K.L.N.D. Harshitha, 2024, 12:5
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Assessing the Impact of Financial Inclusion on Agricultural Productivity in India

K.L.N.D. Harshitha, Assistant Professor Md Abusaad
Department of Economics,
Mittal School of Business, Lovely Professional University, Punjab

Abstract- India's agricultural sector, a cornerstone of its economy and a major source of employment, grapples with various obstacles, including inadequate access to financial services among farmers. While financial inclusion is seen as a potential driver for agricultural advancement, its effects on productivity remain unclear. The research aims to bridge the gap by evaluating how financial inclusion impacts agricultural productivity in India. This study also trying to discuss the extent of financial inclusion in agriculture sector in India. This study has used secondary data taken from the Reserve Bank of India and World Development Indicators from 1970 to 2020. The study employs an ARDL (Autoregressive Distributed Lag) model to examine the relationship between financial inclusion and agricultural productivity. The analysis uncovers both immediate and enduring influences of financial factors on agricultural output. Long-run results suggest that although expansive monetary policies may impede agricultural expansion, enhanced access to credit and increased fertilizer application stimulate productivity. In the near term, fluctuations in broad money supply and easing of financial limitations positively correlate with agricultural growth. Conversely, rising domestic credit growth and prior financial constraints have adverse effects. By shedding light on the intricate interplay between financial inclusion and agricultural productivity in India, this study provides valuable insights for policymakers. It highlights the varied impacts of different financial tools and policies over time, guiding the development of precise strategies to promote financial inclusion in ways that bolster sustainable agricultural development.

Keywords- financial inclusion, agricultural productivity, sustainability, ARDL, domestic credit.

I. INTRODUCTION

India's economy heavily relies on agriculture, with over 70% of its rural population depending on it for their livelihood (Akhtar & Parween, 2015). The rapid expansion of the agricultural sector is crucial for the overall development of the economy, especially given the significant portion of the workforce employed in agriculture (Sharma et al., 2024). The Reserve Bank of India's (RBI) major program, Financial Inclusion, aims to attract people to the formal financial system, facilitating inclusive rural economic growth by providing easy access to affordable financing and creating job opportunities in rural regions. The RBI defines financial inclusion as "the process of ensuring access to appropriate financial products and services needed by all sections of society in general and vulnerable groups such as weaker sections and low-income groups in particular, at a reasonable cost in an equitable and

transparent way by regulated, mainstream institutional players" (Garg & Agarwal, 2014).

Since agricultural growth is a principal component of inclusive growth, it is essential to note that despite India's rapid economic expansion, it has grown in an unequal manner. This growth has been inconsistent and disjointed, with certain economic sectors benefiting more than others (Rathi & Sharma, 2020). Therefore, inclusive growth becomes necessary in the context of India's growing economy. Financial inclusion plays a crucial role in achieving inclusive development by mobilizing resources for economic progress.

The relationship between financial inclusion and agricultural growth can be explained through various factors such as cropping pattern type, cropping intensity, irrigation intensity, and tenurial contracts, including Operation Barga. The degree of financial inclusion in terms of rural credit availability impacts these parameters, thereby influencing agricultural production (Laha & Kumar, 2020).

The United Nations' Food and Agriculture Organization (FAO) envisions a hunger-free planet, aiming to improve living conditions in economically, socially, and environmentally sustainable ways for all people, particularly the poorest, through food and farming (FAO, 2017). Food scarcity is one of the defining issues of the new era, as highlighted by Agbenyo et al. (2019). Esther Boserup's population theory emphasizes that necessity is the mother of invention, suggesting that as population increases, food production will also rise. The demand for food and other basic services has grown with population growth, making it necessary to develop appropriate policies for agricultural growth by understanding its component elements and processes (Soby, 2017).

This study aims to add to the existing knowledge on financial inclusion and agricultural growth by exploring the long- and short-run relationships between financial inclusion and agricultural productivity. Given that the agricultural sector employs a larger portion of the population compared to other sectors, it is crucial to understand the major factors, such as financial inclusion, that influence agricultural productivity. By employing the ARDL (Autoregressive Distributed Lag) approach, this study provides a comprehensive analysis that can assist policymakers, financial institutions, and stakeholders in developing their strategies. As India is a major agrarian economy, this study not only adds to empirical knowledge but also helps improve agricultural growth in practice.

II. REVIEW OF LITERATURE

This section initially reviews the concepts and measurement issues of financial inclusion and the factors which significantly affect the level thereof; then it reviews the available evidence on financial inclusion's impact on agriculture growth.

