International Journal of Social Sciences and Management Review

Volume: 08, Issue: 02 March - April 2025

ISSN 2582-0176

DETERMINANTS OF AGRICULTURAL CREDIT DEMAND AMONG SMALLHOLDER FARMERS IN RURAL ABEOKUTA, NIGERIA

YUSUF K. IBRAHIM[1] & KAMILU A. SAKA[2]

[1]Department of Business Administration and Management / The Federal Polytechnic, Ilaro. Nigeria. Postal Code: 111101 Ilaro, Nigeria. ORCID: 0009-0004-7571-8727

[2](Corresponding Author) Department of Banking and Finance / The Federal Polytechnic, Ilaro. Postal Code: 111101 Ilaro, Nigeria. ORCID: 0009-0006-6190-2974

https://doi.org/10.37602/IJSSMR.2025.8219

ABSTRACT

This study investigates the socioeconomic determinants of smallholder farmers' formal credit decisions in rural Abeokuta, Ogun State, Nigeria. A binary logit model approach was employed to analyse cross-sectional survey data drawn from 768 smallholder farmers in the study area. The study's analyses were performed at three significance levels (1%, 5% and 10%) using STATA 12.1 as the statistical software. Likelihood Ratio test and the Pearson chi-square test at a 1 per cent significance level suggest that the study's empirical model best fits the observed data. The study findings show that getting old, additional education, longer distance and perceived expected inflation significantly reduce the likelihood that smallholder farmers in the study area apply for loans or credit from formal financial institutions. Based on this outcome, the study affirms that socioeconomic factors like age, education, distance and perceived expected inflation significantly discourage smallholder farmers in rural Abeokuta from accessing formal financial products and services. The study suggests that formal financial institutions in the Abeokuta metropolis and the government should redirect their lending models' focus to mainly young rural farmers in the study area. At the national level, monetary and fiscal policies that effectively and timely address rising inflation levels should be implemented.

Keywords: Agriculture, Loan Demand, Rural, Abeokuta, Logit Model

JEL Codes: C35, E41, Q12, Q14

Acknowledgement

This work was supported by the Nigeria Tertiary Education Trust Fund (TETFUND) Institution-Based Research (IBR) Grant in 2024.

1.0 INTRODUCTION

Agriculture is an important driver for the growth and development of developed and developing countries (Apostolidou, Achilleas; Anastasios & Efstratios, 2014). Mainly, agriculture creates employment opportunities and effectively provides raw materials for production and manufacturing activities. In Africa, the agriculture sector has been observed as the largest contributor to economic growth (measured by the gross domestic product – GDP) of many countries including Nigeria and a major source of employment for almost half of the continent's population (World Economic Forum, 2023; PricewaterhouseCoopers Limited, 2018). However, many farmers in African countries reside and do their farming activities in rural areas where conventional financial institutions are sparsely available. The recognized importance of rural agricultural production in developing economies has motivated many governments, non-government organisations (NGOs), and private investors to launch a series of financial interventions for rural farmers. For instance, the microcredit programme was first launched and applied by Muhamed Yunus during the 1970's targeting rural women farmers in Bangladesh and since then many funding interventions have followed.

In Nigeria, some notable financial initiatives and programmes have been designed and implemented to render financial support to smallholder farmers including agribusinesses and small-scale enterprises that engage in agricultural production. At the national level, these funding initiatives include the Bank of Agriculture (BOA), the Anchor Borrowers' Programme, the Fund for Agricultural Finance in Nigeria (FAFIN), and the Commercial Agriculture Credit Scheme (CACS). Despite these funding efforts for agriculture, rural farmers in Nigeria like other developing economies continue to face greater financing challenges (Balana & Oyeyemi, 2022; Manteaw, Folitse, Swanzy, Agyarko-Fosuhene, & Mahama, 2023; Ochanda, 2023; Saka, Akinde & Afolabi, 2023; Chandio et al., 2021; Daemane & Muroyiwa, 2022; Yeasmin et al., 2024). The issue of inadequate or poor funding of smallholding agriculture in rural areas has been empirically established as a factor contributing to low productivity of the agriculture sector in developing countries including Nigeria (Linh et al., 2020; Chandio et al., 2021; Daemane & Muroyiwa, 2022). Unfortunately, the financial issue further limits the ability of these farmers to earn more, boost their chance toward shared prosperity and ultimately push them into extreme poverty situations.

Meanwhile, a lack of better understanding of factors determining the demand for agricultural credit has been censored by existing literature (such as Yeasmin et al., 2024) as one of the principal reasons rural farmers frequently suffer huge financing problems. It is argued that addressing such knowledge issues is critical to improving agricultural productivity in rural areas of developing economies and promoting agriculture-led inclusive economic growth in these countries. Also, achieving optimal production by rural farmers can significantly enable the food market in Africa to reach one trillion US dollars by 2030, according to forecasts by the World Bank (2013) and African Development Bank (2018). Nigeria, in particular, can benefit immensely from the market growth with increased funding in the country's agriculture sector. Against the backdrop, this study seeks to investigate certain economic factors that influence the decision of rural farmers in Abeokuta, Nigeria to demand agricultural credit. A sizeable number of related studies in literature from similar developing countries including Nigeria has extensively found that farmer demand for agrarian credit is determined by social demographics like age, formal education, and living in rural areas (Balana &Oyeyemi, 2022; Chandio et al., 2021; Chivandire, 2019; Daemane & Muroyiwa, 2022; Kayamo, & Ayele, 2023; Manteaw et al., 2023; Mwonge & Naho, 2021; Ochanda, 2023); household factors such as household size, income-making family members (Yeasmin et al., 2024); farm-based factors akin to farm size/landholding size, farming experience, (Chandio et al., 2021; Kayamo, & Ayele, 2023; Daemane & Muroyiwa, 2022; Ochanda, 2023; Yeasmin et al., 2024); and economic considerations viz interest rate, informal savings, asset value, non-farm income, livestock value, road access, having insurance, extension services, application procedure

(Balana & Oyeyemi, 2022; Chandio et al., 2021; Yeasmin et al., 2024; Kayamo, & Ayele, 2023; Mwonge & Naho, 2021).

