Impact of Agricultural Credit on Agricultural Production: Evidence from Bangladesh

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Abstract

This article aims to portray the impact of agricultural credi9933333t on agricultural production in Bangladesh using the Johansen co-integration method. However, the Johansen co-integration test requires the concerned variables to be in the same order of integration. Augmented Dickey-Fuller (ADF), Phillips Perron (PP), and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests have been performed to check whether the variables contain a unit root. ADF, PP, and KPSS tests suggest that all variables- the natural logarithm of agricultural production, agricultural credit, fertiliser use, and agricultural employment- follow the integration of order one. The test results show that credit disbursed in agriculture and fertiliser usage significantly increase agricultural production in the long run. Nonetheless, the findings disclose that agricultural employment has a negative long-run effect on agriculture production. Regarding post-estimation, we did not find any serial correlation in the Vector Error Correction Model (VECM) model, and residuals of the VECM model are also normally distributed. Our findings suggest that credit disbursed in the agricultural sector facilities needs to be augmented to increase and sustain agricultural output.

Key Words: Agricultural Credit, Agricultural Output, VECM Model, Bangladesh

JEL classifications: Q130, Q140, Q180

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Introduction

Bangladesh is primarily dependent on agriculture to feed its around 170 million population. Agriculture is also a primary source of employment generation for its increasingly growing population. Nearly 50 per cent of the country's active labour force directly or indirectly depends on agriculture for livelihood (Ministry of Finance, 2020). It is evident that the agricultural sector directly determines the overall soundness of the economy. However, a growing population and rapid expansion of towns and cities are continuously generating pressures on cultivable lands of the country. Moreover, arable land has declined by around ten percentage points since independence[1]. Therefore, the declining trend of arable land threatens the country's food security.

Due to the declining trend of arable land, agricultural productivity needs to be increased and sustained to safeguard the country's food security. Given the decreased pattern of arable land, higher production requires an improved efficiency of the production function. One major way to foster the efficiency of the production function is by injecting agricultural credit. With access to credit, the farmers can invest the credit in improved seeds, high-yielding varieties (HYV) technology, fertilisers, and other inputs that can escalate their production. Agricultural credit also ensures the on-time supply of production factors. The timely usage of seeds, fertilisers, irrigation, etc., can significantly affect the farm operation (Saboor et al., 2009).

Sustainability in the agricultural sector also requires agricultural diversification. Although diversification ensures profitability and sustainability in farming, low diversification is found in Bangladesh due to credit constraints (Azad, 2021). In addition to the sustainability of agriculture, the country's continuous economic growth and development may also be hampered. However, the smooth growth of agriculture needs unceasing credit injection in this sector. Only the government can support such investment in the agriculture sector. Realising the significance of agricultural credit for sustained economic growth, the government of Bangladesh introduced institutional credit disbursement through its central bank in the 1980s with a small amount. Besides, the government has been increasing the amount of credit each year. Therefore, it is also essential to investigate the effectiveness of agricultural credit on agricultural production and economic growth from a macro view. Moreover, the agriculture sector is the prime source of food security, economic development and poverty reduction in the country.

Hence, investigating the causal relationship between agricultural credit disbursement and agricultural production from the aggregate view is crucial. However, the researchers in this field mainly examined the effectiveness of credit on production at the farm level. As a result, a research gap remains in this field of knowledge. The existing research gap motivated us to study the causality of agricultural credit and output from the macroeconomic perspective in the economy of Bangladesh using an appropriate econometric model. Therefore, the prime objective of our paper is to find out the impact of agricultural credit on the agricultural output of Bangladesh.

In this paper, the first section depicts the study's background, rationale and research objective. The second section seeks to give an overall review of the prevailing literature in the field of agricultural credit. The third section explains data, variables and methodology, whereas the fourth section covers the estimations and interpretation of the obtained results. Finally, the fifth section draws concluding remarks and policy recommendations.

Literature Review

Credit in the agricultural sector plays a central role in making available agricultural inputs and technological improvements in the production process. Improving technical efficiency is also essential for smooth production with cost minimisation (Iqbal et al., 2003). On the other hand, lacking access to credit prevents the farmers from utilising the full potential of other factors of production. Using state-level panel data from India, Narayanan (2016) found that other agricultural production inputs were highly responsive to the increased formal agricultural credit. Saleem and Jan (2011) found that credit facilities promoted crop production technology like the green revolution in Pakistan. In addition to the green revolution technology, increased agricultural credit also facilitated the purchase of other modernised inputs in Pakistan. However, debate prevails on the efficiency of credit if the farmers face constraints on other inputs like technical barriers. Taylor et al. (1986) revealed that only credit inflow could not resolve the technical obstacles of traditional agricultural farmers. Hossain et al. (2019) also suggested that credit access without relaxing other constraints may not guarantee the profits of the marginal and tenant farmers.

Despite the debate regarding efficiency, the agricultural credit facility is considered the most critical and significant factor for small and poor farmers to escalate their production in Bangladesh (Malek et al., 2022). Lack of access to credit is also responsible for lagging behind the full utilisation of factors of production. Islam (2020) showed that a smooth flow of credit is essential for the small and poor farmers in Bangladesh, ensuring healthy and timely output. Iqbal et al. (2003) found that institutional credit with labour and irrigation facilities significantly intensified Pakistan's agricultural GDP growth. Gershon et al. (2020) showed that the farmers with agricultural credit enjoyed three times higher production than those without it in Nigeria. Khandker & Koolwal (2016) found a significant positive effect of official and microcredit on agricultural output for small landowner households.

