JEL: Q12, Q14, C25

Jisha K K[1], Prashobhan Palakkeel[2]

[1]Government College Chittur
[2]Amrita Vishwa Vidyapeetham
India

AVAILABILITY OF AGRICULTURAL CREDIT: DETERMINANTS, MARGINAL EFFECT, AND PREDICTED PROBABILITY

Purpose. *This paper aims to identify the major determinants of agricultural credit and their marginal effects, along with describing the pattern of the predicted probability of getting credit from the agricultural credit cooperatives.*

Methodology / approach. *We used a multi-stage stratified random sampling method to collect data from the paddy farmers of Kerala, India. Descriptive statistics are used to describe the profile of the farmers. Ordered logistic and probit regression models are used to model the credit categories. The authors analyzed the determinants of credit and their marginal effect, while the pattern of the predicted probability is described using tables and graphs.*

Results. *Results show that age, household size, farming experience, and farm size significantly influence the probability of a farmer falling into a particular credit category. However, the estimated coefficients of other factors, like gender and occupation, are not statistically significant. The results from the study clearly show that relatively large paddy farms are not getting enough credit from the cooperatives, contrary to the common perception. An evaluation of the predicted probabilities shows that the very high and shallow categories are much more dispersed than the middle categories.*

Originality / scientific novelty. *This is the first study that describes the predicted probability of credit availability pattern from the agricultural credit cooperatives to the paddy farmers. Moreover, this study describes the determinants and their marginal effects by credit category.*

Practical value / implications. *The results indicate the probability of a farmer falling into a specific credit category based on his/her characteristics or background. The results can help them frame a strategy while approaching a credit cooperative for a loan. The inverse relationship between age and the likelihood of getting higher credit amounts requires government policy intervention. It will be hard for farmers to continue farming while aging if they do not get sufficient credit. The government must develop policies to counteract the influence of age on credit availability, like special schemes for older age groups.*

Key words: *agricultural credit availability, co-operative banks, predicted probability, ordered logit, ordered probit, Heckman's model.*

Introduction and review of literature. Agricultural credit is the basis of agricultural activities, particularly in low-income economies (Afande, 2015; Denkyirah et al., 2016), as its availability improves the financial capacity of farmers and helps them adopt new technologies and other required inputs, which can eventually result in increased productivity (Nkegbe, 2018). Modernization through technology adoption, which results in improvements in agricultural efficiency, is one of the critical aspects of development facilitated by agricultural credit (Mohamed, 2003). Access to credit plays a crucial role in the lives of disadvantaged farmers because it assists them in facing different types of disasters like famine, illness, natural calamities, and financial crises; hence, it ensures their food security, poverty reduction, and enhanced welfare conditions (Reyes & Lensink, 2011) and helps households to smooth their consumption pattern, especially during income losses due to job loss or others (Seefeldt, 2015).

Even though the role of agricultural credit in development is well-established, in the rural areas of many developing countries, farmers struggle with significant credit shortages because of the difficulties in accessing credit from formal institutions (Sekyi et al., 2017; Tang & Guo, 2017). Credit constraints affect farmers with lower-asset bases than more considerable assets (Kumar et al., 2013). Inadequate collateral and lack of permanent sources of income are the major obstacles for smallholder farmers in accessing formal credit (FAO, 2015). They usually get informal sources of credit, like moneylenders. The distinct practices of moneylenders drag small farmers into the perpetual debt trap (Rajeev & Deb, 1998) and cause dependency and abasement (Manig, 1990). The dynamic presence of formal credit institutions in rural areas can extensively reduce dependence on informal credit and augment production and productivity in the agriculture sector (Narayanan, 2016); their creation is necessary for the development of villages.

Understanding the importance of agricultural credit, countries around the world have developed a variety of institutional alternatives. In India, the earlier institutional settings adopted for efficient rural credit deployment include the receipt of the All-India Rural Credit Survey Committee Report (1954), the nationalization of banks (1969 and 1980), the formation of the National Bank for Agriculture and Rural Development (1982), the launching of Kisan Credit Cards (1998–1999), etc. Even though these institutional arrangements positively contributed to the flow of agricultural credit and helped build up an overall institutional structure for rural credit delivery, several issues still need to be addressed regarding the adequacy of agricultural credit in India. Considering the importance of agricultural credit in rural development and its severe shortage amidst formal and informal institutional alternatives, this paper aims to identify the determinants of credit provided by the agricultural credit cooperatives, their marginal effect, and the predicted probability among the paddy farmers in Kerala, India.

