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Adopting an Empirical Perception from the Vector Error Correction Model Technique to Examine the Influence of Credit availability on Rice Productivity in Sierra Leone

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Abstract

Through the help of the vector error correction model technique, this research work explored the effect of credit availability on rice productivity in Sierra Leone in the period 1986–2021. Results from the analysis revealed that an increase in credit availability would cause an upsurge in rice productivity. Furthermore, this work showed that a sudden decrease in labor and investment would bring about a decrease in rice productivity whereas a sudden increase in inflation and money availability would lead to an increase in rice productivity in Sierra Leone. From the evidence on this findings, it is suggested that state owned financial institutions ought to provide a system that will afford loans that are free of interest rate to rice cultivators. Similarly, administrators ought to inspire rice cultivators through the provision of farm inputs such as land, high yield rice seed varieties and fertilizers to rice cultivators.

Keywords: Rice Productivity; Availability of Credit; Vector Error Correction model; Sierra Leone.

1. Introduction

Credit availability is very vital in increasing rice productivity in every nation. This has been documented by numerous agriculturists for over the years. A lots of research work have publicised that the availability of credit to the agricultural division is a strategic stand in attaining sustainable development in the agricultural sector and decrease poverty rate within the population[1]. The accessibility of credit to the rice farmers not only inspires them but again reinforces the development of the agricultural division[2].

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Equally, Gomes, L. and his colleagues [3] detailed that the driver for sustainable development is the accessibility of credit to finance the rice cultivators. Numerous research works have been done to emphasize agricultural credit subsidising hugely to the development of the nation. He, Y and his colleagues [4], their research work stressed the successes of credit availability in interpreting into aggregate productivity in the African economy.

As stated by Anwar, A and his colleagues [5], rice crop is a vital staple food eaten by about 70 % of the world populace. In Sierra Leone, rice is the staple and most eaten food with consumption rate per capital of 60 kg. Report from Statistics Sierra Leone (SSL, 2019) state that household spending on rice yearly accounted for about 40.3 %. In Sierra Leone, rice crop farming is customarily carried out by small-scale cultivators who engaged in using out-dated farming tools, and no accessibility to credit to augment their productivity[6].

In an effort to increase rice output and make Sierra Leone self-sufficiency in rice production, the government of Sierra Leone has increased spending on the Tomabom rice project. The state has provided agricultural inputs such as fertilisers and seedlings and fixed several development structures to inspire rice cultivators. Furthermore, land enterprises were given to large scale rice farmers as a motivation. The state, through the ministry of finance (MOF) provided resources to rice cultivators at cheaper rates through the borrower's scheme.

Nevertheless, in spite of state policies on rice cultivation, rice importation cost for Sierra Leone which stood at $ 250 million in 2019 [7] increased to $330 in 2022 [7] owing to the preference for rice importation by urban traders due to its better quality. As stated by Yu and his colleagues [8] rice importation is caused by the abandonment of agricultural subsector by the state officials.

From various works, empirical analyses have revealed that credit availability positively and significantly influence rice productivity. Thus suggests that through the availability of credit, rice cultivators have been capable of increasing their rice productivity[9].

Since to eliminate poverty rate in Sierra Leone is an immense challenge[10] , noticeable question that this research work aims to address is, does credit availability influence rice productivity in Sierra Leone? Also, the main objective of this study is, to examine the influence of credit availability on rice productivity in Sierra Leone by utilizing the vector error correction model (VECM) technique[11]. However, findings from the research work will help state actors in designing as well as implementing fitting agricultural policies that will create an enabling environment for a sustainable and self-sufficient in rice productivity in the country[12].

