ are the conditional variance estimates or forecasts at time t + h. The above equation produces individual conditional variance forecasts at each point t + h. The square root of the forecast conditional variance ($\sigma_{p(t+h)}$ or $\sigma_{q(t+h)}$), at time t + h, is the SF-commodity price volatility, for instance, for that period.

The variance (i.e., tentatively standard deviation) estimated either by Equations 3.18 or 3.20 are used in the simulation of the price and quantity of the SF linked commodity, at time T – when the SF-loan matures. The commodity price and quantity simulation procedure are illustrated in the next section.

3. 2. 3 Simulation of the Price and Quantity [STEP 3]

The purpose of simulation is to determine the possible market values of the commodity underlying the SF-loan, at time T – when the SF-loan matures. In other words, the purpose of simulation is to generate the possible values of V_T. The parameters that are used in the simulation are the mean and standard deviation (the square root of the variance) of the residuals. The estimation procedure of the mean and variance of the residuals was illustrated in the previous section.

There are two important points that must be put into consideration, when simulating V_T. The first important point is with reference to the assumption (under Merton's model) that the market value of the firm or farm (in our case the market value of the SF linked commodity) at time T is log-normally distributed (Merton, 1974; Katchova and Barry, 2005; and Crouhy *et al.,* 2000, *inter alia*). In other words, V_T is log-normally distributed. Therefore, this implies that the simulated V_T values must be log-normally (or normally) distributed.

[23]The condition $\alpha_1 + \beta_1 < 1$ ensures the long run stability of the GARCH (1, 1) model, when used for forecasting volatility.

The second important point is with reference to the implementation framework of Merton's model, which has been proposed in this study. This study proposed the determination of the market value of the firm or farm (V) from the market value of the commodity linked to the SF-loan. Hence, V_T is the market value of the SF linked commodity at debt maturity. The proposed implementation framework expresses V_T (i.e., Equation 3.8) as a product of the commodity price and commodity quantity normal distributions. Therefore the simulation process will start by simulating the commodity price and quantity and the multiply the simulated price and quantity values to determine simulated V_T values.

3. 2. 3. 1 Generation of the Random Numbers

The price and quantity of the commodity are simulated by generating random numbers using the Random Number Generation Function (RNGF) in Microsoft Excel (in this study Microsoft Excel®2007 was used). The price or quantity is then simulated by adding the generated random numbers to the forecasted Expected Price (P_T) or Expected Quantity (Q_T). The procedure for generating random numbers using RNGF in Microsoft Excel®2007 is as follows:

1. Open the Microsoft Excel Spread Sheet, on the Main Tool bar, select data, and then go to Data Analysis.
2. In the Data Analysis window select the Random Number Generation function.
3. In the Random Number Generation function window, the following data inputs will be required:
    a) The Number of Variables – which in retrospect means the number of simulations you want to perform. Since we are only interested in a single simulation of price or quantity – number one (1) should be entered.
    b) Number of Random Numbers – which in retrospect means the number of random numbers (or simulated price or quantity values) that we want to simulate. Most simulation studies recommend not less than 500 random numbers this study uses 1000 random numbers. Hence, the number 1000 should be entered.
    c) The type of Distribution – according to the Merton model implementation framework proposed by this study, the price and quantity are normally distributed. The simulated price and quantity values must be normally distributed. Therefore, the distribution that must be selected is the normal distribution.
    d) The Mean of the Distribution – the input for this section is the estimated mean of the residuals captured from the ARIMA model that was used to forecast commodity price

or commodity quantity. Note that although, the value might not be equal to zero (0), statistically mean value is insignificantly different from zero.

e) The Standard Deviation of the Distribution – the input for this section is the estimated standard deviation (estimated in Section 3.2.3.3 above).

f) After entering all the data inputs for each section, click OK. Excel will generate (or simulate) 1000 random numbers. The 1000 random numbers are normally distributed.

Abstractly, the above procedure can be illustrated as follows:

$$\varepsilon_p \sim N(\mu_p, \sigma_p) \xrightarrow{\text{Generate}} [1000 \text{ Random Numbers } (P_{N=1,2,..,1000})] \ldots \ldots (3.23)$$

$$\varepsilon_q \sim N(\mu_q, \sigma_q) \xrightarrow{\text{Generate}} [1000 \text{ Random Numbers } (Q_{N=1,2,\ldots,1000})] \ldots \ldots (3.24)$$

Where: $\varepsilon_p \sim N(\mu_p, \sigma_p)$ and $\varepsilon_q \sim N(\mu_q, \sigma_q)$ denotes the normal distribution of the residuals from the price and quantity forecasting ARIMA models, respectively; $N(\cdot)$ denotes normal distribution; μ_p and μ_q are the mean of the residuals from the *price and quantity forecasting ARIMA model*, respectively; σ_p and σ_q are the standard deviation of the residuals from *price and quantity forecasting ARIMA model*, respectively and P_N and Q_N represents the generated price and quantity random numbers. Equations 3.23 and 3.24, in retrospect illustrates the generation of random numbers from the normal distributions of the error terms of the price and quantity forecasting ARIMA model.

3. 2. 3. 2 Simulation of the Price and Quantity

After the random numbers have been generated, the next step is to simulate the price or quantity by adding the forecast Price (P_T) or forecast Quantity (Q_T) to the generated P_N or Q_N. Recall that the P_T and Q_T were estimated in Section 3.2.1.4. The addition of P_T (or Q_T) to P_N (or Q_N) can be abstractly demonstrated as follows:

$$P_T + \begin{bmatrix} P_{N=1} \\ \vdots \\ P_{N=1000} \end{bmatrix} = \begin{bmatrix} P_T + P_{N=1} \\ \vdots \\ P_T + P_{N=1000} \end{bmatrix} = \begin{bmatrix} P_{S=1} \\ \vdots \\ P_{S=1000} \end{bmatrix} \ldots \ldots (3.25)$$

$$Q_T + \begin{bmatrix} Q_{N=1} \\ \vdots \\ Q_{N=1000} \end{bmatrix} = \begin{bmatrix} Q_T + Q_{N=1} \\ \vdots \\ Q_T + Q_{N=1000} \end{bmatrix} = \begin{bmatrix} Q_{S=1} \\ \vdots \\ Q_{S=1000} \end{bmatrix} \ldots \ldots (3.26)$$

Where: $P_{S=1} = P_T + P_{N=1}$ and $P_{S=1000} = P_T + P_{N=1000}$ and $Q_{S=1} = Q_T + Q_{N=1}$ and $Q_{s=1000} = Q_T + Q_{N=1000}$

The addition demonstrated above yields 1000 simulated (random) numbers of Price (P_S) and Quantity (Q_S) at time T. Each of the simulated (random) numbers represents the possible price or quantity of the commodity at time T. Note that the 1000 simulated Price (P_S) and Quantity (Q_S) numbers are normally distributed with the mean equal to the Expected Price (P_T) or Expected Quantity (Q_T) and variance (in essence standard deviation) equal to the variance of price residuals (σ_p) or quantity residuals (σ_q). In distribution notation, the simulated Price and Quantity numbers can be expressed as follows:

$$\begin{bmatrix} P_{S=1} \\ \vdots \\ P_{S=1000} \end{bmatrix} = P_E \sim N(P_T, \sigma_p) \dots\dots (3.27)$$

$$\begin{bmatrix} Q_{S=1} \\ \vdots \\ Q_{S=1000} \end{bmatrix} = Q_E \sim N(Q_T, \sigma_q) \dots (3.28)$$

Where: P_E and Q_E denote the distributions of the simulated Price and Quantity numbers, respectively. Therefore, Equations 3.27 and 3.28 are expressions of the price and quantity normal distributions, respectively, at time T. The two normal distributions are used in the generation of the V_T-Cumulative Density Function (V_T-CDF).

3. 2. 4 Generation of the V_T-Cumulative Density Function [STEP 4]

The V_T-Cumulative Density Function (V_T-CDF) is generated in three (3) steps. The first step involves the ranking (from the smallest to the largest) of the 1000 simulated Price (P_S) and Quantity (Q_S) values. The second step involves the multiplication of the ranked 1000 simulated P_S and Q_S values; the resulting products are the possible market values of the SF linked commodity at time T – when the SF loan matures. The third step involves the convention of the V_T-normal distribution (created by the multiplication of the simulated price and quantity values in step 2) into a V_T-Cumulative Density Function (V_T-CDF). The first and second steps can be abstractly illustrated as follows:

$$\textbf{Step 1}\text{: rank the 1000 simulate } P_S \text{ and } Q_S \text{ values} \begin{cases} \begin{bmatrix} P_{S=1} \\ \vdots \\ P_{S=1000} \end{bmatrix} \xrightarrow{\text{Rank}} \begin{bmatrix} P_1 \\ \vdots \\ P_{1000} \end{bmatrix}; \text{where } P_1 < P_2 < \cdots < P_{1000} \\ \vdots \\ \vdots \\ \vdots \\ \begin{bmatrix} Q_{S=1} \\ \vdots \\ Q_{S=1000} \end{bmatrix} \xrightarrow{\text{Rank}} \begin{bmatrix} Q_1 \\ \vdots \\ Q_{1000} \end{bmatrix}; \text{where } P_1 < P_2 < \cdots < P_{1000} \end{cases}$$

Step 2: Multiplication of the 1000 ranked simulated P_S and Q_S values $\rightarrow \begin{bmatrix} P_1 \\ \vdots \\ P_{1000} \end{bmatrix} \times \begin{bmatrix} Q_1 \\ \vdots \\ Q_{1000} \end{bmatrix} \equiv \begin{bmatrix} V_1 \\ \vdots \\ V_{1000} \end{bmatrix}$

$$\therefore V_T \text{ normal distribution} \equiv \begin{bmatrix} P_1 \\ \vdots \\ P_{1000} \end{bmatrix} \times \begin{bmatrix} Q_1 \\ \vdots \\ Q_{1000} \end{bmatrix} \equiv \begin{bmatrix} V_1 \\ \vdots \\ V_{1000} \end{bmatrix} \dots \dots (3.29)$$

$$\text{where: } V_1 < V_2 < \cdots < V_{1000}; \text{ and } V_1 = P_1 \times Q_1; \cdots; V_{1000} = P_{1000} \times Q_{1000}$$

In Equation 3.26, the random values V_1 to V_{1000} represent the possible market value of the commodity underlying the SF-loan, at time T. In other words, the market value of the commodity underlying the SF-loan at time T will fall or lie within the boundaries, defined by V_1 (minimum) and V_{1000} (maximum).

The third step involves the convention of the V_T-normal distribution (which is in essence a Probability Density Function (PDF)) to a V_T-Cumulative Density Function (V_T-CDF). A Cumulative Distribution Function (CDF) completely describes the probability distribution of a real random variable X (in this case the real random variable X is V_T – which can take on any of the generated V_N (where N= 1, 2, …, 1000) random numbers in Equation 3.29). Therefore the V_T Cumulative Distribution Function can be expressed as follows:

$$F(V_T) = P(V_T \leq V_N) \dots \dots (3.30)$$

$$\text{where } N = 1, 2, \cdots, 1000$$

The right-hand side of Equation 3.30 is the Probability that the random variable V_T takes on a value of less than or equal to V_N. Using the Probability Theories, the V_TCDF will have the following characteristics:

- The Probabilities of the V_T CDF are restricted to lie between zero (0) and (1) - thus:

$$0 \leq P(V_T \leq V_N) \leq 1]$$

- The probability that V_T takes on any of the generated V_N random numbers is equal to 0.001 - thus:

$$P(V_T = V_1, V_2, \cdots \text{or } V_{1000}) = 0.001$$

- The probability that V_T will lie between V_1 and V_{1000} (the generated V_N random numbers) is equal to 1 – thus:

$$P(V_T = [V_1, V_{1000}]) = 1$$

Therefore the probabilities of the V_TCDF are calculated as follows:

$$P(V_T \leq V_1) = P(V_T = V_1) = 0.001;$$

$$P(V_T \leq V_2) = P(V_T = V_1) + P(V_T = V_2) = 0.002;$$

$$P(V_T \leq V_3) = P(V_T = V_1) + P(V_T = V_2) + P(V_T = V_3) = 0.003;$$

$$\vdots$$

$$P(V_T \leq V_{1000}) = P(V_T = V_1) + P(V_T = V_2) + P(V_T = V_3) + \cdots + P(V_T = V_{1000}) = 1.$$

These calculated Probabilities are used in the next section (3.2.4) to determine the Probability of Default.

3. 2. 5 Estimation of the Probability of Default (PD) from the V_TCDF [STEP 5]

In the context of developed Credit Risk Model, the probability of default (PD) is defined as the likelihood that the market value of the commodity underlying the SF loan[24], V_T, will be less than the face value of the SF loan, D, at time T – when the SF loan matures. Equation 3.3, reproduced below, is the mathematical expression of the Credit Risk Model.

$$\mathrm{PD} = \Pr[V_T < D]$$

In the equation above, V_T represents the Cumulative Density Function (V_T-CDF) of the value of the commodity underlying the SF loan. Therefore, the probability of default (PD) is then defined as the probability that V_T takes on any value that is less than or equal to a random number V_N on the V_T CDF [F (V_T)] and such that the random number V_N is equal to the face value of the SF-loan (D). This can be expressed as follows:

$$\mathrm{PD} = \Pr(V_T \leq [V_N = D]) \dots \dots (3.31)$$

Figure 9 is a graphical depiction of Equation 3.31. The figure illustrates how the probability of default (PD) is determined or read from the V_T-CDF. In the figure the blue curve represents the V_T-CDF and PD_X is the probability that V_N = D, which is the Probability of Default (PD).

[24] Recall that the market value of the commodity underlying the SF loan is equivalent to the market value of the farm's assets (see Section 3.2.1, of this chapter).

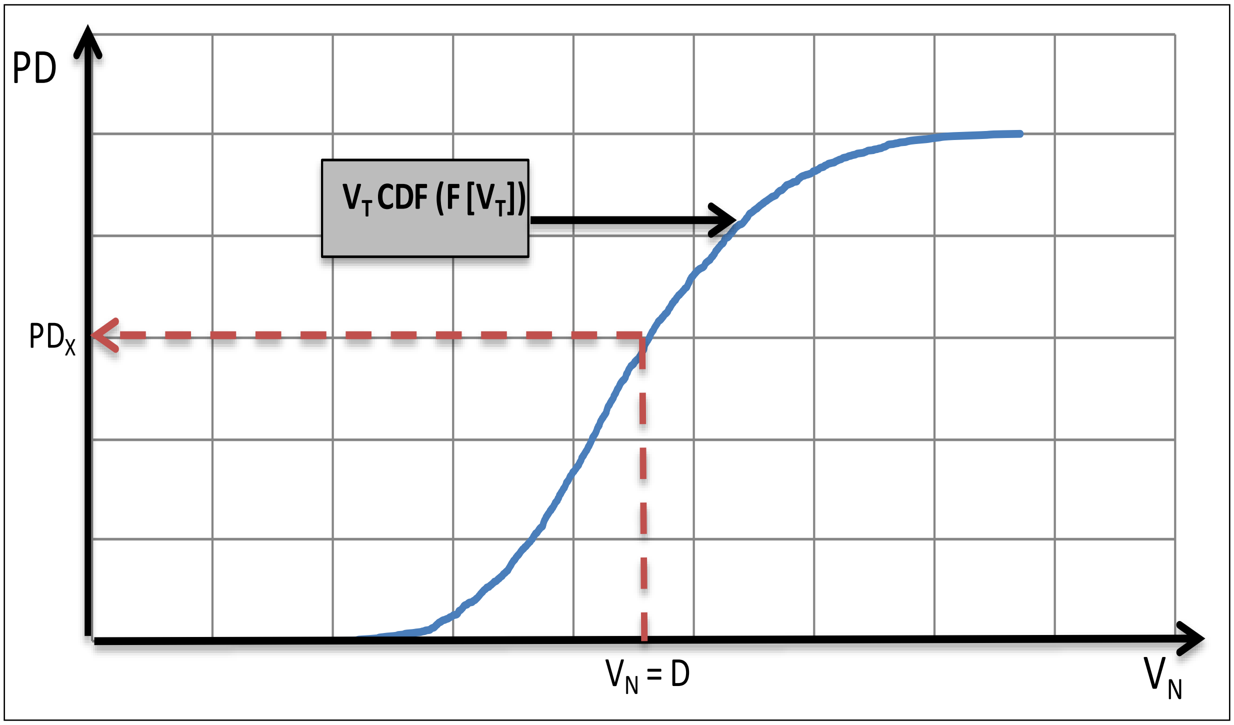

Figure 9: The VT-cumulative distribution function (VT CDF) of VT (F [VT]).

In conclusion, Section 3.2 has illustrated the theoretical as well as the implementation framework of the credit risk model. The section illustrated how the theories proposed by Merton (1974) are used to develop the credit risk model. The section also illustrates how Time Series Econometric Modelling techniques are used to estimate the input parameters of the developed credit risk model (i.e., P_T, Q_T, P_R and Q_R). These parameters are then used to generate the normal distribution of the market value of the farm's assets (V_T). The V_T -normal distribution is transformed into a V_T-CDF, which is then used to determine the Probability of Default (PD).

3. 3 Data Input Requirements

The developed Credit Risk model uses time series modelling techniques (Section 3.2.1) to tentatively determine or estimate the parameters of the normal distribution of the farm's asset value at time T – when the SF loan matures. Therefore like in any other time series modelling technique, the primary data inputs for the developed Credit Risk Model are historical commodity price and commodity yield (quantity) time series data. The time series data should have at least 50 observations.

3. 4 Conclusion

In this chapter, the credit risk model that can be used to measure credit risk in Structured Finance lending transaction has been developed. The theoretical framework of the model is illustrated in Section 3.1. The theoretical framework is based on theories first proposed by Merton (1974). Section 3.2 illustrates the Implementation framework of the model. Unlike other Merton-based credit risk models which calculate the Distance-to-Default (DD) to determine the probability of default, the framework generates the normal distribution of farm asset value at time T and then converts the normal distribution into a Cumulative Density Function (CDF). The model then uses the CDF to determine the probability of default (PD). The probability of default in the model is then defined as the probability of the value of farm assets (V_T) taking on a value on the CDF that is less than or equal to the value of SF loan (D). Therefore, this chapter has achieved the first and second objectives of the study.

CHAPTER FOUR

4.0 APPLICATION OF THE DEVELOPED CREDIT RISK MODEL

This chapter addresses the third objective of the study. This chapter demonstrates the application of the developed Credit Risk Model. In order to demonstrate the application of the developed Credit Risk Model, the study conceptualizes a Structured Finance lending transaction in agriculture. After conceptualizing the SF lending transaction, the study uses the developed Credit Risk Model to measure the credit risk in the lending transaction.

The chapter proceeds as follows: Section 4.1 highlights the conceptualized Structured Finance lending transaction. Section 4.2 illustrates the application of the developed Credit Risk Model. Section 4.3 demonstrates how the Agricultural Lending Institution can use the results, from Section 4.2, in its credit risk management strategy (i.e., the section interprets and demonstrates the result from 4.2). The chapter is concluded in Section 4.4.