Subsequently, these governments in developing countries established many institutions to compensate for credit supply disasters due to market imperfections. Generally, the amount available for credit supply in the market is directly related to the economic environment existing in the country, and it will vary according to its economic fluctuations. When asymmetries arise due to market imperfection or uncertainty, formal credit institutions like commercial banks will be reluctant to provide credit (Mushinski, 2007). The role of credit cooperatives is critical under such circumstances as they are specialized institutions that focus on the credit requirements, even during market imperfection, of specific groups of customers like farmers.

In developing countries, credit cooperatives are generally supported by the government or central bank. Usually, members of them have access to credit unless they are defaulters. However, credit rationing is a common dilemma associated with credit cooperatives. Asymmetric information, moral hazard, and acquaintance (lender-borrower relationship) are associated with credit rationing (Petrick, 2005). Although extensive literature exists on agricultural credit and related issues, studies on credit rationing specific to credit cooperatives are relatively rare.

Grohmann et al. (2018) examine financial inclusion across 141 countries, and their study results show that access to finance is largely dependent on financial literacy. Moreover, financial infrastructure and financial literacy can be considered perfect substitutes among the determinants of financial access.

Nkegbe (2018) identifies that education level, age, savings, parents' occupation, etc., influence the credit availability of young farmers in Ghana. Organizational delays in application processing and loan disbursement create constraints for them in accessing credit, eventually affecting their participation in agriculture activities. A study by Asante-Addo et al. (2017) in the Brong-Ahafo region of Ghana reveals that a level of education of the head of the household, membership in farmer organizations, income level, etc., significantly influence the availability of agricultural credit. Sekyi et al. (2017) examine farmers' access to credit in Ghana's northern savannah ecological zone. The results from the study show that age, literacy rate, farm assets, membership in agricultural groups, etc., influence farmers' access to credit. Credit-constrained families' size, household assets, locality, and group membership significantly affect their credit status.

Adjognon et al. (2017) identify the determinants of agricultural input credit demand in four countries in sub-Saharan Africa. The results show that the gender and education level of the household's head, land holding, size of livestock, crop pattern, cropping region, amount of rainfall, market accessibility, etc., significantly influence input purchases and credit requirements.

Ali & Awade (2019) evaluate credit constraints of soybean farmers in Tongo. There is a significant difference between the constrained and unconstrained farmers regarding their education level and the amount of output sold in the market. Gender is an important factor that influences credit accessibility apart from socio-economic characteristics. The results show that the credit available to them is significantly influenced by their age, type of crop, and their membership in agriculture organizations. In a similar attempt, Ojo & Baiyegunhi (2020) evaluate the determinants of credit constraints among rice farmers in South-West Nigeria. They segregate the constraints into three categories: volume, price, and risk related. Access to improved crop categories significantly affects all three categories. Age influences the risk and price constraints. Location influences risk and price constraints. Credit source influences risk and quantity constraints. Apart from other variables, age, distance to credit source, and annual interest rate also affect the risk constraints.

Chandio et al. (2017) examine the farmers' access to credit in the Sindh region of Pakistan. The study results showed that gender, household size, educational level, farming experience, farm size, income, and collateral availability affect the farmers' credit access. Akhtar et al. (2019) examine how credit access helps manage risk for maize farmers in the Punjab province of Pakistan. According to the study, farming experience, farm size, perceptions of price, biological risks, and risk attitude of farmers significantly influence access of the farmers to agricultural credit. In a previous study conducted in this region, Elahi et al. (2018) identified that farmers with lower education levels face difficulty in accessing agricultural credit.

Saqib et al. (2018) try to understand the significant factors affecting credit access of the farmers in Pakistan's Khyber Pakhtunkhwa areas. According to the study, education level, experience in farming, monthly income, family size, total landholding, and proportion of owned land are the major factors that affect the accessibility of credit. Another study by Ullah et al. (2020) in the same area reveals that adopting new technologies, land size, farm income, availability of collateral, financial literacy, etc., also significantly influences their access to agricultural credit.

Kumar et al. (2017) examine access to agricultural credit from formal institutions in India based on a national representative survey. The results show that age, educational qualification, caste, occupation, and land size are common determinants for households accessing credit. Kaur & Kapuria (2020) observe that the accessibility of institutional credit for the household head is much easier if it is a male. Education levels, household expenditure, size of the land holding, availability of irrigation facilities, bank membership, and caste significantly influence credit accessibility by females in rural India. Chanda (2020) explores the trends in agricultural credit access in India through Kissan Credit Card (KCC) scheme. Farmers from the states with a history of higher levels of agricultural lending continue to access higher credit levels through the KCC scheme. The study also reveals the presence of reverse causation, as the states with higher levels of agriculture growth access more credit than others.

Tang & Guo (2017) analyze the credit demand in rural China from formal and informal sources. The results show that the age and gender of the household head, household size, education, land endowment, distance to the bank, etc., significantly affect the size of the credit. Moreover, some of these variables are critical in choosing between formal and informal sources of credit.

