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Bank Credit and Agricultural Growth in Zimbabwe: Analysing Effectiveness and Impact

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Abstract: Objective: The study examines the efficiency and influence of bank loans on Zimbabwe's agricultural growth. The main objectives are to assess how bank lending affects agricultural output and identify the key factors affecting its effectiveness. **Approach:** This research uses the Vector Error Correction Model (VECM) approach to examine the long-term and short-term relationships between bank credit and agricultural output. **Results:** Extending credit availability may help agricultural development, as the study indicates a strong long-term positive association between bank credit and agricultural production. However, the short-term study yields inconsistent findings, with variations brought on by outside forces, including shifting policies, unstable economies, and unfavourable weather patterns. This suggests that structural problems in the banking or agriculture sectors impede quick recovery. While bank credit is critical in enhancing agricultural growth in Zimbabwe, its effectiveness is contingent upon a stable economic environment and supportive policies. **Implication:** Therefore, to maximise the impact of bank lending, policymakers should focus on improving financial infrastructure, mitigating external risks, and creating a conducive environment for agricultural investments. **Value:** This study uniquely examines the impact of bank credit on agricultural productivity in Zimbabwe using a comprehensive set of economic and non-economic variables and advanced econometric methods, providing new, context-specific insights and practical policy recommendations for enhancing agricultural growth in a challenging environment.

Keywords: Bank lending; Agricultural loans; credit

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1. Introduction

A nation's robust and productive agriculture sector may boost foreign exchange earnings, feed its expanding population, and provide raw materials for other businesses. With agriculture accounting for an estimated 27.01 percent of the GDP, the Zimbabwean economy has always depended on it (Trading Economics, 2024). Since 2000, this industry's performance has declined dramatically (Mbira & Moyo, 2018). Agriculture is one of the significant sectors of the economy, and it has major problems when it comes to accessing credit from formal sources. Since today's farming entails considerable borrowing for money or inputs, this research sought to evaluate the efficiency of lending in line with agriculture.

With most farmers depending on agriculture for a living, funding for farmers is recognised as a tool for ending poverty in developing countries. Agriculture accounts for the largest portion of GDP on the continent, with over 32% of total production (Raihan & Tuspekova, 2022). Most African countries, except for those that produce oil, rely heavily on agriculture for their revenue. More particularly, agriculture production employs over 70% of African labourers. Much of what is produced in most African countries is exported, but in extremely small amounts, given their vast potential. As a result, a large portion of Africa's foreign currency profits come from the agricultural sector. However, the fact that most African nations import food makes them uneasy, and it is not very clear that despite their enormous potential for agricultural production, the continent has produced little.

African farmers have poor adoption of current technology, as observed by Salami et al. (2010) and Ansari et al. (2011) and poor finance investment in the agriculture sector. A vicious cycle brought on by inadequate agricultural investment has ensnared the continent. Peasant farmers are small farms that generate little and keep them in poverty. It has also been shown that expanding investment in agriculture in Africa can only be achieved via better access to financial options. For small-holder farmers, who rely mostly on loans to produce agricultural goods, finance may sometimes be a constraint. A person or corporation that has not had credit can temporarily transfer assets to another that has, according to (Adams, 2021). When credit is due to mature, which may at least take a few days or over many years, it is a package that the lender offers to the borrower and is repayable. To complete the credit transaction, the borrower must provide evidence of their capacity to repay the loan if it solely depends on their creditworthiness, trustworthiness, and financial situation. Akinola et al. (2020) state that the lender may also grant credit to the borrower in the form of its possessions, such as cash.

Ineffective political involvement, hyperinflation, and delays in releasing funding to farmers tarnished the majority of these highlighted remedial approaches for addressing Zimbabwe's agricultural credit scarcity problem. Along with addressing this issue—and in some cases avoiding it altogether—the majority of the initiatives sought to guarantee that agricultural operations would continue even without collateral for the local farmers.

According to González-Vega (2021), farm credit is the term used to describe a variety of credit instruments used to support agricultural operations, including notes, banker's acceptances, bills of exchange, loans, and banknotes. Seasonal planting, harvesting, and marketing requirements inform these financing solutions, specifically designed to meet the special financial needs of farmers. Agriculture equipment is financed with intermediate-term credit, real estate is financed with long-term credit, and operations expenses are funded with short-term credit claims (Bourne & Graham, 2021). Farmers may get significant financial assistance from it to help them close the gap between their revenue and farming expenditures. With control over how they use working capital to boost productivity and revenue, it is an essential tool for empowering farmers. According to Adewale et al. (2022), credit is a key element of the growth plan for the agriculture industry. Tobacco merchants have successfully obtained internal and external financing because of the value chain's efficacy and efficiency. Banks like financing tobacco retailers because growers have a consistent payback schedule (Yi et al., 2021). A key element affecting global productivity is the availability of financial services. For instance, the availability of these services is still limited in sub-Saharan Africa. At the same time, about 70 percent of the region's population lives in rural areas and engages in agricultural practices. However, there is a significant lack of understanding regarding the institutions, policies, and various factors that shape the supply, demand, and overall effectiveness of access to financing for rural agriculture. This is true despite the importance of agriculture in reducing poverty, raising living standards, guaranteeing food security, and supporting industrial links. Determining the effect of bank credit on farmers' agricultural production and the connection between bank credit and capital investment and productivity (output) are thus necessary research objectives.