Institutional agricultural credit also substantially impacts non-farm production and income because it overcomes credit barriers. Mitra et al. (2019) found significantly higher output for credit-recipient farmers in Bangladesh. Azad & Wadood (2017) also depicted that household assets positively affect fisheries production in Bangladesh. Bidisha et. al (2015) showed that credit-recipient farms enjoyed better fortune than non-recipient farms. Wadood et. al (2021) also disclosed a positive relationship between credit borrowing and international migration. Using panel data, Khandker and Koolwal (2016) explained that borrowing credit for agricultural purposes has a strong and positive effect on non-farm income. Therefore, credit support helps the sustainability of agriculture by expanding its horizon. They also showed that access to agricultural credit could also increase household consumption.

Although there are many studies regarding agricultural credit and production worldwide, only a limited number of studies in this field are found in Bangladesh. Most studies in this field focused on a micro view (Miah et al., 2006; Rahman, 2011; Bidisha et al., 2015; Mitra et al., 2019). Although some studies focused on long-run and macro analysis (Rahman, 2011; Alauddin & Biswas, 2014; Khandker & Koolwal, 2016), most studies lacked greater observation or causal analysis. Besides, empirical evidence using apt methodology is needed to formulate an inclusive and substantial agricultural credit policy for the country. By exploring the causal relationship between credit and output, we tried to find the long-run effect of agricultural credit on agricultural production.

Data, Variables, and Methodology

Data and Variables: The study employs data from secondary sources to inspect the long-run relationship between agricultural credit disbursement and agricultural production. We have considered the Cobb-Douglas production function in the agriculture sector to find the long-run relationship. Agricultural credit, fertilisers, and employment in agriculture have been considered the independent variables, whereas total agricultural production has been treated as the dependent variable. Assuming the Cobb-Douglas function for agricultural production, our long-run relationship can be modelled as the following relationship

$$AgrProdn = f(AgrCrdt, Fert, AgrEmpl) \qquad (1.1)$$

Where, AgrProdn stands for the total agricultural production of Bangladesh in a million (Bangladesh Taka) BDT in constant prices using 2005-06 as the base year. Total agricultural production comprises (a) all crops and horticulture, (b) animal and livestock farming, (c) forest and related services, and (d) fishing. On the other hand, AgrCrdt means total agricultural disbursed credit in a million BDT, Fert implies total used fertiliser in the country in Metric Ton (*M. T.*)[2], and AgrEmpl means the employment in agriculture as a percentage of aggregate employment in the country. Data of agricultural output have been collected from Bangladesh Bank, and agricultural credit data have been obtained from the several yearbooks of Bangladesh Economic Review, data on fertiliser usage have been accessed from the different statistical yearbooks of the Bangladesh Bureau of Statistics (BBS), while data of agricultural employment have been taken from the ILO modelled estimated data[3]. The aforementioned time series contain yearly data from 1983 to 2019[4].

Stationarity Test, Specification of Lag Order, and Testing for Co-integration: Conventional time series econometrics estimation of regression with non-stationary variables results in a spurious relationship between the explained and explanatory variables (Granger & Newbold, 1974), though the regression contains a high value of R^2 and statistically significant t value (Enders, 2008). Nevertheless, the linear combination of non-stationary variables may reflect a meaningful long-run relationship if all series have identical order of integration. If any meaningful equilibrium relationship exists, the aberration from the long-run steadiness must be transitory, resulting in a stationary error term (Enders, 2008). From equation (1.1), we can rewrite the econometric specification as follows

$$AgrProdn_t = \theta_1 + \theta_2 AgrCrdt_t + \theta_3 Fert_t + \theta_4 AgrEmpl_t + \epsilon_t \qquad (1.2)$$

If the error term of equation (1.2) is stationary series, the deviation will be temporary. Therefore, the linear combination will be stationary, resulting in a meaningful long-run relationship. Solving for the error term gives us

$$\epsilon_t = AgrProdn_t - \theta_1 - \theta_2 AgrCrdt_t - \theta_3 Fert_t - \theta_4 AgrEmpl_t \qquad (1.3)$$

As long as ϵ_t is stationary to hold a long-run association, the right hand of the above equation must be stationary. That means that the linear grouping of $AgrProdn_t$, $AgrCrdt_t$, $Fert_t$, $and\ AgrEmpl_t$ with the integration of order one is also stationary. Hence, their linear combination will yield a long-run steadiness relationship.

Stationary Test and Specification of Lag Order: the Augmented Dickey-Fuller (ADF), the Phillips Perron (PP), and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) tests of the unit root have been performed to test stationary status of the variables. The general form of a Data generating Process (DGP) z_t with its first difference that follows AR (1) process with drift and the deterministic trend can be modelled by the following regression model:

$$z_t = \gamma + \mu t + \delta_1 z_{t-1} + \omega_t \qquad (2.1a)$$

$$\Delta z_t = \gamma + \mu t + \rho z_{t-1} + \omega_t \qquad (2.1b)$$

Similarly, AR(p) process can be modelled with lag order *p*

$$z_t = \gamma + \mu t + \sum_{i=1}^{p} \delta_i z_{t-i} + \omega_t \qquad (2.2)$$

where, t stands for deterministic trend. After subtracting z_{t-1} from both sides, the above equation 2.2 can be written by following the representation of Kirchgässner & Wolters (2007)

$$\Delta z_t = \gamma + \mu t + \rho z_{t-1} + \sum_{m=1}^{k} \varphi_m \, \Delta z_{t-m} + \omega_t \qquad (2.3)$$

the Augmented Dickey-Fuller (ADF) test estimates the above equation under the null hypothesis of non-stationary variables after Dickey & Fulller (1979), using the parametric estimation to incorporate serial correlation. Although Phillip-Perron (PP) test is estimated under the same null hypothesis, it, unlike the ADF test, adopts the non-parametric method to examine the heteroskedastic disturbance term (Phillips & Perron, 1988). The Phillip-Perron (PP) test estimates equation 2.1b to investigate the existence of unit root in a series.