After reviewing the literature, Linh et al. (2019) list socioeconomic factors which influence the access of households to rural credit markets in developing countries, that include the size of the family, the income of the family, size of the landholding, age, gender, and education level of the household head, etc. In Vietnam, they observed some additional determinants, including ethnicity, community, and livestock value.

In practice, there is a significant difference between accessibility and the availability of sufficient credit. The amount of credit available for agricultural activities significantly affects various dimensions of agriculture activities, like scale and technology adoption in farming. However, most studies have not yet addressed the issue of credit availability (amount of credit) explicitly in their studies. From the lender's side, credit rationing can be based on the factors that maximize their utility (rather than profit, as we consider only the case of agricultural credit cooperatives), and borrowers have almost no information about this. More attempts are required to explore the scenario in detail, particularly regarding cooperative banks. On the other side, indicating the amount of credit available is essential information while planning and preparing for cultivation from the farmers' perspective. So, the present study also aims to depict the pattern of the predicted probability of the available credit after identifying its determinants. The literature review shows that the agrarian conditions of small-scale paddy farmers in rural India are similar to those in rural areas of many other countries in Asia and Africa. So, the scope of the study could be extended further.

The purpose of the article. This paper aims to identify the major determinants of agricultural credit and their marginal effects, along with describing the pattern of the predicted probability of getting credit from the agricultural credit cooperatives.

Methodology. In the literature, credit availability is generally addressed in the framework of credit rationing models (Baltensperger & Devinney, 1985). In one of the earliest attempts, Hodgman (1960) tried to explain the persistence of credit rationing in a rational equilibrium model. Later, these models are further extended by incorporating risk aversion and moral hazard aspects. Jaffee & Modigliani (1969) and Jaffee (1971) provided a model of non-price rationing in which equilibrium conditions can be approximated to a monopoly model with very few contracts (Baltensperger & Devinney, 1985).

The borrower-lender problems are incorporated into the micro models by introducing information asymmetry, adverse selection, and moral hazard in the later years. Especially the works of Akerlof (1970), Jafee & Russel (1976), Keeton (1979) and Stiglitz & Weiss (1981) helped in developing models beyond institutional constraints. Models developed in the later stages have incorporated customer-lender relationships in explaining the issue of rationing (Koskela, 1976; Flannery, 1983).

A methodological survey on credit rationing in agriculture (Petrick, 2005) shows that most of the recent empirical studies use qualitative information and econometric models to identify the determinants of credit supply based on survey data. While their results expose the importance of many factors in determining credit access and affordability, their relative importance is largely determined only locally. Although their impact varies across studies, important factors that affect accessibility or availability of agricultural credit include age, caste, education, marital status, household size, years of experience in agriculture, land size, gender, contacts, awareness etc.

Most studies have scrutinized credit availability from commercial banks, and only a few tried to evaluate the scenario under alternative credit institutions like cooperative banks or agricultural credit societies. Many differences exist between these two types of organizations while framing their objectives (role of interest rate, profit ratio, etc.). Most studies on credit accessibility, credit demand, or participation in credit programs are conducted based on primary surveys and follow similar analytical frameworks. Many studies evaluated the credit program's participation status (yes or no) and its determinants (Chandio et al., 2017; Ouattara et al., 2020). These studies used binary Probit or Logit models because of the nature of the target variable (binary). Some studies explicitly addressed the problem of truncation in the observations primarily because of the non-applicants for credit on the list. These studies used the framework of Heckman (Asante-Addo et al., 2017) or a simple Tobit model. Some studies used linear regression models (Enimu et al., 2017; Grohmann et al., 2018), while others employed alternative frameworks (Ullah et al., 2020).

The present study tries to address the issue of credit availability in an elaborated framework by incorporating the credit category by volume. The targeted variable in this study is the credit category of the farmer. As it is an ordered variable, an ordered regression model will be the most suitable for studying the relationship among the variables (Nouman et al., 2013). Ordered logistic and probit regression models can be used (Long & Freese, 2014). In our case, the dependent variable is credit availability at four levels (category). To summarize, here we portray the basics of the ordered logistic model only.

$$Pr\left(credit\ category_j = i\right) = Pr\left(C_{i-1} < \beta_1 x_{1j} + \beta_2 x_{2j} + \cdots + \beta_c x_{cj} + \varepsilon_j \le C_j\right), \qquad (1)$$

where the residual ε_j is assumed to be logistically distributed. The coefficients (β_1, $\beta_2, \ldots, \beta_k$) and the cut points ($C_1, C_2, \ldots, C_{k-1}$) are estimated together. Where "c" denotes the number of possible outcomes.