2. Literature Review

To enable farmers to sustain and innovate their agricultural operations, they require regular exposure to formal financial facilities, including insurance and other deposit and credit institutions. Various elements, including location, gender, income levels, education, and regulatory frameworks, can influence financial inclusion. Financial access and inclusion refer to how farmers can utilise formal financial services like savings accounts, bank loans, insurance products, and mobile payment solutions. Many developing countries have low levels of financial inclusion; in Zimbabwe, for example, a large number of farmers rely on informal finance sources such as moneylenders or friends and family. Lack of access to and involvement in the financial system may limit farmers' ability to purchase equipment and supplies that boost output.

For these reasons, transactions in credit markets often remain unstable in emerging economies because of high transaction costs, asymmetric knowledge, and a lack of information regarding collateral or credit histories. These defects might lead to credit rationing, making it difficult for credit-worthy farmers with profitable investment opportunities to get loans while charging outrageous interest rates to less productive or riskier borrowers. The obstacles that keep farmers from getting official loans are known as credit market flaws. Lenders' risk aversion, insufficient collateral or credit history information, high transaction costs, and information asymmetry are some obstacles. When most farmers are either completely barred from getting loans or have to pay astronomical interest rates, these defects can also lead to credit rationing, with just a small portion of creditworthy farmers able to obtain loans under reasonable terms. Addressing credit market problems requires improving credit information systems, reducing transaction costs, and boosting risk-sharing mechanisms.

Agricultural productivity may be measured using many methodologies, such as crop yields, profitability, and value-added per unit of labour or land. Various input factors within the production process may be under the beak of productivity, including market access, human capital, water resource and soil fertility, and technology.

Bank loan terms that affect farmers' borrowing decisions and their ability to invest in inputs or productive assets include interest rates, repayment schedules, collateral requirements, and loan amounts. When developing loan solutions, it is critical to consider farmers' cash flows, risk tolerance, and investment demands.

Bank lending can affect agricultural productivity in a number of ways, including better adoption of new technologies and practices, increased risk-taking and innovation, improved access to markets and value chains, improved resilience to shocks and climate variability, increased investment in productive assets (such as land, equipment, or inputs), and improved access to markets and value chains. Bank loans can influence agricultural productivity through mechanisms known as impact pathways. Some of these channels are investing more in productive assets, using new technologies and procedures, opening up markets and value chains, taking more risks and being more innovative. Other ones include enhanced resilience to shocks and climatic variability. Understanding the effect channels is essential to identifying the best loan packages and directing them toward the most productive farmers. Various institutional elements encompass the legal framework, financial institutions' governance and operational efficiency, accessibility and calibre of extension services, and availability. Which loan programs and delivery systems are most successful in helping the most successful farmers? To effectively serve Zimbabwe's most productive farmers, loan products and delivery methods should consider their specific needs, preferences, and financial constraints, in addition to the shortcomings in the credit market that limit their access to capital.

According to Chihambakwe (2018), group lending is a practice in which farmers jointly guarantee the debts of one another. This raises the group's social capital and decreases the need for individual collateral. Group financing has been shown to promote financial inclusion and successfully reduce credit risk, especially among small-scale farmers. Apart from governmental financial establishments, community-based entities like farmer organisations or microfinance institutions can offer group financing.

3. Methodology

In this case, the agricultural output was proxied by Zimbabwean farmers' gross domestic product. Some scholars have questioned the use of bank credit (BC) as a measure of credit, simplifying farmers' financial constraints in the sense that it allows them to purchase inputs. Credit is a problematic variable difficult to account for in agricultural production studies (Nkurunziza, 2010). According to Carter (1989), credit affects agricultural output and varies depending on the availability of improved seeds and other inputs or implements, such as tractor fertilisers, purchased with credit. Capital investments were included for both the independent and explanatory criteria since they could accurately depict the farm's financial responsibilities.

According to the analysis made by Mafuyeka (2021), capital investment (CI) can be defined as an aggregate of plant, machinery, and other productive assets that is either owned or under the control of the individual, business entity or organisation. The analysis covers all bank loans to fund capital acquisitions, working capital needs, and input expenditures, such as seeds and fertiliser. Based on Robert Solow's 1956 neo-classical growth theory model, a positive connection between the variables is expected in this research. The model also incorporates annual rainfall to further highlight the significance of seasonal rainfall in influencing Zimbabwe's agricultural production. As a result, the Zimbabwe Meteorological Department's average annual rainfall data is used to substitute variable rainfall. An overabundance of precipitation may be detrimental to agricultural productivity.

4. Data Sources and Explanation of Variables

The data was extracted from Zimbabwe National Statistics (ZIMSTAT) since it is the main custodian of the required dataset and was accessed secondary time-series data for 2002 to 2022. For compliments and comparison, the Ministry of Agriculture

(MoA), the Agricultural Financing Company (AFC), and the Zimbabwe Metrological Department (ZMD), databases were also used for data supplements.