4. 1 Conceptualized Example of Structured Finance Lending Transaction

Suppose that during the 2009/2010 production season, a South African financial institution (or Bank) wants to use (or used) a Structured Finance lending technique to extend loans to farmers, in the Free State province, for the production of white and yellow maize. The production loans can be appropriately referred to Structured Finance production loans (i.e., white and yellow SF-production loans). Therefore, like in any other lending transaction, the Bank needs to assess the creditworthiness of the farmer (or borrower) so as to make the following decisions:

- Grant or deny the SF-production loans.
- How much interest rate to charge on the SF-production.
- How much capital to hold against any possible loan losses due to credit risk.

The above are tentatively the general objectives of Bank with regards to credit risk management. The key ingredient or variable that most financial institutions (especially banks) use to achieve the objectives of credit risk management, listed above, is the creditworthiness of the borrower (farmer). Creditworthiness, as earlier defined, is the ability and capacity of the borrower to repay over a specified period of time.

According to Michael et al. (2009) and UNCTAD (2001), in Structured Finance the creditworthiness of the borrower is a function of the profitability of the underlying transaction being financed. For instance, in the *structured financing* of maize production, the creditworthiness of the maize producer (farmer) is a function of the profitability of the maize production activity and not a function of the balance sheet standing of the maize producer (or farmer). Therefore in Structured Finance lending transactions, creditworthiness of the borrower can be defined as the ability of the underlying transaction (e.g. maize production activity) to generate sufficient revenue to repay the SF-production loan – when the SF loan matures.

The probability of default (PD), as already mentioned, is the most widely used standard of the borrower's creditworthiness. The Probability of Default is defined as the likelihood that the borrower will fail to repay the loan amount. Therefore in the context of Structured Finance, PD can be defined as the likelihood that the commodity underlying the SF lending transaction will not generate sufficient revenue to repay the Structured Finance loan (SF loan proxy), at time T – when the SF loan matures.

The developed Credit Risk Model is used to measure the creditworthiness of the borrower (farmer), as the Probability of Default (PD) – thus, the probability that the commodity being financed will not generate sufficient revenue to repay the SF loan. However before the developed Credit Risk Model is applied, it is imperative to put the conceptualized example into perspective. The primary facets of any lending transaction includes: the arrangements in the lending transaction; the loan value (amount to be borrowed); and the maturity period of the loan. These facets are explained in details below, within the context of the conceptualized example of a SF lending transaction.

4. 1. 1 Structural arrangements in the conceptualized example of SF lending transaction

The generic arrangement of the Structured Finance lending transaction is graphically illustrated in Figure 10 below. Figure 10 shows the four (4) chronological steps of the SF lending transaction. The first step **[i.e., Step 1]** involves the financial institution (Bank) taking advantage of the relationships in the Maize Value Chain to leverage the provision of white and yellow maize production loan to the farmer. The farmer uses the production loan to produce white or yellow maize, which is subsequently sold to the Off-taker **[i.e., Step 2]**. The contractual arrangements are such that the Off-taker pays the farmer, for the delivered maize, through the financial institution **[i.e., Step 3]**. After receiving the payments, the financial institution (Bank) deducts loan principal and interest payments, and then pays the balance to the farmer **[i.e., Step 4]**.

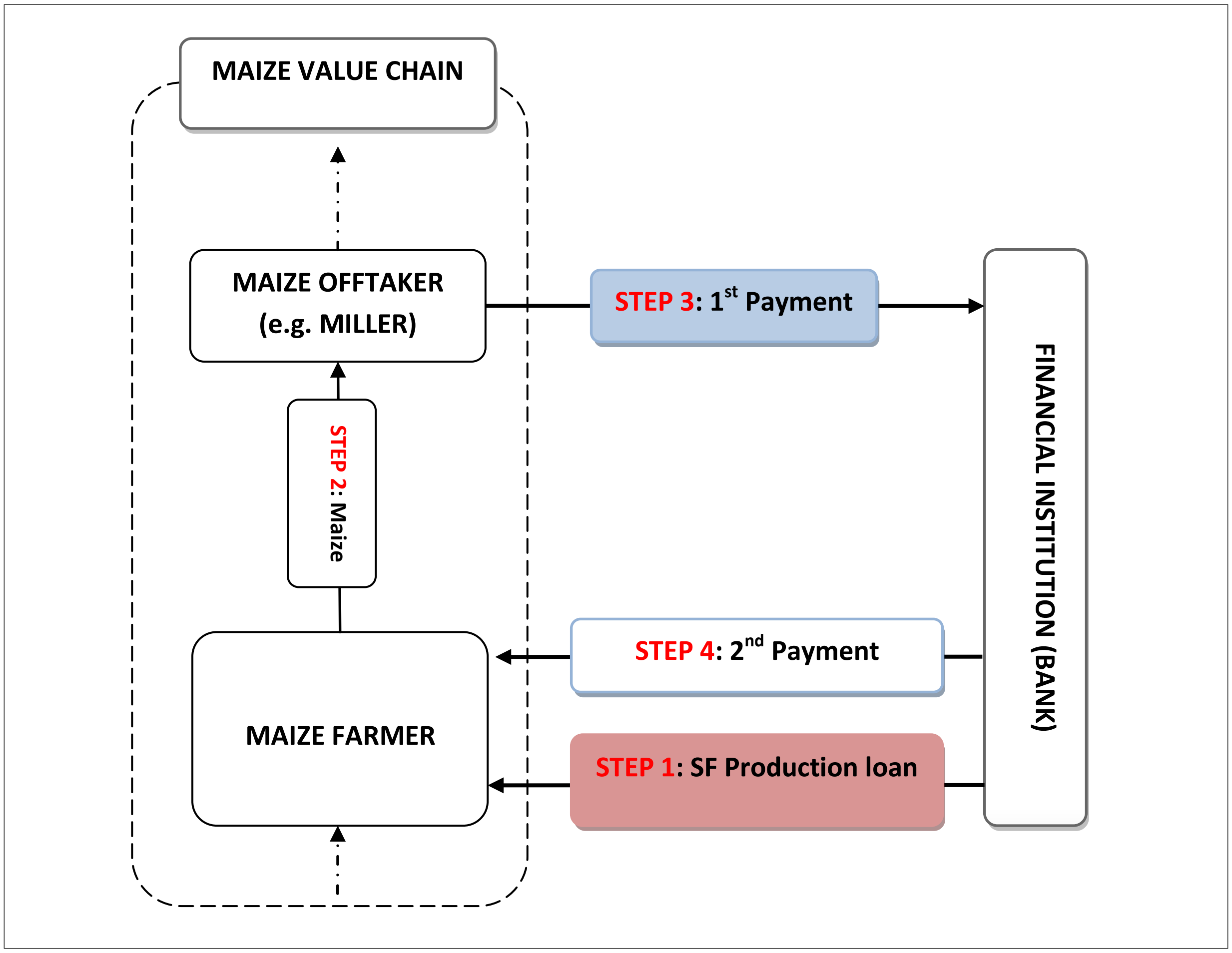

Figure 10: A generic example of a Structured Finance lending transaction for the production of maize.

4. 1. 2 The face value of the Structured Finance loan

For the purposes of demonstrating the application of the developed credit risk model, Structured Finance loan proxies are used[25]. The SF loan proxies are derived from the cost of producing maize on per hectare basis, in the Free State province. The face value of the Structured Finance loan proxies are assumed to be equal to the Total Cost of producing dry-land maize (on per hectare basis) multiplied by the Bank's Target Leverage Ratios (TLR) of 75%, 50% and 25% - thus:

$$\mathrm{D} \;= \text{Total Cost of Production (per HA)} \times \text{TLR [TLR} = 75\%, 50\% \text{ or } 25\%] \ldots\ldots (4.1)$$

Where D – denotes the Structured Finance loan proxy and TLR denotes the Target Leverage Ratio. A TLR of, for instance, 75% means that the Bank is willing to finance 75% of the farmer's Total Variable Cost of

[25] Note that in the practical application of the developed Credit Risk Model, the Bank must use the actual loan value that the farmer is seeking to borrow.

producing white or yellow maize on per hectare basis. In other words, the Bank is willing to contribute 75% towards the Total Cost of producing the commodity, on per hectare basis.

During the 2009/2010 production season the average cost of producing maize (on per hectare basis) in the Free State province was R 5 045.53/ha. This figure, R 5 045.53/ha, is an average calculated from two (2) Dry-land Maize Production Enterprise Budgets for areas in the Free State province[26]. The enterprise budgets were derived or downloaded from Grain South Africa website[27]. The enterprise budgets are given in Appendix I. Therefore, the face values of the Structured Finance loan proxies are given in Table 4 below.

Table 4: Structured Finance Loan Proxies

Structured Finance Loan Proxies	Structured Finance Loan Value (Rand/ha)
D_1 (75% of the Total Cost of production)	3 784
D_2 (50% of the Total Cost of production)	2 522
D_3 (25% of the Total Cost of production)	1 261

4. 1. 3 Maturity period of the Structured Finance loan

In South Africa, maize (yellow and white) is planted during the late spring/early summer months, with optimal planting times between November and December. Planting can, however, start as early as October and extend to January. In a particular season, the rainfall pattern and other weather conditions determine the planting period as well as the length of the production season. The majority of the maize is harvested from late May up to the end of August.

In Structured Finance lending techniques, loan origination period usually coincides with the production season; and the loan maturity period usually coincides with marketing season. In other words, in Structured Finance lending techniques, loan origination and maturity periods are structured around the farmer's inputs purchasing and commodity selling periods, respectively. Therefore in the conceptualized example of SF lending transaction, the loan origination period is assumed to be anywhere between

[26] The enterprise budgets are for areas in the Free State province – thus: Reitz, Bethlehem and Kestell; and Welkom, Odenadaalrus, Wesselbron, Bulfontein and Hoopstald.
[27] www.grainsa.co.za

October 2009 and January 2010 (i.e., this is the period when dry-land maize is planted in South Africa). The loan maturity period will be assumed to be anywhere between August 2010 and December 2010[28].

4. 2 Application of the developed Credit Risk Model

The developed credit risk model is used to measure the credit risk in associated with the white and yellow maize Structured Finance production loans (i.e., D_1, D_2 and D_3). As already mentioned above, the developed Credit Risk Model will measure the credit risk in the Structured Finance production loan as the Probability of Default – thus, the probability that the market value of the yellow or white maize, on per hectare basis, at debt maturity (i.e., between August 2010 and December 2010) will be less than the face value of the SF loan (i.e., D_1, D_2 and D_3).

The five (5) chronological steps of implementation framework of the developed Credit Risk Model are followed or used in order to estimate the Probability of Default (PD). The chronological steps were discussed extensively in Section 3.2, of Chapter three (3). The five (5) chronological steps are applied in this section in order to determine the Probability of Default (PD).

4. 2. 1 Time series modelling [STEP 1]

As illustrated in Section 3.2 of Chapter three (3), objective of this step is to estimate the input parameters of the developed Credit Risk Model. The parameters that must be determined include:

1. The Expected Price (P_T) of white and yellow maize at debt maturity – thus, during the period October 2010 and December 2010.
2. The Expected Quantity or Yield (Q_T) of white and yellow maize (on per hectare basis) in 2010, in the Free State province.
3. The Expected Price Risk (P_R) of white and yellow maize at debt maturity – thus, during the period October 2010 and December 2010. In other words the Expected Price Volatility (or standard deviation) of white and yellow maize during the period October 2010 and December 2010.
4. The Expected Quantity Risk (Q_R) of white and yellow maize in 2010.

Time series modelling techniques are used to determine the four (4) parameters, listed above. The primary data inputs are the price and quantity (yield) time series data for white and yellow maize. The price time series are White and yellow maize monthly Spot prices (Rand/ Ton), from January 1998 to

[28] Note that the SF loan has a maturity period of one (1) year. This is consistent with the maturity period of many agricultural working capital (or production) loans.

December 2009 (132 observations) – these are Randfontein prices. The quantity time series consists of annual white and yellow maize yield data (Tons/ Ha), from 1966 to 2009, for the Free State province. Figures 11 and 12 depicts the white and yellow maize monthly spot price time series, respectively; while Figures 13 and 14 depicts the annual white and yellow maize quantity (yield) time series, respectively.

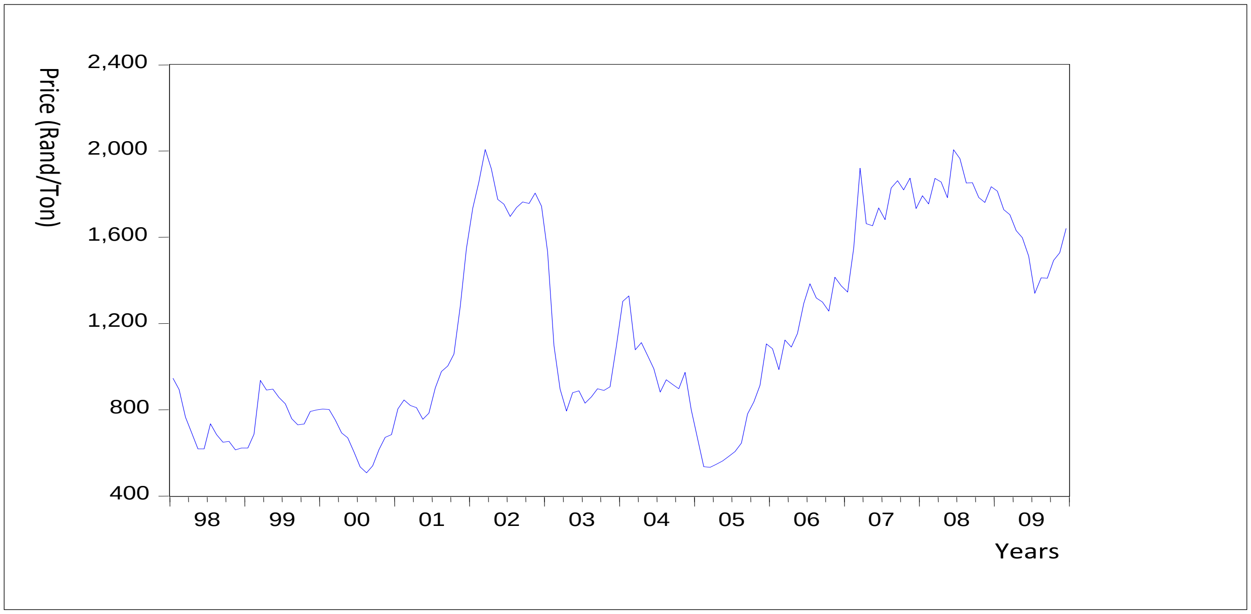

Figure 11: Monthly white maize spot price time series (January 1998 – December 2009)

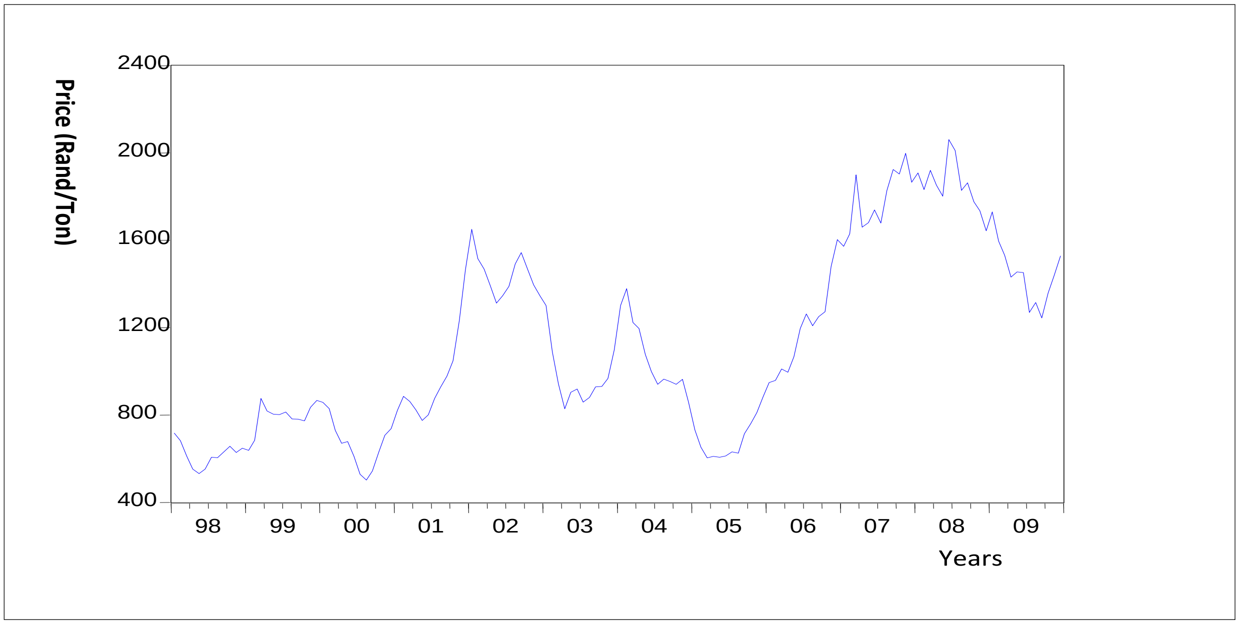

Figure 13: Monthly yellow maize spot price time series (January 1998 – December 2009)

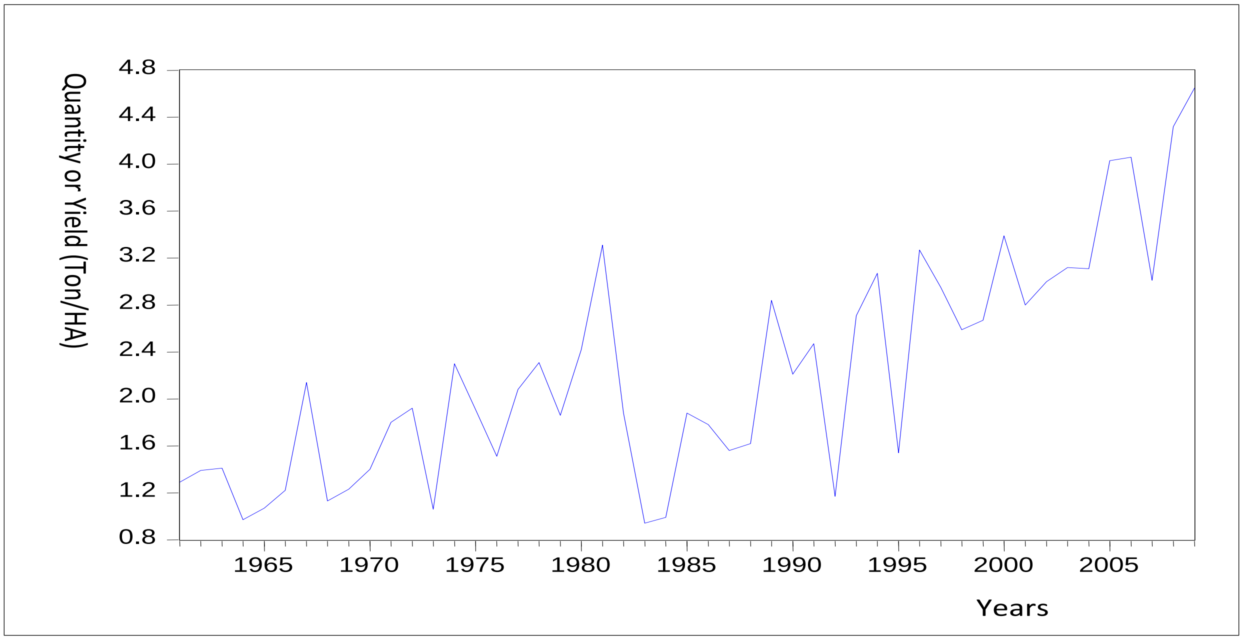

Figure 14: White maize quantity (or yield) time series (1961 -2009)