1. Meaning and Measurement of Financial Inclusion

The notion of financial inclusion has been articulated in a variety of ways in the literature that has already been written, but the results of all of these explanations seem to be similar. According to the World Bank (2014), financial inclusion is the proportion of households and financial services consumers. Financial inclusion was defined by Amidžić et al. (2014) as a situation in which no one is refused access to essential financial services due to motives not related to efficiency standards. Conceptually, Demiurgic -Kunt et al. (2012) Financial inclusion is defined as various populations using formal financial services that benefit the well-being of numerous people. Sarma (2012) provided a thorough definition of financial inclusion based on several dimensions, including accessibility, availability, and usage of the formal financial system for all members of an economy. Sahay et al. (2015) defined financial inclusion as the delivery of financial services at affordable costs to vulnerable segments of society. The idea of financial inclusion is widely accepted, but there isn't a common methodology in the literature to quantify it consistently across economies. By merging bank and MFI account numbers from household survey cross-sectional data in a select few countries, Honohan (2008) created a financial access index. By including the outreach component (geographic and

demographic penetration) and the use dimension (depositors and borrowers), Amidžić et al. (2014) created a composite financial inclusion indicator. They used factor analysis to statistically identify each dimension, normalized each variable, weighted the variables and subindices, and then used a weighted geometric average to aggregate the data. By estimating three sub-indices covering the usage dimension, access dimension, and barriers dimension (barriers causing involuntary exclusion), Cámara and Tuesta (2014) created a composite financial inclusion index. Dimension weights were estimated endogenously using a two-stage principal component analysis. By merging the accessibility, availability, and usage dimensions, Sarma (2012) presented a multidimensional index of financial inclusion that satisfies many essential mathematical criteria and is comparable over time and across national boundaries. Using the normalized Euclidian distance of accomplishment points between the worst and best circumstances, he calculated a dimension index for each dimension, aggregated each index, and then took a simple average. This study employs Sarma's methodology.

2. Determinants of Financial Inclusion

Numerous empirical research has focused on the variables that influence a nation's degree of financial inclusion, but the findings do not support any one theory. Sarma and Pasi (2008, 2011) used a traditional OLS approach for the sample year 2004 to investigate country-specific characteristics linked with the level of financial inclusion. The level of financial inclusion was significantly correlated with a number of potential variables, including adult literacy, income inequality, rural population, physical connectivity indicated by the road network, electronic connectivity indicated by phone subscriptions, information availability indicated by internet usage, bank soundness measured by the ratio of capital assets to non-performing assets, and foreign ownership in the banking sector. Using a dynamic panel data technique, Evans (2016) assessed the factors influencing financial inclusion in 15 African countries between 2005 and 2014. The findings indicate that the following factors are very significant in influencing the degree of financial inclusion in Africa: adult literacy rate, internet access, GDP per capita, money supply as a proportion of GDP, delayed financial inclusion (which suggests a "catch-up effect"), and Islamic banking operations. According to Allen et al. (2014), there is a large negative correlation between natural resources and financial inclusion and financial development in Sub- Saharan Africa relative to the rest of the globe. However, there is a strong positive correlation between GDP per capita and population density. The main barriers to Latin America's low level of financial inclusion, according to Rojas Suarez and Amado's (2014) analysis of the relevant factors explaining the region's financial inclusion gap relative to comparable countries, were socioeconomic factors (represented as income inequality) and institutional deficiencies (measured as rule of law). Macroeconomic weaknesses (represented as inflation volatility) and financial sector deficiencies (measured as overhead costs and bank concentration) were comparatively less significant factors.

3. Empirical Evidence on Financial Inclusion and Agricultural Growth

Agbenyo et al. (2019) studied Ghana's Cointegration Analysis of Financial Inclusion and Agricultural Growth. They used Johansen Cointegration methodology and Fully Modified Ordinary Least Square method (FMOLS) were used to estimate the long-run connection between agricultural growth and financial inclusion in Ghana using time series data from 1980 to 2014.it concluded that the expansion of agriculture is greatly impacted by lending interest rates, which serve as a proxy for the accessibility of financial services to farmers. The link between domestic loans to the private sector and utilization is inverse but considerable. Fowowe, B. (2020) examined the impact of financial inclusion on Nigerian agriculture production. The Living Standards Measurement investigation–Integrated Surveys on Agriculture (LSMS-ISA) is used in this investigation. This is a fresh data collection on agricultural families that includes details on a range of domestic pursuits, such as savings, banking, and insurance behaviour, in addition to agricultural operations. The study uses panel data estimates to take use of the time