2. Literature Review

Various researches in the literature have observed the association between credit availability and agricultural productivity. For example, research findings by Sharma, G.D and his colleagues [13] showed that agricultural credit availability has influence the development of export in Sierra Leone. Also, research findings by Wong, L.-F [14] presented that in Sierra Leone, agricultural credit availability has influenced positively on the agricultural sub sector. Employing logistic regression analysis model, Wong, L.-F [14] resolved that agricultural

credit availability has positive influence on agricultural productivity in Mali. Similarly, using a simple linear regression model, Jayne, T.S and his colleagues [15] presented that because of agricultural credit availability, productivity has increased tremendously. Additionally, Jayne, T.S and his colleagues [15] resolved that credit availability positively influences productivity.

From the utilization of the ordinary least square technique of multiple regressions, research findings by Jin, G and his colleagues [16] showed that in Guinea, credit availability positively influenced productivity. Moreover, research studies done by Ma, L and his colleagues [17] revealed that in Ghana, credit availability significantly influenced productivity. Furthermore, research studies done by Damilola A.T [18] presented that agricultural credit availability positively influenced agricultural productivity in Sudan. Another research studies done by Drebee, H.A [19] specified that in Mali [20], the association between agricultural credit availability and agricultural productivity is a long-run. Again, Anderson, K and his colleagues [21] resolved that credit availability positively influence productivity in Togo.

Several other studies have been carried out to examine whether credit availability positively influenced rice productivity. For example, research findings by Moutouama,F.T and his colleagues [22] disclosed that credit availability significantly enhanced rice cultivation. Theses researchers therefore, endorsed the introduction of excellent credit system for rice cultivation. Additionally, further researches noted that accessibility to credit has assisted rice cultivators to increase their inputs which sequentially has led to upsurge in rice productivity.

From the above literature review, research studies have revealed that credit availability has a positive as well as significant influence on rice productivity. This study used the VECM technique to examine the influence of credit availability on rice productivity in Sierra Leone by employing the variance decomposition as well as impulse response function.

3. Methodology and Data

3.1. Theoretical Framework

The objective of this studies is to examine the influence of credit availability on rice productivity in Sierra Leone. This study follows the Cobb-Douglas productivity function[23]. The overall form of Cobb-Douglas productivity function is specified as follows:

$$\boldsymbol{Y_t} = \boldsymbol{B_t Z_t^{\alpha} P_t^{\beta}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (\mathbf{1})$$

Where $\boldsymbol{Y_t}$ Symbolises rice productivity (RP) at time t,

$\boldsymbol{B_t}$ Symbolises overall factor output (OFO)

$\boldsymbol{Z_t^{\alpha}}$ Symbolizes capital stock at time t

$\boldsymbol{P_t^{\beta}}$ Labor at time t, and α, β are elasticities of productivity

Here, the expectation is that the entire factor output is a function of profitable credit availability to rice farmers (CA). Regarding rice productivity (RP), inflation rate (IF), money supply (M2) in addition to other exogenous factors (EF) were introduced in the model. Accordingly, the entire factor output is model as:

$$\boldsymbol{A_t = f(IF_t, M2_t, EF_t, CA_t)} \quad \ldots\ldots\ldots\ldots \quad (2)$$

Eq (2) can be stated as:

$$\boldsymbol{A_t = CA_t^{\circ}\, IF_t^{\emptyset}\, M2_2^{\vartheta}\, EF_t} \quad \ldots\ldots\ldots\ldots \quad (3)$$

From Eq (3) and (1), we write:

$$\boldsymbol{RP_t = CA_t^{\circ}\, IF_t^{\emptyset}\, M2_2^{\vartheta}\, EF_t Z_t^{\alpha} P_t^{\beta}} \quad \ldots\ldots\ldots\ldots \quad (4)$$

Specification of Model

1. Subsequent to the theoretical context of this research work, the model is stated as:
2. $\boldsymbol{RP_t = f\left(IV_{t}, M2_{t}, LB_{t}, IF_{t}, CA_{t}, EF\right)} \quad \ldots\ldots\ldots\ldots \quad (5)$
3. The econometric formula of Eq (4) can be stated as:
4. $\boldsymbol{RP_t = f\left(IV_{t}, M2_{t}, LB_{t}, IF_{t}, CA_{t}, EF\right)} \quad \ldots\ldots\ldots\ldots \quad (6)$
5. $\boldsymbol{RP_t = c + \theta IF_t + \emptyset CA_t + \pi M2_t + \alpha IV_t + \beta LB_t + \varepsilon} \quad \ldots\ldots\ldots\ldots \quad (7)$
6. Where: c is constant; θ, ∅, α, β and are coefficients of the variables, $\boldsymbol{\varepsilon}$ is an error term and t is the time trend.