However, empirical literature suggests that no study on the analysis of determinants of credit demand by smallholder farmers in rural Abeokuta, Nigeria is specifically available at the current period (caveat, subject to authors' knowledge). This implies that little to no information is known on the credit demand by rural farmers in the study area. Again, there is a lack of studies on expected inflation for the econometric estimation of farmers' credit demand factors. The issue of rising inflation in Nigeria could debar demand for credit by potential rural users, particularly for certain perishable agricultural commodities that need to be sold on time when adequate storage facilities are not available. Consistent with these developments, this study examines economic factors (interest rate, distance, expected inflation and repayment period) that determine whether farmers in rural Abeokuta require funding assistance (in the form of loans or credit) from formal financial institutions using cross-sectional data. The conduct of this study is essential for two reasons. First, agriculture is a prime occupation for many Ogun State citizens particularly those that live in the State's rural areas such as rural Abeokuta. Due to favourable climatic conditions, rural farmers in this state produce substantial agricultural products like cassava, maize, cocoa, rubber, palm trees, kola nuts, and yams (Adamu, 2018; Britannica, 2024).

Given the abundant production, Ogun State can be considered a critical factor in why Nigeria is the largest cassava-producing country in the world. Therefore, to increase the productivity of these rural farmers and ensure sustainable agriculture development in Nigeria, a better understanding of factors that influence their access to formal credit is required via a scientific study of this nature. Second, in the context of rising inflation in Nigeria, how expected inflation affects access to formal credit by rural farmers in developing countries (like Nigeria) deserves scientific process attention. This study is structured into five parts. The first section introduces the study. A review of seemingly related literature is carried out in section two. The methodology that describes how the study achieves its objectives is contained in the third section. While section four presents and discusses the observed findings section five closes the study with a conclusion and recommendations.

2.0 LITERATURE REVIEW

Smallholder agriculture refers to crop production or livestock holding carried out by an individual (a farmer) or group of individuals (usually a farmer and his immediate family) for personal consumption and making profits to earn a living. The basic interesting features of smallholding farms include small-to-medium farm size, use of low technology, and operating with little to no capital. Access to capital is very critical to the operation performance of smallholder farmers in developing countries like Nigeria (Chandio et al., 2021; Mwonge & Noha, 2021; Saka et al., 2023). Smallholder farmers require finance to buy inputs, hire labour and procure less capital-intensive equipment. When farmers have access to necessary funding, it can encourage them to increase productive income-generating capacity, cope with climate-induced agricultural production shocks, and ultimately allow them to alleviate poverty (Ameh & Lee, 2022; Yeasmin et al., 2024). However, market imperfections caused by asymmetric information usually prevent smallholder farmers in these economies from being adequately served by formal financial institutions (Asiamah, Steel & Ackah, 2021; Awotide, Abdoulaye, Alene, & Manyong, 2015; Wossen et al., 2017). In many situations, most developing economies like Nigeria operate bank-based model financing for business firms and less use of the capital market. This position exposes micro, small businesses and smallholder farmers to less access to formal credit from conventional banks as they are considered high-risk borrowers. As a result of such widened financing gaps, the Nigerian government has launched and established various financing schemes to curb the funding issue often faced by micro, small-scale, medium-scale and smallholding farm businesses (Balana & Oyeyemi, 2022; Chivandire, 2019). Examples include the Bank of Agriculture (BOA), the Anchor Borrowers' Programme, the Fund for Agricultural Finance in Nigeria (FAFIN), the Commercial Agriculture Credit Scheme (CACS), the Small and Medium Enterprises Equity Investment Scheme (SMEIEIS) and among others.

Theoretically, this study is underpinned by rational choice theory (RCT) propounded by Adam Smith in an article on self-interest and the invincible hand theory. RCT is a behaviour theory that helps to explain how people select an option that provides them with the greatest total utility or maximum satisfaction (Mwonge & Naho, 2021). According to RCT, rational decision-makers motivated by self-interests usually select an option that provides the greatest benefits based on rational calculation and available information. The theory offers insight into how smallholder farmers in the study area choose formal financial institutions (instead of semi-formal or informal institutions) as their preferences among alternative credit sources and why they do so while considering some socio-economic factors (such as age, education, farm income, interest rate, expected inflation, distance and repayment schedule). Based on the information available about these factors, a rational farmer will opt for formal credit if the expected benefit from using the facility is high and meets his objectives. This is because a prospective borrower (farmer) who farms for commercial reasons will want to maximize his gains or profits out of which transaction expenses (financial cost) will be paid. However, the efficient operation of the RCT framework depends on rational calculation, the desire to be motivated by self-interest, and the quality of information available to the decision-maker.

In recent times, some empirics have evaluated determinants of access to credit among smallholder farmers in developing countries including Nigeria (Ameh & Lee, 2022; Asiamah, et al., 2021; Balana & Oyeyemi, 2022; Chivandire, 2019; Chandio et al., 2021; Kayamo & Ayele, 2023; Mahmud, 2021; Mwonge & Noha, 2021; Daemane & Muroyiwa, 2022; Manteaw et al., 2023; Ochanda, 2023; Yeasmin et al., 2024). In Bangladesh, Yeasmin et al. (2024) found through binary logistic regression that an increase in farming experience and farm size significantly increases farmers' access to agricultural credit. Such access decreases with soaring interest rates, additional income-making household members and the application process. The study concluded that farmers in Bangladesh are influenced by occupational experience and the size of their farm business when making credit decisions but discouraged by high interest rates, and a rise in additional income-earning family members. A study by Manteaw et al. (2023) revealed that informal credit institutions are the most common sources for oil-processing farmers in the Ghana Kwaebibirem municipal assembly. According to the study's binomial logit model analysis, these oil-processor farmers' access to credit is determined by gender, marital status, guarantor and high interest rate. A similar but macro-based study by Asiamah et al. (2021) which employed the Heckman probit model had earlier found that education and marital status are the determinants of credit access among Ghana's rural households. The findings from Manteaw et al. (2023) and Asiamah et al. (2021) show that marital status is an important factor which drives credit access among Ghana's rural farmers.