series and cross-section dimension of the data, as the data are structured so that observations are available for households throughout three time periods. The study's empirical findings demonstrate that, regardless of how it is quantified, financial inclusion has had a beneficial and statistically significant impact on Nigeria's agricultural productivity. Shen et al. (2023) examined Chinese agriculture in relation to digital financial inclusion and green growth. This study makes use of panel data from 26 Chinese cities located in the Yangtze River Delta that spans the years 2012 to 2018. It measures the increase in agricultural green total factor production using a nonparametric technique, both with and without taking environmental restrictions into consideration. Furthermore, the instrumental variable (IV) model and the system generalized moment method (system-GMM) are utilized in this study to do a dynamic panel regression. Despite differences between cities, the results indicate a general improvement in the green performance of agriculture in the Yangtze River Delta area, mostly driven by technical advancements. Furthermore, the growth of inclusive digital finance greatly increases agricultural production gains, and this beneficial effect will only increase if traditional financial channels change as well. Zhai, S. (2023) aimed to identify influence of digital banking inclusion on China's total factor productivity in agriculture. Utilizing panel data from the Peking University digital financial inclusion (DFI) index and panel data from the National rural fixed-point survey from 2011 to 2018, this article applies the dynamic panel fixed effect model to examine the impact of digital inclusive financing platform accessibility on agricultural total factor productivity (TFP) and factors contributing to it at the household level. The findings indicate that agricultural TFP and its two components—agricultural technological advancement and agricultural technical efficiency change—are significantly hysteresis positively impacted by DFI. And among the three components of the DFI index, financial service consumption depth has the most impact. Rathi & Sharma (2020) Their goal of the study is to determine how Madhya Pradesh's agricultural output is affected by loan availability. It is based on secondary data that has been collected from several sources have demonstrated that the official credit for agriculture has risen in actual terms during the last ten years. The panel dataset's nature and accessibility limited the study's capacity to evaluate the combined data analysis to provide findings. The data from the analysis was used to chosen Madhya Pradesh districts from 2008 and 2018. The study's conclusions demonstrate the proof of the long-term connection between agricultural credits and productivity given to marginal and small farmers. Choudhury (2018) investigated the role that social sector spending and financial inclusion play in the rural economy's promotion of inclusive growth and agricultural development in India. He discovered with its over-reliance on agriculture and extreme inequality, India is a developing nation where financial inclusion might provide economic development and inclusive growth the much-needed boost. In India, direct financing to agricultural has increased significantly over the years, but informal lending has decreased at the same time. Nonetheless, the country's diminishing agricultural GDP proportion raises a concern in the eyes of public. In order to provide a comprehensive measure of Financial Inclusion (FI) with a particular focus on SHGs across 33 major Indian states between 2016 and 2020, Kalaiarasi, D. and Rohini, A. (2022) conducted this study. The Indian banking sector's inclusion status was monitored through the use of Principal Component Analysis. Using panel data, the Ordered Probit Random effect model was used to investigate the relationship between FI and development indicators such as access to basic education and growth in the agricultural and industrial sectors. The findings showed that the majority of states in the East and North-East had low financial inclusion (FI), and that there was a favourable correlation between agricultural growth and the Financial Inclusion Index (FII). From 2004 to 2018, Sethy, S. K. and Goyari, P. (2023) investigate how financial inclusion affects agricultural output in South Asian nations. To gauge the degree of financial inclusion, a multidimensional, time-varying financial inclusion index was created using the Human Development Index methodology. Using the FMOLS and DOLS methodologies, the long-run elasticity of financial inclusion on agricultural production is investigated. The empirical findings

support the notion that financial inclusion increases agricultural output. Moreover, there exists a favourable correlation between agricultural production and the interaction term pertaining to financial inclusion and human capital. These findings imply that, over time, South Asian nations may raise agricultural output via expanding the reach of financial inclusion. Farook, U. (2023) The long-term link between financial inclusion and agricultural growth in Pakistan from 1960 to 2018 is the focus of this study. The assessment is conducted using the dynamic ordinary least squares (DOLS) technique, the Johansen co-integration test, and the autoregressive distributed lag (ARDL) methodology. The findings indicate that domestic credit greatly hinders agricultural growth in Pakistan both short- and long-term, whereas broad money and planted area help agriculture flourish in both scenarios. The impact of commercial bank lending on agricultural output in Nigeria was investigated by Udoka et al. in 2016. The Central Bank of Nigeria Statistical Bulletin and published papers provided the study's data. The ordinary least squares regression method was used to estimate the given equation. The estimated findings demonstrated that there was a positive and substantial association between agricultural production in Nigeria and the fund of the Agricultural Credit Guarantee Scheme, according to the data collected. There was a positive and substantial association between commercial banks' loan to the agricultural sector and agricultural production in Nigeria, suggesting that a rise in the fund of the agricultural credit guarantee program might result in an increase in agricultural production in Nigeria.

Although the link between financial inclusion and agricultural growth in India has been studied in the literature, there is still a large body of unanswered research in this area. Most research frequently overlooks a comprehensive grasp of the temporal dynamics in Favor of concentrating just on the short- or long-term effects separately. Furthermore, previous research's methodological techniques might not fully represent the complex interaction. By using the autoregressive distributed lag (ARDL) method, this study seeks to close these gaps by providing a thorough analysis that takes into account both short- and long-term effects at the same time. By doing this, it hopes to fill up a knowledge gap about the complex interactions that occur between financial inclusion and agricultural growth in the Indian setting.

