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AN ECONOMETRIC ANALYSIS OF THE EFFECT OF FORWARD INTEGRATION CREDIT RISK MITIGATION MECHANISMS OF COMMERCIAL BANKS ON THE PERFORMANCE OF THE AGRIBUSINESS FIRMS IN NYANZA REGION, KENYA

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Abstract

Credit risk is historically considered the main risk for banks. Commercial Banks apply Forward Integration Credit Risk Mitigation Mechanisms (FICRMMs) to promote credit access, security and productivity for various sectors. Agribusiness contributes 53% to employment in developing countries, and 80% in Kenya, yet credit to the sector shows decreasing trends, ranging from 6.5% to 2.9%, between 2003 and 2012. Purpose of this study is to investigate the impact Forward Integration Credit Risk Mitigation Mechanisms on performance of agribusinesses in Nyanza region. The study adopted a Descriptive longitudinal research design. The target population comprised of agribusiness firms. The sampling technique used was stratified random sampling. Primary data on practitioners' opinions was obtained using structured questionnaires, while secondary data on credits, capital, FICRMMs and owner equity was obtained from the firms' financial statements. Means, standard deviation, correlation, and Vector Auto-regression (VAR) was used to analyze data. The results from dynamic models of VAR provides R² of 0.7349, 0.8131 and 0.6505 for profit, return on equity and capital growth model respectively; all significant at $p < 0.05$, revealing that over time, the explained variable is affected by its own lagged evolution and the lags of other endogenous variables(FICRMMs), thereby accounting for 73.5% of profits, 81.3% of ROE and 65.1% of capital growth. These results may help in re-

formulating agribusinesses credit policies. The findings reveal that FICRMMs have significant effect on agribusiness performance. It is recommended that sensitivity analysis of the variables be done, establish implementation level of FICRMMs, improve information system, and restructure the mitigation parameters.

Keywords: Forward Integration, Credit Risk Mitigation, Performance, Agribusiness, Vector Autoregressive Models

INTRODUCTION

Credit risk is historically considered the main risk for banks (Gunther, 2010). This requires an inter-temporal equilibrium model that fully integrates the financial and real sector economic players, in not only understanding the mechanisms at work, but also the specific sectoral credit risk mitigating strategies, for enhanced trade and financial flows. Mhalanga (2010) states that commercial banks remain the most appropriate financiers to the agribusiness sector by serving the supply side of credit as the agribusinesses participate on the credit demand side.

The Kenya National Economic Surveys of 2007 -2012 emphasizes agribusiness' need for funding, a reasonable part of which comes from commercial banks' credits. Since credits form part of business capital, the commercial banks share in its provision remains critical. However, Gichira(2010) reveals that credit financing to the agribusiness sector has been declining. He further states that agribusiness requires financing, part of which is done through credit funds from the financial institutions.

The current credit evaluation systems do not take specific agro-industry risk into consideration (David, 2013). The lack of, or limited access to credit, has therefore been a major impediment to the development of primary agriculture as well as the upstream and downstream sectors in all transition economies (Howe, 2003). Available literature mainly point national aggregate of financial, manufacturing and established commercial sectors, with limited focus to agribusiness firm.

According to Gabor, Carlos and Nomathemba(2013), the central banks need to embrace their expanded role as "market maker of last resort" by going forward to expand the borrowers' potential to turn in sufficient profits that enables them to reduce the probability of default (PD). This process, done through commercial banks provide a liquidity backstop for systemically important markets and the shadow banking system that is deeply integrated with these markets. It is therefore necessary to determine the commercial banks' application of mechanisms that expand the borrower capacity or credit market, and establish the amount of credit financing in

the entire agribusiness capital structure, especially those in growth stage, in which most of the agribusiness firms in Kenya and the Nyanza region in particular.

The Kenya National Economic Surveys of 2007 -2012 emphasises agribusiness' need for funding, a reasonable part of which comes from commercial banks' credits. Since credits form part of business capital, the commercial banks share in its provision remains critical. However the banks' share of credits to the sector between 2003 and 2012 shows a decreasing trend from 6.5% to 2.9%; despite the fact that the sector's its contribution to the Kenyan GDP has for the same period shown an increase between 1.8% and 6.9%. Kimathiet *al*, (2008), Agwe and Azeb(2009), Vorley, Fearn, and Ray (2006), UNIDO (2012), Geoff and Grahame (2012) and GoK (2012); have all observed in diverse ratings that lack of capital or its stagnation on agribusiness firms renders them incapable of expanding their operation scope, although credit institutions critical interests, are to improve their returns and general performance. This would help to expand and sustain their credit market by managing critical access barriers for sustainable profitability. Smith (2007) explains that Forward Integration Credit Risk Mitigation Mechanisms (FICRMMs) are measures by the commercial banks to increase credit access credit productivity and also limit default. Consequently, noting that credit is critical for financing agribusiness like any other business' operations and profitability, while credits to the sector is declining against an implied increasing contribution to the GDP, as the banks implement Forward Integration Credit Risk Mitigation Mechanisms (FICRMMs), there is a disconnect between expected increase in credit resulting from implementation of the Forward integration credit risk mitigation mechanism, and reduced credits and its effect on agribusiness performance in terms of profits, Return on Equity, Return on Assets and Capital growth. Therefore, this scenario requires the determination of the impact of the FICRMMs on the performance of the agribusiness enterprises. Furthermore, there is limited information on the effect of the credit supply side operations that influence the credit demand side for the Nyanza region under this study; neither are there studies specific to agribusiness sector financing risk mitigation, examining the variables under this study for the region.

Statement of the problem

Sound risk management is critical for sustainable agricultural finance. Commercial banks' share of credits to the sector between 2003 and 2012 showed a decreasing trend while its contribution to the GDP increased. Agriculture is a main source of employment in Kenya and significantly contributes the GDP. Whereas among its critical challenges is lack of capital and access to affordable credit among others, bankers recognize that client's business performance is key to

identifying and managing the heavy two- tier 'credit risk load' in lending relationships. Commercial banks remain most sustainably appropriate financiers to the agribusiness sector.

This makes it necessary to establish the measure of credit in the entire business capital of all firms and especially those in growth stages; reminiscent of most agribusiness firms. There is however a missing link between expected increases in credits resulting from implementation of the Forward integration credit risk mitigation mechanism, and reduced credits and its effect on agribusiness performance. Credit risk management therefore draws from both the lenders and borrowers' sides; to promote lenders' returns and ensure borrowers' profitability, while at the same time recognizing that the capacity of the borrowers to repay the loans arises from their profits, partly generated through credit finance, yet the contribution of the FICRMMs to the agribusiness profits remain unknown.

It is evident that FICRMMs are being applied but there is a still limited credit to the agribusiness sector. On the other hand, there is little information on the impact of the forward integration credit risk mitigation mechanisms on the performance of these agribusiness firms. This study therefore determined the impact of forward integration credit risk mitigation mechanisms on the performance of agribusinesses in Nyanza region.

Research Objective

To examine the impact of Forward Integration Credit Risk Mitigation Mechanisms on the performance of the agribusiness firms in Nyanza region.

Hypothesis

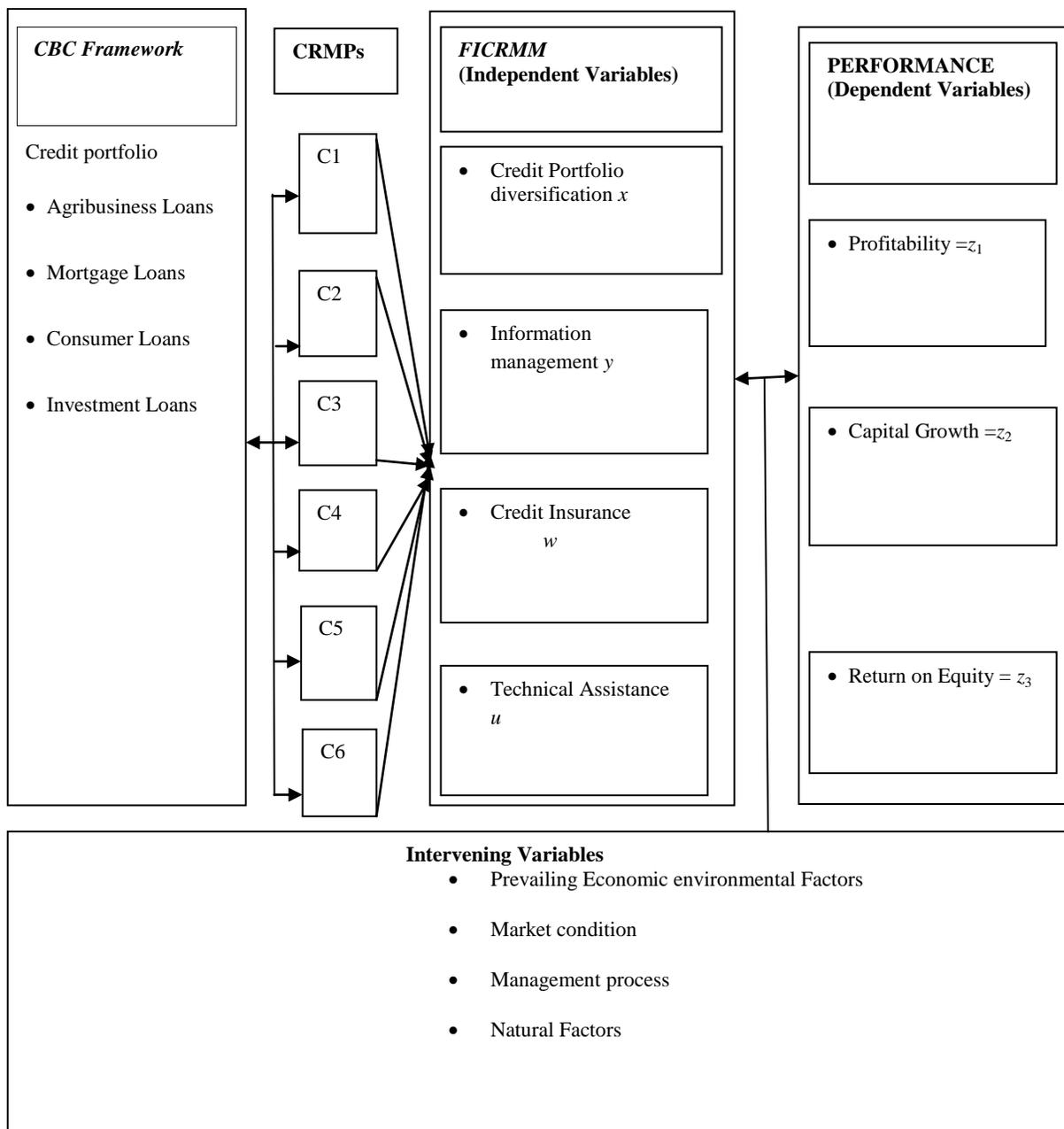
Forward Integration Credit Risk Mitigation Mechanisms does not affect the performance of agribusiness firms in Nyanza region