We assume our model is a proportional odds model in which the odds $(c) = P\ (Y \le c) : P(Y > c)$, then odds ($c1$) and odds ($c2$) have the same ratio for all independent variable combinations.

The coefficients and cut points are estimated using maximum likelihood. Category i = 1 is defined as the minimum value of the variable, i = 2 as the next ordered value, and so on, for the empirically determined c categories.

The probability of a given observation for ordered logit is:

$$p_{ij} = \Pr\left(y_j = i\right) = \Pr\left(C_{i-1} < X_j\beta + \varepsilon \le C_i\right) = \\ = \frac{1}{1+\exp\left(-C_i + X_j\beta\right)} - \frac{1}{1+\exp\left(-C_{i-1} + X_j\beta\right)}\ , \qquad (2)$$

where C_0 is defined as $-\infty$ and Ck as $+\infty$.

The log likelihood is:

$$ln\ L = \sum_{j=1}^{N} w_j \sum_{i=1}^{c} I_i\ (y_j) ln\ p_{ij}\ , \qquad (3)$$

where w_j is an optional weight and

$$I_i(y_i) = \begin{cases} 1, if \quad y_i = i \\ 0, otherwise \end{cases}. \qquad (4)$$

For the general model, credit category (y_i) is the dependent variable. The determinants are age, gender, household size (HH_size), farming experience (Farm_exp), size of the farm (Farm_size), farm size category (Farm_xcat), education (edu), occupation, farm asset (Farm_asst), income from agriculture (Agri_inc), income from other sources (other_inc), total income (Tot_inc), and income category (Inc_cat).

The general model will be revised based on the specifications test results and the significance of the estimated coefficients.

R version 4.2.2 and STATA version 15 are the software used for data analysis and model building.

Data and Sampling. A multi-stage stratified random sampling method was used to collect data from the paddy farmers in Kerala in 2019–2020. In the first stage, the selection of the district is made based on the critical agrarian features existing in the Palakkad district, especially in paddy cultivation. Out of six taluks[1] in the Palakkad district, three taluks, namely Palakkad, Alathur, and Chittur, are selected based on the area under cultivation and production. Primary agriculture cooperative societies (PACS) selection is made in the third stage. There is a total of 54 PACS in the taluks of Alathur (15), Chittur (20) and Palakkad (19). Out of the 54, 42 PACS are qualified for the sample selection. 13 PACS from Palakkad taluk, 14 PACS from Alathur taluk, and 15 PACS from Chittur taluk are qualified based on the criteria of providing loans to the paddy farmers. Three PACS from each taluk are selected using the lottery method. Farmers are selected from the list of all borrowers shown in the ledger of the nine chosen PACS. The total numbers of net borrowers are 2821 in the ledger. To adequately represent all types of farmers, the holdings of the selected borrowers are classified into three groups or three strata based on the size of their operational holdings. For such classification, we followed the methods adopted by the All-India Rural Credit Survey and the All-India Rural Debt and Investment Survey of the Reserve Bank of India. The type of different groups of holding is as follows:

Strata I – Up to 1.00 hectares (Small Farmers);
Strata II – 1.01 to 2.00 hectares (Medium Farmers);
Strata III – 2.01 hectares and above (Large Farmers).

In the final stage, 10 % of farmers from each stratum are selected randomly. A structured questionnaire is used for collecting the information.

The amount of credit available to the farmers and its determinants are the primary focus of this study. During the pilot study, we observed that credit is deployed in a few categories. It is customary to issue the loan in the class by the agencies than fixing the amount at an individual level. Although, some farmers reported minor variations (randomly) in the amount received in each category. The amount of credit available to the farmer is the dependent variable in the study. We received a balanced sample with a similar number of farmers in each credit category. The data set has been examined thoroughly and cleaned following standard procedures. The final data set has 282 observations (Table 1).

Results and discussion. *Exploratory Data Analysis.* Among the 282 farmers, 164 are from small, 90 are from medium, and 28 are from large holding groups. The socioeconomic and demographic profiles of the farmers are presented in Table 2 by their age, sex, educational status, farming experience, and family size to reveal the

[1] "A taluk is a local unit of administrative division in some countries of South Asia, such as India, Pakistan, Bangladesh, and Nepal". Available at: https://en.wikipedia.org/wiki/Tehsil.

demographic characteristics of the surveyed.

Table 1

Final distribution of sample farmers across size of holding

Size of Holding	Taluk								
	Alathur Taluk			Chittur Taluk			Palakkad Taluk		
	PACS			PACS			PACS		
	1	2	3	4	5	6	7	8	9
Up to 1 hectare	33	18	12	20	15	20	22	12	12
1–2 hectare	10	11	5	16	4	11	15	10	8
Above 2 hectares	3	3	2	5	3	4	3	3	2
Total Borrowers	46	32	19	41	22	35	40	25	22
Total of Taluk	97			98			87		
Grand Total	282								

Source: developed by the authors.