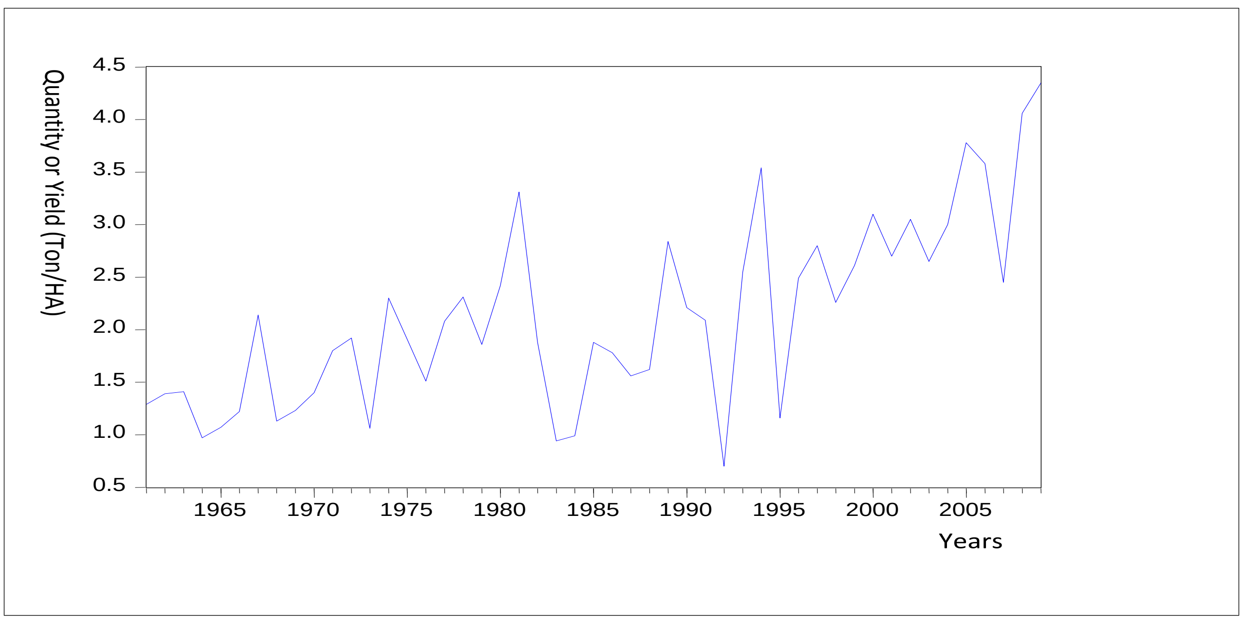

Figure 15: Yellow maize quantity (or yield) time series (1961 – 2009)

The white and yellow maize price time series data was collected from the South African Futures Exchange (SAFEX) website[29] as well as from the Grain South Africa website. The white and yellow maize quantity (or yield) time series data was collected from Grain South Africa website as well as from the

[29] www.safex.co.za

National Department of South Africa (Abstract of Agriculture, 2009). The actual data that was used to generate the above figures are given in Appendix II.

4. 2. 1. 2 Time series forecasting: the Box-Jenkins methodology

This step involves the use of the price and quantity time series (for yellow and white maize) to develop Autoregressive Integrated Moving Average Models (ARIMA). The ARIMA (p, d, q) models are then used to forecast the Expected Price (P_T) or Expected Quantity (Q_T). As already illustrated in Section 3.2.1 (in Chapter 3), the Box-Jenkins (1976) methodology tentatively involves the identification of the parameters number of Autoregressive (AR) terms (p); the time series' order of integration (d) and the number of Moving Average (MA) terms (q).

However, before the parameters of the ARIMA models are determined, the price time series were transformed from Rand/Ton to Rand/Kg in order to work or model with small values. The seasonal component of the yellow and white maize price time series were also removed, using the Seasonal Adjustment Function in Eviews®6. Figures 15 and 16 depict the seasonal adjustment of the white and yellow maize price time series, respectively. The deseasonalized price time series as well as the yield (quantity) time series were converted into natural numbers – by logging the time series.

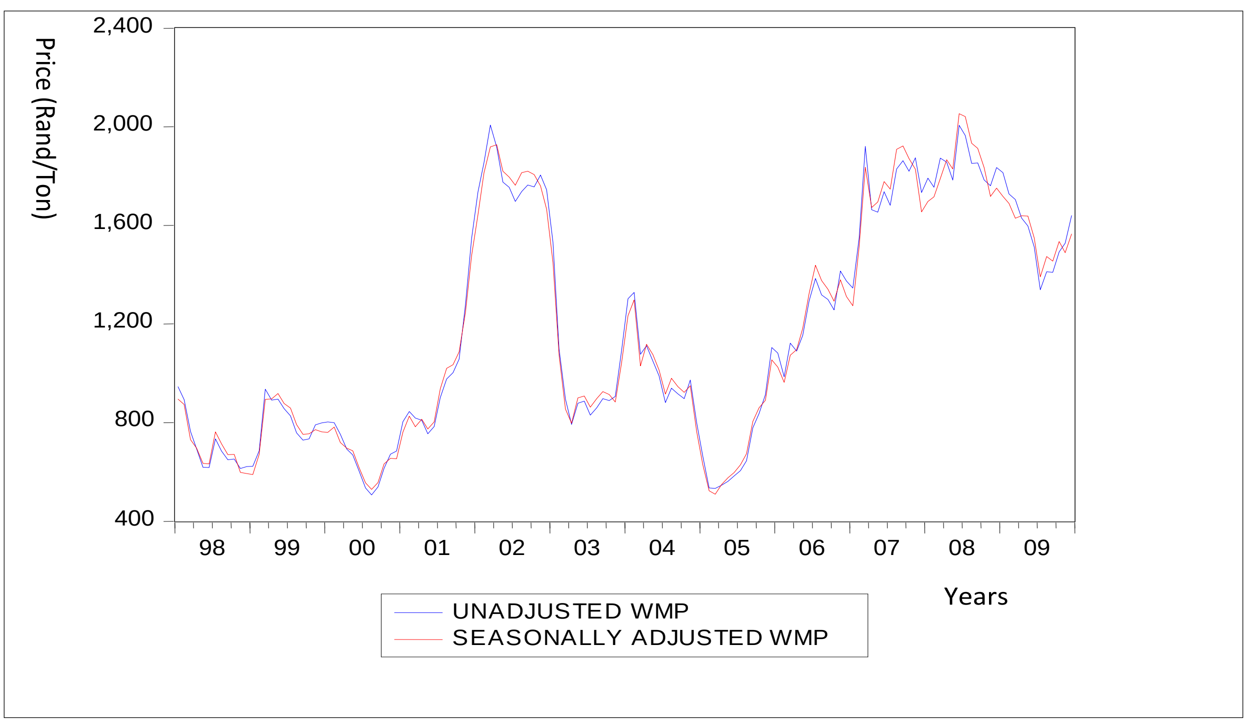

Figure 16: Seasonally adjusted white maize price time series

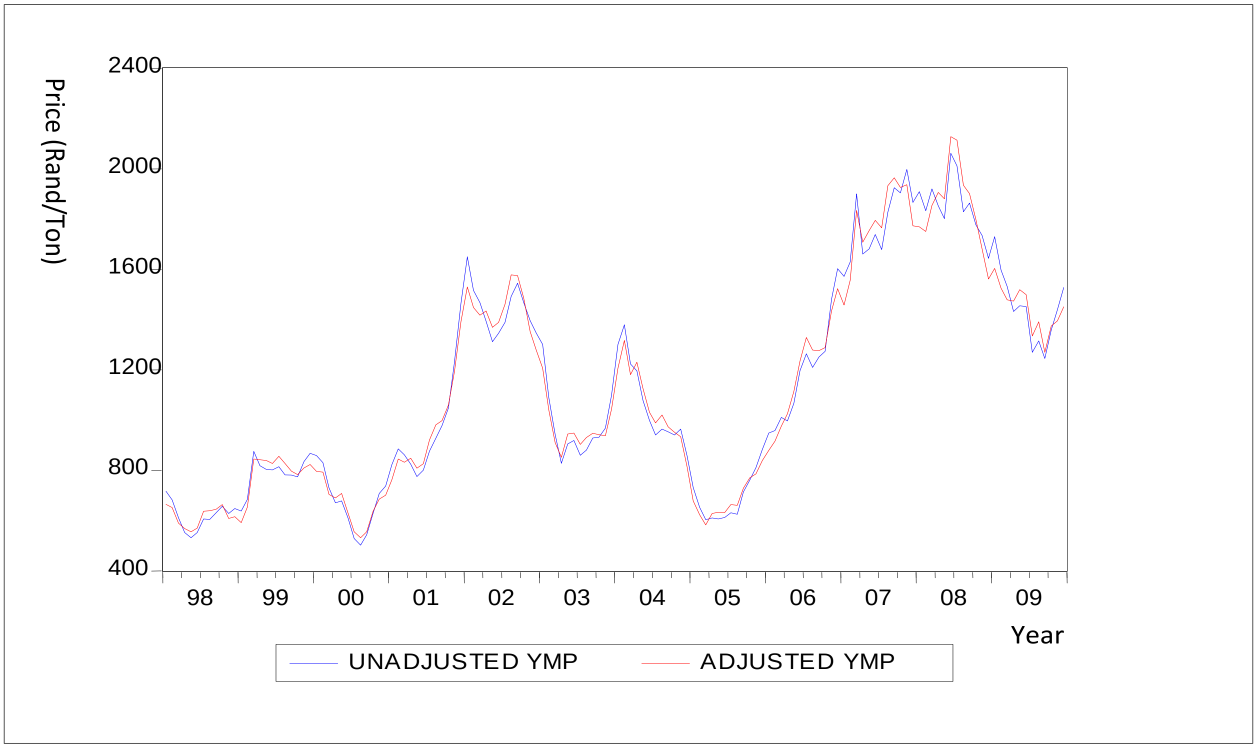

Figure 15: Seasonally adjusted yellow maize price time series

4. 2. 1. 2. 1 Determining the time series' Order of Integration (d)

The Augmented Dickey Test (illustrated in Section 3.2.1.1, in Chapter 3) is used to determine the orders of Integration of the time series. The Augmented Dickey Fuller Tests were performed using Eviews®6 statistical software. The results of the Augmented Dickey Fuller Test are summarized in Table 5 below:

Table 5: Summarized results of the Augmented Dickey Fuller (ADF) test

Commodity	Time Series	Augmented Dickey Fuller Statistic[1]		Critical Values (95%)
		Levels[2]	First Difference	
White Maize	Price	0.289162	-8.103776	-2.581349
	Quantity (yield)	1.216181	-9.055802	-1.948140
Yellow Maize	Price	0.064198	-9.173223	-1.943090
	Quantity (yield)	0.843607	-9.952439	-1.948140

1 Absolute value of the ADF statistic needs to be higher than the absolute value of the critical value to reject the null hypothesis of unit root (non-stationarity).

2 Levels refer to the original series (before it was differenced).

The ADF test results summarized in Table 4 indicates that all the time series had a unit root in their level form. In other words, in their level form, all the time series are non-stationary. This decision is arrived at because the absolute values of the ADF statistic for all the time series are less than the critical value at 95% significant level.

From Table 5, it can be deduced that all the time series become stationary after being differenced once. This is because the absolute values of the ADF statistic for all the time series in the first difference form were greater than the critical values at 95% confidence level. Therefore it can be concluded that all the time series are integrated to the order of one (1), meaning the time series must be differenced once to make them stationary. Hence, the value of ARIMA parameter d is 1 (i.e., d = 1).

Figures 17 and 18 depict the differenced seasonally adjusted white and yellow maize price time series, respectively; while Figures 19 and 20 depicts the differenced white and yellow maize quantity time series. Note that all the four (4) figures clearly show that the time series became stationary after being differenced once. Therefore it can be concluded that all the four time series are Integrated to the Order of one (1).