Conceptual Framework of the Study

Figure 1 shows a conceptual framework of the study, which proposes the chain relationships that exist in the commercial banks' credit risk management framework (CBC), with credit risk management practices (CRMPs) and the forward integration credit risk mitigation mechanisms applied by the commercial banks (FICRMMs), in a constructively innovative approach to reduce the risk load on both the lenders and borrowers. This framework recognizes that the commercial banks' credit framework (CBC) includes the credit products that constitute their credit portfolio. It further proposes the fact that in granting the credit products to the borrowers, the banks assess the borrowers' creditworthiness on the basis of the credit risk management practices (CRMPs) which are resident to the specific action domains, normally referred to as mitigation mechanisms

(x , y , z and u). The action domains selected for this study are those used with forward integration effects (FICRMMs), leaving out the exclusively backward integration parameters. Within the domains are the measurable parameters examinable under each case. The framework consequently proposes a relationship or linkage between the forward integration credit risk mitigation mechanisms and the performance outcomes of the agribusiness enterprises (Z_1 , Z_2 , and Z_3). However, the relationships occur in an environment where there are other intervening variables which exist in every economy and therefore may influence the circumstances under which the variables interact.

Figure 1. Conceptual Framework



Specification of Variables

CBC Framework = Commercial Banks' Credit Framework.

CRMPs = Credit Risk Mitigation Practices

C1= Collateral Management

C2= Capital Requirement

C3= Cost Implications

C4= Character of the borrower

C5= Capacity to repay

C6= Condition of operation

Independent Variables: Forward Integration Credit Risk Mitigation Mechanisms (**FICRMM**)

These take the notation of X elements, where;

x = Credit portfolio diversification

y = Information Management

w = Credit Insurance

u = Technical Assistance

Dependent Variables (**Agribusiness performance**)

These are denoted by z elements, where;

z_1 = Profitability

z_2 = Capital Growth

z_3 = Return on equity

LITERATURE REVIEW

Theory and Concepts of Credit Risk Mitigation

Dwyer (2012), states that the theory of credit risk mitigation draws heavily from historical and contingent operational outcomes of the commercial banks, whose operational environments present dynamic risk inherence. Beverly et al (2001) defines Credit Risk Mitigation as the employment of various methods, tools/practices (mitigants), to reduce the risks to lenders, banks and other business which offer credit.

Basel II Accord (1999) explains that credit risk framework explores the fact that risk is a concept applied to situations where there are several possible outcomes with relevant past experience to produce statistical evidence for predicting the possible outcomes. In contrast, uncertainty exists where there is little previous statistical evidence to enable the possible outcomes to be predicted (Drury, 2011). This implies that credit risk mitigation is dependent

upon determinate bank functions that enable loss reduction arising from default and on the other side promote borrower credit capacity. The building blocks of the framework therefore include probabilities of default, average borrower default rates, and cumulative accuracy profiles (CAP). Financial institutions collect information on mitigation and risk profile to potentially calibrate it to an asset class or loan category specific settings.

According to Steinwand (2002) Financial Institutions (FIs) mitigate transaction risk through borrower-screening, insurance underwriting, and quality information procedures for loan disbursement, monitoring, and collection. Portfolio risk, inherent in the composition of the overall loan portfolio is mitigated through proper portfolio management and relevant insurance covers. Policies on diversification, maximum loan size, loans types and loan structures lessen portfolio risk. Agwe and Azeb (2009) views risk mitigation as a critical operational risk management tool with a forward and backward linkage in a borrower-lender relationship.

Credit Risk Mitigation Mechanisms applied by the Lending Institutions

Calvin Miller's contribution to a policy paper on "Risk mitigation and management for Agricultural Investment (2008), identifies six significant credit risk mitigants as: improving information systems, strengthening rural financial sector, agricultural insurance management, market based price management, credit safety netting, portfolio management and income planning. This study identifies three of these factors for direct analysis (i.e. information system management, agricultural insurance and portfolio management) while the other three contribute moderating effects on the others.

On the determinants of credit risk mitigation in lending to Black Economic Empowerment (BEE) companies, from bankers' perspective, Meyer (2005) explains that Poor credit records, lack of training, resulting in skills and capacity gaps limited commercial banks' entry into the lending market considered to be the main limitations in obtaining finance for the Small, Medium and Micro Enterprises (SMMEs) and agribusinesses. The study findings were that there was lack of or limited personal financial contribution to the small firms, while security was still prevalent in the medium to large market oriented firms. The quality of management (little training and skills) was deemed not to be a limitation as suitable credit risk mitigants were not identified for poor credit record. However he suggests that by determining adopting and applying the identified credit risk mitigants, commercial banks can increase their success rate in lending to BEE companies.

Vorley, *et al.* (2006), underscores the need for the trends towards increasing concentration, vertical financing coordination and contracting in agricultural sectors, as a mechanism for providing an enabling environment for innovative agribusiness enterprises in the

developing countries which are increasingly becoming essential prerequisite for economic development and poverty reduction. According to Larsen (2009) deliberate and strategic interventions on the part of governments can therefore play an important role in fostering the development of agro-industries and the enhancement of their value chains. He identifies critical priority areas that require support and technical assistance as access to capital and financial services, risk management and related legal frameworks, institutions and support services for improved market access and leveraging of producers and agribusinesses in the value chains.

Forward Integration Credit Risk Mitigation Mechanisms and Agribusiness Performance

Forward integration Credit Risk mitigation mechanisms (FICRMMs) are measures undertaken by the commercial banks to increase access to credits by the various sectors of the economy and to enhance and promote credit productivity (Smith, 2007). According to World Bank (2009), sound risk assessment and management is a fundamental element of sustainable agricultural finance at the levels of the farm, financial institutions and value chain.

Felix and Claudine (2008), states that the components of Credit Risk Management (CRM) system differ in Commercial Banks (CBs) operating in a less developed economy from those in a developed economy. The mitigation mechanisms majorly applied to agribusiness by the developing and developed countries have been value chain management, credit insurance, agribusiness enterprise training, asset transformation, diversification and agribusiness appraisal on the basis of adverse collection and moral hazards (Gichira, 2010).

Sessional Paper number 4 (GoK, 1981) explains that gradual government divestiture from the agricultural sector culminated in the opening of the Kenyan economy raises the level of emphasis that should be given to the sector considering the proportion of its supports to other sectors and the significant level of income generated from it. As credit risk mitigation framework caters both for protection from default and borrowers' capacity to limit default (Duffie, 2008). Wolfgang (2005) observes that the Commercial banks' handling of credit risk constantly seeks to ascertain the risk- profit profiling in a way that the interest of lenders and borrowers, including regulators, are satisfied. However, in departure from expectation, the agricultural sector has been receiving the least level of credit facilities from commercial banks with exception of a few banks (Koza, 2007).

UNIDO (2012) asserts that the financing structure should be developed to help grow the sector's capital base for sustainable productivity. According to Angiuse *et al* (2011), all these have been modeled in the risk mitigation schedules of the lending institutions to agribusiness borrowers. Shield (2012), states that disconnect between Africa's agricultural potential and its current state; including macro-level hurdles such as currency risk and market-distorting policies

are challenges that require effective attention. In addition, inadequate credit strategically designed to finance inputs and capital investment in agriculture in general and agribusiness in particular, requires comprehensive approach; in helping to profitably exploit the agricultural sector's potential. This implies that the environment within which the bank operates is an important consideration for a CRM system to be successfully profitable to the lenders and borrowers. Since Commercial banks are the main intermediaries for mobilization of substantial part of a country's funds, it is reasonable to expect their participation in the process by availing financial services to the development of the sector, and be more concerned about the sector's performance.

RESEARCH METHODOLOGY

Research Design

This study adopted a descriptive longitudinal research design which is positivist in philosophical orientation. The method allows for analyzing panel and time series data, deductive theorizing, empirical verification and quantification of qualitative observations. It therefore enabled the study to explain how credit risk mitigants' impact on agribusiness performance indicators over time.

Study Area

The study was conducted in Nyanza region of Kenya; where agriculture caters for up to 86% of the region's employment directly and indirectly. The region is inclusive of the six counties in the current administrative description, i.e. Siaya, Kisumu, Homa bay, Migori, Nyamira and Kisii.

Target population

The target population for the study contained all the agribusiness firms in Nyanza region that have credit contracts with the lending institutions and have been existence from 2002 to 2012. The agribusinesses are divided into the categories agro- processing and farm based enterprises.

Sampling Technique and Sample size

Stratified random sampling was used to select appropriate sample size of 45 firms. Random sampling was found suitable since it allowed for objectivity in selecting a sufficient number of subjects from each stratum, thereby providing a sample size which is fairly representative of the population's characteristics.

Assuming that the distribution of the population is normal then the minimum sample size would be determined using the following formula.

$$n = \frac{z^2 \times \sigma^2}{\beta^2}$$

Applying the same formula on agro-processing and farm based agribusinesses;

- i) $n_1 = (1.96)^2 * 6^2 / 21.84^2 = 19.64$ Agro-processing = 20.
- ii) $n_2 = (1.96)^2 * 6^2 / 12.34^2 = 25.36$ farm based Agri businesses = 25.

Where:

n= Sample size

n_1 = Sample size for agro-processing firms

n_2 = Sample size for farm based agribusiness firms

Z = Z value (e.g. 1.96 for 95% confidence level)

σ^2 = Variance from the mean

β^2 = Population Mean of the businesses

Hence, the sample size for agro-processing= 19.6, \approx 20 while for farm based agribusinesses = 25.3, \approx 25; bringing the total to 45 firms. The 45 selected firms are observed for the ten years period on a quarterly basis, thereby giving a total of $(45 \times 10 \times 4) = 1800$ observations to be analyzed.

Data Collection Instruments

The study primarily utilized secondary data that was gathered from annual Financial Reports of the agribusinesses firms operating in the study area. Existing banking reports from Central Bank of Kenya, and other publications from the Internet and Government Resource Centers was used to gather information on commercial banks' lending to the agribusiness sector.

Data Analysis Approach: The VAR Model Description

In a Vector Autoregressive VAR model, the current values of each one of the variables in the model are expressed as functions of past values of the same variables. This model is most appropriate model for the phenomenon under investigation.