Among the factors, it is found that 70 % of farmers are within the age group of 50–70. In the case of large farmers, it is seen that the majority belongs to the age group of 50–60. Thus, we may infer that the paddy cultivators are relatively aged and the younger generation is not very much attracted to the farming operations. This is underlined by the findings of the National Commission on Farmers that submitted the report in 2006.

The gender-wise classification reveals that 85 % of respondents are males belonging to small farmers. The same trend is seen among large farmers. In the case of medium farmers, about 90 % of the respondents are males. Thus, it highlights that those agricultural activities are prepared mainly by males. This may be because in many households men are the only earning members of the family and in some cases the property that is pledged as collateral for the loan is in the name of the head of the household or the earning member.

Education is considered an essential determinant of the nature and behavior of farmers as it can influence his/her borrowing habit, use of credit, and repayment. In general, well-educated farmers are likely to be non-defaulters because they are supposed to be aware of the consequences of defaulting on loans (Panda, 1985). It is found that over 88.6 % are literates among the surveyed farmers, and the percentage up to primary, high school, plus two, and degree is 57.8 %, 18.8 %, 9.2 %, and 2.8 %, respectively. Across size groups, large farmers are better educated than small farmers.

It is evident that most farmers are engaged primarily in agriculture activities and are deriving a significant source of income from agriculture as against the general picture of agriculture being delegated as a secondary source of income in Kerala. Further, it can be seen in Table 1 that the sample farmers had relatively long farming experience, as 86.9 % of the farmers were engaged in the farming as their main occupation for 21–40 years. This might be attributed to the fact that land ownership rests with the farmers, who are found to lack knowledge and skill in other occupations confining them to the farming vocation.

For family size, the majority (75.1 %) of respondents have a family size of four or above. This is true for small and medium farmers, which accounted for 74.4 % and 77.8 %, respectively. However, about 85.7 % of large farmers have less than four members in the family. It suggests that the majority of farmers still follow the pattern which has been seen in the early stages of development.

Table 2

Socio-economic and demographic profile of sample farmers

Variables	Size of the farm			Total (N = 282)
	Small (N = 164)	Medium (N = 90)	Large (N = 28)	
Age Group				
30–40	10 (6.1)	3 (3.3)	0 (0.0)	13 (4.6)
41–50	23 (14.0)	17 (18.9)	7 (25.0)	47 (16.7)
51–60	66 (40.2)	32 (35.6)	12 (42.9)	110 (39.0)
61–70	53 (32.3)	28 (31.1)	7 (25.0)	88 (31.2)
Above 70	12 (7.3)	10 (11.1)	2 (7.1)	24 (8.5)
Gender				
Male	139 (84.8)	81 (90.0)	24 (85.7)	244 (86.5)
Female	25 (15.2)	9 (10.0)	4 (14.3)	38 (13.5)
Education				
Illiterate	28 (17.1)	4 (4.4)	0 (0.0)	32 (11.3)
Primary	79 (48.1)	65 (72.2)	19 (67.9)	163 (57.8)
High School	36 (22.0)	13 (14.5)	4 (14.3)	53 (18.8)
Plus Two	21 (12.8)	4 (4.4)	1 (3.6)	26 (9.2)
Degree	0 (0.0)	4 (4.4)	4 (14.3)	8 (2.8)
Farming Experience				
Up to 10	2 (1.2)	2 (2.2)	1 (3.6)	5 (1.8)
11–20	3 (1.8)	4 (4.4)	1 (3.6)	8 (2.8)
21–30	30 (18.3)	15 (16.7)	4 (14.3)	49 (17.4)
31–35	73 (44.5)	40 (44.4)	12 (42.9)	125 (44.3)
36–40	39 (23.8)	22 (24.4)	10 (35.7)	71 (25.2)
41–45	17 (10.4)	7 (7.8)	0 (0.0)	24 (8.5)
Family Size				
1–2	41 (25.0)	19 (21.1)	10 (35.7)	70 (24.8)
3–4	81 (49.4)	45 (50.0)	14 (50.0)	140 (49.6)
5–6	41 (25.0)	25 (27.8)	3 (10.7)	69 (24.5)
Above 6	1 (0.6)	1 (1.1)	1 (3.6)	3 (1.1)
Total Income Category				
I	7(4.0)	59(66.0)	25(89.0)	91(32.3)
II	57(35.0)	30(33.0)	3(11.0)	90(32)
III	92(56.0)	1(1.0)	0(0.0)	93(33)
IV	8(5.0)	0(0.0)	0(0.0)	8(0.03)

Note. Values in the parentheses are respective percentage values.