In another Sub-Saharan African country (Zimbabwe, in particular), Chivandire (2019) discovered via binary logit analysis that farness, schooling, age, age squared and gender are the significant drivers of access to formal credit among rural farmers in the Chivi District. Kayamo and Ayele (2023) from Ethiopia examined factors influencing smallholder households' access to formal credit in Bilatte Zuria Woreda, Sidama National Regional State of Ethiopia with a logit model analysis. The study found that only a few farmers with access to formal credit were driven by age, farm size, extension service, less complex lending procedure, livestock size, income level and awareness about credit availability. In a similar investigation on determinants of credit demand among smallholder farmers, Mwonge and Noha (2021) observed with logit model estimation that age, gender, length of education, household size, distance, awareness, crop type, collateral, farm size and interest rate are the significant drivers of smallholder farmers' credit demand in Morogoro, Tanzania. In a thesis-based research study, Ochanda (2023) specifically studied factors determining farmers' credit decisions in seeking financial assistance from the Agricultural Finance Corporation in Lamu County, Kenya. Employing factor analysis and ordinary least regression the study discovered that religion, high interest rates, lack of sufficient collateral or failure to meet/fulfil requirements and burdensome application procedures significantly discouraged farmers from applying for agricultural credit.

In Nigeria, Mahmud (2021) employed the double hurdle method to estimate determinants of crop accessibility to microfinance services among 185 crop farmers in Niger state, Nigeria. It was observed that crop farmers in the study area consider significant factors such as age, farm intensity (or size), income, education, household size, and farming exposure when making credit decisions with microfinance institutions. While age, farm size, income level, and education positively determine their desire for credit household numbers, farming business experience and being a land owner decrease the likelihood of seeking financial assistance from microfinance institutions. From a similar mono-agricultural production-focused study conducted in Lagos State, Ameh and Lee (2022) found via a two-part model and multinomial logit model that rice farmers' loan choices are positively and significantly determined by marital status, farm size and interest rate. Again, the study revealed further that high farm revenue and rising interest rates significantly improve loan access among rice farmers in the study area. The authors explained that farmers with high levels of education are more likely to enjoy the benefits of modern farming and thereby could afford credit facilities from formal sources with high interest rates.

In a large-scale research study that focused on 5,000 rural households in Nigeria, Balana and Oyeyemi (2022) observed with multinomial probit regression that poor/no informal savings and living in rural areas decrease the likelihood that rural farmers will seek financial assistance from formal sources. On the contrary, the study found further that having a land title, high assets and livestock value increases the probability of formal loan access by rural farmers. However, evidence from the above-reviewed empirical articles and within the authors' information suggests that no study on the analysis of determinants of credit demand by smallholder farmers in rural Abeokuta, Nigeria is specifically available at the current period. This implies that little to no information is known on the credit demand by rural farmers in the selected study area. Again, there is a lack of studies on expected inflation for the econometric estimation of farmers' credit demand factors. This study therefore aimed at filling these voids in the empirical literature on determinants of credit access among rural farmers with a specific focus on rural Abeokuta.

3.0 METHODOLOGY

This study applies a quantitative survey research design to draw inferences from the population of smallholder farmers in rural Abeokuta through a sample. The study population consists of all smallholder farmers in rural Abeokuta specifically from Abeokuta North Local Government Area, Ogun State, Nigeria. This study area is selected due to its proximity to formal financial institutions operating in both Abeokuta North LG and Abeokuta South LG respectively. Again, the choice of the study area is informed by its large concentration of several villages and smallholder farmers. These smallholder farmers engage in diverse agricultural production of important cash crops like cassava, maize, cocoa, plantain, rubber, palm trees, kola nuts, and yams. However, due to the lack of record-keeping in developing countries like Nigeria (McKenzie & Sakho, 2010), it was difficult for the researchers to ascertain the precise population of smallholder farmers in the study area. Even visitations to several government quarters produced no statistical evidence. Against this backdrop, the study employs Krejcie and Morgan's (1970) unknown population sample size formula to determine the required sample size. The formula is specified thus:

$$\boldsymbol{S} = \frac{(\frac{\boldsymbol{Range}}{\boldsymbol{2}})^2}{(\frac{\boldsymbol{Accuracy\ Level}}{\boldsymbol{Confidence\ Level}})^2} \ldots (1)$$

Where;

Range = Range of smallholder farmers (assumed to be between 10,000 and 100,000) = 100,000 – 10,000 = 90,000 farmers. Confidence level = 1.96 (2-tailed) at a 5% level of significance

From equation 1, a sample size of 384 farmers is obtained. However, the derived sample size was adjusted to control for at least a 50% response rate. Therefore, equation (1) is adjusted in equation (2) as:

$$\boldsymbol{S}^* = \frac{\boldsymbol{Obtained\ sample\ size}}{\boldsymbol{desired\ response\ rate}} \ldots (\boldsymbol{2})$$

From equation (2), S^* give 768 smallholder farmers in rural Abeokuta as the final sample for the proposed study.

Furthermore, the study adopts a multi-stage sampling technique to select the required sample. First, the precise number of villages selected from Abeokuta rural is determined scientifically. This is achieved by applying Krejcie and Morgan's (1970) sample size for a definite population of villages in rural Abeokuta. According to the number counting principle from ZIPCODE (2022), there are two hundred and thirty-eight (238) villages in rural Abeokuta. Therefore, the number of villages selected was obtained as:

$$\boldsymbol{S} = \frac{\boldsymbol{X^2 \quad NP(1-P)}}{\boldsymbol{d^2\ (N-1) + X^2 \quad P(1-P)}} \ldots (3)$$

Where s = sample size; X2 = table value of chi-square at 1 degree of freedom for desired confidence level (0.95); N = population size (238); and P = population proportion (0.5). The result yields a sample size of 146 villages. Second, 146 villages were randomly selected from the 238 villages following a simple raffle-draw system practice. With this process, each hamlet represented by a specific code (and number) was randomly picked from a pool. Before this stage, the study obtained the names of all the villages from Wikipedia (2024) and assigned each of them a specific code and number. It was from this pool of villages that 146 villages were randomly selected. The list of the selected 146 settlements is provided in the Appendix section.