In this study there are four variables that have been identified (on a *priori* basis) that are relevant and significant in their contributions and each of the values of each one of the four factors/variables at the current time “t” is affected by past values of all the four variables in the system.

This gives rise to a vector autoregressive (**VAR**) model. The general form of the model with z_t as the dependent variable, is represented as

$$z_t = f(z_{t-i}, x_{t-i}, y_{t-i}, w_{t-i}, u_{t-i} \varepsilon_t) \quad t = 1, 2, \dots, T; \quad i = 1, 2, \dots, k \quad 3.1$$

Where:

x_t, y_t, w_t, u_t = Credit risk mitigating mechanisms

z_t = Performance

Assumptions of VAR

- i) The disturbances ε_t is white noises. $E(\varepsilon_t) = 0$, $\sum = Var - Cov(\varepsilon_t) = E(\varepsilon_t \varepsilon_t')$

Each disturbance has zero expectation and constant variance

- ii) The variables are all endogenous (i.e. there are no exogenous variables)
- iii) The disturbances are non- auto correlated $E(\varepsilon_t \varepsilon_{t-i}) = 0$ for $i \neq 0$.
- iv) There is no perfect multicollinearity among the regressors.
- v) The regressors are uncorrelated with the disturbance in each equation
- $$E(Z_{t-i}, \varepsilon_{it}) = 0 \quad i = 1, 2, \dots, p$$

RESULTS AND DISCUSSION

Descriptive Statistics

The study sampled 45 firms of which 43 firms returned the offered data to the study. This represents a response rate of 95.55% of the sample size. Table 4.1 presents the descriptive statistics of the study variables. This section further provides measures of central tendency and variation of the study variables which are important for establishing the behaviour of the variable with each other.

Table 1: Descriptive Statistics for all the Variables (n= 1720)

	CAPEMGR	CREDINS	INFMGT	PORTDIV	PROFIT	ROE	TECHASS
Mean	4.632880	3.465000	7.783250	4.617500	19.18146	11.20542	5.315250
Median	3.850000	3.285000	7.225000	4.800000	20.26000	12.02000	5.265000
Maximum	50.33000	6.140000	12.73000	7.250000	36.42000	33.62000	7.210000
Minimum	-23.12300	0.960000	2.870000	0.890000	-27.32000	-38.96000	3.690000
Std. Dev.	5.853476	1.329202	2.277406	1.338124	10.43752	7.690491	1.023134
Skewness	0.691328	0.234385	0.054471	-0.671313	-1.463601	-1.185314	0.003347
Kurtosis	7.810074	2.157967	2.614888	3.534333	5.594234	7.100471	1.826987
Jarque-Bera	1795.146	66.56149	11.47955	149.6514	1096.397	1607.751	98.61362
Probability	0.000000	0.000000	0.003215	0.000000	0.000000	0.000000	0.000000
N	1720	1720	1720	1720	1720	1720	1720

Skewness, being an indicator used in distribution analysis as a sign of asymmetry and deviation from a normal distribution is a normality test of the elements of each variable. Therefore $\text{Skewness} > 0$ - Right skewed distribution, implying that most values are concentrated on left of the mean, with extreme values to the right. $\text{Skewness} < 0$ - Left skewed distribution implying most values are concentrated on the right of the mean, with extreme values to the left. $\text{Skewness} = 0$ - mean = median, the distribution is symmetrical around the mean. The independent variables' output reveals that; PORTDIV (Credit Portfolio diversification) is negatively skewed at -0.671. This implies that there are more observations of relatively high values. CREDINS (Credit Insurance), INFMGT (Information management) and TECHASS (Technical Assistance) are also positively skewed at 0.234, 0.054, and 0.003 respectively. For the dependent variables, CAPEMGR (Capital Growth) is positively skewed at 0.691, while PROFIT (Profit) and ROE (Return on Equity) are negatively skewed at -1.463 and -1.185 respectively. The standard deviations describing historical volatility of the variables from their means, show that PROFIT is more volatile with $\text{SD}=10.437$, while ROE has a $\text{SD} =7.690$ and CAPEMGR has a $\text{SD} =5.853$. The standard deviations show how unstable the profits, return on equity and capital growth widely vary from expectation for the duration of the study. However, for the FICRMMs, appear to be stably employed by the commercial banks as shown by PORTDIV at $\text{SD} = 1.338$, CREDINS at $\text{SD} = 1.329$, INFMGT at $\text{SD} = 2.277$ and TECHAS $\text{SD} = 1.023$. The fairly wide ranges of dispersions reveal that the commercial banks might have adopted FICRMMs which are almost similarly employed from time to time without great variations. It therefore requires the banks to aggressively adjust to consistently employ technical assistance not only to protect them from default but also to use it as an avenue to expand real credit demand.

Kurtosis, being "the standardized fourth population moment about the mean" (Lawrence, 1997); is a measure of the data's flatness or peakedness of data, where a "Normal" distribution has a Kurtosis of 3. Kurtosis values greater than 3 indicate that the distribution is peaked relative to the normal (leptokurtic); implying a sharper than normal distribution, with values concentrated around the mean and thicker tails. If the Kurtosis is less than three, the distribution is flatter than the ideal normal curve (platykurtic); implying a flatter than a normal distribution with a wider peak. Kurtosis = 3 refers to Mesokurtic distribution - normal distribution. Therefore from the data in Table 4.1. Information management ranges around normal at 2.615, while Capital growth is at 7.810, Return on equity at 7.101, profit at 5.594, and credit portfolio diversification at 3.534 respectively; all being leptokurtic.

The Jarque-Bera statistics measures the normality of an observed distribution (the 'goodness of fit' of a statistical model); and is dependent on the values for Skewness and

Kurtosis. J-B probability is calculated from chi-square table, with 2 degrees of freedom. J-B defines how the random variables stochastically relate to one or more other variables; reveal that the observed results are highly likely under the null hypothesis by random Chance. This is evident from the JB observations and the respective probabilities of their occurrence. Subsequently, Table 4.1 shows that the maximum value of profits attained by the companies within the 10 years' period of the study is 36.42% and a minimum of negative 27.32%. The fluctuation gap of profit movement over time reflects wide extent of profit volatility in respect of agribusiness enterprise in the region. On return on equity, the maximum value attained is 33.62 and minimum of -38.96; similarly showing a wide fluctuation of return on equity over the time as influenced by the FICRMMs. From the results, it means that in the short run, the profit capacity of the agribusiness firms would be reduced by the credit management costs; and only stabilises over time. Capital growth has a maximum change of 50.33% and a minimum of -23.12%. This shows a big depression in capital growth. It implies that the agribusiness sector's capital movement is unstable in the short run, due to productive risks; in agreement with Hull, (2007) assertion that at the onset of the loan contract there are more loan- fund management costs which impact of investment profits. The results indicate that all the variables are not normally distributed in the short run but stabilize over time; implying that the agribusiness operational environment is mainly unstable

Correlation Analysis

Table 2: Correlation Results for all the variables

Correlation	CAPEMGR	CREDINS	INFMGT	PORTDIV	PROFIT	ROE	TECHASS
CAPEMGR	1.0000						

CREDINS	0.680516** (0.0000)	1.0000					

INFMGT	0.829072** (0.0000)	0.800431** (0.0000)	1.0000				

PORTDIV	0.627022** (0.0000)	0.440100** (0.0000)	0.645224** (0.0000)	1.0000			

PROFIT	0.637493** (0.0000)	0.519215** (0.0000)	0.752685** (0.0000)	0.775239** (0.0000)	1.0000		

ROE	0.639675** (0.0000)	0.508111** (0.0000)	0.728044** (0.0000)	0.703711** (0.0000)	0.804185** (0.0000)	1.0000	

TECHASS	0.784481** (0.0000)	-0.127271** (0.0000)	0.514710** (0.0000)	0.799084** (0.0000)	0.533059** (0.0000)	0.669961** (0.0000)	1.0000

Note: The p values are in parenthesis. ** Significant at both 1% and 5% level

From the correlation results, there are significant positive correlations between capital growth (CAPEMGR) and credit insurance (CREDINS) at $r = 0.6805$, $p = 0.0000$. Capital growth (CAPEMGR) and Credit Information management (INFMGT) have a significant positive correlation of $r = 0.8291$, $p=0.0000$. Capital growth (CAPEMGR) and credit portfolio diversification (PORTDIV) have strong positive and significant correlation at $r= 0.6270$, $p = 0.0000$. Capital growth (CAPEMGR) and technical assistance (TECHASS) have strong positive and significant correlation at $r= 0.7845$, $p = 0.000$. Credit Information management (INFMGT) and Credit Insurance (CREDINS) have very strong positive and significant correlation at $r = 0.8004$, $p = 0.0000$. Portfolio diversification (PORTDIV) has weak but significant correlation with Credit Insurance (CREDINS) with $r = 0.4401$, $p = 0.0000$. Technical Assistance (TECHASS) has weak negative correlation with Credit Insurance (CREDINS) with $r = -0.1273$, $p = 0.0000$. Credit Information management (INFMGT) have a significant positive correlation with credit portfolio diversification (PORTDIV) at $r = 0.6452$, $p = 0.0000$. Technical Assistance (TECHASS) has moderate but significant correlation at ($r = 0.5147$, $p = 0.0000$) and strong positive and significant correlation with Portfolio diversification (PORTDIV) $r= 0.7991$, $p=0.0000$.

This implies that as capital growth has strong significant and positive association with Credit Insurance, Information Management, Portfolio Diversification and Technical Assistance also increase. Credit Insurance has strong significant and positive association with information management and weak positive and significant association with portfolio diversification increase. Technical assistance has weak, negative and significant association with credit insurance. Information management has strong significant and positive association with portfolio diversification with Technical Assistance. Subsequently, the correlation results of the independent variables with dependent variables were as follows: Capital growth (CAPEMGR) has strong positive and significant correlation with Profits (PROFIT) with ($r= 0.6375$, $p= 0.0000$) and with Return on Equity ($r = 0.6397$, $p= 0.0000$). Credit Insurance (CREDINS) has moderate but significant correlation with Profits ($r= 0.5192$, $p= 0.0000$) and Return on equity at ($r= 0.5081$, $p= 0.0000$). (0.7527) Information Management has strong and significant positive correlation with Profit ($r= 0.7527$, $p= 0.0000$) and Return on Equity ($r= 0.7280$, $p= 0.0000$). Credit Portfolio Diversification (PORTDIV) has strong positive and significant association with, Profits (PROFIT) ($r= 0.7752$, $p= 0.0000$) and Return on Equity (ROE) ($r= 0.7037$, $p= 0.0000$). Technical Assistance (TECHASS) has a strong positive and significant correlation with ($r= 0.5331$) to; which also points to a strong positive correlation with Return on Equity (ROE) ($r= 0.8041$, $r= 0.0000$), and a moderate and significant correlation with Technical Assistance (TECHASS) ($r= 0.5331$, $p= 0.0000$). Technical Assistance (TECHASS) has moderate but significant correlation with profit (PROFIT) $r= 0.5331$, $p= 0.000$ and Return on Equity (ROE) $r= 0.6670$, $p= 0.0000$.