Source: developed by the authors.

The total family income per annum reported by most farmers is relatively small. Only seven farmers reported an income level above two lakh per annum. To describe the scenario, we categorized these farmers based on income. If we keep the eight farmers (outliers) as a separate category, the average income reported by the other three categories (low, middle, and high on a relative scale) is Rs. 58774.63, Rs. 84528.96 and Rs. 129987, respectively. If we leave the outliers, the average income of the families is less than one lakh rupees (Rs. 91404.7). Contrary to the expectation, small farmers reported higher revenue levels than large farms. These small income figures indicate the economically backward condition and severe challenges paddy farmers face.

Table 3 shows that the small farmers received higher credit levels than the large farmers. The average amount of credit reported in the four categories is Rs. 46112 (category – I), Rs. 59476 (category – II), Rs. 71757 (category – III), and Rs. 89727 (category – IV). Large farmers reported receiving only a minimum amount of credit (category I). This indicates that the authorities have also used many other parameters in deciding on credit delivery.

Table 3

Association between credit category and farm size category

Indicator	Farm size category			Total
Credit category	Small	Medium	Large	
1	23	20	28	71
2	33	37	0	70
3	48	22	0	70
4	51	20	0	71
Total	155	99	28	282
Pearson Chi^2	p-value	Kendall's	tau-a	tau-b
105.1024	0.000	-	-0.2314	-0.3543

Source: developed by the authors.

Data exploration provides some detail about the inherent contradictions existing in the system of agricultural credit dispersion. As per the law, the size of individual paddy farms (or average cultivable land) in Kerala is heavily constrained. So, most of the reported farms are relatively small in size. Naturally, most farmers are not enjoying the benefits of economies of scale. One of the most contrasting observations is the relationship between credit category and farm size. The computed association coefficient is negative and statistically significant (see Table 3). The relatively larger farms could benefit from mechanization. Still, the credit constraint or the negative association indicates a lower probability.

Estimation Results. For the general model of the determinants of credit category, we considered most of the variables commonly used in the literature. We revised the model based on the significance level of the estimated coefficients and specification tests. There are four significant explanatory variables in the specific model (final). Both ordered logistic, and probit models give identical results (Table 4, 5).

To ensure randomness in the sample selection, we did a verification based on the Heckman-type sample selection model (Table 6). In the likelihood-ratio test, the estimated Chi-square value (3.4) is relatively small, and it is not statistically significant (0.100). So, we cannot reject the null hypothesis that the errors for outcome and selection are uncorrelated. We accept that the errors for outcome and selection are uncorrelated. It indicates we should use a simple ordered regression model instead of the sample-selection model.

Table 4

Estimation results from the ordered logit model

Log-likelihood = -345.31676			LR chi^2 = 91.22; p-value = 0.000			
Variables	Coefficients	Standard error	Z	p-value	95% Confidence intervals	
Age	-0.087	0.031	-2.820	0.005	-0.148	-0.027
HH_size	0.242	0.090	2.700	0.007	0.066	0.417
Farm_exp	0.170	0.055	3.060	0.002	0.061	0.278
Farm_size	-1.865	0.235	-7.920	0.000	-2.326	-1.403
/cut1	-1.743	0.775	-	-	-3.261	-0.224
/cut2	-0.320	0.765	-	-	-1.820	1.180
/cut3	0.994	0.770	-	-	-0.515	2.504
Coefficient Estimates as Odds Ratio						
Age	0.916	0.028	-2.820	0.005	0.863	0.974
HH_size	1.273	0.114	2.700	0.007	1.068	1.518
Farm_exp	1.185	0.066	3.060	0.002	1.063	1.321
Farm_size	0.155	0.036	-7.920	0.000	0.098	0.246

Source: developed by the authors.

Table 5

Ordered Probit model

Log-likelihood = -346.549			LR chi^2 = 88.76; p-value = 0.000			
Variables	Coefficients	Standard error	Z	p-value	95% Confidence intervals	
Age	-0.048	0.018	-2.650	0.008	-0.084	-0.013
HH_size	0.148	0.053	2.810	0.005	0.045	0.252
Farm_exp	0.092	0.032	2.860	0.004	0.029	0.156
Farm_size	-1.089	0.137	-7.930	0.000	-1.358	-0.820
/cut1	-1.043	0.450	-	-	-1.925	-0.162
/cut2	-0.217	0.446	-	-	-1.091	0.657
/cut3	0.565	0.448	-	-	-0.312	1.443

Source: developed by the authors.