Table 1. Variables and their Definitions

Variable	Variable definition	Measurement (Proxy)	Source
	Dependent variable		
Agricultural Gross Domestic Product, *AGDP*	a comprehensive measure of agricultural output and productivity. It reflects the total economic value generated by agricultural activities in a given period and is a key dependent variable for assessing agricultural growth.	USD value of agricultural output, annual agricultural GDP	ZIMSTAT
	Independent variables		
Bank credit, *BC*	Bank credit represents the amount of financial resources available to farmers, which can significantly impact investment in agricultural activities, inputs, and technology adoption.	Total agricultural loans or credit (in local currency, adjusted for inflation).	Reserve Bank of Zimbabwe (RBZ), World Bank,
Capital investment, *CI*	The small-scale farmers' yearly changes in animal inventories, equipment, and fixed improvements are expressed in US dollars.	The total value of capital expenditures on agricultural infrastructure, machinery,	Ministry of Agriculture, ZIMSTAT
Farm age, *FA*	Age of the farm in years, Years of Farm Operation," which could better capture the learning curve and productivity trends over time. **Years of Farm Operation**: A more precise measure that captures the effects of experience.	Number of years since farm establishment or ownership change.	Ministry of Agriculture, ZIMSTAT
Annual rainfall, *R*	Annual rainfall in millilitres, Seasonal Rainfall Index" to capture not just the amount but also the timing and distribution of rainfall, which are critical for crop growth. **Seasonal**	Total annual rainfall (mm), seasonal rainfall index,	Zimbabwe Meteorologica l Services,

	Rainfall Index: This will provide a better understanding of the quality and timing of rainfall rather than just the quantity.		
Education, *EDU*	Access to Extension Services" might capture both formal education and practical knowledge. **Access to Agricultural Extension Services**: This could provide a more comprehensive view of how knowledge and skills are transferred to farmers.	Percentage of farmers with agricultural education, or years of schooling, or access to extension services.	Ministry of Agriculture, ZIMSTAT
Age of farmers, *FA*	"Experience" to capture different aspects (innovation potential vs. accumulated knowledge	The average age of farmers in years.	Ministry of Agriculture, ZIMSTAT
Farm Size, *FS*	farm size can directly influence productivity, economies of scale, and the ability to adopt new technologies.	Total farm area in hectares (ha)	Ministry of Agriculture, ZIMSTAT

Source: Researcher 2023

Model Specification

A production function in the context of a time-series model for agricultural productivity typically represents the relationship between inputs (like capital, labour, and other relevant factors) and output (agricultural productivity) was adapted in this analysis. Given the list of variables, a Cobb-Douglas production function is a suitable choice because it captures the non-linear relationships between inputs and outputs and allows for the estimation of elasticities. Bank credit, capital investments, labour availability, and rainfall are the independent input-related components of the study, whereas the dependent variable is agriculture's gross domestic product (AGDP) or output.

Specified Model: Cobb-Douglas Production Function

Agriculture-related GDP (AGDP) has the following Cobb-Douglas production function:

$$\boldsymbol{Y = f\,(X_1, X_2, X_3, \ldots\ldots X_7)} \qquad \textbf{(1)}$$

This led to the following model,

$$AGDP_t = A_t + BC_t^{\beta 1}.CI_t^{\beta 2}.FR_t^{\beta 3}.RA_t^{\beta 4}.ED_t^{\beta 5}.AF_t^{\beta 6}.SF_t^{\beta 7}.e^{\varepsilon t} \quad (2)$$

Where:

$AGDP_t$ (Output at time t, output: agricultural gross domestic production)

A_t= t is the total factor productivity (TFP)

BC_t : At time t, bank credit

CI_t : An investment of capital at time t

FR_t: farm age(years of operation) at time t

RA_t: rainfall in millilitres (seasonal rainfall index) at time t

ED_t : education of farmers in agriculture at the time t

AF_t : Farmers' ages at time t

SF_t : The farm's size at time t

β_1, β_2,β_3 ….. β_7 Output elasticities with respect to each input

ε_t: Error term capturing random shocks or unexplained variations at time t,

Log-Linearised Model

We typically linearise the two sides of the equation's natural logarithm to estimate this model using time-series data. This log-linear form simplifies the estimation of parameters using linear regression techniques and makes interpretation easier:

$$\ln AGDP_t = \ln A_t + B_1 \ln BC_t + B_2 \ln CI_t + B_3 \ln FR_t + B_4 \ln RA_t + B_5 \ln ED_t + B_6 \ln AF_t + B_7 \ln SF_t + \mathcal{E}_t \quad (3)$$

Model Specification

Dependent variable

$\ln AGDP_t$: natural log of agricultural GDP, representing the output

Independent variables

$\ln BC_t$: natural log of bank credit

$\ln CI_t$: natural log of capital investments

$\ln FR_t$: natural log of farm age (years of operation)

$\ln RA_t$: natural log of seasonal rainfall index

$\ln ED_t$: natural log of education level farmers in agriculture

$\ln AF_t$: natural log of the age of farmers

$\ln SF_t$: natural log of the size of the farm

Bank credit, capital investment, and the labour force are all expected to influence agricultural GDP positively. Annual rainfall, on the other hand, might have a favourable or unfavourable effect.

Coefficients:

β_1, β_2, $\beta_3 \ldots$ β_7 ,..Show how agricultural production is elastic with regard to each input. The coefficients of quantified changes comprising the percentage change in agricultural production, for instance, for a 1% change in bank credit, are referred to β_1.