These findings are generally consistent with the findings of Kithinji (2010) who established that profits of commercial banks are not influenced by the amount of credits and non-performing loans but attributes it to other variables that expand and sustain credit market, allowing into play the borrowers' capacity and sustainability as important determinants for commercial banks' performance. A Risk Management Framework for Microfinance Institutions, developed by Microfinance Network (2000); TechnischeZusammenarbeit (GTZ) GmbH, provides a framework which recognises credit information management and technical assistance by either the banking system or other institutionalized advisory units, in not only expanding credit supply but also increasing credit demand. In this study, the two tools are closely related in such a way that they are employed concurrently. Many of the losses expected from the risks inherent in modern agribusiness systems are, in fact, related to uncertain events for which there are no known probabilities, although subjective probabilities can be conjured by expert opinion, poor information systems analysis and insufficient technical assistance (Jaffee, Siegel, and Andrews 2010).

According Grameen Foundation (2010) "Community Knowledge Worker Pilot Report", many risks can be mitigated by timely action and through the application of best credit risk mitigation practices to the sector. Typical risk mitigation actions must be based on both credit demand and supply sides. In this respect, Information management is the most critical for effective risk mitigation. Both credit institutions and farmers need a variety of information setting to make choices on how to manage risk; most important of which are information for risk mitigation are advisory information for farmers prompt decision and response to warnings on the likely occurrence of risk factors. Their findings subsequently establish that the connection between agricultural advisory services as part of information management, lenders' credit portfolio diversification, credit insurance and technical assistance to risk mitigation set an important mitigation framework, because information alone is often not always sufficient to manage risk (Grameen Foundation 2010). This view is partly confirmed by the high positive correlation coefficients. It is evident that only credit insurance has a weak negative correlation with technical assistance. This implies that as credit insurance increases, technical assistance decreases.

Unit Root Test for all the variables

The need for unit root test arises from the fact that stationarity or otherwise of a series can strongly influence its behaviour and properties - e.g. persistence of shocks will be infinite for non-stationary series. If two variables are trending over time, a regression of one on the other could have a high R^2 even if the two are totally unrelated. This gives spurious regressions. If the

variables in the regression model are not stationary, then it can be proved that the standard assumptions for asymptotic analysis will not be valid; i.e. the usual “t-ratios” will not follow a t-distribution, so we cannot validly undertake hypothesis test about the regression parameters.

Therefore, it is important to check whether a series is stationary or not before using it in a regression. The formal method to test the stationarity of a series is the unit root test. This study computed both individual and group unit root test for the seven variables in the study.

Individual unit root test for all the variables

Unit root tests are taken mainly to test for stationarity of the variables’ movement over time to avoid biases that lead to a spurious regression, and also to eliminate the shock effects and therefore make the series stationary. The study tested for unit root using Augmented Dickey-Fuller (ADF) and Phillips Perron(PP) tests . The results for the individual test are shown in Table 3.

Table 3: Individual Unit roots Test

Variables	Augmented Dickey Fuller (ADF) Test		Phillips Perron (PP) Test		Inference
	Intercept with		Intercept with		
	Intercept	Trend	Intercept	Trend	
<i>Level</i>					
CAPEMGR	-8.4592** (0.0000)	-8.5246** (0.0000)	-20.3071** (0.0000)	-20.3322** (0.0000)	I(0)
PROFIT	-12.4867** (0.0000)	-12.6489** (0.0000)	-12.2279** (0.0000)	-12.31195** (0.0000)	I(0)
ROE	-11.6935** (0.0000)	-11.7244** (0.0000)	-11.4207** (0.0000)	-11.4452** (0.0000)	I(0)
CREDINS	-13.5571** (0.0000)	-13.5531** (0.0000)	-32.5677** (0.0000)	-32.5656** (0.0000)	I(0)
INFMGT	-30.3589** (0.0000)	-30.3499** (0.0000)	-12.2857** (0.0000)	-12.2835** (0.0000)	I(0)
PORTDIV	-12.7130** (0.0000)	-12.7092** (0.0000)	-22.8614** (0.0000)	-22.8548** (0.0000)	I(0)
TECHASS	-36.3821** (0.0000)	-36.3705** (0.0000)	-9.1057** (0.0000)	-9.1038** (0.0000)	I(0)
<i>First Difference</i>					
Δ CAPEMGR	-13.7409** (0.0000)	-13.7384** (0.0000)	-165.2336** (0.0000)	-165.8055** (0.0001)	
ΔPROFIT	-17.3743** (0.0000)	-17.3703** (0.0000)	-109.2050** (0.0001)	-108.8824** (0.0001)	
ΔROE	-16.6199** (0.0000)	-16.6150** (0.0000)	-60.5737** (0.0001)	-60.5455** (0.0000)	

Δ CREDINS	-12.2916** (0.0000)	-12.2876** (0.0000)	-353.4855** (0.0001)	-353.3881** (0.0001)
Δ INFMGT	-12.3468** (0.0000)	-12.3426** (0.0000)	-87.8705** (0.0001)	-87.0571** (0.0001)
Δ PORTDIV	-12.6487** (0.0000)	-12.6451** (0.0000)	-269.0802** (0.0001)	-558.7818** (0.0001)
Δ TECHASS	-12.3718** (0.0000)	-12.3684** (0.0000)	-32.1289** (0.0000)	-32.1162** (0.0000)

Notes: The Null hypothesis is that the series has a unit root. The rejection of the null hypothesis for the DF and PP test is based on the Mackinnon critical values. ** indicates the rejection of the null hypothesis of Unit root at 5% level of significance. The parenthesized values are the probability of rejection while Δ denotes the first difference,

The results in Table 3 indicate that all the variables are stationary at levels; that is, they are perfectly integrated at order zero denoted by $I(0)$. This is confirmed by the first difference integration. The series are therefore stationary at level and at first difference, implying that data series evolve around a constant zero mean.

Group Unit Root Test for all variables

Recent literature suggests that panel-based unit root tests have higher power than unit root tests based on individual time series. The study computed following five types of panel unit root tests: Levin, Lin and Chu (2002), IM, Pesaran and Shin (2003), Fisher-type tests using ADF and PP tests. The “Common root” indicates that the tests are estimated assuming a common AR structure for all of the series; “Individual root” is used for tests which allow for different AR coefficients in each series. They used the automatic selection methods: information matrix criterion based on the number of lag difference terms (with automatic selection of the maximum lag to evaluate), and the Andrews or Newey-West method for bandwidth selection (Table 4).

Table 4: Group Unit Root Test: Summary for all variables

Method	Statistic	Prob.**	Cross sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-10.3122	0.0000	7	11913
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-48.7589	0.0000	7	11913
ADF - Fisher Chi-square	829.488	0.0000	7	11913
PP - Fisher Chi-square	976.456	0.0000	7	12033

Series: CAPEMGR, CREDINS, INFMGT, PORTDIV, PROFIT, ROE, TECHASS

Exogenous variables: Individual effects

Automatic lag length selection based on SIC: 0 to 24

Newey-West automatic bandwidth selection and Bartlett kernel

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution

. All other tests assume asymptotic normality.

From the table 4, the results of the four tests (i.e. Levin, Lin and Chu, IM, Pesaran and Shin, Fisher-type tests using ADF and PP tests) indicate the absence of a unit root, as the LLC, IPS, and both Fisher tests reject the null hypothesis of a unit root. This confirms the results of the individual unit root test.

Vector Autoregressive Model

In order to determine the interdependencies and dynamic relationships between variables, the study applied the Vector Autoregressive Analysis (VAR). VAR models have a long tradition as tools for multiple time series. Being linear models, they are relatively easy to work with both in theory and practice. A typical VAR analysis proceeds by Specifying and estimating a model and then checking its adequacy in estimation or prediction. As Mukras (2012) notes, there are a number of issues that have to be taken into account in the process of estimating the VAR model, among them are a number of variables to be included in the model, lag length to be applied and the issue of stationarity/non stationarity. In this study, the number of variables to be included in models follows the finance theory of Risk versus Return for Investors, in which the exogenous factors (as indicators of risk management) take the form of Forward Integration Credit Risk Mitigation Mechanisms while endogenous factors take the form of performance indicators.

Specification (Choosing the Lag order)

The most common procedures for VAR order selection are sequential testing procedures and application of model selection criteria. Given a maximum reasonable order, say p_{\max} for a VAR model and the following sequence, null hypotheses can be tested to determine the lag order $H_o : p_{\max} = 0$. The standard model selection criteria which are used in this context choose the VAR order which minimizes them over a set of possible orders $m = 0, \dots, p_{\max}$. The general form of a set of such criteria is;

$$C(m) = \log \det(\hat{\Sigma}_m) + c_{T\varphi}(m)$$

Where $\hat{\Sigma}_m = T^{-1} \sum_{t=1}^T \hat{u}_t u_t'$ is the residual covariance matrix estimator for a model of order m , $c_{T\varphi}(m)$ is a function of the order m which penalizes large VAR orders and c_T is a sequence which may depend on the sample size and identifies the specific criterion. The term $\log \det(\hat{\Sigma}_m)$ is a non-increasing function of the order m , while $\varphi(m)$ increases with m . The lag

order is chosen which optimally balances these two forces. The criteria of this type are Akaike's information criterion; Akaike (1973, 1974), the Hannan-Quinn criterion; Hannan and Quinn (1979), Quinn (1980), Schwarz criterion Schwarz (1978). The results in Table 4.5 indicate that the optimum lag length chosen is five. This indicates that when the banks invest in the sector it would take five quarters (one and quarter year to get the returns). Thus reducing the risk exposure.