3.2. Vector Error Correction Model (VECM)

Subsequent to the co-integrating variable characteristics, this study used the VECM model. The model is founded on the model called vector autoregressive (VAR). By the VAR model, variables have option to regress on a number of lags of themselves. VECM is the long-run approximation variant of the VAR. Using the Variance Decomposition (VDC) and IRF of the VECM, this technique[23] was utilized to examine the influence of agricultural credit availability on rice productivity (RP) in Sierra Leone. The validation for using the IRF is to establish the influence of shocks in agricultural credit availability on rice productivity in Sierra Leone even though the VDC was employed to quantify the relative significance of shocks in credit availability on rice productivity. Hence, the VECM model can be written as:

$$RP_t = \tau_1 + \sum_{j=i}^{n} \theta_j RP_{t-j} + \sum_{j=1}^{n} \beta_j IV_{t-j} + \sum_{j=1}^{n} \gamma_j LB_{t-j} + \sum_{j=1}^{n} \alpha_j CA_{t-j} + \sum_{j-1}^{n} \rho_j M2_{t-j} + \sum_{j=1}^{n} \pi_j IF_{t-j} + \varepsilon_{1t} \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$IV_t = \tau_2 + \sum_{j=1}^{n} \beta_j IV_{t-j} + \sum_{j=1}^{n} \theta_j RP_{t-j} + \sum_{j=1}^{n} \gamma_j LB_{t-j} + \sum_{j=1}^{n} \alpha_j CA_{t-j} + \sum_{j-1}^{n} \rho_j M2_{t-j} + \sum_{j=1}^{n} \pi_j IF_{t-j} + \varepsilon_{2t} \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

$$LB_t = \tau_3 + \sum_{j=1}^{n} \gamma_J LB_{t-j} + \sum_{j=1}^{n} \theta_j RP_{t-j} + \sum_{j=1}^{n} \beta_j IV_{t-j} + \sum_{j=1}^{n} \alpha_j CA_{t-j} + \sum_{j-1}^{n} \rho_j M2_{t-j} + \sum_{j=1}^{n} \pi_j IF_{t-j} + \varepsilon_{3t} \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

$$CA_t = \tau_4 + \sum_{j=1}^{n} \alpha_j CA_{t-j} + \sum_{j=1}^{n} \theta_j RP_{t-j} + \sum_{j=1}^{n} \beta_j IV_{t-j} + \sum_{j=1}^{n} \gamma_J LB_{t-j} + \sum_{j-1}^{n} \rho_j M2_{t-j} + \sum_{j=1}^{n} \pi_j IF_{t-j} + \varepsilon_{4t} \ldots\ldots\ldots\ldots\ldots (11)$$

$$M2_t = \tau_5 + \sum_{j=1}^{n} \rho_j M2_{t-j} + \sum_{j=1}^{n} \theta_j RP_{t-j} + \sum_{j=1}^{n} \beta_j IV_{t-j} + \sum_{j=1}^{n} \gamma_J LB_{t-j} + \sum_{j-1}^{n} \alpha_j CA_{t-j} + \sum_{j=1}^{n} \pi_j IF_{t-j} + \varepsilon_{5t} \ldots\ldots\ldots\ldots\ldots (12)$$

$$IF_t = \tau_6 + \sum_{j=1}^{n} \pi_j IF_{t-j} + \sum_{j=1}^{n} \theta_j RP_{t-j} + \sum_{j=1}^{n} \beta_j IV_{t-j} + \sum_{j=1}^{n} \gamma_J LB_{t-j} + \sum_{j-1}^{n} \alpha_j CA_{t-j} + \sum_{j=1}^{n} \rho_j M2_{t-j} + \varepsilon_{6t} \ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where $\alpha_j, \beta_j, \gamma_j, \theta_j, \pi_j$coefficient of the parameters are, $\tau_1 - \tau_6$ are constants of the parameters , $\varepsilon_1 - \varepsilon_6$ are the error terms and t is the time trends