In the third stage, five (5) smallholder farmers represented by household heads were systematically selected from each of the 146 villages as every 5th household was approached having identified the first house. This process follows pre-data collection visitations to all the randomly selected 146 villages by the researchers. It is important to state that all information regarding addresses and locations was provided by the Department of Agricultural Extension Services in Abeokuta North LG and aided by Google Maps. The systematic procedure yielded the selection of 730 smallholder farmers across all 146 villages. However, some 38 villages with higher population densities were given preference to have one additional household selected from each of them. Overall, this sampling process produces 768 smallholder farmers in the study area. The cross-sectional study administered a simple well-structured questionnaire among the sampled farmers to solicit information on their socio-economic demographics relating to credit decisions from formal financial institutions. This survey was conducted between 25th March and 21st December 2024 with the support of 15 research students serving as Research Assistants (RAs) for data administration and collection. On average, 8 villages were covered by each RA and the two authors who acted as field supervisors throughout the survey exercise. Literate assistance was rendered when a respondent could not read or understand a question.

Further, the study objectives were examined using the binomial logit model estimation technique. The study adopts the logit model specified in Mwonge and Naho (2021) and calibrates it to suit the study objectives. The logit model is preferred in this study to the probit model with a similar estimation strategy because it has a better analytical capacity (Yeasmin, et. al., 2024; Chivandire, 2019; Hosmer & Lemeshew, 1989). The binomial logit model specification procedures are given thus:

$$\boldsymbol{P_i = F(Z_i) = F(\propto + \sum \beta_i X_i) = \frac{1}{1 + e^{-z}}} \ldots (\mathbf{4})(\boldsymbol{Mwonge} \,\&\, \boldsymbol{Noha}, \mathbf{2021})$$

Where,

P_i= Probability that a farmer is a credit user or non-credit user given a set of predictors (X_i)

e = natural logarithm base (2.7183)

The odds ratio of equation (4) is taken as:

$$\boldsymbol{\left(\frac{P_i}{1 - P_i}\right) = \left(\frac{1 + e^{z_i}}{1 + e^{-z_i}}\right) = e^{z_i}} \ldots (\mathbf{5})$$

The study then takes the natural logarithm of the odds ratio in equation (5) to linearize equation (5) as:

$$\left(\frac{P_i}{1-P_i}\right) = \left(\frac{1+e^{z_i}}{1+e^{-z_i}}\right) = e^{(\propto + \sum \beta_i X_i)} \dots (6)$$

With calibration, equation (6) is expanded to become:

$$logit(AAP_i) = ln\left(\frac{APP_i}{1-APP_i}\right) = \propto + \beta_1 AGE_i + \beta_2 EDU_i + \beta_3 DIS_i + \beta_4 INT_i + \beta_5 EIF_i \dots (7)$$

From equation (7),

Ln = log (logit model); 〖APP〗_i = Probability that a farmer applied for a formal loan in the last 12 months (APP = 1) or did not (APP = 0); i = individual smallholder farmer; ∝ = model constant; (〖APP〗_i/(1-〖APP〗_i)) = odds ratio; AGE = Age; EDU = education of farmers; DIS= distance from farmer's house to formal financial institution; INT= interest rate (cost of borrowing from formal credit institution); EIF= Expected Inflation; β_1- β_5 are slope coefficients.

The exponential form and multiplicative inverse of the two sides in Equation (7) is taken in Equation (8) as:

$$\frac{1 - APP_i}{APP_i} = \frac{1}{\exp\left(\propto + \beta_1 AGE_i + \beta_2 EDU_i + \beta_3 DIS_i + \beta_4 INT_i + \beta_5 EIF_i\right)} \dots (8)$$

Where, exp. = exponential (2.71828)

Further, the partial fraction of the left-hand side of equation (8) is taken with one added to both sides and reflected in equation (9) as:

$$\frac{1}{APP_i} = 1 + \frac{1}{\exp\left(\propto + \beta_1 AGE_i + \beta_2 EDU_i + \beta_3 DIS_i + \beta_4 INT_i + \beta_5 EIF_i\right)} \dots (9)$$

The process in equation (9) leads to the change of 1 to a common denominator in equation (10) as:

$$\frac{1}{APP_i} = \frac{\exp(\propto + \beta_1 AGE_i + \beta_2 EDU_i + \beta_3 DIS_i + \beta_4 INT_i + \beta_5 EIF_i) + 1}{\exp\left(\propto + \beta_1 AGE_i + \beta_2 EDU_i + \beta_3 DIS_i + \beta_4 INT_i + \beta_5 EIF_i\right)} \dots (10)$$

Finally, the multiplicative inverse is obtained again in equation (11) to derive a formula for the probabilityP(APP=1) as:

$$APP_i = \frac{\exp(\propto + \beta_1 AGE_i + \beta_2 EDU_i + \beta_3 DIS_i + \beta_4 INT_i + \beta_5 EIF_i)}{1 + \exp\left(\propto + \beta_1 AGE_i + \beta_2 EDU_i + \beta_3 DIS_i + \beta_4 INT_i + \beta_5 EIF_i\right)} \dots (11)$$

The study uses the log-likelihood estimation method of binomial logistic regression in STATA 12.1 software to analyse equation (11) at 1%, 5% and 10% significance levels while ensuring non-violation of important assumptions. Lastly, the study a priori expectation is stated mathematically as thus: β_1 and β_2>0; and β_3,…β_5<0.