Table 5: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-16878.64	NA	74752.18	19.73556	19.78328	19.75322
1	-14732.96	4271.315	6159.848	17.23944	17.31578	17.26769
2	-14724.38	17.04408	6162.893	17.23993	17.34490	17.27878
3	-14709.52	29.47822	6120.846	17.23309	17.36668	17.28252
4	-14627.58	162.2567	5620.882	17.14787	17.31009	17.20791
5	-14518.26	32.31466*	4899.758*	17.01056*	17.22152*	17.10130*
6	-14510.55	15.21301	5006.811	17.03218	17.25165	17.11340
7	-14490.48	39.52949	4942.492	17.01925	17.26735	17.11106
8	-14474.04	216.0906	4999.264	17.03067	17.28729	17.11297

* indicates lag order selected by the criterion

Endogenous variables: PROFIT CAPEMGR ROE

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Estimation of the VAR

The study estimated the VAR models by use of Ordinary Least Square (OLS). Vector Auto-Regression (VAR) is a system of simultaneous equations. Secondly, the variables have been categorized into endogenous and exogenous variables in the model. Lastly, the VAR allows for regressing each current (un-lagged) variable in the model on the lagged values of the same set of variables in the model (Mukras, 2012).

In this study, the variables Profit (PROFIT), Return on Equity (ROE) and Capital growth (CAPEMGR) are assumed to be endogenous, while Credit Insurance (CREDINS), Information management (INFMGT), Credit portfolio diversification (PORTDIV) and Technical assistance (TECHASS) are exogenous variables. However Vector auto regression model assumes that all the variables are endogenous. Therefore, to avoid losing information, the variables are being

regressed at levels represented by the lag order 1 to 5. The results of the estimates and summary of the statistics are shown in Table 6.

Table 6: Vector Auto- regression Estimates for all Variables for 5 lag lengths

Models	1	2	3	4	5	6	7
	TECHASS	ROE	PROFIT	PORTDIV	INFMGT	CREDINS	CAPEMGR
TECHASS(-1)	0.779868 (0.01719)	0.284168** (0.03071)	0.945601** (0.43635)	1.194652 (0.06834)	-1.204205 (0.09111)	0.603045 (0.07110)	-0.668788** (0.31962)
TECHASS(-2)	-0.087368 (0.02362)	0.933503** (0.42198)	0.003659 (0.68203)	-0.201738 (0.09391)	1.099915 (0.12520)	0.413751 (0.09770)	0.566964** (0.23918)
TECHASS(-3)	-0.167445 (0.02430)	1.809513** (0.43413)	0.752520** (0.30167)	-0.697884 (0.09661)	-0.472515 (0.12880)	0.749087 (0.10051)	0.091503 (0.45182)
TECHASS(-4)	-0.342089 (0.02494)	2.929997** (0.44553)	-0.787983** (0.32009)	0.718413 (0.09915)	0.309334 (0.13218)	0.134938 (0.10315)	-1.110469** (0.46369)
TECHASS(-5)	0.307939 (0.01657)	0.728226** (0.29603)	-0.809570 (0.47846)	-0.386459 (0.06588)	-0.612498 (0.08783)	-1.040998 (0.06854)	-0.012287 (0.30809)
ROE(-1)	-0.005419 (0.00144)	0.815812** (0.02566)	0.154237** (0.04148)	-0.019521 (0.00571)	0.032844 (0.00761)	0.004731 (0.00594)	0.049047** (0.02431)
ROE(-2)	0.006313 (0.00183)	0.014923 (0.03261)	-0.070084 (0.05271)	0.056850 (0.00726)	-0.015831 (0.00968)	0.007201 (0.00755)	-0.023590 (0.03394)
ROE(-3)	-0.008827 (0.00183)	0.065147** (0.03274)	0.019629 (0.05292)	-0.051066 (0.00729)	-0.001109 (0.00971)	0.020807 (0.00758)	0.024902 (0.03407)
ROE(-4)	0.013367 (0.00186)	0.106770** (0.03327)	-0.011811 (0.05378)	0.006566 (0.00740)	0.003558 (0.00987)	-0.009064 (0.00770)	-0.057862 (0.03463)
ROE(-5)	-0.006100 (0.00146)	-0.077632** (0.02615)	-0.030528 (0.04226)	-0.001432 (0.00582)	-0.016744 (0.00776)	-0.020549 (0.00605)	0.008620 (0.02721)
PROFIT(-1)	-0.001241 (0.00090)	0.039094** (0.01603)	0.839781** (0.02591)	0.004584 (0.00357)	0.014651 (0.00476)	0.011559 (0.00371)	0.047549** (0.01668)
PROFIT(-2)	0.000478 (0.00116)	0.041494** (0.02068)	-0.065016 (0.03342)	0.020443 (0.00460)	-0.006254 (0.00614)	-0.012007 (0.00479)	-0.044477** (0.02152)
PROFIT(-3)	0.000917 (0.00116)	-0.005445 (0.02079)	0.001268 (0.03360)	-0.016929 (0.00463)	-0.004588 (0.00617)	0.008957 (0.00481)	0.017699 (0.02164)
PROFIT(-4)	0.002664 (0.00117)	-0.027352 (0.02085)	0.103723** (0.03370)	-0.002624 (0.00464)	-0.002179 (0.00619)	0.003595 (0.00483)	-0.056289** (0.02170)

PROFIT(-5)	-0.002050 (0.00091)	0.035903** (0.01632)	-0.061907** (0.02637)	-0.007195 (0.00363)	-0.001641 (0.00484)	-0.011350 (0.00378)	0.039498** (0.01698)
PORTDIV(-1)	0.072591 (0.00619)	0.826697** (0.11059)	1.247461** (0.17873)	0.263396 (0.02461)	0.428847 (0.03281)	-0.181229 (0.02560)	0.792065** (0.11509)
PORTDIV(-2)	0.201450 (0.00716)	0.306377** (0.12792)	-0.498635** (0.20675)	0.096352 (0.02847)	-0.158819 (0.03795)	-0.753026 (0.02962)	-0.527040** (0.13313)
PORTDIV(-3)	0.035292 (0.00672)	0.188759 (0.12005)	0.610590** (0.19402)	-0.353965 (0.02672)	0.345710 (0.03562)	-0.129316 (0.02779)	0.838995** (0.12494)
PORTDIV(-4)	0.041078 (0.00670)	-0.156298 (0.11966)	0.392558** (0.19340)	-0.008265 (0.02663)	0.232722 (0.03550)	0.083176 (0.02770)	-0.072989 (0.12454)
PORTDIV(-5)	-0.026560 (0.00655)	0.262286** (0.11706)	0.413217** (0.18920)	-0.150017 (0.02605)	0.204619 (0.03473)	-0.637915 (0.02710)	0.261833** (0.12183)
INFMGT(-1)	0.056433 (0.00578)	0.233448** (0.10335)	-0.202590 (0.16703)	0.257646 (0.02300)	0.661518 (0.03066)	0.355147 (0.02393)	0.240695** (0.10756)
INFMGT(-2)	0.020014 (0.00668)	-0.167976 (0.11942)	-0.426623** (0.19301)	-0.157166 (0.02658)	-0.187876 (0.03543)	-0.169131 (0.02765)	-0.282604** (0.12429)
INFMGT(-3)	-0.031108 (0.00659)	-0.177510 (0.11781)	0.116241 (0.19041)	-0.077594 (0.02622)	0.187676 (0.03495)	0.185017 (0.02727)	0.168911 (0.12261)
INFMGT(-4)	0.011077 (0.00632)	-0.316245** (0.11284)	-0.400831** (0.18237)	0.092305 (0.02511)	-0.256698 (0.03348)	-0.085200 (0.02612)	-0.078585 (0.11744)
INFMGT(-5)	0.137490 (0.00500)	0.480159** (0.08938)	0.431610** (0.14445)	0.038182 (0.01989)	0.104185 (0.02652)	-0.152017 (0.02069)	0.205853** (0.09302)
CREDINS(-1)	-0.068116 (0.00547)	-0.211079** (0.09769)	0.155274 (0.15788)	-0.301593 (0.02174)	0.061744 (0.02898)	-0.158334 (0.02262)	-0.594437** (0.10167)
CREDINS(-2)	0.014927 (0.00557)	0.260057** (0.09958)	0.448612** (0.16094)	0.257778 (0.02216)	-0.000946 (0.02954)	0.165283 (0.02305)	0.437269** (0.10363)
CREDINS(-3)	-0.000660 (0.00583)	0.404826** (0.10424)	0.273727 (0.16847)	0.434877 (0.02320)	0.126423 (0.03093)	-0.101274 (0.02413)	0.345436** (0.10849)
CREDINS(-4)	-0.146106 (0.00643)	0.118426 (0.11496)	-0.162493 (0.18581)	-0.213659 (0.02558)	0.109415 (0.03411)	0.421135 (0.02662)	0.647159** (0.11965)
CREDINS(-5)	-0.270910 (0.00738)	-1.278538** (0.13186)	-0.993887** (0.21311)	0.067038 (0.02934)	-0.037254 (0.03912)	0.389018 (0.03053)	-1.231933** (0.13723)
CAPEMGR(-1)	0.006678 (0.00133)	0.405343** (0.02381)	0.029259 (0.03848)	0.026526 (0.00530)	0.008854 (0.00706)	0.013125 (0.00551)	0.698377** (0.02478)

CAPEMGR(-2)	-0.000759 (0.00157)	-0.088029** (0.02798)	-0.114720** (0.04523)	-0.004550 (0.00623)	-0.049320 (0.00830)	0.017880 (0.00648)	-0.151940** (0.02912)
CAPEMGR(-3)	-0.008473 (0.00157)	0.055076 (0.02803)	0.062095 (0.04530)	-0.007464 (0.00624)	0.000674 (0.00832)	-0.066857 (0.00649)	0.059351** (0.02917)
CAPEMGR(-4)	0.013993 (0.00158)	0.062041** (0.02830)	0.025697 (0.04574)	-0.017776 (0.00630)	0.070971 (0.00840)	0.059905 (0.00655)	0.260618** (0.02945)
CAPEMGR(-5)	-0.009883 (0.00137)	-0.055392** (0.02453)	-0.014618 (0.03965)	0.001010 (0.00546)	-0.032776 (0.00728)	-0.027192 (0.00568)	-0.162268** (0.02553)
C	1.318212 (0.04585)	4.272970** (0.81909)	7.129464** (1.32385)	0.086211 (0.18228)	2.719123 (0.24301)	2.811859 (0.18963)	2.926620** (0.85246)