Table 6

Heckman's sample selection with ordered regression model

Log-likelihood = -432.81 LR test of independent equations chi^2 = 3.41; p-value = 0.100			Number of observations = 282; Selected = 211 Non selected = 71; Wald chi^2 = 26.84 p-value = 0.000			
Variables	Coefficients	Standard error	Z	p-value	95% Confidence intervals	
Age	-0.037	0.016	-2.330	0.020	-0.068	-0.006
HH_size	0.112	0.043	2.570	0.010	0.027	0.196
Farm_exp	0.077	0.026	2.990	0.003	0.027	0.128
Farm_size	-0.462	0.166	-2.790	0.005	-0.787	-0.138
Age	-0.019	0.008	-2.300	0.021	-0.035	-0.003
Constant	1.746	0.477	3.660	0.000	0.810	2.681
/cut1	-0.694	0.436	-1.590	0.111	-1.548	0.160
/cut2	-0.001	0.433	0.000	0.998	-0.849	0.847
/cut3	0.575	0.432	1.330	0.184	-0.272	1.423
/athrho	-4.975	86.990	-0.060	0.954	-175.47	165.522

Source: developed by the authors.

Results from the estimation of the general model showed that coefficients of gender, occupation, farm asset, education level, and income variables are not statistically significant and do not contribute to the explanatory power of model. The revised model results are given in Table 4.

The computed Chi-square value of 91.22 with a *p*-value of 0.0000 suggests that the model is statistically significant (Table 7). The test for parallel regression or proportional odds satisfies the assumption of the ordered regression model. The estimated Chi-square value is small (7.46), and the corresponding *p*-value is very high (0.488), so we cannot reject the null hypothesis of proportionality of the odds.

Table 7

Test for parallel regression / proportional odds

Test	Chi^2	df	p-value
Wolfe Gould	3.851	8	0.870
Brant	7.459	8	0.488
Score	5.197	8	0.736
Likelihood ratio	4.759	8	0.783
Wald	5.561	8	0.696
Model	ologit	gologit	difference
AIC	704.63	715.87	-11.24
BIC	730.13	770.5	-40.38
Brant test of parallel regression assumption			
Variables	Chi^2	p-value	df
All	7.46	0.488	8
Age	2.13	0.345	2
HH_size	0.72	0.699	2
Farm_exp	1.76	0.415	2
Farm_size	4.15	0.126	2

Source: developed by the authors.

All estimated coefficients of variables are statistically significant at a 5 % level. In Table 4, coefficients are also displayed as odds ratios in the lower part. For age, the estimated coefficient is negative. This shows that for a one-year increase, the odds of getting a loan in the highest category compared to the lowest categories are 0.916, which is lower than the current state, holding all other variables constant. It indicates that aging may be perceived as a risk factor from the lender's perspective.

Household size (HH_size) contributes positively to avail higher levels of credit. Many family members may indicate the availability of labor or less dependency on others. The odds ratio of 1.273 means the possibility of getting a higher level of credit with the increase in family size.

Farming experience (Farm_exp) also helps a farmer to get a higher amount of credit. The odds ratio of 1.185 indicates a higher probability of getting the next level of credit with increased farming experience.

As mentioned earlier, the negative relationship between credit availability and the size of the farm is also reflected in the regression result. The estimated coefficients of farm size are negative.

The Pattern of the Predicted Probability. One of the main objectives of this study is to depict the pattern of the predicted probability of farmers falling into different credit categories. An evaluation of the predicted probabilities shows that the extreme types (lower and upper) are much more dispersed than the middle categories (Figure 1).