Unlike the ADF and PP tests of unit root, the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) unit root test examine the existence of unit root under the stationary null hypothesis (Kwiatkowski et al., 1992). Under the hypothesis, DGP can be modelled by following the exemplification of L¨utkepohl and Kr¨atzig (2004).

$$y_t = \alpha t + x_t + v_t\,, \qquad where\ x_t = x_{t-1} + \varepsilon_t\,,\ \ \varepsilon_t \sim (0, \sigma_\varepsilon^2)\ \ and\ v_t\ is\ stationary \qquad (2.4)$$

Given the above DGP, D. Kwiatkowski et al., (1992) suggested the KPSS test as follows:

$$KPSS = \frac{\sum_1^T \hat{S}^2}{\hat{\tau}^2}$$

Where, $\hat{S}_t = \sum_1^T \hat{v}_t$ and $\hat{\tau}^2$ is the estimation of the long-run variance of v_t. This test estimate is compared with the critical value at the desired significance level under with and without liner trend hypothesis.

However, the order of the lag selection is crucial in the autoregressive process. The lag length of A.R. (p) process can be examined through lag selection criteria by using the most common methods: AIC, HQIC and SBIC after (Akaike, 1998; Hannan & Quinn, 1979). AIC, HQIC, and SBIC information criteria can be summarised as follows (L¨utkepohl & Kr¨atzig, 2004)

$$AIC\ (n) = log\tilde{\sigma}_e^2(n) + \frac{2}{N}\ n$$

$$HQIC\ (n) = \ log\tilde{\sigma}_e^2(n) + \frac{2\log\log N}{T} n$$

$$SBIC\ (n) = log\tilde{\sigma}_e^2(n) + \frac{\log T}{T}\ n$$

where, $\tilde{\sigma}_e^2(n)$ is the estimate of disterbance variance of OLS residuals from the autoregressive lag order n, while the capital case letter N indicates the sample size. The order of lag that minimises the information criteria is selected as the optimal lag order of the A.R. process.

Testing for Co-integration Rank and Co-integration: To estimate the cointegrating equation, we have first estimated the appropriate order of lag using the multivariate generalisation of AIC, HQIC, and SBIC information criteria to examine the traditional VAR (p) process. Once the appropriate order of p has been obtained, VAR (p) model in standard form has been estimated in the following fashion (Enders, 2008),

$$\boldsymbol{z_t} = \ \Pi_0 + \Pi_1 \boldsymbol{z_{t-1}} + \cdots + \Pi_p \boldsymbol{z_{t-p}} + \boldsymbol{\omega_t} \qquad (\mathbf{3})$$

where, $\boldsymbol{z_t}$ is an (n*1) vector of n $(z_{1t}, z_{2t,} \dots, z_{nt})$ variables, Π_0 is an (n*1) vector of drift term, Π_i is (n*n) coefficient matrices and ω_t is the (n*1) vector of disturbance terms. After estimating the VAR (p) model, the Johansen co-integration test requires identifying the appropriate rank order for identifying the cointegrating vector and equation. To identify the appropriate order of rank, trace and max statistics have been employed as follows:

$$\tau_{trace}(r) = -T \sum_{i=r+1}^{k} \ln(1 - \hat{\tau}_i) \qquad (4.1)$$

$$\tau_{\max}(\mathrm{r}, \mathrm{r}+1) = -\mathrm{T}\ln((1 - \hat{\tau}_{\mathrm{r}+1}) \qquad (4.2)$$

where, $\hat{\tau}_i$ is the calculated value of eigenvalues, and the number of observations is given by *T*. Trace test is run under the null hypothesis that the order of rank of the cointegrating vector is maximum r , while r is assumed as the cointegrating vector under the null hypothesis against the alternative $\mathrm{r}+1$ for the max statistic. Once the rank or cointegrating vector is obtained, the Johansen cointegrating test can be applied to S. Johansen (1988). From equation (3), the Vector Error Correction Model (VECM) can be reparamaterized in the following way

$$\Delta z_t = \Pi_0 + \beta \boldsymbol{z}_{t-1} + \sum\nolimits_{i=1}^{p-1} \theta_i z_{t-1} + \omega_t \qquad (\mathbf{5})$$

where, Π_0 is an (n*1) vector of drift, β is the cointegrating vector that shows the number of linear combinations among the variables of concern. A null matrix of β indicates no cointegrating relationship, while the existence of stationary linear combination results in some nonzero parameters of β matrices. Therefore, the trace and max statistics of equations 4.1 and 4.2 will determine the r number of ranks, given that all series in z_t are I(1) (Engle & Granger, 1987). However, if the series are not cointegrated, the number of ranks in β in the above VECM equation will be zero even though all the variables are I(1).

Post Estimation: In order to identify the existence of no serial correlation, we have estimated the Lagrange-Multiplier test of autocorrelation under the assumption that there is absence of autocorrelation, i.e., $H_0: E(\omega_t, \omega_{t-i}) = 0, \quad i = 1, 2, ...$ On the other hand, Jarque-Bera (J.B.) test for normality has been applied to investigate the normality assumption of the VECM model under the null hypothesis that the disterbance terms are normally distributed.

Results

Summary Statistics: The summarised information of the relevant variables employed in the study has been presented in Table 1 below. Table 1 displays that the mean value of total agricultural production in Bangladesh during 1983-2019 in constant prices is around 820 billion BDT using the base year 2005-06. Agricultural credit disbursement is considered a crucial catalyst for agriculture sector output. Considering the indispensability of agricultural credit support, the government of Bangladesh is working on expanding the disbursement of credit in the country. The country has supported the agriculture sector with a mean credit disbursement of around 65 billion BDT with more than 15% average credit growth during the period mentioned above.