Estimation Methodology:

Vector Error Correction Model (VECM): Because the variables (AGDP, BC, and CI) in this time-series model are co-integrated and non-stationary, they suggest a long-term equilibrium connection. The VECM technique captures long-term connections between these variables as well as short-term dynamics.

Test for Stationarity

Time series analysis requires stationarity because false regression findings might arise from non-stationary data. The model's result will be skewed if the data are non-stationary because their statistical properties—such as variance and mean—will change with time. While testing for or against stationarity, at level or after differencing, it is equally important to know the order of integration of each variable in the model. Both Phillips-Perron (PP) and Augmented Dickey Full (ADF) tests were employed during the study to test for stationarity.

Co-integration Test

As for the sequence of integrating the variables, the co-integration test is applied after the stationarity test. Therefore, a long-run equilibrium connection between two or more series is evaluated as part of the co-integration test. This test is usually utilised when deciding whether to investigate the association between the variables using a confined VAR (VECM) or an unconstrained VAR (ordinary VAR). In the opinion of Khetsi (2014), the Johansen co-integration test should only be done if it has first been resisted that each of the variables in the data sets is of the same order of integration. When the sequence of variable integration is kept, the Johansen technique must be used to look for a co-integrating relation (Algaeed, 2021). A multivariate time series was used to analyse the data, and the Johansen co-integration test was used in this study.

Vector Error Correction Model

Afterwards, according to the construction of the co-integration, the vector error correction model is established for the analysis of long-run properties. Vector error correction (VEC) is the multivariate, stochastic time series model composed of numseries equations with m different, different response variables. Co-integrated variables—or co-integrating interactions—are investigated using the VECM model. Short-term dynamics and long-term equilibrium connections may both be found using VECM.

Diagnostic and Stability Tests

The Jarque-Bera residual test can help assess the model's validity, stability, and dependability and determine if the residuals are normal. In this case, a non-normal distribution is the other option, while the null hypothesis concerns the normal distribution of residuals. We fail to retain the null hypothesis when we have the Jarque-Bera statistics equal to or above the critical level. The null hypothesis remains true when the Jarque-Bera statistics show no significant variation. The Breusch-Godfrey LM test lets one look for serial correlation. While the alternative hypothesis asserts serial correlation, the null hypothesis makes no such claims. The Lung-Box statistic test was used to ascertain whether or not autocorrelation—the alternative hypothesis—occurs absent from the null hypothesis. There was a counterargument even though the model was suggested to have heteroscedasticity. Whether there was heteroscedasticity was evaluated using the ARCH heteroscedasticity testIn the process of co-integration and VECTOR ERROR CORRECTION MODEL, the root graph of AR was also carried out to check the model's stability. Consequently, one may identify the location of the roots of AR at the AR root graph as the inverted normal AR position. Hence, the VAR is said to be stable if every root is inside the unit cycle and all are less than or equal to one.

5. Results Discussion

Descriptive Statistics

The research used time series data on agriculture from January 2002 to December 2022. Information was gathered from the Reserve Banks of Zimbabwe, the Meteorological Department, the Ministry of Agriculture, and ZIMSTAT (Zimbabwe National Statistics).

Table 2. Descriptive Statistics

	AGDP	AGE	BC	CI	EDU	FA	FS	MR
Mean	4.047532	46.46032	2.878671	53.79365	0.900794	24.66234	7.868006	290.0171
Median	4.170500	46.00000	2.914500	51.30000	1.000000	25.01000	6.527050	291.6000
Maximum	6.832000	58.00000	4.941000	100.6000	1.000000	41.61000	19.62800	700.0000
Minimum	1.002000	32.00000	0.667000	13.90000	0.000000	5.220000	2.000000	66.70000
Std. Dev.	1.312814	3.217608	0.956016	20.47624	0.299534	8.178308	4.751469	98.71547
Skewness	-0.135771	0.025989	-0.117319	0.275674	-2.681442	-0.182874	0.756695	0.127504
Kurtosis	2.280313	6.696885	2.286784	2.232381	8.190132	2.271716	2.502872	3.200957
Jarque-Bera	6.212691	143.5314	5.919194	9.378828	584.8290	6.973771	26.64361	1.106833
Probability	0.044764	0.000000	0.051840	0.009192	0.000000	0.030596	0.000002	0.574982
Sum	1019.978	11708.00	725.4250	13556.00	227.0000	6214.910	1982.738	73084.30
Sum Sq. Dev.	432.5935	2598.603	229.4056	105238.4	22.51984	16788.07	5666.692	2445931.
Observations	252	252	252	252	252	252	252	252

These results indicated that the AGDV had created a minimum of thousand US$ 1. 002 and a maximum of thousand US$ 6. 832 only by the agricultural gross domestic product. Farmers are between the ages of 32 and 58, on average 46 years old. US$4.941 thousand was the rise in Bank Credit (BC) from US$0.667 thousand. Capital investment (CI) increased similarly, rising from a low of US$13900 to a peak of US$100,000. Minimum and highest farm sizes were recorded as 2 and 569 hectares, respectively. Monthly rainfall (MR) ranged from 66 mm to 700 mm, averaging 73084 mm. All variables have a standard deviation less than the mean when using nominal data. The descriptive statistics of Jorque-Bera have revealed that food production and the independent variables do not deviate significantly from the normal distribution in the time series data.