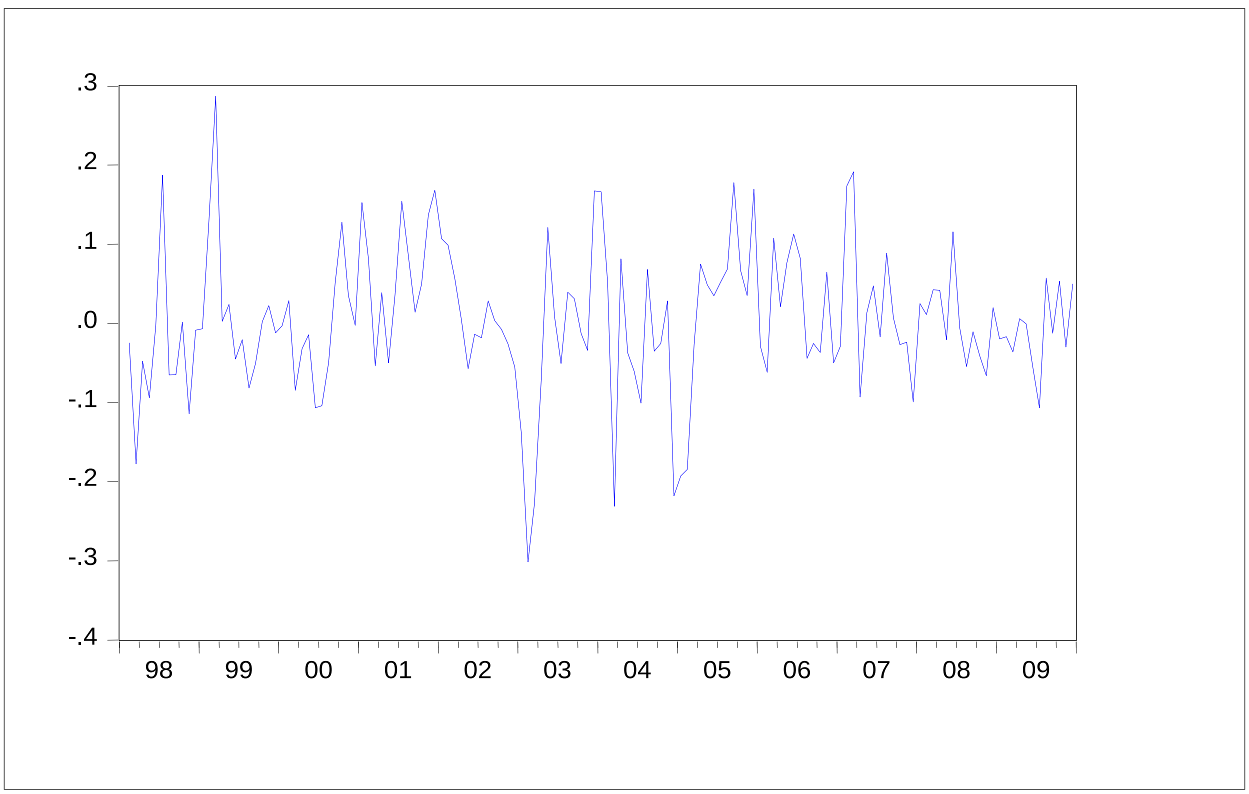

Figure 17: Differenced seasonally adjusted white maize price time series

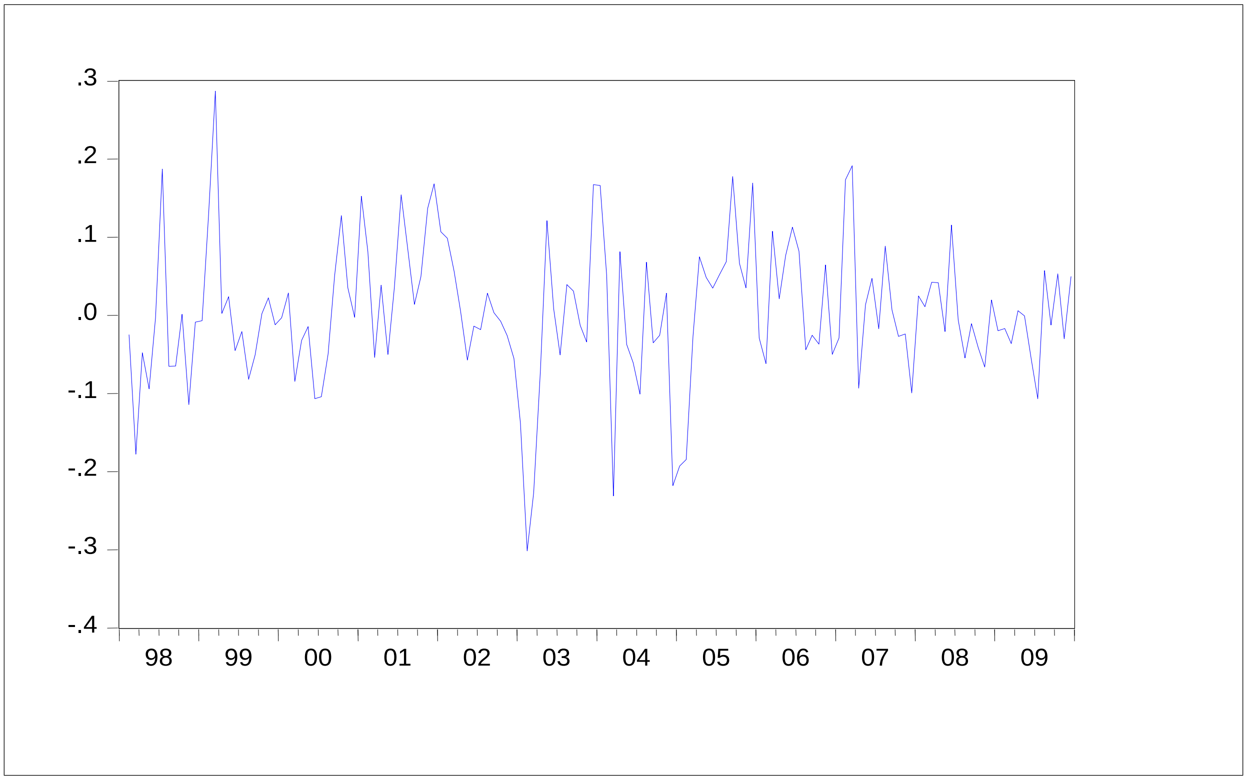

Figure 18: Differenced seasonally adjusted yellow maize price time series

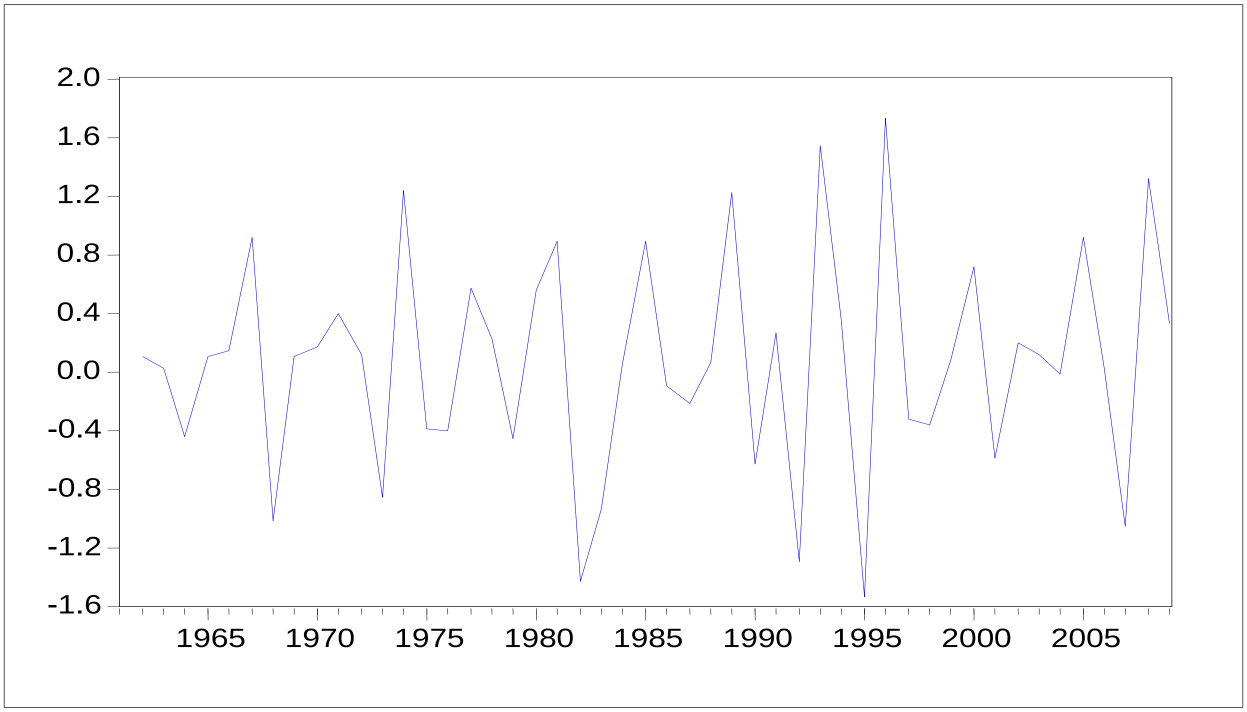

Figure 19: Differenced white maize quantity (yield) time series

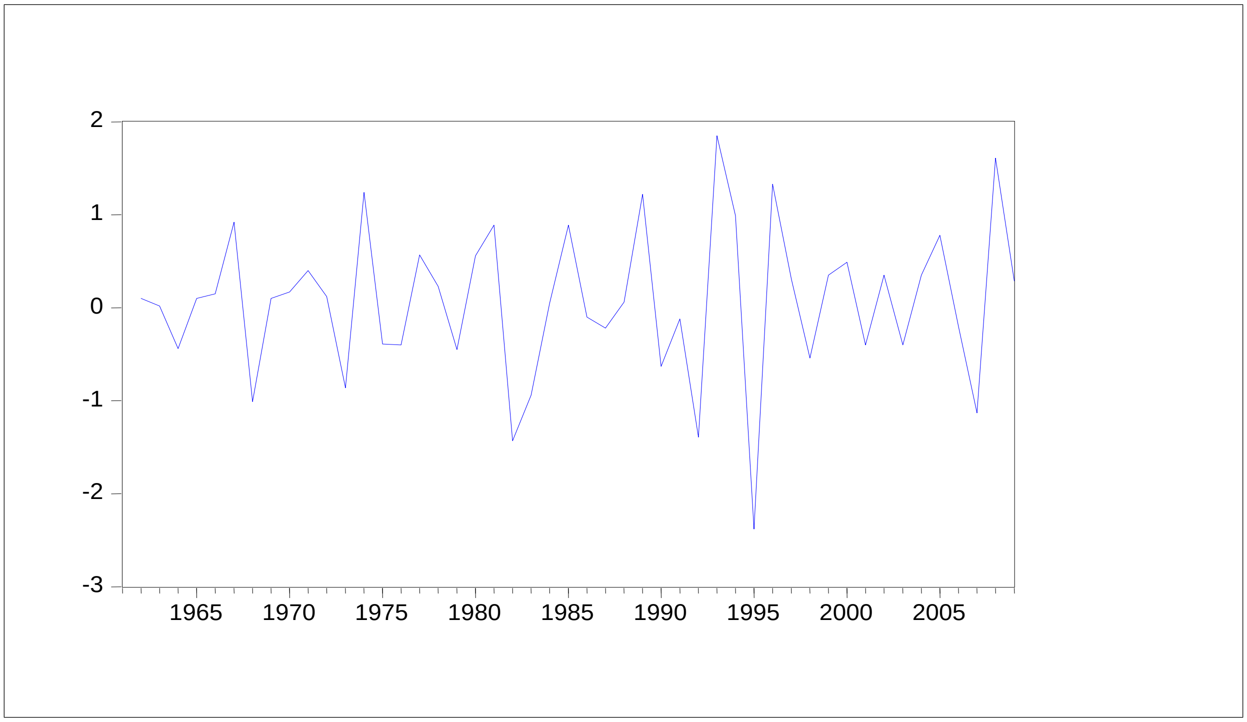

Figure 20: Differenced yellow maize quantity (yield) time series

4. 2. 1. 2. 2 Determination of the ARIMA model parameters p and q

Based on the methodology illustrated in Section 3.2.1 (in Chapter 3), Table 6 highlights the ARIMA models that fit the white and yellow maize price and quantity time series. These ARIMA models passed the diagnostics test highlighted in Section 3.2.1.3 (in Chapter 3). The best ARIMA model for each time series is selected based on the R-squared (R^2) and Akaike Information Criterion (AIC). The ARIMA model with the highest R^2 and lowest AIC is selected, and used in further analysis.

The white maize price time series can be modelled as (or can follow) ARIMA (3, 1, 2); ARIMA (2, 1, 3); ARIMA (0, 1, 1) and ARIMA (1, 1, 0). ARIMA (3, 1, 2) is the best ARIMA model or process for the white maize price time series because it has the highest R-squared and the lowest AIC (see the last two columns in Table 6). Therefore ARIMA (3, 1, 2) is the time series model that is used to forecast or determine the Expected Price of white maize. This model will also be used to estimate the Expected Price Volatility (Standard Deviation) of white maize.

The white maize quantity time series can be modelled as ARIMA (3, 1, 0); ARIMA (0, 1, 1); ARIMA (2, 1, 0) and ARIMA (1, 1, 0). ARIMA (3, 1, 0) is the best ARIMA model or process for the white maize quantity time series because it has the highest R-squared and the lowest AIC. Therefore, ARIMA (3, 1, 0) is the time series model that will be used to forecast the Expected white maize quantity in 2010. The model will also be used to estimate the white maize quantity volatility.

Table 6: ARIMA Models that fit White and Yellow Maize Price and Quantity Time Series

Commodity	Time Series	ARIMA Models			R – Squared (%)	AIC
		p	**d**	**q**		
White Maize	Price	3	1	2	20.72	-2.1567
		2	1	3	19.20	-2.1428
		0	1	1	13.34	-2.1136
		1	1	0	13.02	-2.1035
	Quantity	3	1	0	40.79	1.9507
		0	1	1	37.50	1.9692
		2	1	0	36.14	1.9702
		1	1	0	14.78	2.1920
Yellow Maize	Price	5	1	4	25	-2.6219
		3	1	2	20.79	-2.6102
		1	1	0	12.25	-2.5713
		0	1	1	11.54	-2.5704
	Quantity	3	1	0	42.32	2.0644

The yellow maize price time series can be modelled as ARIMA (5, 1, 4); ARIMA (3, 1, 2); ARIMA (1, 1, 0) and ARIMA (0, 1, 1). ARIMA (5, 1, 4) is the best model for the yellow maize price time series because it has the highest R-squared and the lowest AIC. Therefore, ARIMA (5, 1, 4) will be used to forecast the Expected Price yellow maize. This model will also be used to estimate the Expected Price Volatility of yellow maize.

The yellow maize quantity time series can only be modelled as ARIMA (3, 1, 0). This model will be used to forecast the Expected Quantity (yield) of yellow maize (per hectare) in 2010. The model will also be used to estimate the Expected Quantity Volatility of yellow maize.

4. 2. 1. 2. 3 Forecasting the Expected Price (P_T) and Expected Quantity (Q_T) of white and yellow maize

The best ARIMA models identified in Section 4.2.2.1.2, above, are used to forecast the Expected Price (P_T) and Expected Quantity (Q_T) of yellow and white maize in 2010. The forecasting procedure is illustrated in the Eviews®6 User Guide II.

4. 2. 1. 2. 3. 1 Estimation of the Expected Price (P_T) of white and yellow maize at debt maturity period

ARIMA (3, 1, 2) and ARIMA (5, 1, 4) were selected as the best models for forecasting the price of white and yellow maize, respectively. Figures 21 and 22 below are the Eviews ®6 outputs for the ARIMA (3, 1, 2) and ARIMA (5, 1, 4), respectively.

Dependent Variable: D(LNWMP)
Method: Least Squares
Date: 03/14/10 Time: 09:27
Sample (adjusted): 1998M05 2009M12
Included observations: 140 after adjustments
Convergence achieved after 37 iterations
MA Backcast: 1998M03 1998M04

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.885520	0.102853	-8.609574	0.0000
AR(2)	-0.426631	0.110125	-3.874072	0.0002
AR(3)	0.322305	0.082024	3.929407	0.0001
MA(1)	1.321822	0.072177	18.31366	0.0000
MA(2)	0.911064	0.070602	12.90430	0.0000

R-squared	0.207213	Mean dependent var	0.005782
Adjusted R-squared	0.183723	S.D. dependent var	0.089519
S.E. of regression	0.080879	Akaike info criterion	-2.156670
Sum squared resid	0.883085	Schwarz criterion	-2.051611
Log likelihood	155.9669	Hannan-Quinn criter.	-2.113977
Durbin-Watson stat	1.979296		

Inverted AR Roots	.36	-.63+.70i	-.63-.70i
Inverted MA Roots	-.66+.69i	-.66-.69i	

Figure 21: Eviews®6 output for ARIMA (3, 1, 2) – the best ARIMA model for forecasting white maize price

Dependent Variable: D(LNYMP)
Method: Least Squares
Date: 03/14/10 Time: 10:17
Sample (adjusted): 1998M07 2009M12
Included observations: 138 after adjustments
Convergence achieved after 39 iterations
MA Backcast: 1998M03 1998M06

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	0.255424	0.085588	2.984350	0.0034
AR(2)	-0.491154	0.033626	-14.60654	0.0000
AR(3)	0.151365	0.054638	2.770313	0.0064
AR(4)	-0.863532	0.032277	-26.75381	0.0000
AR(5)	0.317653	0.079923	3.974460	0.0001
MA(1)	0.096952	0.021636	4.481080	0.0000
MA(2)	0.610376	0.023305	26.19064	0.0000
MA(3)	0.102351	0.021694	4.718012	0.0000
MA(4)	0.949152	0.014727	64.44855	0.0000

R-squared	0.254030	Mean dependent var	0.006768
Adjusted R -squared	0.207769	S.D. dependent var	0.071426
S.E. of regression	0.063574	Akaike info criterion	-2.610217
Sum squared resid	0.521380	Schwarz criterion	-2.419310
Log likelihood	189.1050	Hannan -Quinn criter.	-2.532637
Durbin -Watson stat	1.961038		

Inverted AR Roots	.55+.78i	.55 -.78i	.36	-.61 -.77i
	-.61+.77i			
Inverted MA Roots	.55 -.82i	.55+.82i	-.60 -.78i	-.60+.78i

Figure 22: Eviews®6 output for ARIMA (5, 1, 4) – the best ARIMA model for forecasting yellow maize price

In the two Eviews®6 outputs below, D(LNWMP) and D(LNYMP) denote the logged and differenced (once) white and yellow maize price time series, respectively. D(LNWMP) is the dependant variable for the ARIMA (3, 1, 2) model and D(LNYMP) is the dependant variable for the ARIMA (5, 1, 4) model. Note that the coefficients of all the AR and MA terms are all significant at 1% confidence level[30]. Also note that the AR and MA roots are inverted (the last two rows in the outputs), which implies that the residuals of ARIMA (3, 1, 2) and ARIMA (5, 1, 4) are white noise. This means that the two ARIMA models fit their respective time series properly.

In terms of the general statistics of the models, ARIMA (3, 1, 2) and ARIMA (5, 1, 4) have R-squared value of 0.207213 (approx. 20.72%) and 0.254030 (approx. 25.40%) respectively. The R-squared imply that ARIMA (3, 1, 2) has an in-sample white maize monthly price prediction accuracy of 20.72%; while ARIMA (5, 1, 4) has an in-sample yellow maize monthly price prediction of 25.40%. It is assumed that the model's prediction accuracy also holds, when out-sample forecasts are done. The Durbin-Watson

[30] The probability values (P-value), the last column in Figures 22 and 23 are all less than 1%.

statistic for the two ARIMA models is close to 2, implying that there is no serial autocorrelation in the models.

The two ARIMA models are used to forecast the Expected monthly spot prices of white and yellow maize at debt maturity. In other words the two ARIMA models are used to determine the Expected Price of white and yellow maize during the period October 2010 and December 2010. The out-of-sample forecast was done using Eviews®6. Since both time series contained monthly spot prices, 12 out-of-sample forecasts were done. The results of the forecast are given in Table 7 below.

Table 7: Forecast white and yellow maize monthly prices

Month	Forecast White Maize Price			Forecast Yellow Maize Price		
	Price (R/Kg)[a] [Natural log]	Price (R/Kg)[b] [Real Number]	Price [c] (R/Ton)	Price (R/Kg)[a] [Natural log]	Price (R/Kg)[b] [Real Number]	Price [c] (R/Ton)
Jan 2010	0.47899	1.61444	1614.44	0.36495	1.44044	1440.44
Feb 2010	0.51555	1.67456	1674.56	0.35390	1.42641	1424.61
Mar 2010	0.51281	1.66998	1669.98	0.32413	1.38283	1382.83
Apr 2010	0.49453	1.63973	1639.73	0.30863	1.36156	1361.56
May 2010	0.52367	1.68822	1688.22	0.38752	1.47332	1473.32
Jun 2010	0.50478	1.65663	1656.63	0.40150	1.49406	1494.06
Jul 2010	0.50318	1.65398	1653.98	0.38616	1.47131	1471.31
Aug 2010	0.52205	1.68548	1685.48	0.39126	1.47884	1478.84
Sep 2010	0.49994	1.64862	1648.62	0.32916	1.38980	1389.80
Oct 2010	0.51095	1.68880	1688.80	0.32153	1.37924	1379.24
Nov 2010	0.51672	1.67651	1676.51	0.36855	1.44564	1445.64
Dec 2010	0.49979	1.64837	1648.37	0.36558	1.44134	1442.34

[a] Forecast price of white and yellow maize in natural log form (units: Rand/Kg)
[b] Forecast price of white and yellow maize in real numbers (units: Rand/Kg).
[c] Forecast price of white and yellow maize (units: Rand/Ton).

Table 7 shows that ARIMA (3, 1, 2) and ARIMA (5, 1, 4) models predicts or forecasts the average Expected white and yellow maize monthly spot prices (P_T) during the period in October 2010 and December 2010 to be R1666.88/ton and R1379.24/ton, respectively. These prices will be used later in the generation of the white and yellow maize price normal distributions.

4. 2. 1. 2. 3. 2 Forecasting the Expected Quantity (Q_T) of White and Yellow Maize in 2010

In Section 4.2.1.2.2, ARIMA (3, 1, 0) was selected as the best model for forecasting both the Expected Quantity of white and yellow maize in 2010. Note that ARIMA (3, 1, 0) is a pure Autoregressive (AR) process, with three (3) AR terms. Figures 23 and 24 are the Eviews®6 outputs for the white and yellow maize ARIMA models, respectively. In Figures 24 and 25, D(WMQ) and D(YMQ) – i.e., the dependant variables, denotes the differenced white and yellow maize quantity time series

Dependent Variable: D(WMQ)
Method: Least Squares
Date: 05/14/10 Time: 16:49
Sample (adjusted): 1965 2009
Included observations: 45 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.063470	0.034273	1.851909	0.0712
AR(1)	-0.723427	0.150295	-4.813379	0.0000
AR(2)	-0.678694	0.161587	-4.200164	0.0001
AR(3)	-0.276566	0.156446	-1.767810	0.0845

R-squared	0.409796	Mean dependent var	0.081778
Adjusted R-squared	0.366611	S.D. dependent var	0.772891
S.E. of regression	0.615111	Akaike info criterion	1.950659
Sum squared resid	15.51283	Schwarz criterion	2.111252
Log likelihood	-39.88984	Hannan-Quinn criter.	2.010527
F-statistic	9.489188	Durbin-Watson stat	2.058805
Prob(F-statistic)	0.000069		

Inverted AR Roots	-.12-.74i	-.12+.74i	-.49

Figure 23: Eviews®6 output for ARIMA (3, 1, 0) – the ARIMA model for forecasting white maize Quantity

Dependent Variable: D(YMQ)
Method: Least Squares
Date: 05/14/10 Time: 17:24
Sample (adjusted): 1965 2009
Included observations: 45 after adjustments
Convergence achieved after 3 iterations

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(1)	-0.669473	0.149414	-4.480666	0.0001
AR(2)	-0.727257	0.152082	-4.782001	0.0000
AR(3)	-0.273708	0.156989	-1.743483	0.0886

R-squared	0.423171	Mean dependent var	0.075111
Adjusted R-squared	0.395702	S.D. dependent var	0.846159
S.E. of regression	0.657775	Akaike info criterion	2.064432
Sum squared resid	18.17205	Schwarz criterion	2.184877
Log likelihood	-43.44973	Hannan-Quinn criter.	2.109333
Durbin-Watson stat	2.062102		

Inverted AR Roots	-.12+.78i	-.12-.78i	-.44

Figure 24: Eviews®6 output for ARIMA (3, 1, 0) – the best ARIMA model for forecasting yellow maize Quantity

In terms of the general statistics of the models, ARIMA (3, 1, 0) for white maize has an in-sample prediction or forecasting accuracy of about 40.98% (i.e., the R-squared). ARIMA (3, 1, 0) for yellow maize has an in-sample prediction or forecasting accuracy of about 42.32%. The Durbin-Watson statistic for both models is close to 2, meaning that there is no serial autocorrelation.