Table 1. Summary Statistics

Variables	Description of the variables	Mean	Std. Dev.	Minimum	Maximum
AgriProdn	Total Agricultural Production including forestry and Fisheries (Billion BDT)	816.88	307.20	462.45	1451.37
AgrCrdt	Agricultural credit (Billion BDT)	63.592	70.04	5.96	236.16
Fert	Total fertilisers use (in thousand Metric Ton (*M.T.*)	3058.57	1278.88	968.40	5422.00
AgrEmpl	Agricultural employment (percentage of total employment)	56.00	9.750	38.30	69.51

Source: Authors' calculation

The country's agricultural sector has used more than 3000 thousand metric tons, including all types of fertilisers, on average during the time used. In contrast, more than 50% of the country's total employment was employed in agriculture in the given period. Despite the decline in employment, almost half of the total employment comes from the agricultural sector in Bangladesh.

Unit Root Test Results: Unit root tests of the series are carried out to study the stationarity of the variables, as regression of stationary variables is crucial to shun the spurious regression. Therefore, the classical econometric texts emphasise the stationary property of series to estimate the regression of the given variables. According to the stationary property, a z_t sequence is stationary if its disturbance term has zero mean and constant variance (Enders, 2008). The test of stationarity is more formally carried out through ADF, PP and KPSS tests. These tests allow different specifications –for instance, only drift, drift and trend, or without drift and trend – to estimate the unit root test. While ADF and PP tests allow all three different specifications in their estimation, the KPSS test allows only drift and trend stationary specifications. On the other hand, the former two tests perform the tests under the assumption that the series is non-stationary, while the latter is carried out under the stationary null hypothesis. Therefore, the acceptance of the null hypothesis represents the series as the I(0) series, whereas the rejection of the null regards the series as higher-order integrated. On the other hand, rejection of the null implies that the series contains a unit root and failure to reject the null indicates the opposite one under the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

Table 2 illustrates the summarised the unit root test results using ADF, PP, and KPSS tests of unit root. In contrast, Table A1, A2, and A3 in the appendix section depict the details of test results, including test statistics and probability (p-value) of the above three tests of the unit root, respectively. Since the test estimates are sensitive to the number of lag orders, the test results of all specifications have been presented by minimising the information criteria in line with the direction of AIC, HQIC, and SBIC in these tables.

Table 2. Summary of unit root test

	Augmented Dickey-Fuller (ADF) test			**Phillips-Perron (PP) test**			**Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests**	
	N	D	DT	N	D	DT	DT	D
LnAgriProdn	S	NS	NS	S	NS	NS	NS	NS
D(LnAgrProdn)	NS	S	S	S	S	S	NS	NS
LnAgrCrdt	S	NS	S	S	NS	NS	NS	NS
D (LnAgrCrdt)	S	S	S	S	S	S	S	NS
LnFert	S	NS	NS	S	NS	NS	NS	NS
D(LnFert)	S	S	S	NS	S	S	S	NS
AgrEmpl	NS	NS	S	S	NS	NS	NS	NS

D(AgrEmpl)	S	NS	NS	S	NS	NS	S	S

Notes: N, D, and DT stands for 'no Drift and Trend', 'Drift only', 'both Drift and Trend', respectively, whereas NS and S stand for 'Non-Stationary' and 'Stationary', respectively

The summarised test results offered in Table 2 and the detailed test results presented in Tables A1, A2, and A3 illustrate that the hypothesis cannot be rejected in the level form of LnAgriProdn, LnAgrCrdt, and LnFert under ADF and PP test. In contrast, null can be rejected in the first difference form of LnAgriProdn, LnAgrCrdt, and LnFert in all specifications except some variations in 'no drift and trend' specification. This implies that ADF and PP test suggest that LnAgriProdn, LnAgrCrdt and LnFert series are I(1) series. On the other hand, although the KPSS test can identify LnAgrCrdt and LnFert series as I(1) series in one specification, it cannot regard LnAgriProdn as I(1) in both of the specifications. However, since most of the test specifications under ADF, PP and KPSS testify the series as I(1), we can regard these series as I(1) series. Although the AgrEmpl series is not I(1) in the specification of 'drift' and 'drift and trend', it is I(1) in the specification of 'no drift and trend' specification under both ADF and PP tests.

On the other hand, both specifications of the KPSS test classify the AgrEmpl series as I(1) series. Besides, the Dickey-Fuller test has very limited power to distinguish stationary series under a small number of observations (Enders, 2008). Since our sample is 37 observations, the KPSS test may reflect better identification resulting AgrEmpl series is I(1) series. Considering all the scenarios, we can conclude that all series considered in our model are I(1).

Test results of Co-integration Rank and Co-integration test: The co-integration test by Johansen requires that all variables should have identical order of integration. Unit root tests also confirm that all the concerned variables in our model have integration of order one. After assessing the same order of integration, vector autoregressive (VAR) model estimation should be carried out after selecting the optimal lag order of the VAR model. Moreover, VAR model estimation needs to be run using the level form data (Enders, 2008). The results of the multivariate generalisation of AIC, HQIC, and SBIC information criteria estimation have been scheduled in Table A4 in the appendix section. The test results of AIC and HQIC show that information criteria are minimised at the length of lag order 4, while the results of SBIC suggest one lag as the optimal order of lag. Since most of the information criteria suggest that the optimal lag order should be 4, we have selected four as the appropriate order of lags for our VAR model. In addition to identifying the same order of integration and VAR model estimation, the Johansen methodology requires the estimation of the appropriate rank of matrix β to assess the number of linear combinations among the variables. The Johansen co-integration rank test results have been pictured in Table 3.