Data and Variables Description

This study employs time series data spanning the period 1986–2021. The data was retrieved from the data bases of Statistics Sierra Leone (SSL), Sierra Leone Agricultural Research Institute (SLARI) and Food Agriculture Organization (FAO). The variables employed in the model are:

Rice productivity (RP), which is the total quantity of rice produced in a specific year.

Investment (IV), this is the gross national investment.

Inflation rate (IF), this is the overall increased in the prices of goods as well as services

Credits availability (CA), these are loans given to the rice farmers by community banks

Money Supply (M2), the total quantity of money disbursed

Labor (LB), this is the workforce.

4. Results and Discussion

4.1. Unit Root Test

Table 1 below shows the stationarity test result. This study used the Kwiatkowski, Phillips, Schmidt [24] as well as Shin test to establish the order of integration as well as stationarity of the variable in the model[24]. The result of the unit root test[25] shown that all the variables become stationary [25] at first difference.

Table 1: KPSS unit root test result

Critical value					
Series	***LM-Stat***	***1%***	***5%***	***10%***	***Integration Order***
RP	0.0642	0.2200	0.1334	0.1150	1 (1)
M2	0.2023	0.2200	0.1334	0.1150	1 (1)
IF	0.0431	0.2200	0.1334	0.1150	1 (1)
CA	0.1327	0.2200	0.1334	0.1150	1 (1)
LB	0.0542	0.2200	0.1334	0.1150	1 (1)
IV	0.1122	0.2200	0.1334	0.1150	1 (1)

Source: Authors" computations

4.2. Optimum Lag Selection Criteria and Co-integration Test

Table 2 below displays the result of the optimum lag selection criteria[26]. The outcome shows that all the test criteria[26] selected the optimum lag length 2. Therefore, for the drive of our approximation, lag 2 will be used in the estimation of the co-integration[27] test in conjunction with the VECM model.

Table 2: Optimal lag Selection Criteria

Lag	**Log L**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	−3322.010	NA	$1.15e^{+89}$	222.1105	231.0003	222.3121
1	−3412.326	276.7732	$1.33e^{+86}$	210.0761	212.4071	210.3213
2	−32123.312	74.4514*	$3.43e^{+80*}$	209.4331*	214.4562*	231.8951*

Source: Authors' Computation. *Designates order of lag selected through the criterion.

Since all the variables are integrated at 1(1). the trace in addition to the maximum eigenvalue tests [28] of Johansen-Juselius co-integration test [28] was used to ascertain the existence of a long-run [29] association between the variables [29]. The null hypothesis of non-appearance of co-integration [29] is rejected at 5 % level of significance if the likelihood value does not surpass the 5 % . The co-integration test is stated in Table 3.

Table 3: Johansen-Juselius Co –2integration outcome

Trace test			***Maximum eigenvalue***		
Null hypothesis	***T-test***	***P -value***	***Null hypothesis***	***T-test***	***P-value***
r=0*	161.2246	0.0001	r=0*	72.6231	0.0002
r≤1*	105.4532	0.0003	r≤1	32.9876	0.0300
r≤2*	68.6547	0.0008	r≤2	28.4651	0.0331
r≤3*	31.79490	0.0140	rr≤3	22.3341	0.0211
r≤4	12.4371	0.2001	r≤4	9.6332	0.3431
r≤5	4.4321	0.1461	r≤5	4.30021	0.1412

Source: Authors" estimation. *Designates P ≤ 0.05 and the rejection of Null hypothesis.