The two ARIMA models were used to forecast the Expected white and yellow maize quantity (yield) in 2010. Since the time series has annual yield (quantity) data, only one (1) out-of-sample forecast was done. The results of the forecasts are given in Table 8 below. The white and yellow maize quantity ARIMA (3, 1, 0) models predicts or forecasts the Expected White and Yellow Maize yield (or Quantity) to be 3.87 ton/ha and 3.29 ton/ha, respectively, in 2010.

Table 8: Forecast Annual White and Yellow Maize Quantity (yield)

Year	Forecast White Maize Quantity (yield)		Forecast Yellow Maize Quantity (yield)	
	Quantity (natural log)[a]	Quantity (real)[b]	Quantity (natural log)[a]	Quantity (real)[b]
2010	1.354	3.87	1.191	3.29

The values in column a are in natural log form; while the values in column b are real numbers. The value in column b is the exponential of the value in column a.

4. 2. 2 Estimation of the Mean and Variance of the Residuals [STEP 2]

As illustrated in Section 3.2.3, in Chapter three (3), the residuals from the ARIMA models that were used to forecast the Expected Price (P_T) and Quantity (Q_T) of white and yellow maize were captured and then the ARCH-LM Test was performed in order to determine, which procedure to use for estimating the variance. The results from the ARCH-LM Test are summarized in Table 9 below.

Table 9: Summarized results from the ARCH-LM test

Commodity	Time Series	Residuals from	F-statistic	Probability
White Maize	Price	ARIMA (3, 1, 2)	3.616905	0.593
	Quantity (yield)	ARIMA (5, 1, 4)	3.242100	0.079
Yellow Maize	Price	ARIMA (3, 1, 0)	0.408220	0.524
	Quantity (yield)	ARIMA (3, 1, 0)	0.092069	0.763

In Section 3.2.3.1 (Chapter 3), it was highlighted that the Null Hypothesis in the ARCH-LM Test is that there is No ARCH effect – meaning the variance of the residuals (or time series) is homoscedastic (or constant over time). Section 3.2.3.1 also highlighted that in this study a 5% (0.05) significance level is used to make the decision of either accepting or rejecting the Null Hypothesis. In Table 8, the probabilities of the F-statistic (the last column), for all the time series, are greater than 5% (0.05). This implies that the Null Hypothesis of No ARCH effect is **accepted** for all the time series (i.e., the variances of all the time series are homescedastic – time invariant).

The variance of the residuals (or time series) is estimated using the procedure illustrated in Section 3.2.3.2 (in Chapter 3). Hence, the Standard Deviation of the residuals (time series) is determined using Equation 3.19. Figures 25 to 28 illustrates the Histogram of the residuals, plotted using Eviews®6. Note that the histograms for all the residuals have a characteristic bell shape associated with normal Probability Density Functions (PDF). The figures also show the Mean and Standard Deviation of the residuals.

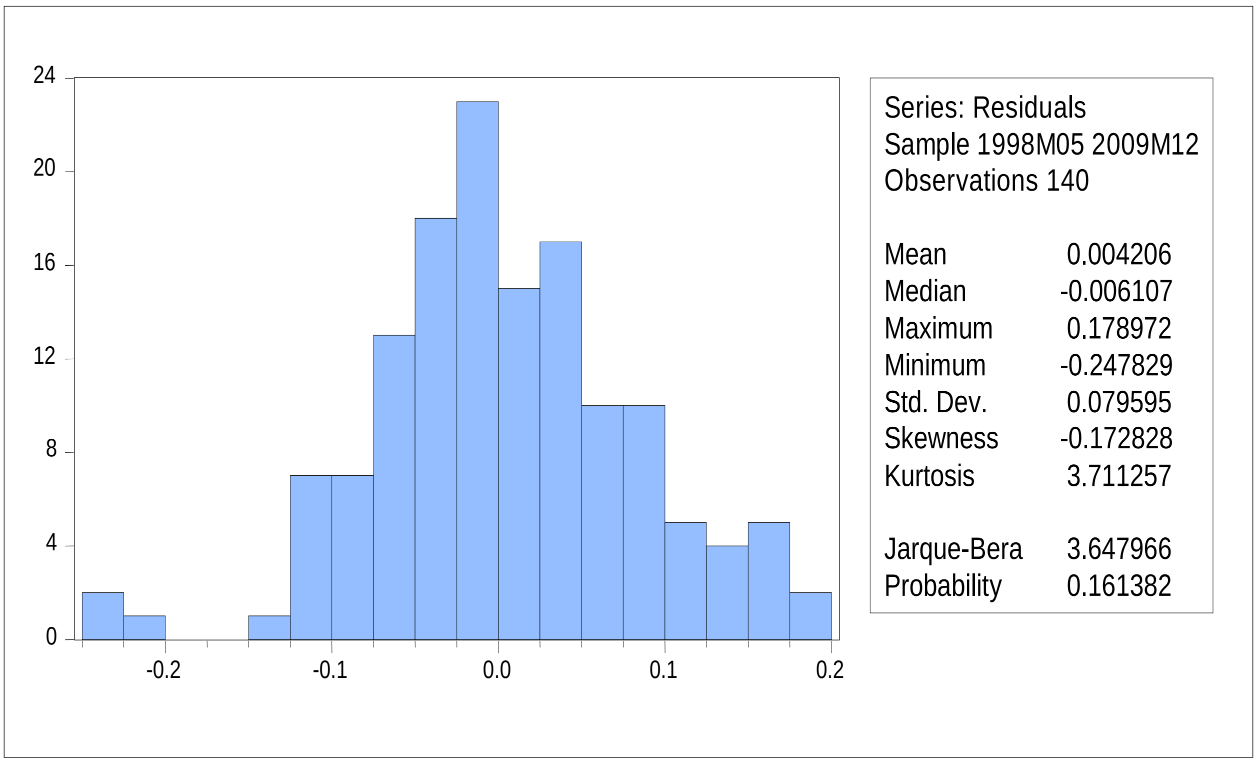

Figure 25: Histogram of residuals from the white maize price forecasting ARIMA (3, 1, 2) Model

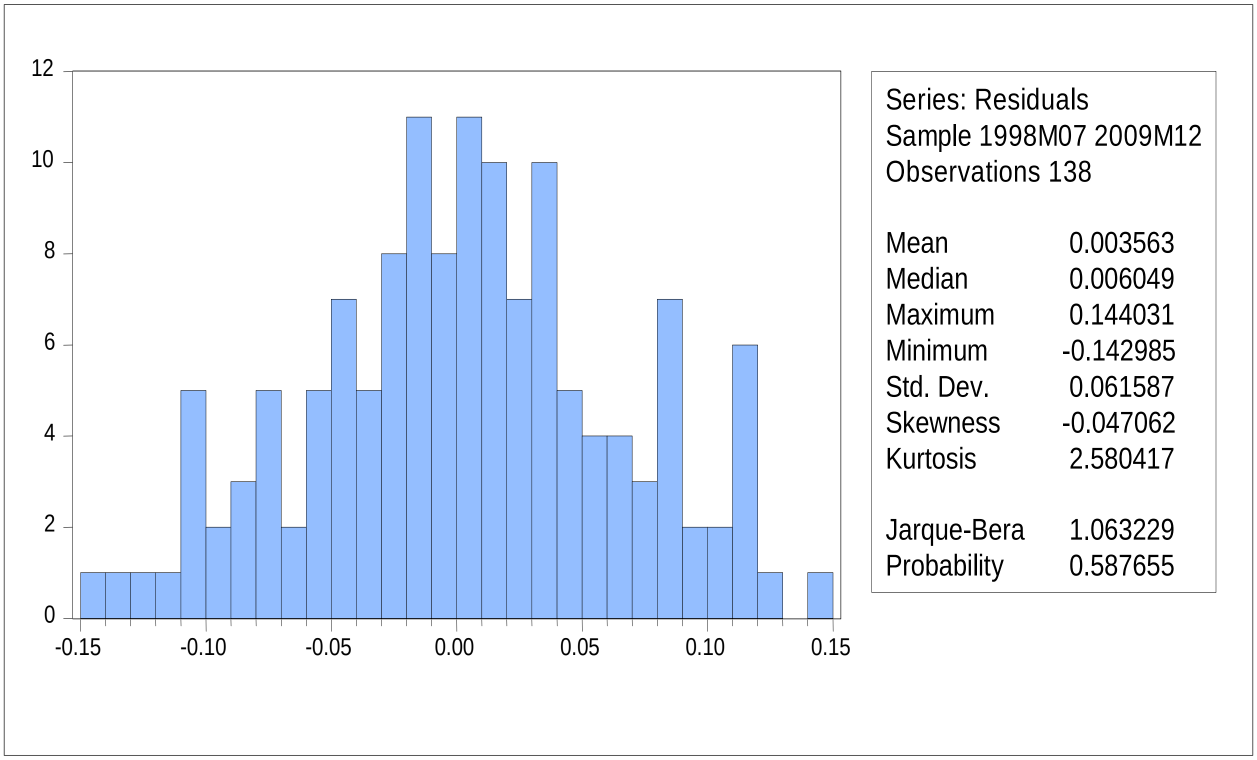

Figure 26: Histogram of residuals from the yellow maize price forecasting ARIMA (5, 1, 4) Model

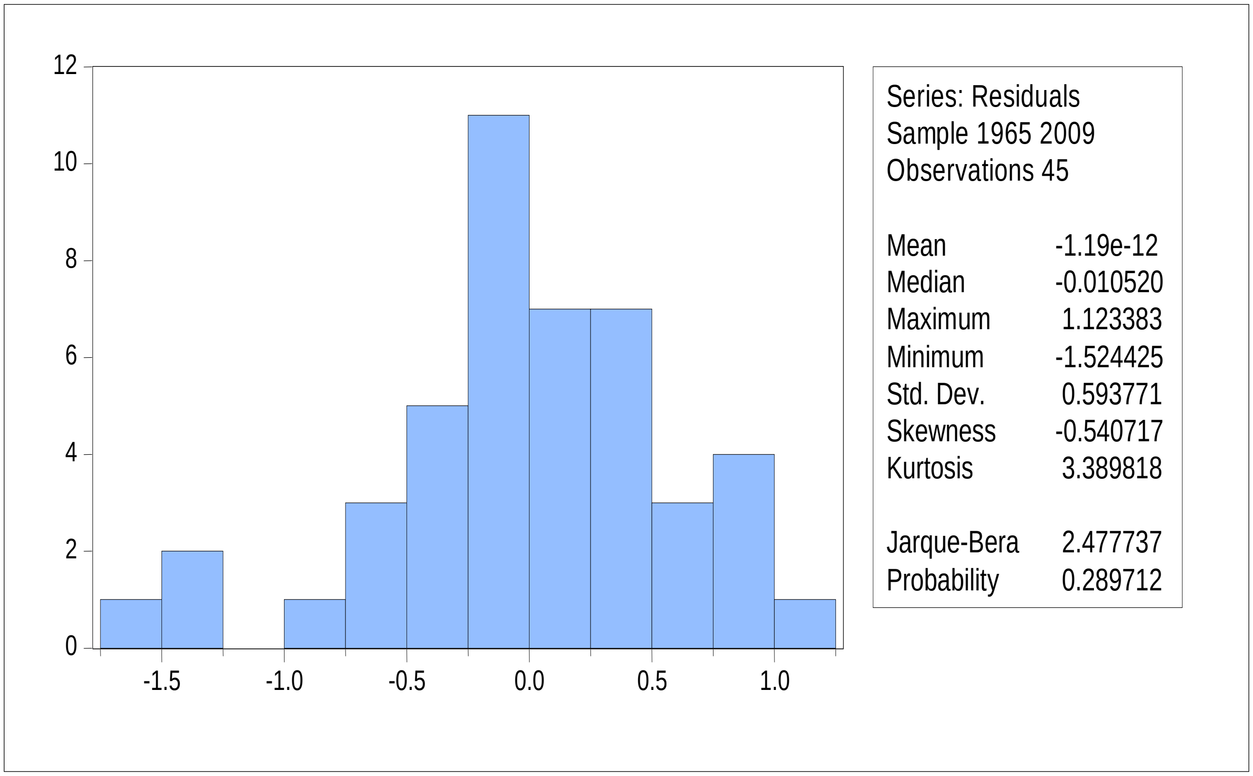

Figure 27: Histogram of residuals from the white maize quantity forecasting ARIMA (3, 1, 0) Model

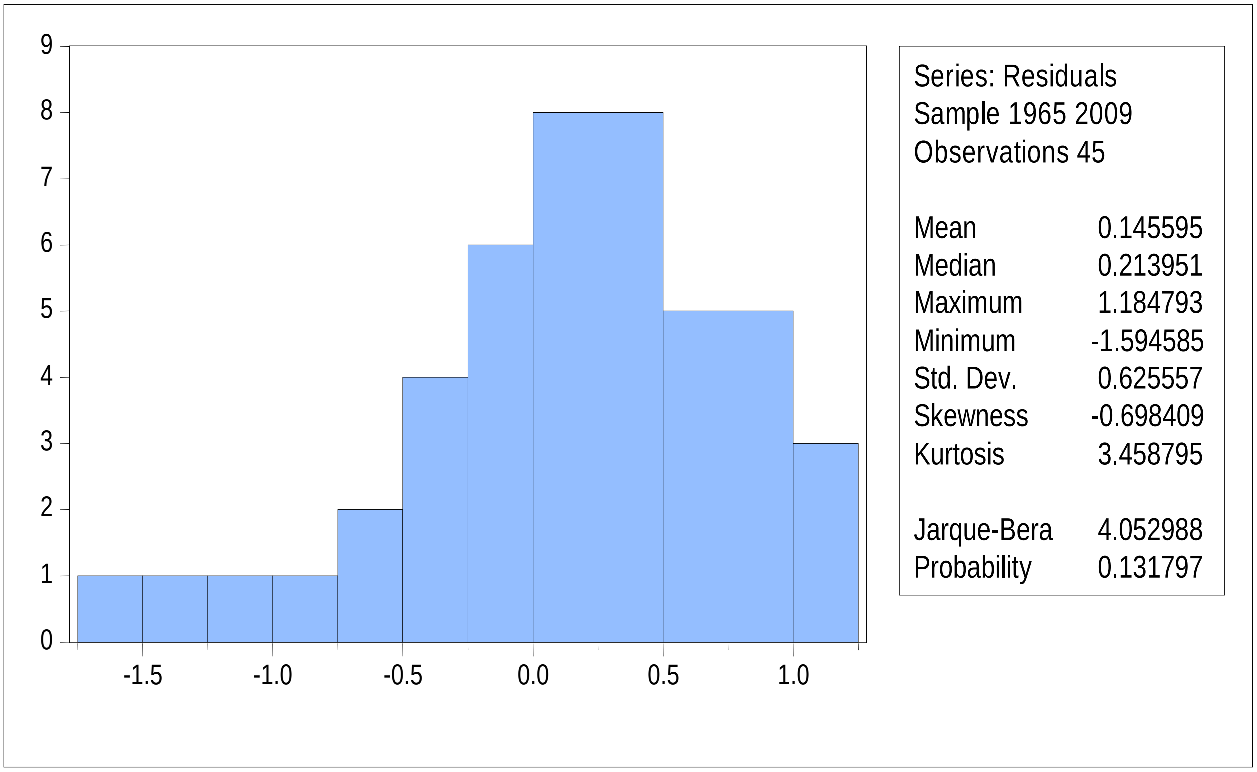

Figure 28: Histogram of residuals from the yellow maize quantity forecasting ARIMA (3, 1, 0) Model

The Jarque-Bera (JB) statistics, in the histograms, also confirm that the residuals of all the time series are normally distributed. The Jarque-Bera statistic is used to test for normality of a time series; it was developed by Jarque and Bera (1987). The Null Hypothesis in the JB Test is that the residuals are normally distributed. The Null Hypothesis is accepted (rejected) if the probability value of the JB statistic is greater (less) than the significance level (in this study 5% or 0.05). Note that the JB statistics of all the residuals are greater than 0.05 – implying that the Null Hypothesis is accepted (i.e., the residuals are normally distributed).

Table 10: Estimated Means and Standard Deviations of the Residuals

	White Maize Residuals		Yellow Maize Residuals	
	Mean (μ)	Standard Deviation (σ)	Mean (μ)	Standard Deviation (σ)
Price	0.004206	0.079595	0.003563	0.061587
Quantity	-1.19×10^{-12}	0.593771	0.145595	0.625557

Table 10 above, shows the Mean and Standard Deviation of the residuals derived from respectively ARIMA forecasting models. The Mean and Standard Deviation values are extracted from the histograms of the residuals, in Figures 25 to 28. The mean and standard deviation of the white and yellow maize price and quantity residuals highlighted in Table 10 above are used in the next section to generate random numbers that are used in the simulation.

4. 2. 3 Simulation of the price and quantity of white and yellow maize [STEP 3]

As already mentioned earlier, the main objective of simulation is to determine the possible values of the commodity price and quantity at time T – when the SF loan matures. The random numbers, generated from the normal distributions of price (ε_p) and quantity (ε_q) residuals, as well as the forecast price (P_T) and forecast quantity (Q_T), are used to simulate the price and quantity.

This section uses white maize quantity simulation as an example to demonstrate how the simulation of price and quantity is quantitatively done. This is the same simulation procedure demonstrated that is used in the simulations of white maize price, yellow maize price and yellow maize quantity. The results of the simulation of price and quantity of white and yellow maize are given in Table 11 below.

As illustrated in Section 3.2.4 (in Chapter 3), the simulation of white maize quantity is done in two steps, namely:

1. Generation of random numbers (1000 random numbers were generated) from the normal distribution of white maize quantity residuals.
2. Adding the 1000 generated random numbers to the forecast white maize quantity (Q_T).

Sections 4.2.3.1 and 4.2.3.2 below; illustrate the white maize quantity simulation. The random number generation and the simulations of white maize quantity were done using Microsoft Excel ®2007.

4. 2. 3. 1 Generation of Random Numbers from the white maize quantity residuals

The procedure for generating the random numbers is illustrated in Section 3.2.4.1 (in Chapter 3). To generate 1000 random numbers from the normal distribution of white maize quantity residuals (ε_{wmq}), the mean and the standard deviation of the white maize quantity residuals, estimated in Section 4.2.2, are used. In the context of Equations 3.23 and 3.24 (in Chapter 3), the generation of the 1000 random numbers from the normal distribution of the white maize quantity residuals can be abstractly illustrated as follows:

$$\varepsilon_{wmq} \sim N(\mu_{wmq}, \sigma_{wmq}) \xrightarrow{\text{generate}} [1000 \text{ random numbers}] \dots \dots (4.2)$$

Where: ε_{wmq} denotes the white maize quantity residuals; $N(\cdot)$ denotes the normal distribution; μ_{wmq} is the mean of the white maize quantity residuals; and σ_{wmq} is the standard deviation of the white maize quantity residuals. In Table 4.6; μ_{wmq} is equal to -1.19 X 10^{-12} (i.e., $\mu_{wmq} = -1.19 \text{ X } 10 - 12$), and σ_{wmq} is equal to 0.0593771 (i.e., $\sigma_{wmq} = 0.0593771$). Therefore, Equation 4.2 above can be rewritten as follows:

$$\varepsilon_{wmq} \sim N(-1.19 \text{ X } 10 - 12, 0.0593771) \xrightarrow{\text{generate}} [1000 \text{ random numbers}] \xrightarrow{\text{rank}} \begin{bmatrix} 1.76 \\ \vdots \\ -1.64 \end{bmatrix} \dots \dots (4.3)$$

Equation 4.3 above illustrates the generation of 1000 random numbers from the normal distribution of the white maize quantity residuals. The 1000 generated random numbers range from 1.76 (largest generated random number) to -1.64 (smallest random generated number).