4.0 PRESENTATION AND INTERPRETATION OF RESULTS

This part presents and interprets the estimation outcomes of traditional binary logistic (logit) regression and odds ratios computed from STATA 12.1 statistical software. As shown in Table 1, all analyses are performed at three levels of significance (1%, 5%, and 10%).

4.1 Econometric Model Estimation of Determinants of Rural Farmers' Agricultural Credit Demand

Table 1: Traditional Binomial Logit Estimation and Odds Ratio

DV	Predictor	Cat.	Coeff.	SE	OR	WT
Application	Age		-0.21*	0.11	0.80	
	Education					18.84***
		OND/NCE	-1.01***	0.24	0.36	
		HND/B.Sc.	-0.51**	0.36	0.60	
		M.Sc./MBA	0.03	0.70	1.03	
	Distance		-0.25***	0.07	0.78	
	Interest rate		-0.09	0.07	0.09	
	Inflation		-0.66***	0.10	0.51	
	Constant		5.94***	0.70	381.29	
	Observations		629			
	LR chi2(7)		103.99***			
	Pearson chi2(124)		490.68***			
	Pseudo R^2		0.14			
	Correctly classified		73.77			

Notes: DV = Dependent Variable (Application = 1; No Application = 0); Cat = category; Coeff. = slope coefficient; SE = Standard Error; OR = Odds Ratio; WT = Wald Test (overall significance); SSCE/WASSCE = Reference Category for Education; *, **, and *** denote 10%, 5% and 1% significance levels respectively

Source: Authors' Computations from STATA 12.1 (2024)

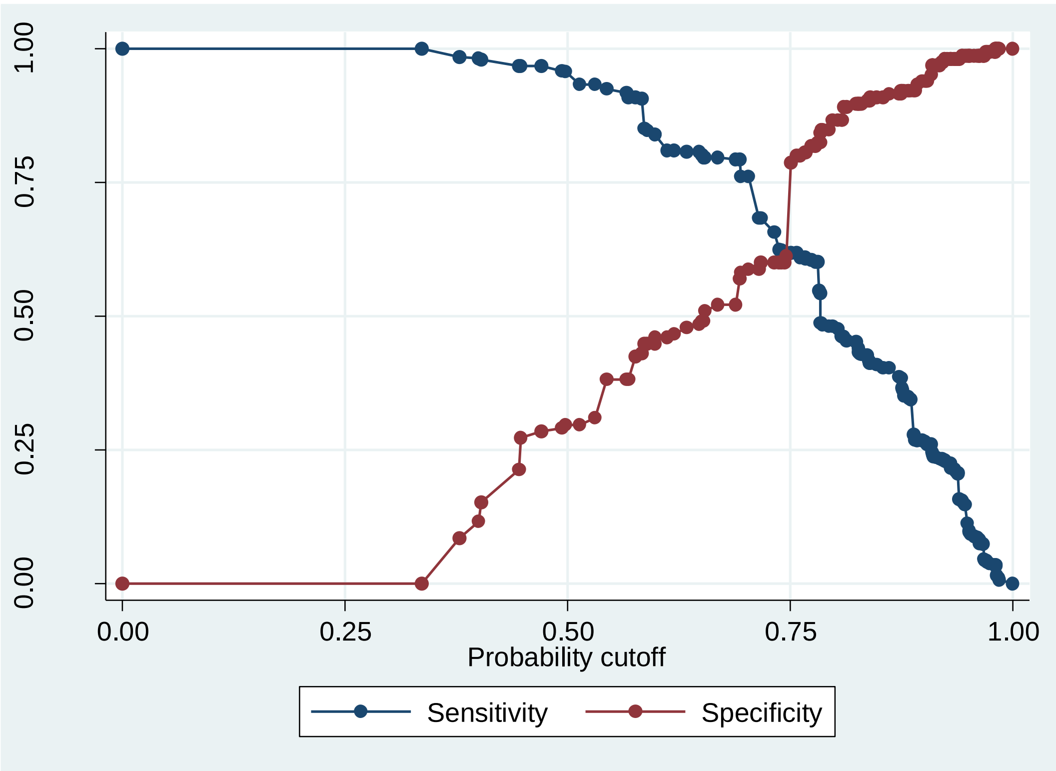
The results of agricultural credit demand determinants among farmers in rural Abeokuta are presented in Table 1. Following the study methodology, 768 farmers were systematically and randomly selected to obtain information on the socioeconomic conditions of these farmers. Out of this sample size, 680 responses were obtained while the attrition rate was minimized at 11 percent of the total sample. The attrition was due to the inconsistency of a few respondents fully participating in the study, the dropout of selected participants due to sickness, and absenteeism. Some 51 questionnaires out of those collected were found unsuitable due to

ISSN 2582-0176

missing data on key variables of interest. In other words, a final number of 629 questionnaires was used for the study analysis. These final observations represent approximately 82% retrieval rate. The outcomes in Table 1 indicate that age, education, distance and perceived expected inflation were negative and significant factors that determined farmers' agricultural credit decisions at 10%, 1%, 1% and 1% significance levels respectively. The test statistic of Likelihood ratio (chi2 = 103.99; p-value = 0.000) is significant at 1%; hence, suggesting the rejection of the null hypothesis that the baseline model is the same as the study empirical model. The LR result implies that socio-economic factors considered in this study had significant effects on credit or loan demand by rural farmers in the study area. Apart from the LR test, the Pearson chi-square test (chi2 = 490.68; p-value = 0.000) which is also significant at a 1 per cent significance level indicates that the study's empirical model best fits the observed data. Thus, inferences drawn based on the estimation outcomes are consistent, reliable and efficient. The Pseudo R-squared statistic (0.14) suggests that age, education, distance, interest rate and expected inflation as socioeconomic factors account for 14% variations in the rural farmers' credit demand decisions regarding rural Abeokuta. Also, Table 1 shows that the study can correctly predict that 73.77% of the smallholder farmers in the study area will embrace formal loans or credit if socioeconomic factors considered in this study are effectively addressed.