Table 3 shows the existence of long-run association. For example, the Trace test together with Maximum-Eigenvalue test both show the existence of 4 co-integration equation at 5% [30]. In summary, therefore, this study states that employing both tests, there is an existence of long-run association among the variables. Accordingly, VECM technique becomes applicable.

4.3. Variance Decomposition (VDC)

Table 4 below shows the outcome of the VDC of RP. This result detailed that credit availability (CA) contributes for the key variation in RP. For example, in period 4 credit availability contributes 14.57 % variation in RP relative to other economic variables[30]. In period 7, credit availability accounts for 23.35 % variation in RP relative to other economic variables[30]. In period 9, credit availability contributes 27.32 % variation in RP relative to other economic variables[31].

Table 4: Variance Decomposition (VDC) of Rice Productivity (RP)

Periods	***S.E.***	***RP***	***M2***	***LB***	***CA***	***IF***	***IV***
1	409234.1	106.0006	0.00061	0.00034	0.00003	0.00067	0.00023
2	589345.4	71.72303	17.00873	0.24521	5.114532	13.45271	73.24129
3	814563.9	74.56432	10.79045	0.35212	12.00743	4.99452	1.09452
4	925673.5	67.98574	9.21342	0.53128	14.57340	6.42909	2.14261
5	1094561	64.69431	13.53241	0.36720	18.90567	9.00054	2.67281
6	1456701	60.66231	8.956430	2.09845	21.79034	3.36132	2.01341
7	1632115	59.46532	12.45361	2.19052	23.34562	7.02431	2.32210
8	1754218	57.94741	11.66423	2.43610	25.00465	8.11454	2.53139
9	1596832	55.64532	14.43255	2.42107	27.32120	2.96700	2.62012
10	1945231	53.90700	16.19067	2.63261	29.33643	5.42311	2.00261

Source: Authors' Computation. Figures illustrate the VDC of Credit Availability (CA)

4.4. Diagnostic Result

Table 5 illustrates the result of the serial correlation test as well as the heteroscedasticity test [32]. The serial correlation test in addition to the heteroscedasticity test [32] show that there are no serial correlation and heteroscedasticity in the model. For instance, the P-value[33], of the serial correlation LM-Stat [33], is greater

than 5 % level of significance. Thus, the null hypothesis [33] of no serial correlation is accepted. Similarly, the P-value of the Chi-square [34] for the heteroscedasticity is greater than 5 % level of significance which shows that this model is free from heteroscedasticity [34].

Table 5: Diagnostic Test

VEC residual serial correlation LM tests			***VEC residual heteroscedasticity tests***		
Lags	***LM-Stat***	***P***	***Chi-square***	***df***	***P***
1	39.67321	0.2067	623.1210	611	0.4321

Source: Authors' computation

4.5. Conclusion and Recommendations

By employing the VECM technique, this study examined the influence of agricultural credit availability on rice productivity in Sierra Leone within the period 1986–2021. The variables used in this study are rice productivity (RP), credit availability (CA), money supply (M2), investment (IV), labor (LB) and inflation rate (IF). Results from the research disclosed that the variables are co–integrated. Additionally, the study disclosed that an increase in credit availability would lead to an upsurge in rice productivity. Similarly, the study showed that a shock in national investment and labor would lead to a reduction in rice productivity. Again, though a surprise increase in money supply in addition to inflation rate would lead to an increase in rice productivity in the country. Thus, this research study presented that the main variation in rice productivity is credit availability.

From the results of the study, it is suggested that state authorities in collaboration with financial credit institutions ought to generate a system that will give an interest free loan to rice farmers, as these will inspire them and increase rice productivity in Sierra Leone. Correspondingly, it is necessary for state authorities to motivate rice cultivators by providing them with farm inputs such as fertilizers, high yielding rice varieties and land at a subsidizes price.

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