4. 2. 3. 2 Simulation of white maize quantity

Continuing with the white maize quantity simulation, for example, the 1000 random numbers (whose generation is illustrated by Equation 4.3 above) and the expected (or forecast) white maize quantity in 2010, P_T, are added. The addition results in 1000 quantity values, which are appropriately called simulated white maize quantity values. White maize quantity in 2010 was forecast to be 3.87 Ton/Ha (Table 8, in Section 4.2.1.2.3.2). Therefore, in the context of Equation 3.26 (in Section 3.2.4.2, Chapter 3) the simulation of white maize quantity can be expressed as follows:

$$Q_T + \begin{bmatrix} Q_{N=1} \\ \vdots \\ Q_{N=1000} \end{bmatrix} = \begin{bmatrix} Q_T + Q_{N=1} \\ \vdots \\ Q_T + Q_{N=1000} \end{bmatrix} = \begin{bmatrix} Q_{S=1} \\ \vdots \\ Q_{S=1000} \end{bmatrix}$$

Where: Q_T = 3.87; $Q_{N=1}$ = 1.76; and $Q_{N=1000}$ = -1.64

$$\therefore 3.87 + \begin{bmatrix} 1.76 \\ \vdots \\ -1.64 \end{bmatrix} = \begin{bmatrix} 3.87 + 1.76 \\ \vdots \\ 3.87 + (-1.64) \end{bmatrix} = \begin{bmatrix} 5.63 \\ \vdots \\ 2.23 \end{bmatrix} \dots \dots (4.4)$$

Equation 4.4 yields 1000 simulated white maize quantity values. The 1000 simulated quantity values lie between the interval 2.23 and 5.63. Note that Equation 4.4 also yields a normal distribution of 1000 stochastic quantity values. Table 11, below summarizes the results for the white and yellow maize price and quantity simulations.

Table 11: Summarized results of the simulation of price and quantity of white and yellow maize

Commodity	Simulated Variable	Maximum Value[1]	Minimum Value[2]
White Maize	Price	R 1 892.666/ton	R 1 219.211/ton
	Quantity	5.63 Ton/ha	2.23 Ton/ha
Yellow Maize	Price	R 1 668.968/ton	R 1 118.807/ton
	Quantity	5.32 Ton/ha	1.71 Ton/ha

[1] Maximum simulated value.
[2] Minimum simulated value.

The results in Table 11 can be interpreted as follows: the average white maize monthly spot price, during the period between October 2010 and December 2010, will be anywhere between R1892.666/ton and R 1 219.211/ton; while the average monthly spot price for yellow maize, during the same period, will be anywhere between R 1 668/ton and R 1 118.807/ton. In other words, R1892.666/ton and R 1 219.211/Ton and R 1 668/Ton and R 1 118.807/ton are the forecast bands for white and yellow price, respectively. The forecast bands represent the interval in which the price of white and yellow is expected to lie in at debt maturity.

The results in Table 11 also show that the average yield of white maize, in the Free State province, in 2010, will lie somewhere between 5.63 ton/ha and 2.23 ton/ha. While average yield of yellow maize, in the Free State province (in 2010), is expected to lie anywhere between 5.32 ton/ha and 1.71 ton/ha. The uncertainty associated with where the actual price and quantity of white and yellow maize (SF linked commodity) is what drives credit risk in the SF loan.

Note that the simulation of the price and quantity of white and yellow maize yields their respective normal probability distributions. The normal probability distributions of white and yellow maize price and quantity basically represents the intervals in which the price and quantity of white and yellow maize is expected to fall in at debt maturity.

The generated white and yellow maize price and quantity normal probability distributions are used in the next section to create a Cumulative Density Function of the market value (V_T) of white and yellow maize (on per hectare basis), during the period between October 2010 and December 2010.

4. 2. 4 Generation of the V_T-Cumulative Density Function [STEP 4]

As illustrated in Section 3.2.4.3 (in Chapter 3), the Cumulative Density Function of the market value of the white and yellow maize (in this on per hectare basis) at time T (V_T) is generated in three (3) chronological steps, namely:

1. Ranking of the simulated price and quantity values.
2. Multiplication of the ranked simulated price and quantity values to determine the possible market values (V_T) of the SF linked commodity.
3. Generation of a Cumulative Density Function (CDF) of the market value of the SF linked commodity at time T (i.e., V_T-CDF).

The three steps highlighted above were used to generate the CDF for the market value of white and yellow maize, on per hectare basis, during the period between October 2010 and December 2010. Note that the first step has been achieved, since the simulated price and quantity of white and yellow maize were already ranked (see Section 4.2.2.4.1 of this chapter). Therefore, the only remaining steps are the second and the third steps.

The 1000 ranked Simulated Price (P_S) and Simulated Quantity (Q_S) values for both white and yellow maize are multiplied. The multiplication of the simulated price and quantity values yields 1000 possible market values of white and yellow maize. Equation 3.29 (in Section 3.2.4.3, chapter 3) demonstrated the multiplication procedure – thus:

$$\mathrm{V_T}\ \text{normal distribution} \equiv \begin{bmatrix} \mathrm{P}_1 \\ \vdots \\ \mathrm{P}_{1000} \end{bmatrix} \times \begin{bmatrix} \mathrm{Q}_1 \\ \vdots \\ \mathrm{Q}_{1000} \end{bmatrix} \equiv \begin{bmatrix} \mathrm{V}_1 \\ \vdots \\ \mathrm{V}_{1000} \end{bmatrix}$$

$$\text{where: } \mathrm{V}_1 < \mathrm{V}_2 < \cdots < \mathrm{V}_{1000};\ \text{and } \mathrm{V}_1 = \mathrm{P}_1 \times \mathrm{Q}_1;\ \cdots;\ \mathrm{V}_{1000} = \mathrm{P}_{1000} \times \mathrm{Q}_{1000}$$

In the above equation: P_1 and P_{1000} denote the minimum (smallest) and maximum (largest) simulated price value, respectively, of white maize or yellow maize in October 2010. Q_1 and Q_{1000} denote the minimum (smallest) and maximum (largest) simulated quantity value, respectively, of white maize or yellow maize. V_1 is a product of the multiplication of the minimum simulated price value (P_1) and minimum simulated quantity value (Q_1) of white or yellow maize; while V_{1000} is a product of the multiplication of the maximum simulated price value (P_1) and maximum simulated quantity value (Q_{1000}) of white or yellow maize – thus:

$$V_1 = P_1 \times Q_1 \ldots\ldots (4.5)$$

and

$$V_{1000} = P_{1000} \times Q_{1000} \ldots\ldots (4.6)$$

Therefore, V_1 and V_{1000} denote the minimum (smallest) and maximum (largest) simulated market value, respectively, of white or yellow maize. The V_1 and V_{1000} for both white and yellow maize are calculated using the results in Table 11, above.

For white maize price, P_1 is equal to R 1 301.831/ton and P_{1000} is equal to R 2 186.296/ton, while for white maize quantity, Q_1 is equal to 2.23 ton/ha and Q_{1000} is equal to 5.63 ton/ha. For yellow maize price, P_1 is equal to R 1 118.07/ton and P_{1000} is equal to R 1 668.968/ton, while for yellow maize quantity, Q_1 is equal to 1.17 ton/ha and Q_{1000} is equal to 5.32 ton/ha.

Therefore, V_1 and V_{1000}, for white and yellow maize are calculated using Equations 4.5 and 4.6, respectively. The calculations are demonstrated by Equations 4.7 and 4.8 below; and the results of the calculations are summarized in Table 4.8 below.

$$V_T \text{ normal distribution} \equiv \begin{bmatrix} P_1 \\ \vdots \\ P_{1000} \end{bmatrix} \times \begin{bmatrix} Q_1 \\ \vdots \\ Q_{1000} \end{bmatrix} \equiv \begin{bmatrix} V_1 = P_1 \times Q_1 \\ \vdots \\ V_{1000} = P_{1000} \times Q_{1000} \end{bmatrix}$$

$$\therefore V_T \text{ normal distribution for White Maize} \equiv \begin{bmatrix} 1301.831 \times 2.23 \\ \vdots \\ 2186.296 \times 5.63 \end{bmatrix} \equiv \begin{bmatrix} 2903.083 \\ \vdots \\ 12308.846 \end{bmatrix} \ldots\ldots (4.7)$$

and

$$\therefore V_T \text{ normal distribution for Yellow Maize} \equiv \begin{bmatrix} 1118.07 \times 1.17 \\ \vdots \\ 1668.968 \times 5.32 \end{bmatrix} \equiv \begin{bmatrix} 1308.142 \\ \vdots \\ 8878.910 \end{bmatrix} \ldots\ldots (4.8)$$

Table 12: Summarized results of the simulated market value of white and yellow maize

Commodity	Simulated V_T Values	
	Minimum Value	Maximum Value
White Maize	R 2 903.083/ha	R 1 2308.846/ha
Yellow Maize	R 1 308.142/ha	R 8 878.910/ha

The results in Table 12, indicate that the market value (on per hectare basis) of the white and yellow maize (whose production is financed by a Structured Finance loan) in October 2010, will lie somewhere between the range defined by the maximum and minimum simulated V_T values. In other words, the market value of white maize, during the period October 2010 and December 2010, will lie anywhere between R 12 308.846/ha (maximum) and R 2 903.083/ha (minimum); while that of yellow maize will lie somewhere between R 1 308.142/ha (maximum) and R 8 878.910/ha (minimum).

Each of the ranges, defined in Table 12, has 1000 simulated V_T values. Each of the simulated V_T values represents the possible market value of white maize or yellow maize, in October 2010. The probability that market value of white maize or yellow maize will be equal to any of the simulate V_T values is the same. Based on the procedure illustrated in Section 3.2.4.3 (in Chapter 3), the Cumulative Density Functions for the market value of white and yellow maize, in October 2010, were generated. Figures 29 and 30, illustrates the CDFs for white and yellow maize, respectively.

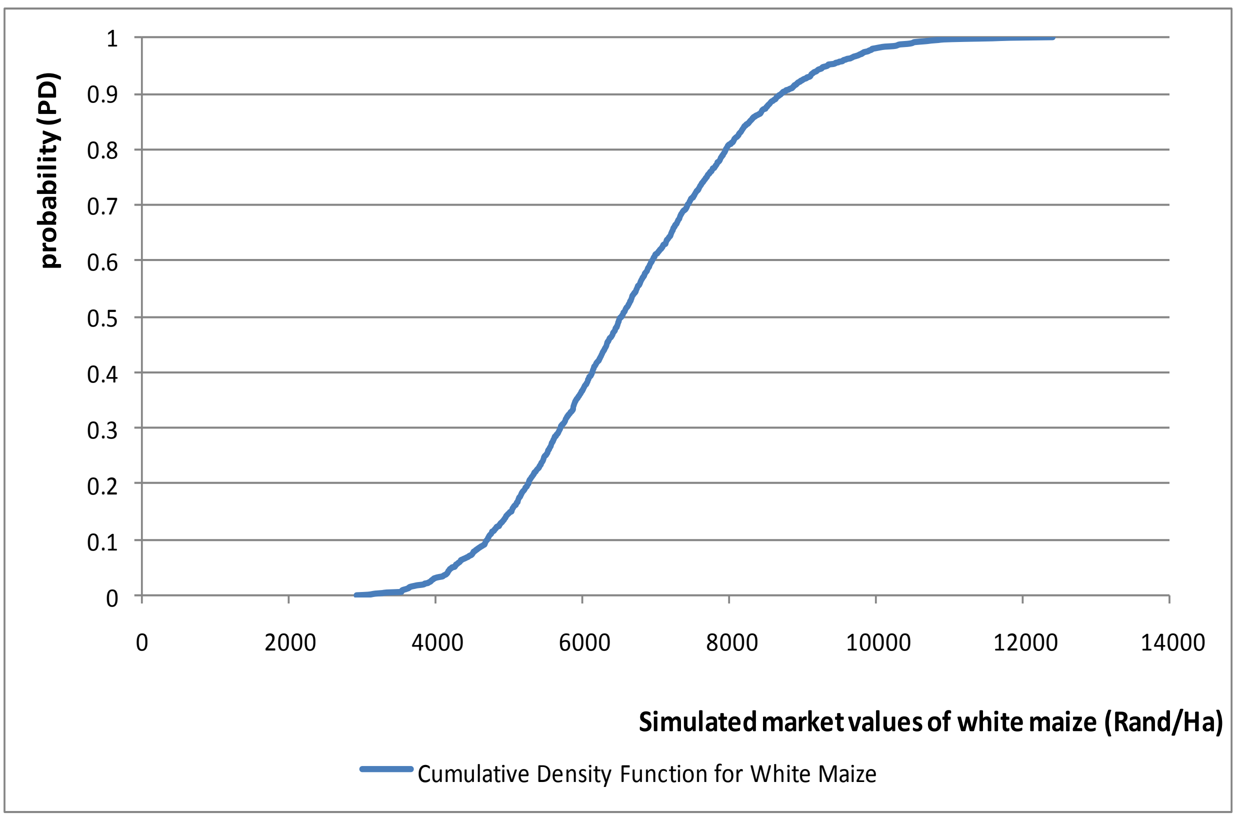

Figure 29: Cumulative Density Function of the market value (VT) of white maize (per hectare), at debt maturity

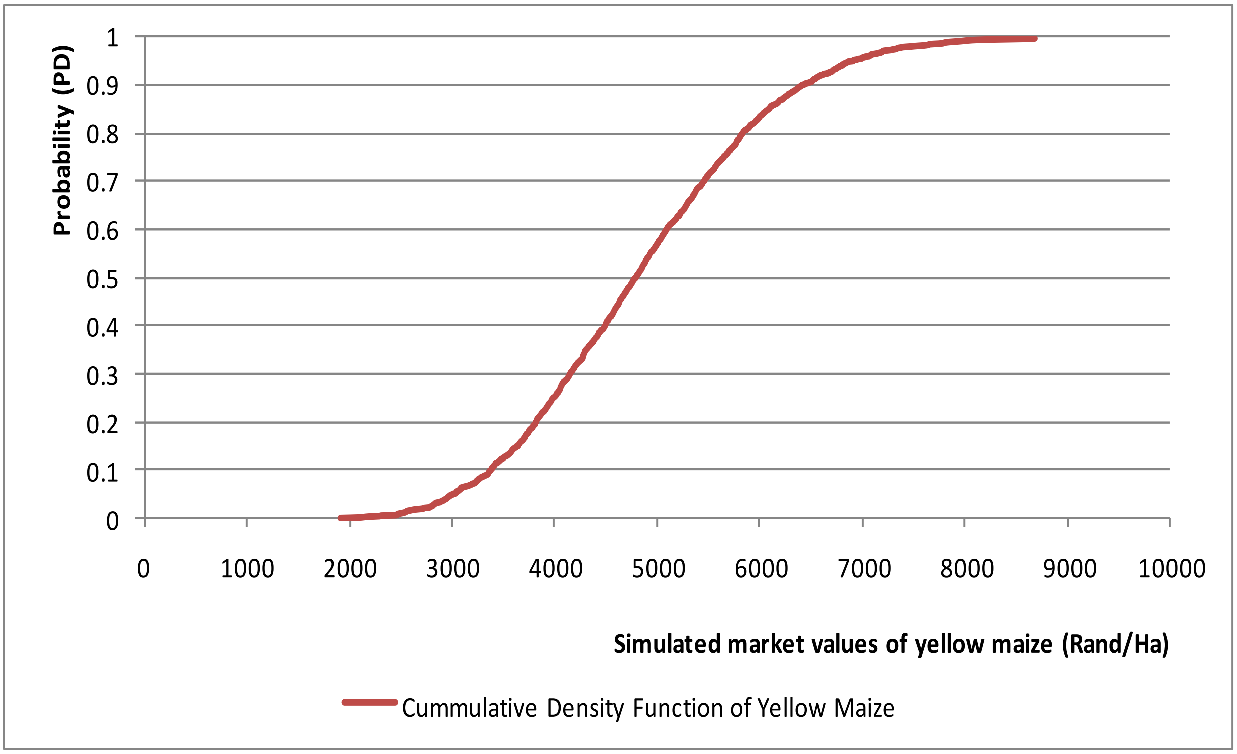

Figure 30: The Cumulative Density Function of the market value (VT) of yellow maize (per hectare) at debt maturity

4. 2. 5 Determination of the Probability of Default [STEP 5]

The CDFs of the market value (V_T) of white and yellow maize (Figures 29 and 30, above) are used to determine the probability of default. Recall that under Merton's model, the probability of default (PD) is defined as the likelihood that the market value of the farm's assets (in this case the market value of the SF linked commodity, i.e., white maize or yellow maize) will be less than the value of debt (in this case SF loan), at time T – when the SF loan matures. Equation 3.3, gives the mathematical expression of default in Merton's model.

In the context of the developed Credit Risk Model, the probability of Default is defined as the likelihood that the market value of the Structured Finance (in this case white and yellow maize) at time T, V_T, will take on a value on the CDF of white or yellow maize (Figures 29 and 30, respectively) that is less than or equal to the value of the SF loan (D). Therefore, the probability of default can be determined easily by plotting the SF loan value (D) on the Cumulative Density Functions (CDFs) of the market value of white or yellow maize and then reading the probability on the vertical axis as demonstrated in Figure 9 (in Chapter 3).

To determine the probability that the farmer (borrower) will default on the SF white or yellow maize production loan, the probabilities of the calculated D_1, D_2, and D_3 values (in Table 4) are read from the generated CDFs of market value of white and yellow maize, at debt maturity. As already mentioned earlier, the probability of a farmer default on the SF white or yellow maize production loans, D_1, D_2 or D_3, is equal to the probabilities of D_1, D_2 or D_3, on the CDF of the market value of white or yellow maize, at debt maturity. Figure 9, in Section 3.2.6 (in Chapter 3), graphically demonstrated how the probability of default (PD) is determined.