Table 3. Correlation Analysis

	AGDP	AGE	BC	CI	EDU	FA	FS	MR
AGDP	1.000000	-0.146114	0.995733	0.814586	0.150244	0.993048	0.663127	0.932651
AGE	-0.146114	1.000000	-0.134760	-0.311390	-0.349272	-0.118214	-0.376723	-0.140433
BC	0.995733	-0.134760	1.000000	0.817447	0.151925	0.997681	0.664173	0.938798
CI	0.814586	-0.311390	0.817447	1.000000	0.317605	0.778404	0.953911	0.750447
EDU	0.150244	-0.349272	0.151925	0.317605	1.000000	0.131814	0.316732	0.081373
FA	0.993048	-0.118214	0.997681	0.778404	0.131814	1.000000	0.618369	0.938504
FS	0.663127	-0.376723	0.664173	0.953911	0.316732	0.618369	1.000000	0.616217
MR	0.932651	-0.140433	0.938798	0.750447	0.081373	0.938504	0.616217	1.000000

As a result of negative R-values, it can be noted that in Table 3, age and all other parameters have a negative relationship and are also insignificant. Positive and significant associations were seen for all other variables, indicating that when all variables are coupled, there is a strong and meaningful link.

6. Graphical Presentation

Since most of the data points fall between 0 and 100, Figure 1 below depicts several lines on a chart that are almost identical.

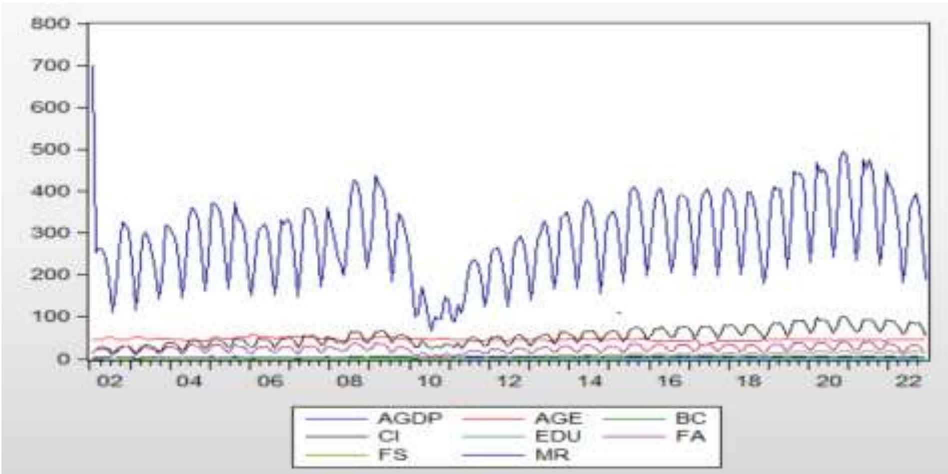

Figure 1. Graphical Presentation

Although there are significant swings, the trend of the agricultural GDP is nearly constant. Since the data is entirely steady and falls within the same range, all other factors suggest that the data is almost identical.

Unit Root Test Results and VECM

Stationarity tests were conducted based on the data required in this investigation. The Augmented Dickey-Fuller (ADF) test was used to employ stationarity of the variables. In this test, the null hypothesis is that there is a unit root in the series, whereas the alternative hypothesis is that the series is stationary. It is set like this:

H0= There is a series unit root

H1 = The series does not include any unit roots.

One discovered logarithms for every series. The ADF test results for every variable are shown in Table 4 below.

Table 4. ADF Test Result

Variable	Intercept	Trend and Intercept	Order of Integration
AGDP	2,060	2,070	
	0,0240	0,0270	
BC	6,540	6,410	1
	0,00	0,00	
AGE	1,970	1,560	1
	0.125	0.133	
CI	3,970	3,450	
	0,0270	0,0430	
FA	5,340	4,890	1
	0,00	0,00	
FS	2,010	2,1020	
	0,0120	0,0110	
ED	3.42	1.325	1
	0.000	0.000	
MR	6.90	6.35	1
	0.000	0.000	

Hence, the ADF test with the combination of intercept and trend showed that while AGDP, CI, and FS were stationary at the first difference I(1), other variables BC, AGE, FA, EDU, and MR were stationary at levels I(0). Thus, since it is established that most of the tested variables, AGDP, CI, and FS, were found to be I(1), it was mandatory to carry out the Johansen co-integration test to test whether the analysed non-stationary variables were co-integrated or not. This implies that order one (1) integration of all the variables is possible. I (1), and so are the variables.

VAR lag Order Selection Criteria

This is a requirement of the Johansen approach to show how the VAR's deterministic trend assumption and lag order work. An asterisk (*) denotes the least important information criteria.