Exogenous Variables: CREDINS, INFMGT, PORTDIV, TECHASS. ROE, PROFIT and CAPEMGR

**estimates that are statistically significant.

(cont.) Summary of Vector Auto- regression Estimates

Models	1	2	3	4	5	6	7
R-squared	0.967557	0.816929	0.740280	0.699312	0.816222	0.671030	0.657675
Adj. R-squared	0.966881	0.813113	0.734866	0.693044	0.812391	0.664172	0.650539
Sum sq. resids	58.28759	18605.51	48602.24	921.4362	1637.681	997.2442	20152.62
S.E. equation	0.186321	3.328859	5.380254	0.740811	0.987619	0.770682	3.464499
F-statistic	1430.687	214.0663	136.7331	111.5673	213.0584	97.85161	92.16283
Log likelihood	466.3961	-4477.798	-5301.180	-1900.771	-2393.921	-1968.566	-4546.292
Akaike AIC	-0.501920	5.263904	6.224116	2.258625	2.833728	2.337687	5.343781
Schwarz SC	-0.387577	5.378247	6.338459	2.372968	2.948071	2.452030	5.458124
Mean dependent	5.313300	11.21180	19.19595	4.613254	7.785574	3.468047	4.639442
S.D. dependent	1.023824	7.700269	10.44889	1.337116	2.280148	1.329894	5.860588

Determinant resid covariance (dof adj.)	17.16364
Determinant resid covariance	14.79502
Log likelihood	-19344.71
Akaike information criterion	22.85331
Schwarz criterion	23.65371

Exogenous Variables: CREDINS, INFMGT, PORTDIV, TECHASS. ROE, PROFIT and CAPEMGR

Sample (adjusted): 6 1720 Included

observations: 1715 after adjustments Standard

errors in ()

Considering that, $S(\hat{b}_i)$ - is the standard error and \hat{b}_i -is the estimate

The concentration was on model 2, 3 and 7, with **ROE**, **PROFIT** and **CAPEMGR** as dependent variables.

The rules:

$S(\hat{b}_i) < \frac{\hat{b}_i}{2}$ Then the estimate is statistically significant thus reject the $H_0 : b_i = 0$

$S(\hat{b}_i) > \frac{\hat{b}_i}{2}$ Then the estimate is not statistically significant thus Accept the $H_0 : b_i = 0$

Using standard errors of the lagged estimate coefficient; the results reveals that the variables generally yield statistically significant coefficients when lagged; on Profits, Return on Equity and growth on Capital employed.

In model 2 of table 6 depicts Return on Equity (ROE) as the dependent variable and all the others including itself as independent variables. The R-squared in model 2 is 0.813113, indicating that 81.31% of the variations in the Return on Equity (ROE), as the dependent variable are accounted for by its own evolution based on its own lags and the lags of other variables in the model (Table 6 column 2). The evidence reveal that ROE affects itself positively (0.8398) atlag 1. A unit change in Technical Assistance (TECHASS) for instance, results in 0.28 changes in ROE in lag (-1), 0.93(-2), 1.81(-3), 2.92(-4) and 0.73(-5). All the lagged estimate coefficients of TECHASS to ROE are statistically significant. A unit change in ROE affects itself by 0.82(-1), 0.015(-2), 0.07(-3), 0.10(-4) and 0.08(-5); all statistically significant except for lag 2. Similarly a unit change in PROFIT yields the following lagged estimate coefficients on Return on Equity (ROE): 0.4(-1), 0.4(-2), 0.01(-3), 0.03(-4) and 0.04(-5); significant at lags 1, 2 and 5. A unit change in Portfolio diversification (PORTDIV), contributes to ROE results as 0.83(-1), 0.31(-2), 0.19(-3), -0.15(-4) and 0.03(-5). They are significant except for lags 3 and 4. Unit change in Information management (INFMGT) to Return on Equity provides estimate coefficients as, 0.23(-1), -0.17(-2), -0.17(-3), -0.32(-4) and 0.48(-5); which are all significant except for lag 2. The results of Credit Insurance (CREDINS) to Return on Equity were 0.21(-1), 0.26(-2), 0.40(-3), 0.11(-4) and -1.28(-5). These are all statistically significant except for lag 4. Subsequently the results for Growth in Capital Employed (CAPEMGR) reveal 0.40(-1), 0.09(-2), 0.06(-3), 0.06(-4) and 0.055(-5). These are also significant except for lag 3. Therefore all the endogenous variables significantly impact on the Return on Equity (ROE). It yields an R^2 of 0.8169, which implies that the independent variables account for 81.69% of ROE over a longer period of time including itself.

The VAR results have mixed estimate coefficients at different lag orders but yield a higher coefficient of determination; R^2 being 0.8169. This implies that the 81.31% variations in the Return on Equity (ROE), as the dependent variable are accounted for by its own evolution based on its own lags and the lags of other variables in the model over time. Therefore the null hypothesis that Forward Integration Credit Risk Mitigation Mechanisms do not significantly contribute to Return on Equity changes is therefore rejected implying that Forward Integration Credit Risk Mitigation Mechanisms significantly contribute to Return on Equity changes of agribusiness enterprises in Nyanza region.

In model 3 of table 6 depicts Profit as the dependent variable and all the others including itself as independent variables. Considering Profit as a dependent variable the adjusted R-squared is 0.734866 indicates that the independent variables account for 73.49% of the variations in profit, over the ten years period when the evolving variables were observed on a quarterly basis. On the other hand, profit (PROFIT), is affected by its own evolution based on its own lags and the lags of other variables in the model (Table 6 column 3). A unit increase in Technical Assistance results in 0.94 increase in Profit in lag (-1), 0.003(-2), 0.75(-3), 0.79(-4) and -0.81(-5). All the lagged estimate coefficients of Technical Assistance to Profit are statistically significant except for lags 2 and 5.

A unit change in ROE affects PROFIT by 0.15(-1), -0.07(-2), 0.02(-3), -0.01(-4) and -0.03(-5); all statistically insignificant except for lag 1. Evident from these results although majorly insignificant, the industry practice is that, 'the higher the return on Equity in the current period the lower the firm's financial reserve capacity to maximise on future short run investment opportunities' (Edward, Jose, and Zhenyu, 2003). Similarly a unit change in PROFIT yields the following lagged estimate coefficients on Profits as 0.84(-1), 0.06(-2), 0.001(-3), 0.10(-4) and 0.06(-5); significant at lags 1, 4 and 5. For a unit change in Portfolio diversification (PORTDIV), the lagged changes in Profit results are 1.25(-1), 0.49(-2), 0.61(-3), 0.39(-4) and 0.41(-5). They are statistically significant. Information management (INFMGT) on the other hand provides estimate coefficients on Profit; -0.20(-1), -0.42(-2), 0.11(-3), -0.40(-4) and -0.43(-5); which are all significant except for lags 1 and 3. The results of Credit Insurance (CREDINS) on Profit were 0.15(-1), 0.44(-2), 0.27(-3), -0.16(-4) and -0.99(-5). These are only statistically significant in lags 2 and 5. Subsequently the results for Growth in Capital Employed (CAMEMGR) on Profit reveal 0.03(-1), 0.11(-2), 0.06(-3), 0.02(-4) and 0.014(-5). These are also significant except for lag 3. Therefore all the endogenous variables significantly affect the PROFIT. Therefore the Null hypothesis, that Forward Integration Credit Risk Mitigation Mechanisms do not affect profit of agribusiness enterprises in Nyanza region is rejected and therefore accepting the alternative

hypothesis that Forward Integration Credit Risk Mitigation Mechanisms affect profit of agribusiness enterprises in Nyanza region.

Model 7 of table 6 depicts Growth on Capital Employed (CAPEMGR) as the dependent variable and all the others including itself as independent variables. In model 7, when capital growth (CAPEMGR) as the dependent variable, the adjusted R-squared is 0.650539, indicating that 65.05% of the variations in the dependent variable are accounted for by the independent variables. The results also indicate that capital growth is affected by its own evolution based on its own lags and the lags of other variables in the model (Table 6 column 7). A unit change in Technical Assistance results (TECHASS) in -0.67 changes in Capital employed growth (CAPEMGR) in lag (-1), -0.6(-2), 0.09(-3), -1.11(-4) and 0.01(-5). All the lagged estimate coefficients of Technical Assistance to Capital employed growth are statistically significant except for lags 3 and 5. A unit change in Return on Equity (ROE) affects Capital employed growth by 0.05(-1), -0.02(-2), -0.02(-3), -0.06(-4) and 0.01(-5); all being statistically insignificant except for lag 1. Subsequently a unit change in Profit yields the following lagged estimate coefficients on Capital employed growth: 0.05(-1), -0.04(-2), 0.02(-3), 0.06(-4) and 0.04(-5); significant at all the lags except at lag 3. For Portfolio diversification (PORTDIV) results on Capital employed growth are 0.79(-1), -0.52(-2), 0.83(-3), -0.07(-4) and 0.26(-5). They are statistically significant except at lag 4. Information management (INFMGMT) on the other hand provides estimate coefficients of, 0.24(-1), -0.28(-2), 0.17(-3), 0.08(-4) and -0.20(-5); which are all significant except for lags 3 and 4. The results of Credit Insurance (CREDINS) were -0.59(-1), 0.43(-2), 0.34(-3), 0.64(-4) and -1.23(-5). They are all statistically significant in all lag levels. Subsequently the results for Growth in Capital Employed (CAMEMGR) on itself reveal -0.69(-1), -0.01(-2), 0.06(-3), 0.26(-4) and 0.16(-5). These are all significant except for lag levels. Therefore all the endogenous variables significantly affect the CAPEMGR. It yields an R^2 of 0.6578, which implies that the independent variables account for 65.78% of CAPEMGR over a longer period of time including itself. Subsequently the null hypothesis that forward integration credit risk mitigation mechanisms do not significantly contribute to capital employed growth is rejected, this implies that, Forward integration credit risk mitigation mechanisms significantly contribute to capital employed growth of agribusiness enterprises in Nyanza region.