Microsoft Excel® can also be used to determine the probabilities of the D_1, D_2 and D_3 from the generated CDFs of the market value of white and yellow maize. The procedure of using Microsoft Excel involves the calculation of the Mean and Standard Deviation of the generated Cumulative Distribution Functions (CDFs) of white and yellow maize, and then entering the following formula in Cell in Microsoft Excel:

$$= \text{NORMDIST}\ (\text{X}, \text{MEAN}, \text{STANDARD DEVIATION}, \text{TRUE}) \ldots \ldots (4.9)$$

Where: X is the value whose probability on the CDF is being determined (i.e., in our case X = D_1, D_2, or D_3); MEAN is the arithmetic mean of the Cumulative Distribution Function (i.e., the mean of the generated white or yellow maize CDFs); STANDARD DEVIATION is the standard deviation of the Cumulative Distribution Function (i.e., the standard deviation of the generated white or yellow maize CDFs) and TRUE is a logical value – for a Cumulative Distribution Function the word TRUE is used, and for a Probability Density Function (PDF) the word FALSE is used. For instance, the probability of the SF loan value proxy, D_1, on the white maize CDF was determined by the entering the following formula in cell in Microsoft Excel® 2007:

$$= \text{NORMDIST}\ (3554, 6623.071, 1564.751, \text{TRUE}) \ldots \ldots (4.10)$$

Where: D_1 = 3783; MEAN = 6623.071 (i.e., the mean of the generated white maize distribution); STANDARD DEVIATION = 1564.751 (i.e., the standard deviation of the generated white distribution); and TRUE because a Cumulative Distribution Function is being used. When the above formula (Equation 4.10) is entered, in Cell, in Microsoft Excel® 2007, a probability value of 0.0347 is retained in the cell. The retained value (0.0347) is the probability of the D_1 value on the generated white maize CDF.

Equation 4.9 was used, in Microsoft Excel®2007, to determine the probabilities of the D_1, D_2 and D_3 values; the results are given in Table 13 below. Note that the probabilities of the D_1, D_2 and D_3 values are the probabilities of a farmer (borrower) defaulting on the SF white maize or yellow maize production loans, D_1, D_2 and D_3.

Table 13: The probabilities of default (PDs) on the SF production loan proxies

Structured Finance Loan		White Maize		Yellow Maize	
Proxy	Loan Value (R/a)	PD	PD (%)	PD	PD (%)
D_1	3 783	0.0347	3.47	0.1831	18.31
D_2	2 523	0.0044	0.44	0.0242	2.42
D_3	1 261	0.0003	0.03	0.0011	0.11

The results given in Table 13 (i.e., in the third, fourth, fifth and sixth columns) above are the ultimate outputs of the developed Credit Risk Model. In Table 13, the third and fourth column gives the probabilities of defaulting on the SF white maize production loans, D_1, D_2 and D_3 – the associated probabilities of default are 3.47%, 0.44% and 0.03%, respectively. The fifth and sixth columns, in Table 4.10, give the probabilities of defaulting on the SF yellow maize production loans, D_1, D_2 and D_3 – the associated probabilities of default are 18.31%, 2.42% and 0.11%, respectively.

The results, in Table 13, are interpreted, under the context of the *conceptualized example*, as: there is a 3.47%, 0.44% or 0.03% probability that a farmer (borrower) will default on a SF white maize production loan, with a face value equal to D_1, D_2 or D_3, respectively. And also there is also an 18.31%, 2.42% or 0.11% probability that a farmer (borrower) in October 2010, will default on a SF yellow maize production loan, with face value equal to D_1, D_2 or D_3, respectively.

There are two observations that can be deduced from the results given in Table 13. The first observation is that there is a positive relationship between the probability of default and the SF loan amount. The Probability of Default (PD) increases as the SF loan amount increases. This is consistent with other credit risk evaluation studies, where it is observed that the likelihood of the borrower defaulting increases as the loan amount increases.

The second observation is that the results in Table 13 show that the probability of default (PD) is a function of the profitability of the underlying transaction (in this case the underlying transactions are white and yellow maize production). Since white maize production is relative profitable compared to yellow maize production, the probability of farmer defaulting on a SF loan for maize production loan is relatively lower than the probability of defaulting on a SF yellow maize production loan, even when the SF loans for white and yellow production are equal in terms of value. For instance, the probability of default on the SF white maize production loan, D_1, is 3.47%, while the probability of default on the SF yellow maize production loan of the same value (D_1) is 18.31%.

4. 3 Application and use of the Probability of Default (PD) results

Continuing with the conceptualized example that was illustrated in Section 4.1, the Agricultural Lending Institution's objectives for evaluating the credit risk associated with the Structured Finance white and yellow maize production loans are to enable it:

- Appraise Structured Finance white and yellow maize production loans.
- Determine how much interest to charge on the SF white and yellow maize production loans.
- Determine the amount of capital that it needs to hold against loan losses due to credit risk.

Therefore, this section demonstrates how the Agricultural Lending Institution can use the developed Credit Risk Model's outputs, given in Table 13, to achieve three objectives listed above.

4. 3. 1 Appraisal of Structured Finance white and yellow maize production loans

The chief tool that is used in loan appraisal, by Lending Institutions, is the Probability of Default (PD). In other words, the Lending Institution's decision to grant or deny a loan largely depends on the probability of default. In loan appraisals, Lending Institutions use probability of default thresholds, beyond (before) which they will deny (grant) a loan. Therefore using the probabilities of default in Table 4.10, the Lending Institution can objectively make the decision of whether to grant or deny a loan, based on whether the estimated PD is greater or less than the acceptable PD threshold.

Financial institutions appraise loans to also identify weak credits from strong credit. The identification of weak or strong credit is done by using statistical credit risk models to measure the probability of default and then mapping measured PD to its Internal Rating System (IRS). The IRS is a classification of loans, on the financial institution's books, into groups or classes based on their probabilities of default (usually historical probabilities of default). In the IRS, loans in the same class have the same probability of defaulting over the next twelve (12) months. The class in which the loan belongs gives an indication whether it is a weak or bad credit.

For the purposes of demonstrating the identification of whether the Structured Finance white and yellow maize production loans given in Tables 4.9 and 4.10, are weak or strong credits, the Internal Rating System is used by the Amalgamated Banks of South Africa (ABSA). ABSA bank is one of South Africa's leading banks and also it is a major lender to the South African agricultural sectors. It is for this reason that its Internal Rating System was used.

The ABSA Group Limited, which is a parent company of ABSA bank, categories its current exposures (or loans) according to a 21-grade internal rating scale DG that corresponds to a statistical probability of the loan in that rating class defaulting within a 12 month period. Table 14 below shows the ABSA Group's DG rating scale as well as its mapping to International Rating Agency Scales.

Table 14: The ASBA group's DG rating scale, and its mapping to international rating agency scales

DG Mapping (to risk-rated or credit score models)				Rating Agency Mappings (International rating scale)		
DG	Min PD (>)	Max (≤)	PD (midpoint)	Standard & Poor	Moody's	Fitch
1	0.000%	0.019%	0.010%	AAA	Aaa	AAA
2	0.020%	0.029%	0.025%	AA	Aa	AA
3	0.030%	0.049%	0.040%	A+	A1	A+
4	0.050%	0.099%	0.075%	A/A-	A2/A3	A/A-
5	0.100%	0.149%	0.125%	BBB+	Baa1	BBB+
6	0.150%	0.199%	0.175%	BBB+/BBB	Baa1/Baa2	BBB+/BBB
7	0.200%	0.249%	0.225%	BBB	Baa2	BBB
8	0.250%	0.299%	0.275%	BBB/BBB-	Baa2/Baa3	BBB/BBB-
9	0.300%	0.399%	0.350%	BBB-	Baa3	BBB-
10	0.400%	0.499%	0.450%	BBB-/BB+	Baa3/Ba1	BBB-/BB+
11	0.500%	0.599%	0.550%	BB+	Ba1	BB+
12	0.600%	1.199%	0.900%	BB	Ba2	BB
13	1.200%	1.549%	1.375%	BB/BB-	Ba2/Ba3	BB/BB-
14	1.550%	2.149%	1.850%	BB/BB-	Ba2/Ba3	BB/BB-
15	2.150%	3.049%	2.600%	BB-	Ba3	BB-
16	3.050%	4.449%	3.750%	B+	B1	B+
17	4.450%	6.349%	5.400%	B+/B	B1/B2	B+/B
18	6.350%	8.649%	7.500%	B	B2	B
19	8.650%	11.349%	10.000%	B-	B3	B-
20	11.350%	18.649%	15.000%	CCC+	Caa1	CCC+
21	18.650%	99.999%	30.000%	CCC	Caa2	CCC
Defaulted	100.000%	100.000%	100.000%	D	D	D

(Source: ABSA Group Limited Shareholder report for the year ending 31 December 2008 – pages 226)

The DG rating scale (i.e., the first column in Table 14) is classified into three (3) main grades, namely: default grades 1 – 11; default grades 12 – 19 and default grades 20 – 21. The three (3) main default grades are described below as follows:

1. **Default grades 1 – 11**

   Financial assets (loans) belonging to grades have a lower probability of default than other assets. Typically these loans will have a probability of default of less than 0.5%.

2. **Default grades 12 – 19**

   Financial assets (loans) belonging to these grades typically requires more detailed management attention where clear evidence of financial deterioration or weakness exists. Assets in this category, although currently protected, are potentially weaker credits. These loans contain some credit deficiencies but not to the point of including the loans in a watch list.

3. **Default grades 20 – 21**

   These loans' (or financial assets') probability of default have deteriorated to such an extent that they are included in a watch-list for regular review. Loans so classified must have well-defined weaknesses that exacerbate the probability of default. They are characterized by a distinct possibility that the obligator will default, and should the collateral pledged be insufficient to cover the loan, the Group (or bank in this case) will sustain some loss when default occurs.

Therefore using the ABSA's Internal Rating Scale (DG), the Structured Finance white and yellow maize production loans, D_1, D_2 and D_4, are classified in Table 15 below:

Table 15: Mapping of the estimated SF loan PDs to ABSA's DG and international rating agency scales

Commodity	SF Loan	PD	Mapping the PD to ABSA's DG		International Rating Agency Scales		
			DG	Category	S&P[1]	Moody's	Fitch
White Maize	D_1	3.47%	16	12 – 19	B+/B	B1/B2	B+/B
	D_2	0.44%	10	1 – 11	BBB-/BB+	Baa3/Ba1	BBB-/BB+
	D_3	0.03%	3	1 – 11	A+	A1	A+
Yellow Maize	D_1	18.31%	21	20 – 21	CCC	Caa2	CCC
	D_2	2.42%	15	12 – 19	BB-	Ba3	BB-
	D_3	0.11%	5	1 – 11	BBB+	Baa1	BBB+

[1] Standard and Poor

Table 15, shows the mapping of the estimated probabilities of default (PD) on the SF loans (i.e., D_1, D_2 and D_3) to the Internal Rating Scale (DG) of ABSA as well as International Agency Rating Scales. The 5th

column in Table 15 is of interest. The SF white maize production loan D_1 can be classified into Default Grades 12 – 19; while D_2 and D_3 can be classified into Default Grade 1 – 11. Therefore, according to the interpretation of the Default Grades above, SF loans for maize production D_1 and D_2 are potentially weaker credits; while D_3 is potentially a stronger credit.

For yellow maize production: the SF loans D_1 is classified into Default Grades 20 – 21; D_2 is classified into Default Grades 12 – 19 and D_3 is classified into Default Grades 1 – 11. According to the interpretation of the Default Grades above, D_1 and D_2 are weaker credits; D_3 is a potentially weaker credit and D_4 is a stronger credit. Therefore SF loans D_1 and D_2 must be put on the watch list.

In conclusion, this subsection has demonstrated, using ABSA's Internal Rating System, how an Agricultural Lending Institution can use the results from the developed Credit Risk Model to classify its SF loans and hence identify SF loans or credits that needs close monitoring (i.e., potentially weaker and weaker credits).

4. 3. 2 Determine how much interest to charge

Lending institutions charge interest on loans to compensate them for the risk of the borrower defaulting on the loan. The amount of interest to charge is largely related to the likelihood of the borrower defaulting on the loan (i.e., the probability of default). Again financial institutions use their Internal Rating System (IRS) to determine how much interest rate to charge on the loan. Each of the categories in the IRS has specified interest that must be charged. The amount of interest rate that is charged on a loan increases with the increase in the probability of default.

Financial institutions determine how much interest rate to charge by first estimating of the borrower's (or loan's) probability of default (i.e., the credit risk associated with the loan) and then mapping the estimated probability of default to its Internal Rating System to determine the class or group the loan belongs to and then using the interest rate for that class or group.

Therefore, going back to ABSA's Internal Rating System, DG loans in the Default Grades 1 – 11 have the lowest interest rate charge; followed by loans in the Default Grades 12 – 19; loans in Default Grades 20 – 21 will have the highest interest charge. The actual interest rate charge for each of the Default Grades is proprietary information that is not available to the public.

4. 3. 3 Determination of how much capital to hold against possible loan losses due to credit risk

The 2008 global financial crisis has increased the importance of capital adequacy and management in financial institutions. Regulators of formal financial institutions, such as the South African Reserve Bank, require financial institutions to hold capital against possible loan losses due to market, credit and operational risks. One of the popular and widely used methods for calculating the minimum capital requirement for credit risk is the Basel Capital Accords, which are proposed and formulated by the Basel Committee on Bank supervision under the auspices of the Bank of International Settlement (BIS)[31]. So far there have been two (2) Basel Accords, Basel I and Basel II. Basel II is the Capital Accord that is currently being used. The South African Reserve Bank is also encouraging formal financial institutions in South Africa to Implement Basel II (South African Reserve Bank, 2005).

Under the Basel II Capital Accords, the capital that needs to be held must be equal to the Expected Loss (EL) of an individual loan or a loan portfolio (Basel Committee, 2000). The Expected Loss (EL) is determined by multiplying the probability of default (PD), Loss Given Default (LGD) and the Exposure at Default (EAD) (Allen *et al.*, 2006; Kim, 2006; and Luybov, 2003). Therefore, the EL for loan or loan portfolio can be expressed as follows:

$$\mathrm{EL} = \mathrm{PD} \times \mathrm{LGD} \times \mathrm{EAD} \ldots\ldots (4.11)$$

Where EL is the Expected Loss for a loan or loan portfolio over a specified period of time PD is an indication of the likelihood and frequency that a loan will enter default status. LGD measures the impact on the financial institution from default. LGD is the net of any recovery the institution has received, either through liquidation of collateral or deficiency judgments rendered from foreclosure or bankruptcy proceedings. EAD is what the financial institution has at risk when the loan does enter default status. Both PD and LGD are usually expressed in percentage terms, while EAD is usually expressed as a dollar (in this case Rand) amount.

Therefore, Equation 4.11 is used to determine the capital that needs to be held against possible losses due to credit risk in SF loans for white and yellow maize production (i.e., D_1, D_2 and D_3). PD for each of the white and yellow maize SF production loans have been estimated and are given in Table 4.10. EAD is

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[31] Details on the Basel Capital Accords can be found on the website of the Bank of International Settlement, namely, www.bis.org

equal to the respective SF loan values, D_1, D_2 and D_3. LGD is the only term or parameter that is unknown in Equation 4.11. Hence, the study assumes that the LGD is equal to 100% (1); in other words the Bank expects to lose the whole loan amount, when the default occurs. Hence, Table 16 gives the Capital (EL) that the Agricultural Lending Institution needs to hold against possible SF loan losses due to credit risk.

Table 16: Capital Requirements for the white and yellow maize SF loans

Commodity	SF Loan	EAD	PD	LGD	Capital Requirement (EL) [Rand/Ha][1]
White Maize	D_1	3783	3.47%	100%	131.27
	D_2	2523	0.44%	100%	11.10
	D_3	1261	0.03%	100%	0.38
Yellow Maize	D_1	3783	18.31%	100%	692.67
	D_2	2523	2.42%	100%	61.06
	D_3	1261	0.11%	100%	1.39

[1] The Capital requirement is the product of EAD, PD and LGD.

Results in Table 16 (last column) indicate that, for instance, R65.64/Ha needs to be held to cushion against possible losses on the white maize production SF loan, D_1. The same interpretation applies to the other SF loans. As shown in Equation 4.11, the amount of capital that is required to be held against credit risk depends on the size of loan amount (i.e., EAD), the probability of default (PD) and the loss given default (LGD). It is for this reason that the calculated capital requirement amounts given in Table 16 are small amounts because of the loan amounts and the probability of default are small values.

Although the capital requirements given in Table 16 may appear to be small amounts; however, they become substantially large amounts when aggregated to the total number of hectares used in the production of maize. For instance, if it is assumed that the total size of and used in white maize production is 20 hectares. Therefore the face value of the SF loan, for the total hectarage, would be about R 75, 660. Using the Equation 4.11, the capital that needs to be held against possible losses due to credit risk in the SF production loan is going to be R 2 625[32].

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[32] EL = R75, 660 x 0.034x1 = R2, 625.403

In conclusion, this subsection has demonstrated how the estimated probabilities of default (PD) can be used by the Agricultural Lending Institution to determine the capital that it needs to hold against possible SF loan losses due to credit risk. Table 16 demonstrates how the capital required to cushion loan losses due to credit risk is determined.

4. 4 Conclusion

In conclusion, this chapter has demonstrated how the developed Credit Risk Model can be adapted and used to measure the credit risk in commodity production SF loans. A conceptualized example of SF lending transaction was used to demonstrate the application of the developed Credit Risk Model. Under the context of the conceptualized example of SF lending transaction, the developed Credit Risk Model measures credit risk in SF commodity production loans as the probability of default, on per hectare basis. The chapter also demonstrates how the results from the developed Credit Risk Model (i.e., PD) can be used by a financial institution to achieve the fundamental objectives of credit risk management. Therefore, the chapter has addressed and achieved the third objective of the study.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5. 1 Conclusion

This research was broadly motivated by the recent observations in agricultural finance that Structured Finance lending techniques have the potential of deepening credit services in the agricultural sectors of developing and emerging economies. The primary motivation of the research was that although the application of Structured Finance lending techniques are being promoted, there has not been a study done that focuses on the fundamental question or issue that is of importance to lender or lending institution, namely: how to evaluate the credit risk inherent in Structured Finance lending techniques being promoted in agriculture. It was largely because of that reason that this research was undertaken.

The research had three (3) main objectives: the first objective was to develop a credit risk model that can be used to measure or evaluate credit risk in Structured Finance lending transactions in agriculture; the second objective was to develop a framework that acts as a guide when using the developed credit risk model in the measurement of credit risk in Structured Finance lending transactions in agriculture and the third objective was to demonstrate how the developed credit risk model is used to measure credit risk. The first and second objectives of the study were achieved in Chapter Three (3), while the third objective was achieved in Chapter Four (4). However, in order to the lay the foundation for the study, literature review on the subject matter of the research was done in Chapter Two (2).

Chapter Two (2), literature review, was divided into two major parts. The first major part reviewed literature on Structured Finance lending techniques in agriculture, while the second major part reviewed literature on credit risk modelling techniques in agricultural lending transactions. From the reviewed literature on Structured Finance, the study concludes that there are two (2) fundamental concepts that govern any Structured Finance lending transaction. The first fundamental concept is the use of existing assets and commodities and/or future cash flows as security for financing. In other words, in Structured Finance lending techniques assets other than fixed assets (such as buildings and land) can be used as loan security (collateral). This is one of the advantages of Structured Finance lending techniques, especially in developing and emerging economies where commodity producers’ access to credit (especially from formal financial institutions) is constrained by lack of traditional loan collateral (i.e., fixed assets such as land and buildings).