Table 5. Lag Order of VAR

Lag	Log L	LR	FPE	AIC	SC	HQ
0	122.371	NA	2.041	-5.118	-6.536	-4.981
1	264.262	239.784*	5.877	-11.663	-10.300*	-12.006*
2	268.410	34.125	6.325*	-11.760*	-9.323	-10.421
3	**303.600**	**25.017**	**1.192**	**-11.014**	**-7.605**	**-9 .963**

Notes In the case of S-FS, the bar indicates the lag order selected based on the considered criterion. Sequential modified LR test statistic (LR): Even for each test, only 5 percent significance level was used. Last prediction error, or FPE is the error of a predictor based on one sample taking into account the conditions provided by the last instance that was employed to form the predictor. What acronyms for is AIC? Well, A I C stands for Akaike Information Criterion. Schwarz information criterion (SC) Based on the analysis of the research issues, the following information criteria of Hannan-Quinn headquarters were determined:

The study's overall findings also showed that the FPE, the modified LR test statistic, the AIC, SC, and the HQ warned a suitable lag length of one. AIC and SC are used more often than most empirical investigations. According to the findings of this study, the determination of the AIC and SC for selecting the best lag period was used. Following the initial difference, the ADF and PP tests showed the variables to be stationary. It is necessary to identify and analyse the long-term relationship between such factors. The process of achieving the co-integration of two or more time series is commonly used to find the equilibrium relationship between two or more time series. The long-term link between the variables is found for this study using co-integration.

Co-integration Test

While employing the stationary and co-integration tests, it would be possible to identify whether two or more series had a long-term equilibrium relationship after integrating the concerned variables. Johansen's Test of Co-integration (Kare et al., 2020) is a technique for determining the co-integrating vector or connection count. According to the VECM model, estimation is made when the number of co-integrating vectors is greater than zero but less than the total number of variables in the model. In addition, to ascertain the variables existed in long-term equilibrium, we employed the Trace and the Maximum Eigenvalue tests in order to determine co-integration. Table 6 below presents the results based on these two statistical measures, which are measures of relative standing.

Table 6. Maximum Eigenvalue Statistic

Hypothesised No of CEs	Eigen Value	Trace Statistic	0.05 Critical Value	Prob	Max Eigen Statistic	0.05 Critical Value	Prob
None*	00,6760	0111,4320	084,7630	00,0010***	040,3340	035,3960	00,0210**
At most 1*	00,5390	056,6400	061,0380	00,0230**	029,6030	029,3180	00,0910
At most 2*	00,4120	031,4320	040,3150	00,1420	020,0080	023,8230	00,1300
At most 3	00,1570	010,1110	022,4560	00,5430	08,64530	017,1260	00,6510

*The trace test at the 0. 05 significance shows that the number of co-integrating equations is two. It should be noted that the max-eigenvalue test helps identify one or more co-integrating equations at the same 0. 05. From the results presented in Table 4, you may deduce that the null hypothesis is rejected at a 1 % and 5 % significance level, as well as the symbols *** and **, respectively.*

The co-integration test of the model was considered based on the Johansen co-integration test presented in the above-noted tables. As mentioned earlier, in case of estimating a long-run CE, if the intercept and the trend are present in the equation and in the VAR specification, what is being identified in the data is no intercept but a deterministic linear trend only. Where the null hypothesis assumes such a relationship does not exist, there is the assertion of the existence of co-integration. The Max-Eigen statistic is equal to 40. 336, which is higher than the cut-off value of 35. 399 Therefore, the null hypothesis that no CE can be said at a 5% level for both statistics has been abandoned. Thus, it is for this purpose that when doing the Max-Eigen statistic, it cannot be replaced with the critical value of 35. 399. Therefore, dismissing the partial of the null hypothesis of no co-integrating vectors At most fewer vectors, the p-values of the trace statistic, 0. 001 and the maximum eigenvalue stat, 0.028, are significant at 5 percent level. While the Max-Eigen test shows the existence of only one co-integrating equation, the trace statistic shows two co-integrating equations. Akankabi, 2012 has observed that the statistics utilised is the maximum eigenvalue because although the latter generates a more precise specification of the form of the null hypothesis ; the statistic that it intends to identify is the number of co-integrating vectors. Furthermore, Ssekuma (2011) emphasised the preference for the maximum eigenvalue test, even when conflicting with trace results, as t-statistic coefficients may lack an asymptotic t-distribution. This suggests that no asymptotic t-distribution is guaranteed for co-integration despite serial correlation among the variables. The results indicate long-term co-integration among agricultural output, bank credit, investment, farm size, farm age, and monthly rainfall.

Vector Error Correction Estimates

A vector error correction model examines the long-term relationships after the co-integration connection. The short-term and long-term VECM explain the relationship between the bank lending agri GDP in the following manner. This approach was chosen as the gross domestic product of agriculture and bank loans have a long-term link. After all, farmers need time to increase their agricultural output with financial support. Furthermore, this technique may estimate both short- and long-term associations simultaneously. The co-integrated series' short-term characteristics are verified in the study using VECM.

Table 7. VECM Estimation Results

Error Correction:	D(AGDP)	D(CI)	D(FS)	D(MR)
R-squared	0.5273810	0.5233410	0.4422060	0.4705000
Adj. R-squared	0.5095840	0.5053910	0.4212010	0.4505610
Sum sq. resids	112.18830	11569.080	380.84880	624120.80
S.E. equation	0.6851330	6.9574560	1.2623430	51.101700
F-statistic	29.632530	29.156260	21.052590	23.596610
Log likelihood	-254.05500	-831.22620	-406.22190	-1327.7330
Akaike AIC	2.1209240	6.7568370	3.3431480	10.744840
Schwarz SC	2.2621870	6.8981000	3.4844110	10.886110
Mean dependent	-0.0043370	0.1084340	0.0299170	-0.2995980
S.D. dependent	0.9783460	9.8928070	1.6592560	68.940690
Determinant resid covariance (dof adj.)		093,332170		
Determinant resid covariance		079,218310		
Log likelihood		-01957,6030		
Akaike information criterion		016,077130		
Schwarz criterion		016,698690		

These results also have short term effects as well as the short-run correction coefficients in addition to long-run co-integrating relationship between the dependent and independent variables. Results show that the dependent variables' mean and standard deviation are very small for each variable, the F-statistic is tiny, and the R-squared is modest. It is suggested by this that there is a medium to moderate long-term association between the variables being studied.