Table 3: The Johansen Co-integration rank test

Maximum Rank	Eigenvalues	Trace Test of cointegrating vector			Max Test of cointegrating vector		
		Trace statistics	5% critical value	1% critical value	Max statistics	5% critical value	1% critical value
0	-	85.556	47.21	54.46	55.572	27.07	32.24
1	0.814	29.985***	29.68	35.65	20.732***	20.97	25.52
2	0.466	9.253**	15.41	20.04	8.964	14.07	18.63
3	0.238	0.289	3.76	6.65	0.289	3.76	6.65
4	0.009	-	-	-	-	-	-

Notes: *** and ** stands for statistical significance at 1% and 5% respectively * p<0.10, ** p<0.05, *** p<0.010.

Table 3 depicts that the optimal rank order is one under both Trace and Max test of co-integration at the 1% level of significance. However, the Trace test also shows vector autoregressive model can also contain two cointegrating vectors at 5% level of significance. Since both the Trace test and Max test of co-integration confirm 1 cointegrating vector at 1% significance level, we have selected 1 as the maximum number of rank and hence the cointegrating vector.

Given that we have the appropriate order of cointegrating vector r=1, and the optimal number of multivariate lag lengths, we can estimate the vector autoregressive model (VECM) modelled by equation five after S. Johansen (1988). The test results of the long-run equilibrium relationship of the Johansen co-integration test have been presented in Table 4 below. The results have been derived after imposing the Johansen normalisation restriction.

Table 4: Estimated Results from the Johansen Co-integrating Equations

Variables	Coefficients	Standard Error	z-statistic
LnAgriProdn	1	-	-
LnAgrCrdt	-0.1401496	0.016***	-8.72
LnFert	-0.2887401	0.031***	-9.36
AgrEmpl	0.0101444	0.001***	8.39
Constant	-10.44596	-	-

Notes: *** stands for statistical significance at 1% statistical level * p<0.10, ** p<0.05, *** p<0.010.

Table 4 shows that all long-run coefficients are significant at a 1% significance level. Therefore, all of the coefficients are highly statistically significant. According to the estimated results, agricultural credit and fertiliser use have a long-run positive effect on agricultural production in

Bangladesh. Since the coefficients are taken in the natural logarithm form, we can interpret the obtained results in terms of elasticity. Assuming all other variables- fertiliser use and employment - as constant in the agricultural sector, a 1% increase of agricultural credit disbursement increases the agricultural production on average by 0.14%. The statistically significant coefficient implies that agricultural credit disbursement significantly impacts agricultural production in Bangladesh. On the other hand, holding agricultural credit and employment constant, 0.28% of agricultural production is escalated by a 1% increase in fertiliser use. Therefore, it is evident that fertilisers also have a significant role in agricultural production. However, although one can expect that employment in the agricultural sector can increase agricultural output, the obtained results have revealed the exact opposite result. The opposite result may come because of several reasons. Firstly, Bangladesh has already experienced disguised unemployment in the agriculture sector that may negatively impact output (Jabbar, 1988). Secondly, the share of employment in the agricultural sector has been continuously being decreased since independence (Ministry of Finance, 2020).

Post estimation plays a vital role in shaping how the model is good and how the model fits the data well. We have estimated the Lagrange-Multiplier test of autocorrelation and the Jarque-Bera test of normality to check the model's fitness. Table A5 of the appendix section presents the result of the Lagrange-Multiplier test of autocorrelation, while Table A6 of the appendix shows the test result of the Jarque-Bera normality test. Lagrange-Multiplier test displays that there is no serial correlation in the model. Besides, Table A6 also shows that residuals of the VECM model follow the normal distribution. The cointegrating equation and the estimated residuals have been graphed in figure A2 in the appendix section. Besides, stability test also revealed that the VECM model is highly stable as all of the roots of the VECM model are within the unit value. Overall, all post estimations tests predict that the chosen VECM model fits the data well.

Conclusion and Discussion

Credit facility in the context of Bangladesh is essential for poor farmers. Access to credit services helps the farmers enhance their agricultural production and escalate the productivity of other inputs. Our obtained findings confirmed that agricultural credit and fertiliser usage significantly increases the agricultural output in the long run (Iqbalet al., 2003; Saboor et al., 2009). These findings may significantly impact the agricultural policy formulation of a capital-scarce country like Bangladesh. However, a surge in agricultural employment can not increase the outcome of this ancient means of livelihood. Even we found a contrary result for employment input. It may imply that the agriculture sector of Bangladesh has already employed more than the optimum level of labour input and the marginal productivity of labour in agriculture is negative. Therefore, the farmers should employ more non-labour inputs to enhance the effectiveness of their production function.

The sustained growth of agricultural production has showed a key role in alleviating the perils of hunger and reducing poverty since independence in Bangladesh. The ancient sector is also considered one of the main catalysts of economic growth. However, technological innovation, intensive use of mechanisation, credit facility, etc., have contributed to sustained agricultural growth. Among the factors, availability and accessibility of credit in the agricultural sector is indispensable to facilitate agricultural expansion in a country like Bangladesh, where credit constraint is a fundamental problem for poor farmers. We found that agricultural credit has played a significant role in achieving continuous and sustained agricultural growth through a comprehensive investigation. The obtained findings have revealed that an additional 1% increase in agricultural credit disbursement significantly increases the agricultural output by around 0.14%, holding all other inputs constant. In addition, fertiliser use also significantly increases the agricultural output. According to the results, a 0.28 % additional agricultural output can be achieved through a one % increase in fertiliser. It indicates that agricultural credit support needs to be expanded among the farmers, especially poor and small farmers, as agriculture credit has a noticeable impact on agricultural output. Though the government of Bangladesh is expanding the agricultural credit program among the farmers, these are not sufficient compared to its enormous demand. Therefore, based on the findings, we suggest that the government should expand and continue credit support to the agricultural sector at an affordable cost. Ensuring agricultural credit support can turn the agriculture sector of Bangladesh into more sustainable by fostering sustained agricultural production.