The second fundamental concept is that, in Structured Finance lending transactions the borrower's creditworthiness is a function of the profitability of the underlying transaction that is being financed and not a function of the borrower's balance sheet standing. In other words, in Structured Finance lending transactions, what is important is the profitability of the transaction being financed. Therefore Structured Finance lending techniques provide avenues of financing enterprises and commodity producers beyond their balance sheets. This fundamental concept of SF lending techniques is taken into consideration when developing the credit risk model.

Literature on credit risk modelling reviewed the different types of techniques that are used to measure credit risk. The study highlights that credit risk modelling techniques can be classified into two (2) major groups, namely: traditional and modern credit risk modelling techniques. In agricultural finance, traditional credit risk modelling techniques are widely used in measuring credit risk. The application of modern credit risk modelling techniques in agricultural finance is still its infancy. The study assessed the different types of credit risk modelling techniques, both traditional and modern, with the objective of identifying a credit risk modelling technique that is appropriate for Structured Finance lending transactions.

The literature on credit risk modelling highlighted that traditional credit risk modelling techniques (especially Credit Scoring Models) are the most widely used in the measurement or evaluation of credit risk in agricultural finance. However, traditional credit risk modelling techniques cannot be used in SF lending transactions because of their data input requirements. The data inputs for traditional credit risk models are accounting ratios, such as leverage, liquidity and profitability ratios, *inter alia*, which are derived from the borrower's balance sheet. In SF lending transactions the borrower's balance sheet is not important, what is important is the profitability of the underlying transaction being financed. Therefore, traditional credit risk modelling techniques are not appropriate for measuring credit risk in SF lending transactions.

Chapter three (3) addresses the first and second objective of the study. From the reviewed literature on credit risk modelling, the study identifies the credit risk modelling technique first proposed by Merton (1974) and extensively used in finance studies, as the appropriate technique of modelling credit risk in SF lending transactions in agriculture. Theories underlying Merton's model are used to develop the credit risk model. Under Merton's model, the market value of the farm (or firm) is the fundamental source of uncertainty driving credit risk. Credit risk is measures as the probability of default (PD) – thus, the probability that the market value of the farm (firm) assets will be less than the face value of the farm's debt, at debt maturity.

In order to measure the credit risk, Merton's model makes the assumption that the evolution of farm asset value, over time, follows a Geometric Brownian Motion (GBM), which ultimately makes the farm asset value to be not only stochastic (random), but also lognormally distributed; at any time T in the future. This strong assumption about the farm asset value being lognormally distributed at time T in the future makes it possible to determine the probability of default (PD). Figure 7 is the graphical illustration of how the probability of default (PD) is determined under Merton's framework.

To implement Merton's model, the study starts by first deriving the market value of farm assets from the market value of the commodity underlying the SF lending transaction and then generates tentatively the lognormal distribution of the market value of farm assets. The market value of commodity underlying the SF lending transaction (i.e., market value of farm asset) is basically the product of the price and quantity of the commodity. To determine the market value of farm asset at debt maturity (one year ahead), the study uses time series econometric forecasting techniques; as illustrated in Section 3.2.1.

The study also develops a procedure that is used to simulate the possible market values of farm assets (i.e., market value of the commodity underlying the SF lending transactions). The simulation procedure was also illustrated in Section 3.2.1. The simulation procedure yields a normal distribution of farm asset value at time T – when the SF loan matures. The probability of default (PD) is determined from the generated normal distribution of the market value of farm asset. Figure 8 is the graphical illustration of the framework of the developed Credit Risk Model. Figure 9 graphically illustrates the how the Probability of Default (PD) is determined.

Chapter four (4) addresses the third objective of the study. The chapter demonstrates the application of the developed credit risk model in a conceptualized example of the Structured Finance lending transactions, where white and yellow maize are the underlying commodities. In the conceptualized example, it is assumed that the production of white and yellow maize (in the Free State province of South Africa) during the 2009/2010 season was financed by SF production loans. Therefore, the developed credit risk model is used to quantify the credit risk in *"Structured Finance white and yellow maize production loans"*.

Results from the model indicates that if a farmer borrowed R3784/Ha, for instance, to produce white or yellow maize in the Free State province of South Africa, the probabilities of the farmer defaulting on the white maize and yellow maize Structured Finance production loans are 3.47% and 18.31%, respectively. In other words, there is a 3.47% and 18.31% chance that white and yellow maize SF production loans (with a face value of R3784/Ha), respectively, will fall into default at debt maturity.

Chapter four (4) also demonstrates how the probability of default, as well as the results from the developed credit risk model, can be used by a financial institution in its management of credit risk. Using the internal rating system of ABSA group, South Africa's largest bank, the study rates the hypothetical loans into different rating classes. The study also demonstrates how the determined probabilities of default, on the SF white and yellow maize production loans, are used in the calculation of the capital that is needed to be held by a financial institution as a cushion against possible loan losses due to credit risk.

In conclusion the research study has achieved the set-out objectives. The developed Credit Risk Model can be adapted and used to measure the credit risk in any SF lending transaction in agriculture. The developed Credit Risk Model can assist financial institutions in the prudential deepening of credit services, using SF lending techniques in agricultural sectors of developing and emerging economies. The deepening of credit services will ultimately help to unlock the agricultural potential of developing and emerging economies.

5. 2 Recommendations

The study has three (3) main recommendations. The first recommendation is with regard to the application of Structured Finance lending techniques in agriculture; the second recommendation is with regards to the practical application of the developed credit risk model; and the third recommendation is with regards to adaptation of the developed Credit Risk Model.

Recommendation 1: The application and use of Structured Finance Instruments is still in its infancy, therefore there is a need to increase the awareness of SF lending techniques among agricultural lenders. Once the agricultural lenders understand the principles and concepts underlying SF lending techniques, it will become easy for them to adopt and use the lending techniques. Therefore, the study recommends increased dissemination of information about the application of SF lending techniques in agriculture, to agricultural lenders. Governments, academicians, agricultural based donor organisation and financial institutions will play a crucial role in the dissemination of information on Structured Finance techniques in agriculture.

Recommendation 2: In essence this study has developed a Theoretical Credit Risk Model that can be used to measure credit risk in agricultural based SF lending transactions. Therefore, the study recommends a **practical** application of the developed Credit Risk Model (in the measurement of credit risk) in **real** Structured Finance lending transaction in agriculture, so as to assess the accuracy of the developed credit risk model in predicting or determine the probability of default (PD).

Recommendation 3: The developed Credit Risk Model can be applied in any lending transaction, where Structured Finance is used, as long as production quantity and price data is available. The developed Credit Risk Model can be adapted and applied in the Structured Finance of the production, processing and marketing of agricultural commodities, in any country.

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APPENDICES

APPENDIX I: ENTERPRISE BUDGETS FOR DRY-LAND MAIZE PRODUCTION IN THE FREE STATE PROVINCE

Appendix I. A: Maize Production Enterprise Budget for Reitz, Bethlehem and Kestell

Produsent prys raming vir droëland WIT KONVENSIONELE MIELIES vir die / Producer price framework for dry land CONVENTIONAL MAIZE for the			PRODUKSIEJAAR 2009-10 PRODUCTION YEAR 2009-10			
Huidige Produkprys op plaas vir beste graad / Current product price for the best grade		1,227.00	Rand/ton			
Beplanningsopbrengs / Estimated yields (ton/ha)	2.5	3.0	3.5	4.0	4.5	5.5
Bruto produksiewaarde / Gross production value (R/ha)	3,019.38	3,623.25	4,227.13	4,831.00	5,434.88	6,642.63
Direk Toedeelbare veranderlike koste / Direct Allocated Variable costs (R/ha)						
Saad / Seed	489.67	527.33	565.00	565.00	621.50	621.50
Kunsmis / Fertiliser	717.20	915.30	1,150.10	1,367.00	1,690.60	2,057.00
Kalk / Lime	211.00	211.00	211.00	211.00	211.00	211.00
Brandstof / Fuel	444.83	454.37	463.91	473.45	482.99	498.47
Reparasie / Reparation	526.25	529.32	532.38	535.45	538.51	544.64
Onkruiddoders / Herbicide	183.60	183.60	183.60	183.60	183.60	183.60
Plaagdoder / Pest control	195.55	202.33	209.11	209.11	219.28	219.28
Insetversekering / Input insurance	59.82	71.78	83.74	95.71	107.67	131.60
Graanprysverskansing / Grain price entrenchment	479.65	526.93	580.19	623.29	694.65	769.28
Kontrakstroop / Contract Harvesting	-	-	-	-	-	-
Oesversekering / Harvest insurance	114.74	137.68	160.63	183.58	206.53	252.42
Lugspuit / Air gun	-	-	-	-	-	-
Losarbeid / Casual labour	-	-	-	-	-	-
Droogkoste / Drying cost	-	-	-	-	-	-
Verpakking en Pakmateriaal / Packaging and packaging material	-	-	-	-	-	-
Produksiekrediet rente / Interest on production R/ha	222.45	244.38	269.08	289.07	322.16	356.77
Totale Direk Toedeelbare veranderlike koste / Total Direct Allocated Variable Cost (R/ha)	3,644.75	4,004.02	4,408.75	4,736.25	5,278.49	5,845.56
Totale Oorhoofse koste / Total overhead cost R/ha	1,509.36	1,509.36	1,509.36	1,509.36	1,509.36	1,654.99
Totale Koste per ha voor fisiese bemarking / Total cost per ha before marketing cost	5,154.11	5,513.38	5,918.11	6,245.61	6,787.85	7,500.55
Totale koste per ton voor fisiese bemarking R/Ton / Total cost per ton before marketing cost R/Ton	2,061.64	1,837.79	1,690.89	1,561.40	1,508.41	1,363.74
Verwagte minimum Safex prys met wins ingesluit /Expected minimum Safex price, profit included	2,458.11	2,211.87	2,050.28	1,907.84	1,849.55	1,690.41

Appendix I. B: Maize Production Enterprise Budget for Welkom, Odendaalsrus, Wesselbron, Bulfontein and Hoopstad

Produsent prys raming vir droëland WIT KONVENSIONELE MIELIES vir die / Producer price framework for dry land CONVENTIONAL MAIZE for the		PRODUKSIEJAAR 2009-10 PRODUCTION YEAR 2009-10				GRAIN SA GRAAN SA
Huidige Produkprys op plaas vir beste graad / Current product price for the best grade		1,204.00 Rand/ton				
Beplanningsopbrengs / Estimated yields (ton/ha)	3.0	3.5	4.0	4.5	5.0	6.0
Bruto produksiewaarde / Gross production value (R/ha)	3,554.25	4,146.63	4,739.00	5,331.38	5,923.75	7,108.50
Direk Toedeelbare veranderlike koste / Direct Allocated Variable costs (R/ha)						
Saad / Seed	282.50	282.50	339.00	339.00	376.67	376.67
Kunsmis / Fertiliser	678.50	821.50	1,036.00	1,250.50	1,411.00	1,821.00
Kalk / Lime	105.50	105.50	105.50	105.50	105.50	105.50
Brandstof / Fuel	546.71	556.25	565.79	575.33	584.87	600.35
Reparasie / Reparation	546.20	549.26	552.33	555.39	558.46	564.59
Onkruiddoders / Herbicide	257.97	257.97	257.97	257.97	257.97	257.97
Plaagdoder / Pest control	187.10	187.10	187.10	187.10	187.10	187.10
Insetversekering / Input insurance	70.43	82.17	93.91	105.65	117.39	140.87
Graanprysverskansing / Grain price entrenchment	466.77	498.31	551.11	594.52	635.23	718.30
Kontrakstroop / Contract Harvesting	-	-	-	-	-	-
Oesversekering / Harvest insurance	135.06	157.57	180.08	202.59	225.10	270.12
Lugspuit / Air gun	-	-	-	-	-	-
Losarbeid / Casual labour	-	-	-	-	-	-
Droogkoste / Drying cost	-	-	-	-	-	-
Verpakking en Pakmateriaal / Packaging and packaging material	-	-	-	-	-	-
Produksiekrediet rente / Interest on production R/ha	212.99	227.38	251.47	271.28	289.85	327.76
Totale Direk Toedeelbare veranderlike koste / Total Direct Allocated Variable Cost (R/ha)	3,489.74	3,725.52	4,120.27	4,444.85	4,749.14	5,370.23
Totale Oorhoofse koste / Total overhead cost R/ha	1,508.40	1,508.40	1,508.40	1,508.40	1,508.40	2,369.12
Totale Koste per ha voor fisiese bemarking / Total cost per ha before marketing	4,998.14	5,233.92	5,628.67	5,953.25	6,257.54	7,739.35
Totale koste per ton voor fisiese bemarking R/Ton / Total cost per ton before marketing cost R/Ton	1,666.05	1,495.41	1,407.17	1,322.94	1,251.51	1,289.89
Verwagte minimum Safex prys met wins ingesluit /Expected minimum Safex price, profit included	2,048.25	1,860.55	1,763.48	1,670.84	1,592.26	1,634.48

APPENDIX II

APPENDIX II.A1: MONTHLY WHITE MAIZE SPOT PRICE (RAND/ TON): JAN 1998 – DEC 2009

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1998	945.6	893.3	764.9	693.2	618.7	618	734.3	684.7	649.1	652.5	613.9	621.8
1999	622.5	686.1	935.3	891.3	895.2	857.1	827.1	758.5	729.4	733.7	791.4	798.6
2000	802.7	800.2	752.2	692.5	669.4	602.7	535	506.8	539.4	615.1	672	684.8
2001	804.1	844.9	819	809.3	755.1	784	901.3	977.4	1002.8	1057.7	1279.3	1546.6
2002	1735.2	1854.9	2006.9	1917.3	1775.8	1754.1	1697.1	1737.7	1763.6	1756.5	1804.7	1744.4
2003	1531.9	1097.7	894.9	793.5	878.4	887	830.7	859.8	897.2	889	905.9	1094
2004	1302.5	1327.7	1077.7	1111.6	1050.2	989.8	881.6	939.1	917.2	897.52	973.5	799.5
2005	664.6	535.3	532.85	545.95	562.2	583.1	605.3	645.2	779.5	836.2	913.3	1105.15
2006	1082.4	985.7	1122.7	1090	1154	1294	1384	1318	1299.8	1257.2	1414.3	1374
2007	1345.68	1550.2	1920.48	1663.22	1653.5	1736.43	1681.55	1828.46	1862.26	1819.83	1874.23	1733.67
2008	1792	1755	1873	1856.62	1783.85	2005.78	1964.87	1851.81	1853.27	1784.43	1761.38	1835
2009	1814.05	1727.8	1704.55	1630.22	1597.7	1512.43	1339.48	1411.65	1410.14	1492.82	1527.86	1640.24

APPENDIX II.A2: ANNUAL WHITE MAIZE YIELD (TON/ HA) IN THE FREE STATE PROVINCE OF SOUTH AFRICA: 1961 – 2009.

YEAR	TON/ HA	YEAR	TON/ HA	YEAR	TON/ HA	YEAR	TON/ HA	YEAR	TON/ HA
1961	1.29	**1972**	1.92	**1983**	0.94	**1994**	3.07	**2005**	4.03
1962	1.39	**1973**	1.06	**1984**	0.99	**1995**	1.54	**2006**	4.06
1963	1.41	**1974**	2.30	**1985**	1.88	**1996**	3.27	**2007**	3.01
1964	0.97	**1975**	1.91	**1986**	1.78	**1997**	2.95	**2008**	4.32
1965	1.07	**1976**	1.51	**1987**	1.56	**1998**	2.59	**2009**	4.65
1966	1.22	**1977**	2.08	**1988**	1.62	**1999**	2.67		
1967	2.14	**1978**	2.31	**1989**	2.84	**2000**	3.39		
1968	1.13	**1979**	1.86	**1990**	2.21	**2001**	2.80		
1969	1.23	**1980**	2.42	**1991**	2.47	**2002**	3.00		
1970	1.40	**1981**	3.31	**1992**	1.17	**2003**	3.12		
1971	1.80	**1982**	1.88	**1993**	2.71	**2004**	3.11		

APPENDIX II.B1: MONTHLY YELLOW MAIZE SPOT PRICE (RAND/ TON): JAN 1998 – DEC 2009

YEAR	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
1998	717	682.1	611.18	552.11	531.9	552.57	606.17	604.39	631.52	656.45	628.11	647.45
1999	638.1	684.6	875.32	818.58	803.57	801.75	813.84	781.89	781.14	773.57	835.27	867.05
2000	858.15	829.57	729.33	670.53	678.64	610.47	528.48	502.35	543.64	629.49	707.41	737.89
2001	821.76	885.02	861.38	823.67	774.73	800.38	875.95	927.68	978.11	1047.96	1232.05	1463.89
2002	1650.18	1516.25	1467.68	1393.76	1312.09	1345.79	1389.09	1491.86	1543.85	1467.83	1395.67	1346
2003	1301.18	1088.75	942.25	828.21	904.52	918.55	859.13	880.33	928.76	931.09	967.75	1098.7
2004	1301.18	1378.7	1223.27	1195.56	1077.33	998.57	940.77	964.38	953.48	940.81	963.68	857.47
2005	731.95	652.55	603.8	610.45	606.43	612.24	630.76	624.77	713.86	760.76	810.45	883.6
2006	948.33	958.45	1010.62	996.12	1066.95	1196.24	1263.33	1208.91	1250.55	1273.23	1479.82	1602.63
2007	1572.14	1629.4	1899.81	1660.39	1681.24	1738.71	1678.59	1827.36	1924.68	1903.96	1997.95	1866.39
2008	1909	1832.52	1920	1852.38	1801.95	2061.45	2010.96	1829.24	1863.38	1776.96	1734.65	1643.7
2009	1730	1596.3	1531.45	1431.94	1455.15	1452.19	1269.57	1315.15	1244.62	1358.27	1439.29	1527.9

APPENDIX II.B2: ANNUAL YELLOW MAIZE YIELD (TON/HA) IN THE FREE STATE PROVINCE OF SOUTH AFRICA: 1961 – 2009

YEAR	TON/HA	YEAR	TON/HA	YEAR	TON/HA	YEAR	TON/HA	YEAR	TON/HA
1961	1.29	**1972**	1.92	**1983**	0.94	**1994**	3.54	**2005**	3.78
1962	1.39	**1973**	1.06	**1984**	0.99	**1995**	1.16	**2006**	3.58
1963	1.41	**1974**	2.30	**1985**	1.88	**1996**	2.49	**2007**	2.45
1964	0.97	**1975**	1.91	**1986**	1.78	**1997**	2.80	**2008**	4.06
1965	1.07	**1976**	1.51	**1987**	1.56	**1998**	2.26	**2009**	4.35
1966	1.22	**1977**	2.08	**1988**	1.62	**1999**	2.61		
1967	2.14	**1978**	2.31	**1989**	2.84	**2000**	3.10		
1968	1.13	**1979**	1.86	**1990**	2.21	**2001**	2.70		
1969	1.23	**1980**	2.42	**1991**	2.09	**2002**	3.05		
1970	1.40	**1981**	3.31	**1992**	0.70	**2003**	2.65		
1971	1.80	**1982**	1.88	**1993**	2.55	**2004**	3.00		