Co-integration Regression Analysis

Tests for co-integration of the series are conducted using co-integration analysis. The analysis examines every variable, probability, t-statistic, coefficient, and standard error.

Table 8. Co-integration Regression analysis

variable	coefficient	Std.Error	t-statistic	Prob
AGE	(0,00941)	0,00352	(2,6722)	0,0081
BC	2,550687	0,659092	3,8699	0,0001
CI	(0,01184)	0,005015	(2,2392)	0,0191
EDU	(0,01874)	0,037922	(0,4941)	0,6216
FA	(0,1193)	0,069707	(1,7114)	0,0883
FS	0,020828	0,010088	2,0647	0,0004
MR	(0,00477)	0,000281	(1,6983)	0,0907
C	0,712677	0,018588	3,8340	0,0002
R-squared	00,991833		Mean Dependent var	4,055108
Adjusted R-squared	00,991598		S.D. dependendt var	1,309906
S.E.of regression	00,120069		Sum squared resid	3,503208
Durbin -Watson stat	01,551086		long-run variance	0,021115

As shown in Eviews, the only variables that are insignificant are FA (farm age), MR (rainfall) & and EDU (farmer education), while other variables depicted below have p-values less than 0. 05. Because t values are less than 2 and p-values are all higher than the significance threshold of 0.05, EDU and FA are not statistically significant. The p-values of AGE and MR are all less than 0.01 at the 1% level, which makes them statistically significant even if they are not at the 5% level. Other research findings show a substantial correlation between the researched variables, as seen by the large R-squared (close to 1) and the Durbin-Watson stat of 1.551, above 1.5. The factors most likely have a modest, long-term correlation because of the very low long-run variation.

VECM Equation

$$AGDP = 0.7127 - 0.0094 * AGE + 2.5507 * BC - 0.0118 * CI - 0.0187 * EDU - 0.1193 * FA + 0.0208 * FS - 0.0005 * MR$$

The above-stated results describe the long-run co-integration equation. The equation represents the relationship that holds, whereby the change in the gross domestic product (GDP) from agriculture (AGDP) from one period to the other depends on changes in bank credit (BC), capital investment (CI), farm size (FS), Farm age (FA) and Monsoon rainfall (MR). This means that, to get the solution, all the coefficient sign must be changed, and then we get the value as shown in the above equation. In VECM, this procedure is used to normalise the long-run equation, as explained in the next section of this paper. Interpreting the coefficient values which have been estimated from the constant 2. After analysing the following 5507 numbers, it is noticeable that the bank credit positively affected agriculture production while capital investment had a negative impact due to the 0. 0118 constant term. From Table 8 above, we also endorse the findings that there are some indications that bank lending has some bearing to agriculture production in Zimbabwe.

When this hypothesis is rejected, it will also reject the other one that posited that bank lending has no positive relationship with broad-based agricultural food production. The rise in bank credit, which is a one-percentage point, will indicate that the agricultural output will improve by 0. 67 percent. This will increase agriculture's production capacity by 2. 5507 percent when capital investments are increased under other controlling factors remaining constant. In general, the findings align with the study by Mdoda et al. (2019), which found a positive and significant relationship between bank credit and agricultural productivity in South Africa. The expected relationship between farm age and agricultural productivity has positive and substantial effects. The agricultural production decreases by 2.08 percent for every 1% increase in farm size, all other variables being equal.

On the other hand, it was shown that the rainfall coefficient was large and negative. There will be a 0.005 percentage drop in agricultural production for every percentage decrease in rainfall. This results from Zimbabwe's semi-arid environment. Agriculture uses irrigation to supplement its water demands. During times of excessive rain, crops get soggy, which lowers yields. Crops that are drought-prone wither and provide subpar yields.

Table 9. VAR Granger Causality

Dependent variable: AGDP			
Excluded	Chi-sq	Df	Prob.
CI	012.834350	2	0.00160
FS	09.7150190	2	0.00780
MR	058.896720	2	0.000000
All	086.802810	6	0.000000
Dependent variable: CI			
Excluded	Chi-sq	Df	Prob.
AGDP	080.793700	2	0.000000
FS	010.475000	2	0.005300
MR	046.035100	2	0.000000
All	0164.04350	6	0.000000
Dependent variable: FS			
Excluded	Chi-sq	Df	Prob.
AGDP	055.530040	2	0.00000
CI	024.266460	2	0.00000
MR	025.054770	2	0.00000
All	0107.08230	6	0.00000
Dependent variable: MR			
Excluded	Chi-sq	Df	Prob.
AGDP	055.457540	2	0.00000
CI	012.014390	2	0.00250
FS	07.2042340	2	0.027300
All	074.723430	6	0.00000

The findings of Table 6 above show larger Chi-Sq values and lower prob (p) values. The p-values all show that the lag values are significant since they are all less than the 0.05 significance threshold. Consequently, the agricultural gross domestic product, or agdp, is not affected by every lag in a variable's value in the model. This statistic seeks to ascertain the precise number of co-integrating vectors and has a more well-defined alternative hypothesis (Akanbi, 2012). This is further corroborated by Enders (2004), who proposes that the t-statistics coefficients lack an asymptotic t-distribution.