Objectives of the Study

- To discuss the extent of financial inclusion in agriculture sector in India
- To analyse the impact of financial inclusion on agriculture productivity in India

Research Hypotheses

There is no significant association between the level of financial inclusion and agriculture productivity in the emerging Indian economy.

III. DATA SOURCE AND RESEARCH METHODOLOGY

The study utilizes data for India from 1970 to 2020 to understand the relation between financial inclusion and agricultural productivity using variables agriculture, fishing, forestry value added % of GDP as proxy of agriculture value added, Domestic credit to private sector (% of GDP), broad money, fertilizer consumption in lakh tone, this data is collected from world bank data indicators and RBI handbook of statistics.

Table 1: Data narrative

Variables	Indicators	Measurement Unit	Sources WDI, 2022
Agriculture, Fishing, Forestry Value Added	AGR	% of GDP	WDI, 2022
Domestic Credit to Private Sector	DCP	% of GDP	WDI, 2022
Broad Money	BM	% of GDP	WDI, 2022
Fertilizer Consumption	FC	Lakh Tone	RBI, 2021

This research studies the long run and short run relation between financial inclusion and agricultural productivity in India. This study used uses variable AGR is agricultural value added as a percentage of GDP, DCP is domestic credit to private sector as a percentage of GDP, BM is broad money, FC is fertilizer consumption in lakh tone. Similar variables used in Farooq et al. 2021.

This study acquired ARDL approach to analyse relation between financial inclusion and agricultural productivity. ARDL approach is more suitable for this paper since Farooq (et al.) (2021) used the same approach. and it ARDL bound testing cointegration is more suitable than Engle and Granger (1987) approach and the Johansen (1988) method because it is more applicable and more consistent regardless of the order of integration I(0) or I(1).

Long Run Equation

$$AGR = \beta 0 + \beta 1 BM + \beta 2 DCP + \beta 3 FC + e$$

Agriculture's value added as a proportion of GDP (AGR) is determined by three separate factors: fertilizer consumption (FC), domestic credit to the private sector (DCP), and broad money (BM). The whole amount of money in the economy, including cash, checking and savings accounts, and easily convertible near money, is referred to as broad money (BM). The percentage of GDP that is made up of domestic credit given to the private sector is known as Domestic Credit to the Private Sector (DCP). Fertilizer Consumption (FC), which represents the overall amount of fertilizer consumed, is expressed in lakh tons.

AGR is dependent variable

BM, DCP, FC is independent variable

β0 is constant term β1, β2, β3 are coefficients of BM, DCP, FC respectively, e is error term.

Short run equation

$$\Delta AGR = \alpha 0 + \alpha 1\ \Delta BM + \alpha 2\ \Delta DCP + \alpha 3\ \Delta FC + \alpha 4\ \Delta FC\ (-1) + \lambda\ cointEQ\ (-1) + e$$

Δ represents first order differentiation, (-1) shows lagged one year variable

α0 is constant term, α1, α2, α3, α4 are coefficients of ΔBM, ΔDCP, ΔFC, ΔFC (-1) respectively

λ is coefficient of coint EQ (-1)

IV. EMPIRICAL RESULTS

1. Descriptive statistics

	AGR	DCP	BM	FC
Mean	25.272	31.6	52.66	150.72
Median	24.457	25.3	46.02	148.02
Maximum	41.603	54.5	87.78	214.344
Minimum	16.031	11.2	21.373	113.40
Std. Dev	7.924	13.7	19.897	26.70
Skewness	0.3993	0.38	0.12431	0.6392
Kurtosis	1.8722	1.66	1.6434	2.626
Jarque Bera	4.2176	5.23	4.2005	3.918
Probability	0.1213	0.07	0.122	0.14099
Observations	53	53	53	53

Source: Authors calculation

Before pursuing parameters estimation, it is imperative to perform a preliminary test to confirm data properties. Based on the attributes of data an ARDL model was preferred and most appropriate, to show the nexus between financial inclusion and agricultural productivity in India.

Table 2: Unit Root test results

Variables	At level		First difference	
	t-statistic	critical value	t-static	critical value
AVA	-1.233	1% -3.577 5% -2.928 10% -2.599	-8.060	1%-4.148 5%-3.499 10%-3.179
DCP	-2.309	1% -3.577 5% -2.928 10% -2.599	-5.928	1%-4.148 5%-3.499 10%-3.179
BM	-2.289	1% -3.577 5% -2.928 10% -2.599	-5.401	1%-4.148 5%-3.499 10%-3.179
FC	-2.547	1% -3.577 5% -2.928 10% -2.599	-7.691	1%-4.148 5%-3.499 10%-3.179

Source: Author calculation

The variables AVA, DCP, BM, and FC at both levels and initial differences were tested using the Augmented Dickey-Fuller (ADF) unit root test.