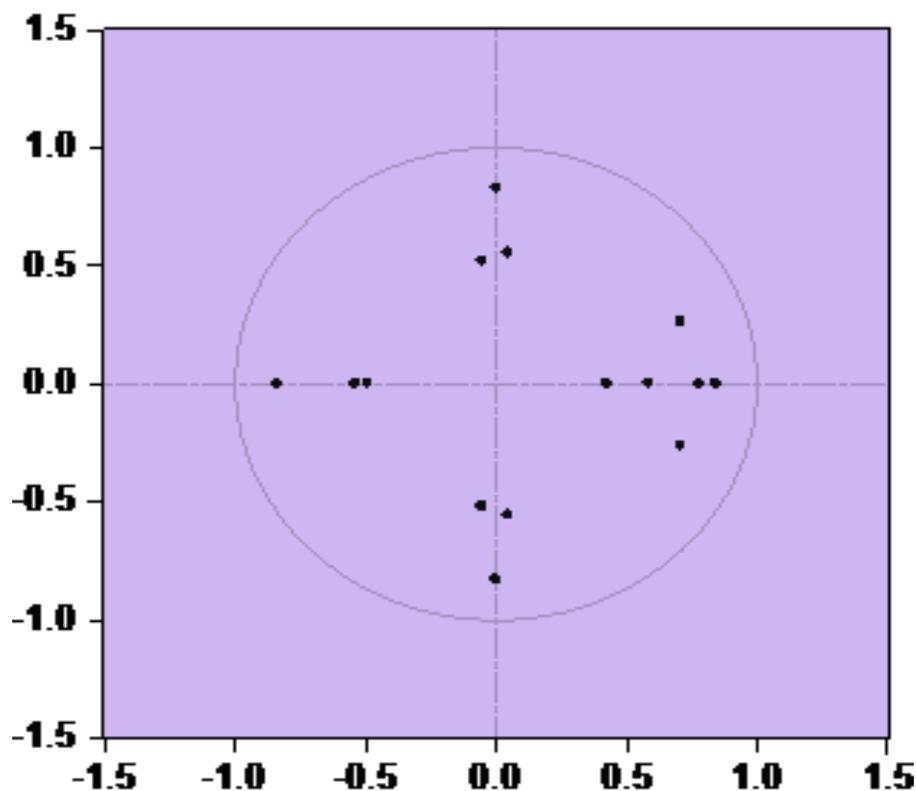
Therefore when the endogenous variables are lagged to avoid loss of information on economic variables, the output becomes stable in terms of effect of the explanatory variables on the explained variables. To fit the autoregressive output on Table 6 on the model equation, the following sets of equations would be used as a summary for each of the objectives 2, 3 and 7.

Stability Tests for VAR

One important characteristic of VAR process is its stability. This means that it generates stationary time series with time-invariant means, variance, and covariance structure, given sufficient starting values. This can be checked by evaluating the reverse characteristic polynomial.

The results indicate that the root lies within 1 unit circle that is $|Z| \leq 1$. This is shown in figure 2.

Figure 2: Inverse Roots of AR Characteristic Polynomial



On the other hand, in practice, the stability of an empirical VAR process can also be analyzed by considering the companion form and calculating the eigenvalues of the coefficient matrix. If the moduli of the eigenvalues are less than one, then the VAR process is stable. The results in Table 7 below indicate that all the modulus are less than one ($m < 1$), thus VAR satisfies the stability condition.

Table 7: Roots of Characteristic Polynomial

Root	Modulus
0.843285	0.843285
-0.838663	0.838663
0.000533 - 0.829711i	0.829711
0.000533 + 0.829711i	0.829711
0.779776	0.779776
0.708707 - 0.263786i	0.756207
0.708707 + 0.263786i	0.756207
0.585954	0.585954
0.046278 - 0.554773i	0.556700
0.046278 + 0.554773i	0.556700
-0.540806	0.540806
-0.053668 - 0.519332i	0.522098
-0.053668 + 0.519332i	0.522098
-0.491140	0.491140
0.424480	0.424480

No root lies outside the unit circle. VAR satisfies the stability condition.

Lag specification: 1 to 5 ; Endogenous variables: PROFIT CAPEMGR ROE

Exogenous variables: C CREDINS

Exogenous variables: C CREDINS INFMGT

INFMGT PORTDIV TECHASS

PORTDIV TECHASS

Further diagnostic Tests for VAR

A wide range of procedures are available for checking the adequacy of VARs. They should be applied before a model is used for a specific purpose to ensure that it represents the data generation process (DGP) adequately. A number of procedures consider the estimated residuals and checks whether they are in line with the white noise assumption.

Serial Correlation LM test

For testing the lack of serial correlation in the residuals of a VAR model, the LM test proposed by Breusch-Godfrey was applied. The results in Table 8 indicate the acceptance of the Null hypothesis that there is no serial correlation.

Table 8: VAR Residual Serial Correlation LM Tests

Lags	LM-Stat	Prob
1	443.1545	0.1321
2	250.5463	0.4126
3	150.2441	0.1912
4	87.42412	0.5690
5	181.9505	0.1783

			Table 8...
6	136.4391	0.9725	
7	63.67412	0.2300	
8	112.6161	0.1540	
9	18.22557	0.0526	
10	10.99499	0.2761	
11	12.04695	0.2107	
12	37.88595	0.7280	

Probs from chi-square with 9 df.

Null Hypothesis: no serial correlation at lag order h

Residual Heteroskedasticity Tests

White's (1980) test is a test of the null hypothesis of no heteroskedasticity against heteroskedasticity of an unknown, general form. The no cross terms specification runs the test regression using only squares of the regressors. The results in Table 9 indicate acceptance of the null hypothesis that there is no heteroskedasticity in the VAR Models.

Table 9: VAR Residual Heteroskedasticity Tests for the variables

Joint test:		
Chi-sq	Df	Prob.
2316.786	336	0.18340

Note: No Cross Terms (only levels and squares)

Normality Test for all the variables

Although normality is not a necessary condition for the validity of many of the statistical procedures related to VAR models, deviations from the normality assumption may indicate that model improvements are possible. Therefore, non-normality tests are common in applied work. Multivariate versions can be applied to the full residual vector of the VAR model and univariate versions can be used for the errors of the individual equations. The study used the VAR residual normality test and plotted the residual in a graph (see Table 10 and Figure 3).

Table 10: VAR Residual Normality Tests

Component	Jarque-Bera	Df	Prob.
1	5325.606	2	0.9130
2	4275.467	2	0.1720
3	18719.34	2	0.3400
Joint	28320.41	6	0.7120

Note: Orthogonalization: Cholesky (Lutkepohl), Null Hypothesis: residuals are multivariate normal.

Figure 3: VAR Residuals for all the Variables

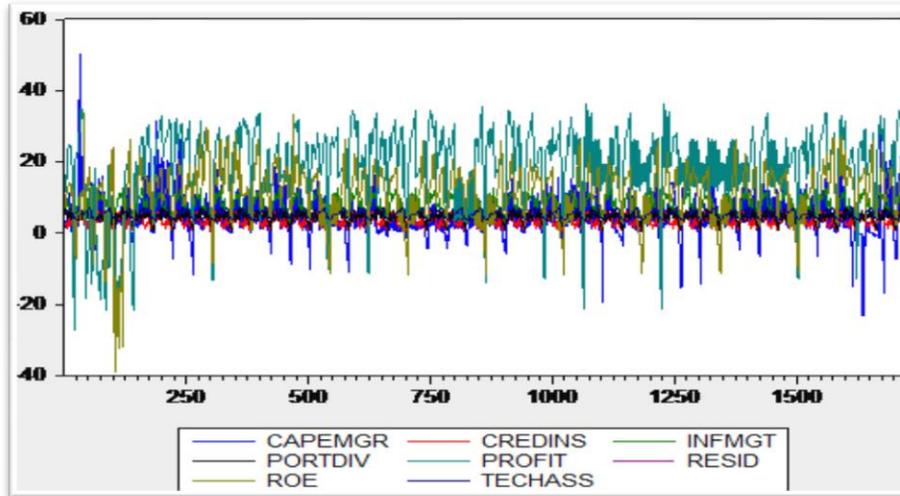


Figure 4: Individual Residuals for Dependent variables in VAR

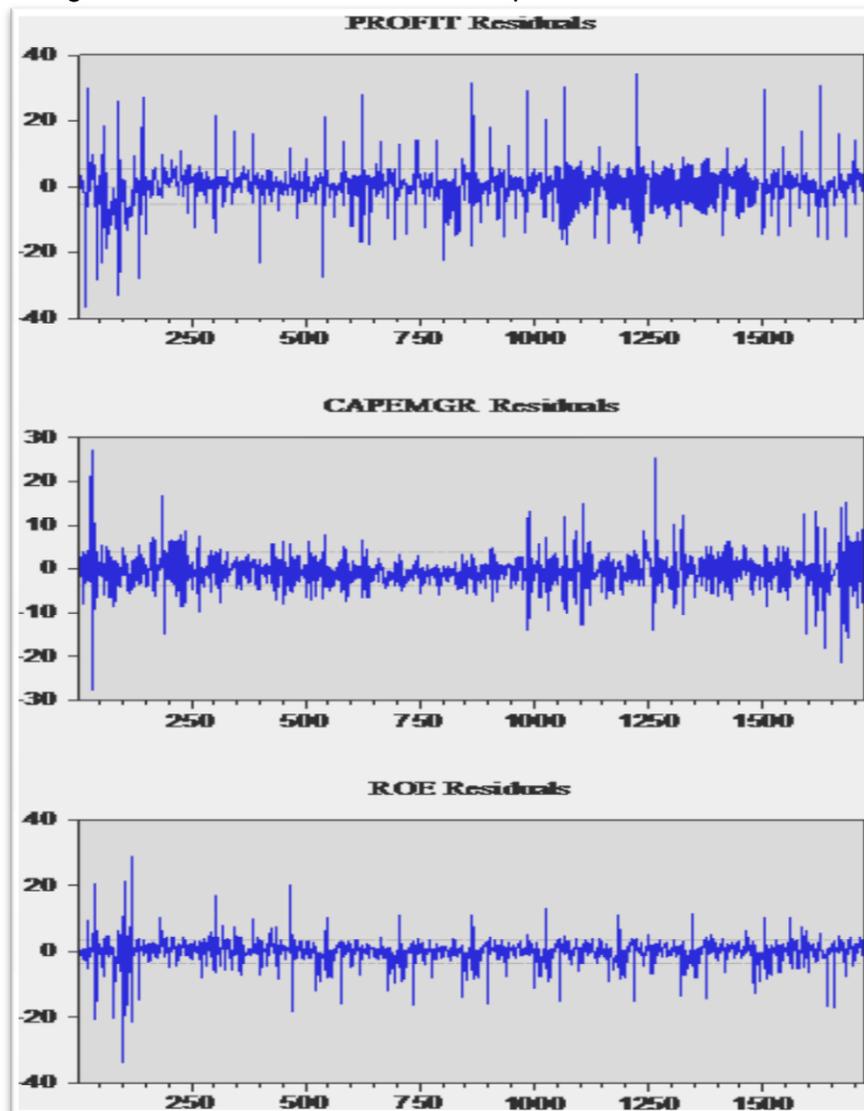


Figure 3 reveals that the variables are normally distributed since they devolve around the mean or zero line over the period under study. However the outliers attributed to the dependent variables i.e. Profit, Return on Equity and Capital growth, are as result of the volatile environment within which the agribusiness enterprises anchor. For the explanatory variables, they reveal a narrower range of variables' dispersion as they evolve around the mean; reflecting a limited level of variability of the predictor variables.