Endnotes

1. Arable land (% of total land) was about 70% in 1972, while it is now around 60% of total land (data have been extracted from World bank Development indicators at 16th January 2022.
2. Natural logarithm has been taken for $Agrprodn, AgrCrdt, Fert$ variables, whereas AgrEmpl variable has been kept as level for the analysis.
3. ILO modelled estimate provides data only from 1991. Data of earlier years have been collected from different statistical yearbooks of BBS, as the study has covered the yearly data from 1983. However, we did not find the employment data for 1983, 1986 and 1987 in the available statistical publications. We employed the linear estimation technique of missing data to generate the data of missing years. We calculate the missing values using the formula, $m = \frac{m-m_0}{x_1-x_0}(x-x_0)+m_0$, where we have calculated m at x by using the closest point of data between (m_1, x_1) and (m_0, x_0).
4. Agricultural production, agricultural credit and usage of fertilisers data were in fiscal year, while employment data were in calendar year format. Nevertheless, we have used calendar year data and treated fiscal year, for instance, 2982-83 as 1983 calendar year format.

References

Akaike, H. (1998). Information Theory and an Extension of the Maximum Likelihood Principle. In E. Parzen, K. Tanabe & G. Kitagawa (Eds.), *Selected Papers of Hirotugu* Akaike: pp. 199-213. Springer. doi.org/10.1007/978-1-4612-1694-0_15

Alauddin, M. and Biswas, J. (2014). Agricultural credit in Bangladesh: Present trend, problems and recommendations. *Journal of Economics and Sustainable Development*, Vol. 5, No. 27: pp 11-22. Available at: citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.663.3720&rep=rep1&type=pdf [Accessed 23 April 2021].

Azad, A. K. (2021). Determinants of Crop Diversification in Bangladesh: An Econometric Analysis. *Asia-Pacific Journal of Rural Development*, Vol. 31, No. 2: pp. 195–217. doi.org/10.1177/24551333211069752

Azad, A. K. and Wadood, S. N. (2017). Climate change and Bangladesh fisheries and aquaculture: Evidences from the Household Income and Expenditure Survey (HIES) 2010. *Social Science Review*, Vol. 34, No. 1: pp. 193–210. Available at: mpra.ub.uni-muenchen.de/81552/

Bidisha S.H., Khan A., Khondker B.H. and Imran K. (2015). Returns to Agricultural Microcredit: Quasi-experimental Evidence from Bangladesh. *The Bangladesh Development Studies*, Vol. 38, No. 4: pp. 31-46. Available at: www.jstor.org/stable/pdf/26538717.pdf [Accessed 23 April 2021].

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, Vol. 74, No. 366a: pp. 427-431. doi.org/10.1080/01621459.1979.10482531 [Accessed 23 April 2021].

Enders , W. (2008). *Applied conometric time series* (2nd edition). John Wiley & Sons. Inc.

Engle, R. F. and Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica*, Vol. 55, No. 2: pp. 251-276. Available at: www.jstor.org/stable/1913236?seq=1 [Accessed 12 August 2021].

Gershon, O., Matthew, O., Osuagwu, E., Osabohien, R., Ekhator-Mobayode, U.E. and Osabuohien, E. (2020). Household access to agricultural credit and agricultural production in Nigeria: A propensity score matching model. *South African Journal of Economic and Management Sciences,* Vol. 23, No. 1: pp. 1-11. Available at: www.researchgate.net/publication/338820870_Household_access_to_agricultural_credit_and_a gricultural_production_in_Nigeria_A_propensity_score_matching_model [Accessed 23 April 2021].

Granger, C. and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics*, Vol. 2 (1974): pp. 111-120. Available at: www.climateaudit.info/pdf/others/granger.1974.pdf [Accessed 12 August 2021].

Hannan, E. J. and Quinn, B. G. (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society*, Vol. 41, No. 2: pp. 190–195. doi.org/10.1111/j.2517-6161.1979.tb01072.x

Hossain, M., Malek, M. A., Hossain, M. A., Reza, M. H. and Ahmed, M. S. (2019). Agricultural microcredit for tenant farmers: Evidence from a field experiment in Bangladesh. *American Journal of Agricultural Economics*, Vol. 101, No. 3: pp. 692-709. doi.org/10.1093/ajae/aay070

Iqbal, M., Ahmad, M., Abbas, K. and Mustafa, K. (2003). The impact of institutional credit on agricultural production in Pakistan [with comments]. *The Pakistan Development Review*, Vol. 42, No. 4: pp. 469-485. Available at: www.jstor.org/stable/41260420?seq=1 [Accessed 12 August 2021].

Islam, M. M. (2020). Agricultural credit and agricultural productivity in Bangladesh: An econometric approach. *International Journal of Food and Agricultural Economics*, Vol. 8, No. 3: pp. 247-255. Available at: ageconsearch.umn.edu/record/305327/ [Accessed 12 August 2021].

Jabbar, M. A. (1988). Some aspects of unemployment, migraton and income in the Bangladesh rural labour market. *Bangladesh Journal of Agricultural Economics*, Vol. 11, No. 2: pp. 35-48. Available at: ageconsearch.umn.edu/record/208734 [Accessed 12 August 2021].