4.2 Post-Analysis Model Diagnosis

Figure 1: Sensitivity and Specificity Test for the Study Logit Model



Source: STATA 12.1 Outputs (2024)

Figure 1 shows sensitivity and specificity tests to confirm the suitability of the logit model employed and analysed for the study. The sensitivity test refers to likelihood that rural farmers in the study area will respond to formal agricultural funding facilities offered by formal credit institutions including government agencies such as the Bank of Agriculture (BOA) and Anchor Borrowers. Specificity on the other hand implies the opposite. From Figure 1, the sensitivity and specificity curves cross each other at 0.75 which serves as the optimum probability cut-off value. The obtained high value of the optimum cut-off confirms further that the study's empirical logit model is good.

5.0 DISCUSSION OF EMPIRICAL RESULTS

Table 1 shows that the age coefficient is statistically significant at 10% and reveals that age harms the credit decisions of rural farmers in the study area. Compared to younger ones older farmers are 20% less likely to demand agricultural loans from formal financial institutions when holding all other predictors constant. That is, for every one per cent increase in age demand for farming credit among rural farmers in the study area decreases by 20% as the odds ratio value for age is 0.80. The obtained negative coefficient of age is unexpected and by implication does not confirm with the study a priori expectation. Again, it is not also consistent with previous findings by Chivandire (2019); Kayamo and Ayele (2023); Mwonge and Noha (2021); Mahmud (2021); and Adigun (2022) who contended that higher age motivates rural farmers to increase borrowing. However, as farmers' age increases, their physical capacity to do farming may likely fall; thus reducing their desire to borrow money for financing production. In addition, the Wald Test of education coefficient (chi2 (2) = 18.84; p-value = 0.000) as shown in Table 1 is statistically significant (overall significance) at a 1 per cent level. However, there is a mixed result for coefficients of education categories with the SSCE/WASSCE category as a benchmark. From the results, the OND/NCE category coefficient has a negative and significant effect (at 1%) on the loan application of farmers in the study area suggesting that farmers with OND/NCE certificates are 64% less likely to demand agricultural credit compared to farmers with SSCE/WASSCE certificates with odds ratio being 0.36 and holding all other predictors constant. By implication, out of every 100 rural farmers with OND/NCE certificates, only 36 will apply for funding from formal financial institutions.

Similarly, the HND/B.Sc. category has a negative and significant effect (at 5%) on loan applications by rural farmers in the study area. The result implies that rural farmers who are graduates are 40% less likely to borrow from formal financial institutions compared to those with secondary education as the odds ratio is 0.60 and given that all other predictors remain unchanged. A very close observation of the odds ratios of OND/NCE and HND/B.Sc. categories reveal that although loan demand by rural farmers decreases with a higher level of education the reduction in loan requests starts to vanish when a rural farmer is an HND/B.Sc. graduate. The evidence obtained on the coefficient of the MSc. / MBA category buttresses this point as a higher level of education (postgraduate) improves the likelihood that a rural farmer will demand a formal loan compared to farmers with secondary education. Unfortunately, the higher impact of postgraduate education is negligible as the odds ratio shows that postgraduate rural farmers are 3% more likely to request formal loans than those with secondary education. Also, the requests are found insignificant at all significance levels. Meanwhile, the negative and significant effects of education categories (OND/NCE and HND/B.Sc.) on rural farmers' loan applications being observed are inconsistent with the study's a priori expectation. Again, these findings on education do not align with the previous results from Adamu (2018); Asiamah et al. (2021); Chivandire (2019); Daemane and Muroyiwa (2022); Mahmud (2021); Chandio et al. (2021) and Adigun (2022) who observed that higher level of education motivates rural farmers to increase their loan access. However, higher education is a motivation to seek white-collar jobs. An educated rural farmer who is more likely to be aware of a better job opportunity in his environs may decide to reduce his farming activities instead and thus limit his loan request from formal sources. This scenario might be the reason for such unexpected results on education in the study area. Meanwhile, the results confirm that in the long-run higher stage of education of rural farmers in the study area will improve loan application or any other form of credit demand from formal credit institutions.

The distance between the farmer's residence and the office of a formal credit institution is negatively related to loan applications by the sampled rural farmers. The odds ratio of 0.78 indicates that with an additional 1 kilometre covered rural farmers in the study area are 22% less likely to apply for financial assistance (either in the form of loan or credit) from formal credit institutions including microfinance banks. Transaction costs such as transportation increase when formal financial institutions are miles away from the potential users; thus, rural farmers overlook credit sources beyond their reach. This evidence is consistent with the a priori expectation and previous results by Chivandire (2019), and Mwonge and Noha (2021) that long distance as a significant factor discourages rural farmers from accessing formal financial products. The coefficient of perceived expected inflation is statistically significant at one per cent and is indicated to hurt formal loan applications by rural farmers in the study area. The result implies that as rural farmers perceive expected inflation to increase by 1% farmers are 49% less likely to apply for formal loans or credit, as highlighted by the odds ratio of 0.51 and holding all other predictors constant. At the current period, high rising levels of goods and services prices (an indicator of inflation) have become a common phenomenon among Nigerians including those in rural areas and everyone expects the surge. In anticipation of increased transaction costs, an expectation of high inflation discourages potential users from optimally accessing formal financial products and services that could have been more useful for their businesses including agriculture. This evidence of a negative relationship between perceived expected inflation and formal credit accessibility aligns with the study’s a priori expectation. However, an existing empirical study that supports or disproves the evidence of such an inverse relationship between expected inflation and formal credit accessibility among rural farmers in developing countries is rarely found in the literature owing to the authors’ information.