CONCLUSIONS

The results indicate that the optimum lag length chosen is five. This indicates that when the banks invest in the sector it would take five quarters (one and quarter year to get the returns). Thus reducing the risk exposure.

In model 2, the R-squared for Return on Equity (ROE) is 0.813113, indicating that 81.31% of the variations in the Return on Equity (ROE), as the dependent variable are accounted for by its own evolution based on its own lags and the lags of other variables in the model. The evidence reveal that ROE affects itself positively (0.8398) atlag 1. Concerning establishing the impact of Forward integration credit risk mitigation mechanisms on Return on equity of agribusiness enterprises in Nyanza region the study results depict that Forward Integration Credit Risk Mitigation Mechanisms (FICRMMs) significantly contribute to Return on equity. When examined over time as specified by the selected lag length the VAR output, provides an R^2 value of 0.816929, adjusted to 0.813113; implying that all the variables including return on equity itself explain up to 81.3% of changes in Return on equity. It is evident that the Forward integration credit risk mitigation mechanisms significantly contribute to Return on Equity over time as shown by the lagged coefficients.

Considering Profit as a dependent variable the adjusted R- squared is 0.734866 indicates that the independent variables account for 73.49% of the variations in profit, over the ten years period when the evolving variables were observed on a quarterly basis. On the other hand, profit (PROFIT) is affected by its own evolution based on its own lags and the lags of other variables in the model.

Further analysis of the variables in a Vector Auto- Regression model, lagged 5 times, revealed increased effect of their aggregate account on the variability of profits to R^2 of 0.7349, implying that the independent variables account for 73.49% of the variations in profit. This implies that agribusiness profit is a function of all the variables including itself, under a VAR model. The high coefficient of determination of profit (0.7349), and the related significance levels of the lagged coefficients of profit and other variables on itself depicts Forward integration

credit risk mitigation mechanisms as significant determinants of agribusiness profit with $p = 0.000 < 0.050$

When capital growth (CAPEMGR) as the dependent variable, the adjusted R-squared is 0.650539, indicating that 65.05% of the variations in the dependent variable are accounted for by the independent variables. The results also indicate that capital growth is affected by its own evolution based on its own lags and the lags of other variables in the model. This implies that all the variables, including return on equity itself, thereby explaining up to 65.05% of changes in capital employed growth. Because the Forward integration credit risk mitigation mechanisms have significant contribution on capital employed growth of agribusiness at $p = 0.000 < 0.050$, and the coefficient of determination values also increasing with time; $R^2 = 0.531$ to $R^2 = 0.650$, it is evident that the Forward integration credit risk mitigation mechanisms significantly contribute to capital employed growth over time.

RECOMMENDATIONS

From the preceding conclusions the following recommendations can be raised. The effectiveness of each parameter in the FICRMMs should also be reviewed and sensitively analysed so as to establish their responsiveness in addressing the demand-side credit factors for the agribusiness enterprises. This would enable the commercial banks to expand credit demand.

There is need to strengthen the financial sector in order to formalize the informal agribusiness sector. The Credit sufficiency for the agribusiness sector should be established, so as to help determine the capital needs of the sector, in terms of its contribution to the national productivity and employment.

Forward Integration Credit Risk Mitigation Mechanisms (FICRMMs) should be restructured into few critically and knowledgeably implementable operational practices. The agribusiness firms should also be exposed to the facts of these practices so as to enable them to appraise their outcomes on a score- card. The banks need to have a keen look at agribusiness firms reduce credit risk and promote uptake of loans and developing products for agribusiness.

Further studies can be done on backward integration credit mitigation mechanism in relation to performance and the uptake of financial products of the agribusiness firms.

REFERENCES

Agwe, J., & Azeb, F. (2009). Managing risk in financing agriculture. Expert Meeting Convened and co-sponsored by AFRACA, FAO, the Land Bank of South Africa, and the World Bank April 1-3, Johannesburg, South Africa

- Akaike, H. (1973). Information theory as an extension of the maximum likelihood principle. Pp 267-281 B. N. Petrov, and F. Csaki, (Eds.) in Second International Symposium on Information Theory. Akademiai Kiado, Budapest.
- Akaike, H. (1974). A new look at the statistical model identification. IEEE Transactions on Automatic Control AC, 716-723.
- Angius, S., Carlo, F., Arno, G., Philipp, H., Marco, P., & Uwe, S. (2011). Risk modeling in a new paradigm. Developing new insight and foresight on structural risk, International Journal of Financial Research, 2(1) 178-196.
- Basel Accord, (1999). Principles for the management of credit risk, consultative paper issued by The Basle Committee on banking Supervision, Capital Requirements and Bank Behaviour. The Impact of the Basle Accord, Basle- Switzerland, 35-45.
- Beverly, J. H., Mark, L., Marc. S., Stefan, W., & David, W. (2001). Using Credit Risk Models for Regulatory Capital FRBNY Economic Policy Review. Journal of Banking & Finance, 25(10), 731- 748.
- David, R. M. (2013) Who Gets What? Determinants of Loan Size and Credit Rationing Among Microcredit Borrowers. Nicaragua Journal of International Development. 26(1), 77-90.
- Drury, C. (2011). Management and Cost Accounting (6th Edition), Cengage Learning Private Ltd, New Delhi, India.
- Duffie, D. (2008). Innovation in Credit Risk Transfer; Implications for Financial Stability, Bank for International Settlement (BIS) working papers- Monetary and Economic Department.
- Dwyer, D. W. (2012). A Theory of Monitoring Credit Risk. Moody's analytics Quantitative Research methodology journal, 7(24), 114-127, USA.
- Felix A.T. and Claudine T.N. (2008): "Bank Performance and Credit Risk Management", Unpublished Master Dissertation in Finance, University of Skovde retrieved from <http://www.essays.se/essay/55d54c0bd4/>
- Felix, A.T., & Claudine, T.N. (2008), Bank Performance and Credit Risk Management. Unpublished Master Dissertation in Finance. University of Skovde - Ugoslavia.
- Gabor, K., Carlos, A. S & Nomathemba, M. (2013). Enabling Environments for agribusiness and agro-industries development. Food and Agriculture Organization of The United Nations. 113-142
- Geoff, T., & Grahame, D., (2012), Investments in Agribusiness: a retrospective view of a development bank's investments in agribusiness in Africa and East Asia. The World Bank Committee for Food Security, 39th Session Responsible Agricultural Investment: The Way Forward
- Gichira, R. (2010). Financing Agriculture through Micro-Financing Institutions in Kenya. International Journal of Economics and Finance, 7(8), 69-89.
- Government of Kenya (1981). National Food and Nutrition Security Policy. Ministry of Agriculture, Nairobi Kenya. (pp. 26-37)
- Government of Kenya (2012). National Agribusiness Strategy Making Kenya's agribusiness sector; a competitive driver of growth. Ministry of Agriculture, Nairobi Kenya. (pp. 89-125)
- Gunther, T. (2010). Credit Approval Process and Credit Risk Management; Guidelines on Credit Risk Management. Oesterreichische National bank (OeNB) in cooperation with the Financial Market Authority (FMA).
- Howe, G. (2003). Agricultural Marketing Companies as Sources of Smallholder Credit in Eastern and Southern Africa. International Fund for Agricultural Development (IFAD), 97-113.
- Hull, C., & John, R. (2007). Risk Management & Financial Institutions. Pearson Education Inc. Kindersleg International Publishing international, 271-300.
- Im, K. S., Pesaran, M. H., and Y. Shin (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115: 53-74.

- Jaffee, S., Siegel P., & Andrews, C. (2010). Rapid Agricultural Supply Chain Risk Assessment. A Conceptual Framework Agriculture and Rural Development Discussion Paper, 47, 359-323.
- Kimathi, M., Mbita, M. N., Calvin, M. Nduku, D. & Kipsang, K. (2008). Africa Agricultural Value Chain Financing, 3rd AFRACA Agribanks forum; Synthesis report; African Rural and Agricultural Credit Association (AFRACA) & Food and Agriculture Organization (FAO) of the United Nations.
- Kithinji, A. M. (2010), Credit Management and Profitability of Commercial Banks in Kenya. School of Business, University of Nairobi- Kenya, pp. 47-79.
- Koza, A. (2007). The Case of Financial Sector Liberalization in Ethiopia, Research Seminar in International Economics. Gerald R. Ford School of Public Policy, the University of Michigan, Discussion No. 565.
- Larsen, K., Florian, T., & Ronald, K. (2009). Agribusiness and innovation systems in Africa. A publication sponsored by the World Bank Institute and Agriculture and Rural Development, 4(2), 74-92.
- Meyer, P.G. (2005). Determinants of credit risk mitigation in lending to Black Economic Empowerment (BEE). A banker's perspective- College of Economics & Management Sciences University of South Africa.
- Mhalanga, N. (2010), Private Sector Agribusiness Investment in Sub-Saharan Africa, Agricultural Management, Marketing and Finance document, (FAO), 8-23.
- Microfinance Network (2000). A Risk Management Framework for Microfinance Institutions. Financial Systems Development financial.systems@gtz.de, 1(41), 33-47.
- Mukras, M. (2012). Fundamental Principles of Time Series Econometrics, Theory and applications. (II), 57 – 91, Lambert Academic Publishing, Deutschland/Germany
- Shields, J. (2012). The Key to Unlocking Africa's Multi-Billion Dollar Agriculture Opportunity. Harvard Kennedy School, USA.
- Smith, B. B., & Thompson, C. J. (2007) "Managing credit risk with info-gap uncertainty". The Journal of Risk Finance. 8(1), 24 – 34.
- Steinwand, Dirk. (2002). A Risk Management Framework for Microfinance Institutions; Financial Systems Development and Banking Services, Micro Finance Network, 733(15), Washington, D.C. 20005
- United Nations Industrial Development Organization (UNIDO), (2012). The Global Financial Crisis and the Developing World. Impact on and Implications for the Manufacturing Sector, 4-29.
- Vorley B., Fearne A. & Ray D. (2007). Regoverning markets: a place for small-scale producers in modern agri-food chains? Gower Publishing, UK.
- Wolfgang, B. (2005), Qualifying Risk. Zurich University of Applied Science Winterthur, Switzerland.
- World Bank (2009). World Development Report, a better investment climate for everyone. Washington, DC. <http://siteresources.worldbank.org/intwdr2005/report>.