7. Model Diagnostic Checking

Residual Plot

The residual plot revealing the result of actual observation of the VECM is presented below.

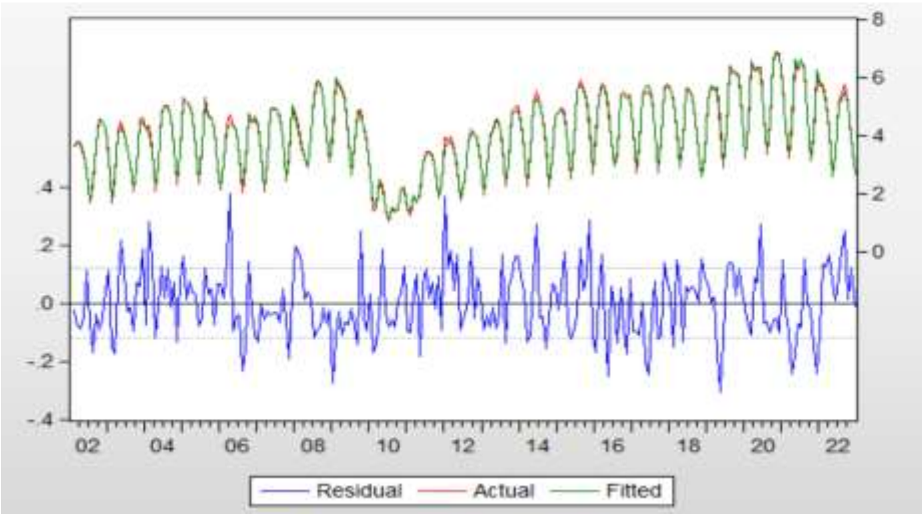

Figure 2. Residual Plot

The data utilised in this study matches well for co-integration VECM, as seen by the residual plot above, where observations are dispersed around the zero line. Like the fitted observation, the actual fits display a varying tendency. Therefore, this confirms our previous hypothesis that the residuals of the regression model are independent.

Normality Test

A histogram graphic is utilised to analyse normalcy, data skewness, and model fit. This figure's x- and y-axes show the theoretical quantiles and the standardised residuals, respectively.

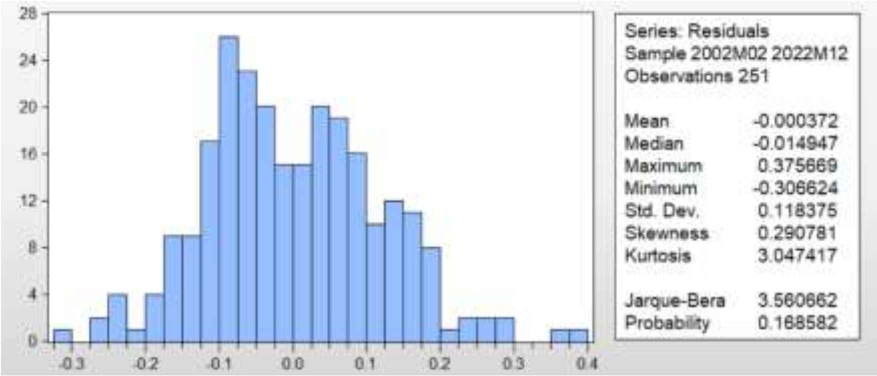

Figure 3. Normality Test

The picture illustrates that although the data has a positive skewness of 0.290781, the AGDP (agricultural gross domestic product) is normal. The data set contains little or a light tail, as shown by the kurtosis of 3.047. The skewness and kurtosis of the test sample data are consistent with a normal distribution, suggesting a goodness-of-fit, according to the Jarque–Bera test value of 3.56, which is close to zero. This satisfies the previous premise, which stated that the regression model's residuals are regularly distributed.

8. Conclusion

This study investigates the effectiveness of bank credit in enhancing agricultural productivity in Zimbabwe, a country facing unique economic and environmental challenges. By employing a Vector Error Correction Model (VECM) and using a comprehensive set of variables—including agricultural GDP, bank credit, capital investments, farm age, rainfall, farmer education, age of farmers, and farm size—the research provides robust empirical evidence on the dynamic relationship between financial intermediation and agricultural growth. The findings indicate that while bank credit positively impacts agricultural productivity in the long term, its effectiveness is influenced by factors such as capital investment, education, farm size, and climatic conditions. The study's original contribution lies in its context-specific analysis, the inclusion of diverse variables, and advanced econometric techniques, offering valuable insights for policymakers seeking to improve credit policies and financial support mechanisms for agriculture in Zimbabwe. These results underscore the critical role of tailored financial strategies in promoting sustainable agricultural development in similar developing economies.

Future research could explore the impact of alternative financing options, such as microfinance or digital lending, on agricultural productivity in Zimbabwe. Additionally, studies could examine the role of policy reforms, climate resilience strategies, and technological adoption in enhancing the effectiveness of bank credit in the agricultural sector.

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