Along with the crucial values at the 1%, 5%, and 10% significance levels, the test statistic for each variable is included.

AVA, DCP, BM, and FC all have test statistics at the level that are below the critical values across all significance levels. As a result, it seems that the null hypothesis of a unit root is not successfully rejected, suggesting that the variables were not initially stationary.

The test stats for AVA, DCP, BM, and FC become -8.060, -5.928, -5.401, and -7.691 in accordance with taking the initial difference of the variables. At the 1%, 5%, and 10% significance levels, these test statistics are all significantly lower than the crucial values. As an outcome, we reject the unit root null hypothesis, suggesting that these variables become reliable during differencing.

The variables AVA, DCP, BM, and FC are non-stationary at the level but remain stationary after taking the first difference, according to the findings of the ADF unit root test. Given their stationarity, this indicates that the initial differences of these variables are probably more feasible for time series analysis.

2. Cointegration Testing Results

Cointegration is the word used to describe an overarching, secure equilibrium involving two or more variables. Economic research indicates that ultimately a link should form between two or more variables, even if the measured variables depart from the equilibrium trajectory. However, equilibrium is eventually attained (Harris & Sollis, 2003). Numerous approaches, including the maximum probability-based Engle-Granger (1987), Johansen-Juselius (1990), and Johansen (1991, 1995) tests, can be used to conduct the cointegration test. We utilized unit root tests to determine the variables' stationarity. Because of the limits of restricted power and other problems with the Engle-Granger technique, Johansen Juselius used the ARDL approach to cointegration in 1990. With the F-statistic, the hypothesis of this approach may be checked.

According to Pesaran et al. (2001), both the upper and lower limits of the F-statistic in the model are influenced by incorporating the trend, intercept, or both variables. If the F-statistic that we computed is more than the critical limitations, cointegration can be established with absolute certainty. The null hypothesis is rejected in the absence of cointegration when the computed F-statistic is greater than the upper bounds of the critical values. It is considered legitimate to make assumptions about cointegration if the computed F-statistic is smaller than the lower bound. If the F-statistic estimate falls between the lower and upper bounds, the result is not conclusive.

Table 3: Bound test for cointegration

Test Statistics	Value	K
F Statistics	4.398109	3
Critical Value Bounds		
Significance	I(0)	I(1)
10%	2.37	3.2
5%	2.79	3.67
1%	3.65	4.66

Source: Authors' own calculation

The test's degrees of freedom (K) correspond to an F-statistic value of 4.398109. This value is compared to critical values at different significance levels in order to ascertain statistical significance. For example, at the 10% significance level, the critical values for I(0) and I(1) are 2.37 and 3.2, respectively, and since the F-statistic surpasses both of these values, the results are significant at this level. At the 5% significance level, the critical values increase to 2.79 and 3.67, and the F-statistic still exceeds these thresholds, proving significant at this level as well.

The F-statistic finally surpasses the first value but not the second at the 1% significance level, with critical values of 3.65 and 4.66. This indicates significance for I(0) but not for I(1) at the 1% level. To summarize, the F-statistic value of 4.398109 indicates a statistically significant difference between the group averages at these levels of significance. It is significant at the 10%, and 5% at I (0) and at the 10% and 5% at I (1).

3. Long-run and Short-run Analysis

Table 4: Long run ARDL results

Variables	Coefficient	St. Error	T-Statistics	Prob.
BM	-0,84675	0.425483	2.80478	0,0023
DCP	0.128578	0.371939	-1.938	0.015
FC	0.448079	0.38176	-2.56798	0.0058
C	3.637568	2.384176	-3.08534	0.006

Source: Authors' own calculation

In the long run, the variable AGR, likely representing agricultural output or growth, is influenced by various factors. For every 1-unit increase in BM (indicating broad money supply or a monetary policy variable), AGR decreases by 0.82 units, assuming other factors remain constant. Conversely, a 1-unit increase in DCP (domestic credit to the private sector) leads to a rise of 0.13 units in AGR.

Similarly, a 1-unit increase in FC (fertilizer consumption) is associated with an increase of 0.45 units in AGR, holding other variables steady. The constant term of 3.64 represents the portion of AGR not accounted for by the other variables in the model. Overall, this long-term equation suggests that agricultural output or growth is positively affected by domestic credit to the private sector and fertilizer consumption but negatively influenced by broad money supply or monetary policy variables.