Moreover, this study is constrained by at least two limitations that can affect its wider application. First, the incidence of rural loan facilities availability by government and education which facilitates awareness among potential beneficiaries can be positively related. However, the ability of a smallholder rural farmer to demand a formal loan from a formal credit source supposedly depends on his inherent physical capacity to engage in farming. Thus, a correlation between loan application and inherent capacity leads to an endogeneity issue. This study fails to observe this inherent physical capacity though difficult to measure. In other words, this study provides direction for future research in this area. Second, the sole focus on rural farmers from Abeokuta North LG can limit the inferences of this study’s findings to the study area and prevent broader generalisation. Essentially, consideration of several villages in Abeokuta South

LG by future research studies can significantly help to determine the wider generalisation of this study's findings in Abeokuta as a whole and in some rural areas in South-West Nigeria with similar individual and farm characteristics. Notwithstanding, the findings of this study are reliable and efficient from two standpoints. First, the study seems to be the largest survey in the study area. Again, the study is one of the largest studies in the literature to survey over 700 smallholder rural farmers in a single study. The study ensures that all villages and smallholder farmers in the study are fairly represented; thus, stimulating greater coverage. Also, applying the binary logit estimation technique which has a better analytical capacity confirms that the inferences drawn from the study are efficient. The findings obtained have two important implications for policy interventions. First, it shows that younger smallholder rural farmers in the study area use formal financing more than older farmers. This insinuates that formal financial institutions including the government require many business policies and models that focus on young smallholder rural farmers. Second, the finding on education as a predictor of the study disproves human capital theory and upholds rational choice theory instead. It explains that an increase in education leads to a decrease in loan access among rural farmers but demand for formal credit picks again after a rural farmer obtains a postgraduate certificate specifically an MBA or Master of Science. Lastly, the high elasticity of formal loan demand caused by perceived expected inflation implies that inflation is an important economic variable that requires frequent attention by the federal administration.

6.0 CONCLUSION

This study was carried out to investigate the socioeconomic determinants of smallholder rural farmers' formal credit decisions using the binary logit model approach. Through this approach, the study identifies socioeconomic variables that affect the credit decisions of smallholder farmers in a rural setting. This research activity was conducted in a climate-friendly rural area of Abeokuta where major cash crops are abundantly produced, specifically Abeokuta North Local Government with a sample size of 768 smallholder farmers. The study findings show that getting old, additional education, longer distance and perceived expected inflation significantly reduce the likelihood that smallholder farmers in the study area apply for loans or credit from formal financial institutions. Based on this outcome, the study affirms that socioeconomic factors like age, education, distance and perceived expected inflation significantly discourage smallholder farmers in rural Abeokuta from accessing formal financial products and services. The study suggests that formal financial institutions in the Abeokuta metropolis and the government should redirect their lending models' focus to mainly young rural farmers in the study area. Again, more attention is required by the government to design and establish additional lending programmes that target less educated smallholder farmers in villages of Abeokuta North LG. At the national level, monetary and fiscal policies that effectively and timely address rising inflation levels should be implemented.

REFERENCES

Adamu, C. O. (2018). Analysis of access to formal credit facilities among rural women farmers in Ogun State, Nigeria. Nigerian Agricultural Journal, 49 (1), 109-116

Adigun, G. T. (2022) Determinants of Credit Access among Smallholder Women Farmers in Kwara State, Nigeria. Nigerian Agricultural Journal, 53 (2), 121-128

African Development Bank (2018) Africa agribusiness, a US$1 trillion business by 2030.Retrieved from https://www.afdb.org/en/news-and-events/africa-agribusiness-a-us-1trillion-business-by-2030-18678

Ameh, M. & Lee, S. H. (2022) Determinants of Loan Acquisition and Utilization among Smallholder Rice Producers in Lagos State, Nigeria. Sustainability, 14, 3900. https://doi.org/10.3390/su14073900

Apostolidou, I., Achilleas, K., Anastasios, M. & Efstratios, L. (2014) The Role of Agriculture in Economic Growth: A Comparison of Mediterranean and Northern Views in Europe, International Journal of Economic Sciences and Applied Research, 7(3), 81-102

Asiamah, T. A., Steel, W. F. & Ackah, C. (2021) Determinants of credit demand and credit constraints among households in Ghana. Heliyon, 7(10), e08162

Awotide, B. A., Abdoulaye, T., Alene, A. & Manyong, V. M. (2015) Impact of access to credit on agricultural productivity: evidence from smallholder cassava farmers in Nigeria. Paper presented at the IAAE Conference, August 9-14, Milan, Italy

Balana, B. B. & Oyeyemi, M. A. (2022) Agricultural credit constraints in smallholder farming in developing countries: Evidence from Nigeria. World Development Sustainability, 1, 1-12

Britannica (August 16, 2024). The Editors of Encyclopaedia. "Ogun". Encyclopedia Britannica. Available at https://www.britannica.com/place/Ogun-state-Nigeria/Accessed 25-December-2024.

Chandio, A. A., Jiang, Y., Rehman, A., Twumasi, M.A., Pathan, A.G. & Mohsin, M. (2021). Determinants of demand for credit by smallholder farmers': A farm level analysis based on survey in Sindh, Pakistan. J. Asian Bus. Econ. Stud., 28 (3), 225-240

Chivandire, L. (2019) Determinants of Smallholder Farmers' Access to Formal Credit: The Case of Chivi District (May 29, 2019). Available atSSRN: https://ssrn.com/abstract=3395707 or http://dx.doi.org/10.2139/ssrn.3395707

Daemane, T. & Muroyiwa, B. (2022) Factors influencing credit access for rural small-scale farmers in Lesotho: Evidence from maize farmers in Masianokeng. World Journal of Advanced Research and Reviews, 15(01), 757–768

Hosmer, D.W. & Lemeshow, S. (1989) Applied Logistic Regression. John Wiley & Sons, Inc., New York.

Kayamo , H. Y. & Ayele, G. (2023). Determinants of smallholder farmers' access to formal credit: A case of Bilate Zuria Woreda, Sidama national regional state, Ethiopia. African Journal of Economic and Business Research, 2(1), pp. 83-101. Available at: https://journals.hu.edu.et/hu-journals/index.php/ajebr/article/view/803 (Accessed: 27December 2024).