Johansen, S. (1988). Statistical analysis of co-integration vectors. *Journal of Economic Dynamics and Control*, Vol. 12, No. 2-3: pp. 231-254. doi.org/10.1016/0165-1889(88)90041-3

Khandker, S. R. and Koolwal, G. B. (2016). How has microcredit supported agriculture? Evidence using panel data from Bangladesh. *Agricultural Economics*, Vol. 47, No. 2: pp. 157-168. doi.org/10.1111/agec.12185

Kirchgässner, G. and Wolters, J. (2007). *Introduction to modern time series analysis*. Springer, Science & Business Media.

Kwiatkowski, D., Phillips, P. C., Schm, P. and Shin, Y. (1992). Testing the Null Hypothesis of Stationarity Against the Alternative of a Unit Root. *Journal of Econometrics*, Vol. 54 (1992): pp. 159-178. doi.org/10.1016/0304-4076(92)90104-Y

L¨utkepohl, H. and Kr¨atzig, M. (2004). *Applied time series econometrics*. Cambridge University Press.

Malek, A. M., Kikkawa, A., Azad., A. K. and Sawada, Y. (2022). Rural Development in Bangladesh over Three Decades: Findings from Mahabub Hossain Panel Data and the Way Forward. ADBI Working Paper 1350. Tokyo: Asian Development Bank Institute. Available: https://doi.org/10.56506/PPXG8315

Miah, M. K., Alam, A. A. and Rahman, A. H. M. A. (2006). Impact of agricultural credit on MV Boro Rice cultivation in Bangladesh. *Journal of Agriculture & Rural Development*, Vol. 4, No. 1: pp. 161-168. doi.org/10.3329/jard.v4i1.784

Ministry of Finance (2020). *Bangladesh Economic Review*. Ministry of Finance, Governement of Bangladesh (GoB). Avalable at: mof.portal.gov.bd/site/page/28ba57f5-59ff-4426-970a-bf014242179e/Bangladesh-Economic-Review-2021 [Accessed 12 August 2021].

Mitra, S., Khan, M.A. and Nielsen, R. (2019). Credit constraints and aquaculture productivity. *Aquaculture Economics & Management*, Vol. 23, No. 4: pp. 410-427. doi.org/10.1080/13657305.2019.1641571

Narayanan, S. (2016). The productivity of agricultural credit in India. *Agricultural Economics*, Vol. 47, No. 4: pp. 399-409. doi.org/10.1111/agec.12239

Phillips , P. C. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, Vol. 75, No. 2: pp. 335-346. doi.org/10.1093/biomet/75.2.335

Rahman, M.W. (2011). Policies and performances of agricultural/rural credit in Bangladesh: What is the influence on agricultural production? *African Journal of Agricultural Research*, Vol. 6, No. 31: pp. 6440-6452. Available at: www.academicjournals.org/AJAR [Accessed 12 August 2021].

Saboor, A., Hussain, M. and Munir, M. (2009). Impact of micro credit in alleviating poverty: An Insight from rural Rawalpindi, Pakistan. *Pak. J. Life Soc. Sci*, Vol. 7, No. 1: pp. 90-97. Available at: www.pjlss.edu.pk/pdf_files/2009_1/90-97.pdf [Accessed 12 August 2021].

Saleem, M. A. and Jan, F. A. (2011). The impact of agricultural credit on agricultural productivity in Dera Ismail Khan (District) Khyber Pakhtonkhawa Pakistan. *European Journal of Business and Management*, Vol. 3, No. 2: pp. 38-44. Available at: www.iiste.org/Journals/index.php/EJBM/article/view/159 [Accessed 12 August 2021].

Taylor, T.G., Drummond, H. E. and Gomes, A. T. (1986). Agricultural credit programs and production efficiency: an analysis of traditional farming in southeastern Minas Gerais, Brazil.

American Journal of Agricultural Economics, Vol. 68, No. 1: pp. 110-119. doi.org/10.2307/1241655

Wadood, S. N., Choudhury, N. N. and Azad, A. K. 2021. Does Migration Theory Explain International Migration from Bangladesh? A Primer Review. *Social Science Review*, Vol. 38, No. 2: pp. 51-69. https://doi.org/10.3329/ssr.v38i2.64460

Appendices

Table A1: Augmented Dickey-Fuller Unit Root Test Results

Variables	H_0 = *The series has unit root*		
	Model specification		
	Test Statistics (None)	Test Statistics (Constant)	Test Statistics (Constant & Trend)
LnAgriProdn	4.332***	1.245	-2.520
D(LnAgrProdn)	-1.519	-4.494***	-4.934***
LnAgrCrdt	2.738**	0.535	-3.558**
D (LnAgrCrdt)	-3.811***	-5.033***	-5.440***
LnFert	2.209**	-2.479	-2.845
D(LnFert)	-1.945*	-3.053**	-3.491**
AgrEmpl	-0.815	-0.390	-3.760**
D(AgrEmpl)	-2.194**	-2.382	-2.970

Note: * p<0.10, ** p<0.05, *** p<0.010.

Table A2: Phillips-Perron Unit Root Test Results

Variables	H_0 = *The series has unit root*		
	Model specification		
	Test Statistics (None)	Test Statistics (Constant)	Test Statistics (Constant & Trend)
LnAgriProdn	8.236***	1.539	-2.419
D(LnAgrProdn)	-2.108***	-5.088***	-5.432***
LnAgrCrdt	3.154***	0.155	-2.522
D (LnAgrCrdt)	-5.471	-6.535***	-6.727***
LnFert	3.372***	-2.429	-2.666
D(LnFert)	-5.999	-6.903***	-7.181***
AgrEmpl	-1.422***	0.398	-1.703
D(AgrEmpl)	-2.257**	-2.415	-2.818

Note: Note: ** p<0.05, *** p<0.010

Table A3: Kwiatkowski, Phillips, Schmidt and Shin (KPSS) Unit Root Test Results

Variables	H_0 = *The series does not contain unit root*	
	Model specification	
	Test Statistics (Constant)	Test Statistics (Constant & Trend)
LnAgriProdn	0.492**	0.143*
D(LnAgrProdn)	0.367*	0.156**
LnAgrCrdt	0.474**	0.127*
D (LnAgrCrdt)	0.201	0.139*
LnFert	0.499**	0.134**
D(LnFert)	0.286	0.136*
AgrEmpl	0.396*	0.131*
D(AgrEmpl)	0.274	0.116

Note: * p<0.10, ** p<0.05. Without trend, the critical values are 0.739, 0.463 and 0.347 for 1%, 5% and 10% level of significance respectively, whereas with trend the critical values are 0.216, 0.146 and 0.119 for 1%, 5% and 10% level of significance respectively.