In the short term, changes in various factors significantly influence agricultural output growth. Firstly, a 1-unit increase in broad money growth corresponds to a 0.400481 unit rise in agricultural output growth, holding other variables constant. This coefficient is statistically significant at the 5% level, indicating its reliability. Conversely, a 1-unit increase in the growth of domestic credit to the private sector results in a decrease of 0.468006 units in agricultural output growth. This coefficient is statistically significant at the 1% level, suggesting a robust association. Additionally, a 1-unit increase in financial constraints leads to a 0.154209 unit increase in agricultural output growth, a relationship also significant at the 5% level. Moreover, the lagged change in financial constraints from the previous period (D (FC (-1))) shows a negative impact on agricultural output growth, with a coefficient of -0.134465, significant at the 5% level.

Finally, the coefficient of the lagged error correction term (CointEq (-1)), at -0.163669 and significant at the 1% level, indicates the speed of adjustment towards the long-run equilibrium.

It suggests that approximately 16.37% of the disequilibrium is corrected in each period, facilitating convergence to the equilibrium. In essence, in the short term, broad money growth and increased financial constraints positively affect agricultural output growth, while an upsurge in domestic credit to the private sector and lagged financial constraints have negative repercussions.

The inclusion of the error correction term ensures the model's adjustment towards the long-run equilibrium relationship between agricultural output growth and the other variables.

Table 5: Short-run ARDL results

Variable	Coefficient	St. Error	T - statistic	Prob.
D(BM)	0.40081	0.138086	2.900239	0.0059
D(DCP)	-0.46806	0.108100	-4.32936	0.0001
D(FC)	0.154209	0.048376	3.187722	0.0027
D (FC -1))	-0.134465	0.050182	-2.67954	0.00105
CointEq (-1)	-0.163669	0.033350	-4.90763	0.0000

Source: Authors' own calculation

Table 6: Results of Diagnostic test and Stability test

Jarque-Bera Test - Normality			
Jarque - Bera	4.216	Probability	0.1213
Ramsey Rest Test - Dunctional Form			
	Value	DF	P Value
F - statistic	5.1911400	(1,41)	0.0680
Heteroskedascity Test: Breaush -Pagan -Godfrey			
F statistic	3.3137	Prob.(8,42)	0.067
Obs-R squared	19.784848	Prob chi square (8)	0.48767
Scaled explained	17.58544	Prob chi square (8)	0.787
Breush -Godfrey Serial Corelation Lm Test			
F- statistics	1.792023	Prob(2,40)	0.373
Obs R Squared	4.93882	Prob chi square	0.1810

Source: Authors calculation

Given that the probability value of 0.1806 obtained by the Jarque-Bera test above the widely accepted threshold of 0.05, it may be inferred that the residuals follow a normal distribution. A desired attribute for reliable statistical judgments is this one. The F-statistic's p-value of 0.0680 for the Ramsey RESET Test is higher above the 0.05 cutoff. This suggests that the regression model does not include any convincing evidence of a functional form that is incorrect or of missing any important variables. With a p-value of 0.067 for the F-statistic, the Breusch-Pagan-Godfrey heteroskedasticity test is marginally over the 0.05 threshold, indicating that there isn't any substantial evidence of heteroskedasticity (non-constant variance of residuals) in the model.

The Breusch-Godfrey Serial Correlation LM Test additionally demonstrates insufficient proof of serial correlation (autocorrelation) in the residuals, with a p-value of 0.1810 for the Observed R-squared statistic, larger than 0.05. All things considered, the test results suggest that the regression model meets the essential requirements of normalcy, accurate functional form, homoskedasticity (constant variance of residuals), and lack of serial correlation. This shows that the model has a good degree of specification and that the statistical conclusions obtained from the regression analysis are probably reliable and precise.

During the whole duration, the CUSUM statistic (blue line) should fluctuate at random and stay under the 5% significant boundaries (dashed red lines). It may be inferred from this that there are no notable structural fractures or instability and that the model parameters remain steady over time. The CUSUM of Squares statistic (blue line) should also fluctuate randomly and stay well below the 5% significance boundaries (dashed red lines) throughout the duration of the test. This shows that there is no indication of parameter instability or structural changes, and the model parameters are consistent and stable. The current graph, however, satisfies these two requirements to indicate unbiased statical interference.

V. RECOMMENDATIONS FOR POLICYMAKERS

Enhancing finance availability for farmers and agricultural businesses is crucial, as evidenced by the favourable correlation between long-term agricultural production and domestic loans to the private sector (Farooq et al., 2021; Fowowe, 2020). The main priorities for policymakers should be to support agricultural credit programs, improve rural financial infrastructure, and remove obstacles that smallholder farmers encounter when trying to get loans (Choudhury, 2018; Rathi & Sharma, 2020). Initiatives to increase the accessibility, cost-effectiveness, and effective distribution of fertilizers and other essential inputs have to be given top priority by policymakers (Kumar, 2020; Sharma et al., 2024). Agricultural production and output may also be increased by making investments in transportation networks, storage facilities, and irrigation infrastructure (Sethy & Goyari, 2023; Chand, 2017). To help farmers overcome their financial obstacles, policymakers should put in place targeted measures like income assistance programs, crop insurance plans (Bhagat et al., 2018), and the facilitation of alternative funding sources such as cooperative lending or microfinance (Kalaiarasi & Rohini, 2022; Sharma, 2015).