Krejcie, R. V. & Morgan, D. W. (1970). Determining Sample Size for Research Activities. Educational and Psychological Measurement. 30, 607-610

Manteaw, S. A., Folitse, B. Y., Swanzy, F. K., Agyarko-Fosuhene, F. & Mahama S. (2023) Exploring the constraints of accessing agricultural credit by small-scale oil palm processors: evidence from the Kwaebibirem municipal assembly, eastern region, Ghana. Fayoum Journal of Agricultural Research and Development, 37(2), 156 168

McKenzie, D. & Sakho, Y. (2010) Does it pay firms to register for taxes? The impact of formality on firm profitability. Journal of Development Economics, Elsevier, 91(1), 15-24

Mwoge, M. A. & Naho, A. (2021) Determinants of credit demand by smallholder farmers in Morogoro, Tanzania. Academic Journal, 17(8), 1068-1080

Ochanda, D. (2023). Factors affecting credit access from agricultural finance corporations among smallholder farmers in Lamu County [Strathmore University]. http://hdl.handle.net/11071/13420

Saka, K. A., Akinde, M. A., and Afolabi, A. R. (2023). Credit Financing and Agricultural Development in Nigeria. Archives of Business Research, 11(10). 01-15

Yeasmin, S., Haque, S., K.M. Mehedi Adnan, K.M. M. Parvin, T., Rahman, M. S., Rahman, K. M., Salman, M. & Hossain, M. E. (2024) Factors influencing demand for, and supply of, agricultural credit: A study from Bangladesh. Journal of Agriculture and Food Research, 16(16), 101173

Wossen, T., Abdoulaye, T., Alene, A., Haile, M.G., Feleke, S., Olanrewaju, A. & Manyong, A. (2017) Impacts of extension access and cooperative membership on technology adoption and household welfare. J. Rural Stud., 54, 223-233

World Bank (2013) Unlocking Africa's Agricultural Potential. Sustainable Development Series. World Bank, Washington

World Economic Forum (March 13, 2023) How Africa's new Free Trade Area will turbocharge the continent's agriculture industry. Retrieved from https://www.weforum.org/stories/2023/03

ZIPCODE (2022) List All Areas in Abeokuta: Ogun State. Retrieved from https://www.zipcode.com.ng/2022/05/list-all-areas-inabeokuta.html#google_vignette

Appendix

List of Randomly Selected 146 Villages

1. Abule Oba; 2. Abule Ojo; 3. Adelabu; 4. Ajegunle; 5. Akiegun; 6. Alagbede; 7. Alowo Esin; 8. Apata-Oke odo; 9. Aragudu; 10. Arobajo; 11. Asipa; 12. Atoku; 13. Baba Ellegun; 14. Dasofunjo; 15. Fagbenro; 16. Fapota; Idera; 17. Idi Ori; 18. Idiemi; 19. Ijala Orile; 20. Ijaye

Volume: 08, Issue: 02 March - April 2025

ISSN 2582-0176

Oke Odo; 21. Ilugun Orile; 22. Ope Oluwa Village; 23. Iwelode; 24. Iwofin; 25. Iyalode Tibo; 26. Kesan; 27. Kesan Orile; 28. Kojala; 29. Moloso; 30. Odango; 31. Ogbon Elegba; 32. Ogenne; 34. Ogunte; 35. Ojo; 36. Ojubo Lade; 37. Ojubu Akinwande; 38. Ojugbele; 39. Ojumo; 40. Okooko; 41. Oloko; 42. Olorunda Market; 43. Olukosi; 44. Omilende; 45. Onlado; 46. Oyan Lawn; 47. Sangowole; 48. Tofi; 49. Yawo; 50. Are Elebute; 51. Abese; 52 Abesin Oke; 53. Abomolaso; 54. Abule-Aje; 55. Sabo Area; 56. Abule Adelanwa; 57. Abule Nla; 58. Abule Ohori; 59. Abule Oko; 60. Abule Olowun; 61. Abule Owe; 62. Abule Titun Village; 63. Adeleye; 64. Adeyori; 65. Afagba; 66. Afonja; 67. Agarawu; 68. Agbawo; 69. oja Agbo; 70. Agunmona; 71. Ajana; 72. Akala; 73. Akere; 74. Akinmade Oloro; 75. Akinwunmi; Akiode; 76. Akomoje; 77. Alapako Idi-Emi; 78. Alapo; 79. Alaru; 80. Amukankan; 81. Anifa; 82. Anigbagbo; 83. Anima-Saun; 84. Apana; 85 Apo-Owu; 86. Araromi - Aiyetoro; 87. Aro village; 88. Aseeso; 89. Ata; 90. Atapa Ishaga; 91. Ate; 92. Babalogun; 93. Banjoko; 94. Base Olodi; 95. Bosero; 96. Dasogunjo; 97. 98. Ekefun; 99. Ekerin; 100. Eko; 100. Elepo; 102. Eruku; 103. Fafunke; 104. GAA; 105. Gbolaku; 106. Gbomolese; 107. Gbopa; 108. Iwo, 109. Idere; 110. Idi emi; 111. Idi Igba; 112. Idi-Iya/Onisasa; 113. Lanlowo; 114. Idofin; 115. Igbo - Aje; 116. Igosun; 117. Ija Ofa,Ikeye; 118. Ijaiye Deyorin; 119 Ika Ajibefun; 120.Ika Oloba; 121 Ila -Olona; 122. Ilakan; 123. Ita - Kinoshi; 124. Ita Balogun; 125. Oke Iddo; 126 Iyaye Obirintin,; 127. Jebode; 128. Keere; 129. Km 3 (mile 2 -a Stream); 130. Kukudi; 131. Kumapayi; 132. Layeni; 133. Lukosi; 134. Makinde; 135. Malomo; 136. Ogboye;137. Ogongo; 138. Ogungbade; 139. Ojangangagan; 140. Ojokodo/Ijaye; 141. Oke Oko; 142. Oke Pape; 143. Olorogun Village; 144. Olose; 145. Olowo Odunjo; 146. Oniyanrin village.

Source: Authors' Compilation (Names of Villages culled from Wikipedia, 2024)