Table A4: Selection-order criteria of VAR (p) model where, LnAgriProdn, LnAgrCrdt, LnFert, LnAgrEmpl are the endogenous variables

Lags	**LR**	**AIC**	**HQIC**	**SBIC**
0	-	3.98958	4.05061	4.17097
1	315.72	-4.60786	-4.3027	-3.70089*
2	48.168	-5.09782	-4.54851	-3.46526
3	35.765	-5.2119	-4.41846	-2.85376
4	51.882*	-5.81439*	-4.77682*	-2.73068

Notes: * indicates optimal order of lag

Table A5: Lagrange-multiplier autocorr*elation test

Lag order (K)	H_0**= no autocorrelation at lag order (K)**	
	Chi-square statistic	Probability
1	16.1422	0.44308
2	10.1184	0.86037
3	6.8684	0.97571
4	12.6129	0.70082

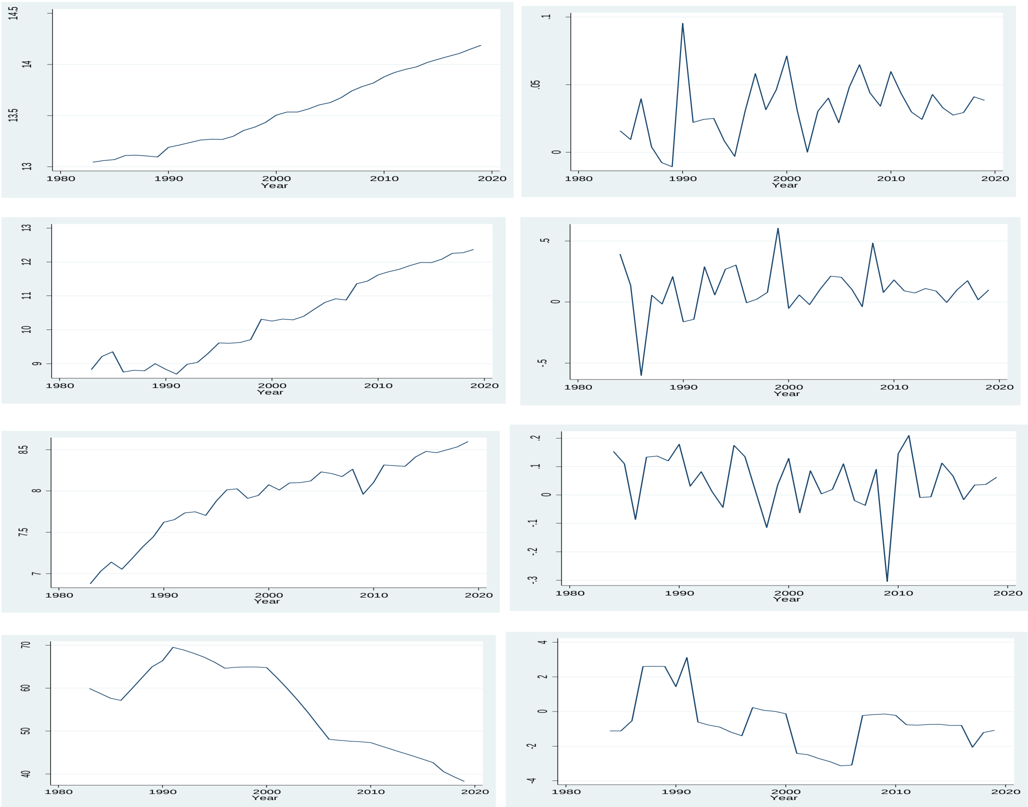
Source: Authors' calculation

Table A6: Jarque-Bera test of normality

Equation	**Chi-square statistic**	**Probability**
D_lnagrigdpm	0.435	0.804
D_lnagricreditm	1.763	0.414
D_agriemppercenttot	1.415	0.4493
D_lnfertthousmt	7.887	0.019
ALL	11.500	0.175

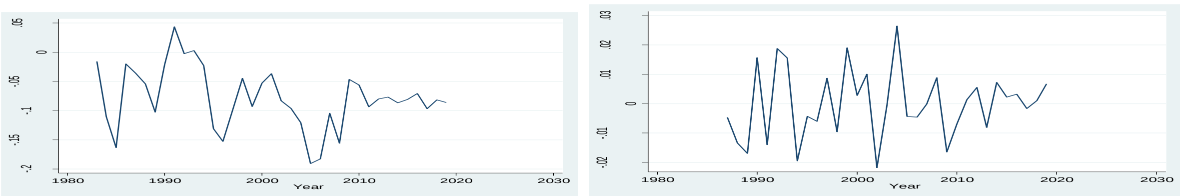
Source: Authors' calculation

Figure A1: Time series line graph of LnAgriProdn, LnAgrCrdt, LnFert, & AgrEmpl with level and first order respectively.



Source: Prepared by authors

Figure A2: Time Series line graph of predicted cointegrating equation and residuals, respectively



Source: Prepared by authors