V. CONCLUSION

Enhancing finance availability for farmers and agricultural businesses is crucial, as evidenced by the favorable correlation between long-term agricultural production and domestic loans to the private sector (Farooq et al., 2021; Fowowe, 2020). The main priorities for policymakers should be to support agricultural credit programs, improve rural financial infrastructure, and remove obstacles that smallholder farmers encounter when trying to get loans (Choudhury, 2018; Rathi & Sharma, 2020). Initiatives to increase the accessibility, cost-effectiveness, and effective distribution of fertilizers and other essential inputs have to be given top priority by policymakers (Kumar, 2020; Sharma et al., 2024). Agricultural production and output may also be increased by making investments in transportation networks, storage facilities, and irrigation infrastructure (Sethy & Goyari, 2023; Chand, 2017). To help farmers overcome their financial obstacles, policymakers should put in place targeted measures like income assistance programs, crop insurance plans (Bhagat et al., 2018), and the facilitation of alternative funding sources such as cooperative lending or microfinance (Kalaiarasi & Rohini, 2022; Sharma, 2015).

REFERENCES

1. Agbenyo, W., Jiang, Y.S. & Antony, S. (2019). Cointegration Analysis of Agricultural Growth and Financial Inclusion in Ghana. Theoretical Economics Letters, 9:895-911. https://doi.org/10.4236/tel.2019.94058
2. Akhtar, S. M. J., & Parveen, S. (2015). Role of Education in Small Farmer's Empowerment in India. Journal of Exclusion Studies, 5(1): 92-102. https://doi.org/10.5958/2231-4555.2015.00007.8
3. Allen, F., Carletti, E., Cull, R., Qian, J. Q., Senbet, L.W, & Valenzuela, P. (2014). The African financial development and financial inclusion gaps. Policy Research Working Paper Series 7019. https://doi.org/10.1596/1813-9450-7019
4. Amidic, G., Massara, M. A., & Mialou, A. (2014). Assessing countries' financial inclusion standing-A new composite index. International Monetary Fund. https://doi.org/10.5089/9781498386516.001
5. Bhagat, R. B., Kumar, S., & Mohanty, S. K. (2018). "Pradhan Mantri Fasal Bima Yojana (PMFBY): An assessment." Economic & Political Weekly, 53(16), 58-64.
6. Cámara Izquierdo, N., & Tuesta, D. (2015). Factors that matter for financial inclusion: Evidence from Peru. https://doi.org/10.2139/ssrn.2634637
7. Cámara, N., & Tuesta, D. (2014). Measuring financial inclusion: A muldimensional index. BBVA Research Paper, (14/26). https://doi.org/10.2139/ssrn.2634616
8. Chand, R. (2017). "Doubling farmers' income: Rationale, strategy, prospects and action plan." NITI Policy Paper, NITI Aayog, Government of India.
9. Choudhury, S. (2018). Financial Inclusion and Agricultural Development in India. International Journal of Research-GRANTHAALAYAH, 6(9):421–433. https://doi.org/10.29121/granthaalayah.v6.i9.2018.1254
10. Demirgüç-Kunt, A., & Klapper, L. F. (2012). Measuring financial inclusion: The global findex database. World bank policy research working paper, (6025). https://doi.org/10.1596/1813-9450-6025
11. Dev, S. M. (2016). "Financial inclusion: Issues and challenges." Economic & Political Weekly, 41(41), 4310-4313.
12. Evans, O. (2016). Determinants of financial inclusion in Africa: A dynamic panel data approach. https://doi.org/10.2139/ssrn.3163998
13. FAO (2017). Food and Agriculture Organization of the United Nations, Rome, Italy.
14. Farooq, U., Gang, F., Guan, Z., Rauf, A., Chandio, A. A., & Ahsan, F. (2021). Exploring the long-run relationship between financial inclusion and agricultural growth: evidence from Pakistan. International Journal of Emerging Markets, 18(7):1677-1696. https://doi.org/10.1108/IJOEM-06-2019-0434
15. Fowowe, B. (2020), "The effects of financial inclusion on agricultural productivity in Nigeria", Journal of Economics and

Development, 22(1):61-79. https://doi.org/10.1108/JED-11-2019-0059
16. Garg, S., & Agarwal, P. (2014). Financial inclusion in India–a Review of initiatives and achievements. IOSR journal of business and Management, 16(6):52-61 https://doi.org/10.9790/487X-16615261
17. Honohan, P. (2008). Cross-country variation in household access to financial services. Journal of Banking & Finance, 32(11), 2493-2500. https://doi.org/10.1016/j.jbankfin.2008.05.004
18. Harris, R., & Sollis, R. (2003). Applied Time Series Modelling and Forecasting.
19. Johansen, S. (1988). Statistical analysis of cointegration vectors. Journal of economic dynamics and control, 12(2-3):231-254. http://doi.org/10.1016/0165-1889(88)90041-3
20. Kalaiarasi, D., & Rohini, A. (2022). Financial Inclusion through Self Help Groups–An Economic Catalyst to transform Rural India. Madras Agricultural Journal, 109(December (10-12)), 1.
21. Kumar, S. (2020). Impact of Subsidies on Agriculture Sector in India. Agri mirror: Future India,1(2):40-44.
22. NABARD. (2019). "Annual Report 2018-19." National Bank for Agriculture and Rural Development.
23. NABARD. (2020). Enhancing Farmer Income through Farmer Producer Organizations. National Bank for Agriculture and Rural Development.
24. Olaniyi, E. (2017). Back to the land: The impact of financial inclusion on agriculture in Nigeria. Iranian Economic Review, 21(4), 885-903. https://doi.org/10.22059/ier.2017.64086
25. Patil, S., & Rehman, T. (2021). Effectiveness of Financial Literacy Programs for Farmers: A Review. Agricultural Finance Review. https://doi.org/10.1108/AFR-06-2021-0077
26. Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. Journal of applied econometrics, 16(3), 289-326. https://doi.org/10.1002/jae.616
27. Rathi, M. R., & Sharma, D. (2020). Fuelling Agricultural Growth In Madhya Pradesh Through Formal Credit-A Way Towards Financial Inclusion. BSSS Journal of Commerce, 12(1):1-15. https://doi.org/10.51767/joc1201
28. Rojas-Suarez, L., & Amado, M. (2014). Understanding Latin America's financial inclusion gap. Centre for Global Development Working Paper, (367). https://doi.org/10.2139/ssrn.2458138
29. Sahay, M. R., Cihak, M., N'diaye, M. P., Barajas, M. A., Mitra, M. S., Kyobe, M. A., ... & Yousefi, M. R. (2015). Financial inclusion: can it meet multiple macroeconomic goals? International Monetary Fund. https://doi.org/10.5089/9781513585154.006
30. Sarma, M. (2012). Index of Financial Inclusion–A measure of financial sector inclusiveness. Centre for International Trade and Development, School of International Studies Working Paper Jawaharlal Nehru University. Delhi, India.
31. Sarma, M., & Pais, J. (2011). Financial inclusion and development. Journal of international development, 23(5), 613-628. https://doi.org/10.1002/jid.1698
32. Sethy, S. K., & Goyari, P. (2023). Examining financial inclusion-agricultural productivity connection in south asian countries: evidence from FMOLS and DOLS approaches. Italian Review of Agricultural Economics, 78(1), 33-48. https://doi.org/10.36253/rea-13922
33. Sharma, P. (2015). "Microfinance in India: Progress and perspectives." Economic & Political Weekly, 50(16), 69-73.
34. Sharma, R., & Singh, P. (2019). Role of Regional Rural Banks and Cooperative Banks in Financial Inclusion in India. International Journal of Rural Management. https://doi.org/10.1177/0973005219876180
35. Sharma, S., Inubushi, K., Mukherjee, S. (2024). Roles of Agricultural Sciences for Achieving Sustainable Development in India: Perspectives and Challenges. In: Sobti, R.C. (eds) Role of Science and Technology for Sustainable Future. Springer, Singapore. https://doi.org/10.1007/978-981-97-0710-2_11
36. Shen, Z., Hong, T., Blancard, S., & Bai, K. (2023). Digital financial inclusion and green growth: analysis of Chinese agriculture. Applied Economics, 56(46), 5555–5573.

https://doi.org/10.1080/00036846.2023.2257038

37. Singh, S. (2018). "Farmer Producer Companies in India: Evaluating performance and sustainability." Indian Journal of Agricultural Economics, 73(3), 408-418. https://doi.org/10.5958/0974-0279.2018.00056.1
38. Soby, S. (2017). Thomas Malthus, Ester Boserup, and agricultural development models in the age of limits. Journal of Agricultural and Environmental Ethics, 30(1):87-98. https://doi.org/10.1007/s10806-017-9655-x
39. Udoka, C.O., Mbat, D.O. & Duke, S.B. (2016) The Effect of Commercial Banks' Credit on Agricultural Production in Nigeria. Journal of Finance and Accounting, 4:1-10. https://doi.org/10.11648/j.jfa.20160401.11
40. World Bank (2014). World Development Indicators.
41. Zhai, S., Peng, C., & Sheng, Y. (2023). Assessing the impact of digital financial inclusion on agricultural total factor productivity in China. International Food and AgribusinessManagementAssociation26(3):519-533. https://doi.org/10.22434/IFAMR2022.0132