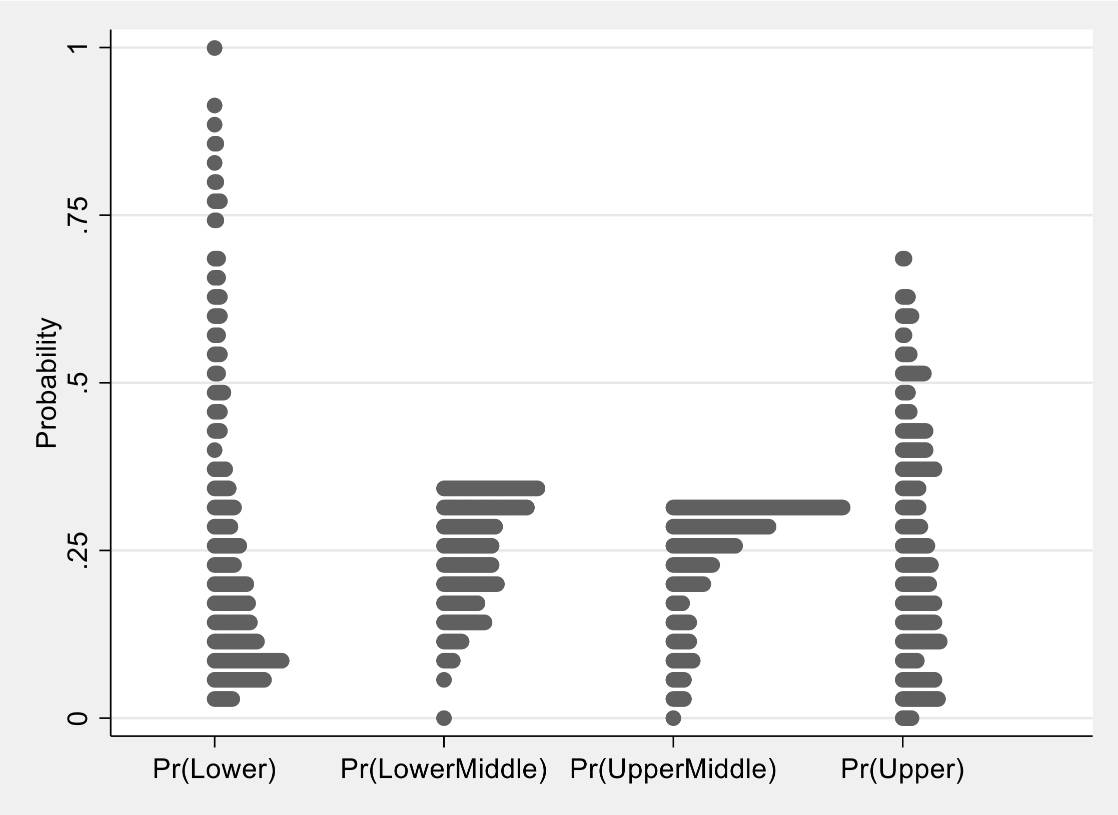

Figure 1. Predicted Probabilities

Source: developed by the authors.

In the cases of intermediate categories, most of the predictions fall between the 15 to 40 range. The data was reexamined because of the long tail in the lower credit category, but we did not find any specific issue related to that.

On average, a standard deviation increase in the age of a farmer (10 years) is associated with a 0.116 decrease in the probability of falling into the upper credit category and a 0.141 increase in the probability of falling into the lower credit category (Table 8, Figure 2a).

Similarly, on average, a standard deviation increase in farm size (0.64 acres) is associated with a 0.149 decrease in the probability of falling into the upper credit category and a 0.203 increase in the probability of falling into the lower credit category (Table 8, Figure 2b). In the case of household size, on average, an increase in the number of members is associated with an 0.041 increase in the probability of falling into the upper credit category and a 0.033 decrease in the probability of falling into the lower credit category (Table 8, Figure 2c). An increase in farming experience by a standard deviation (5.52 years) is associated with a 0.171 increase in the probability of getting into the upper credit category and a 0.111 decrease in the probability of falling into the lower credit category (Table 8, Figure 2d).

Table 8

Marginal Effect

Indicator		Credit Category			
Variable	Change	Lower	LMiddle	UMiddle	Upper
	+1	0.013	0.004	-0.003	-0.014
Age	p-value	0.005	0.004	0.021	0.003
	SD	0.141	0.024	-0.049	-0.116
	p-value	0.010	0.001	0.029	0.000
	Marginal	0.013	0.005	-0.003	-0.014
	p-value	0.004	0.005	0.019	0.004
Farm_size	+1	0.337	-0.011	-0.129	-0.197
	p-value	0.000	0.503	0.000	0.000
	+SD	0.203	0.021	-0.075	-0.149
	p-value	0.000	0.037	0.000	0.000
	Marginal	0.268	0.098	-0.064	-0.303
	p-value	0.000	0.000	0.000	0.000
HH_size	+1	-0.033	-0.014	0.006	0.041
	p-value	0.005	0.012	0.022	0.008
	+SD	-0.042	-0.018	0.007	0.053
	p-value	0.004	0.013	0.024	0.008
	Marginal	-0.035	-0.013	0.008	0.039
	p-value	0.007	0.008	0.027	0.006
Farm_exp	+1	-0.024	-0.01	0.005	0.028
	p-value	0.001	0.003	0.012	0.002
	+SD	-0.111	-0.063	0.003	0.171
	p-value	0.000	0.005	0.817	0.003
	Marginal	-0.024	-0.009	0.006	0.028
	p-value	0.002	0.002	0.012	0.002

Source: developed by the authors.

The Marginal Effects of the Determinants. In Figure 3, the horizontal axis shows the magnitude of the effects, and the letters indicate the discrete change for each outcome. The letters U, MU, LU, and L indicate upper, upper middle, lower middle, and lower credit categories, respectively. In the cases of farm size and age, the impact is more on the lower category than other categories. On the other hand, the effect is relatively higher in the cases of farm experience and household size. While considering the overall impact, changes in the farm size have the highest impact (wider), and changes in the household size have the lowest (narrow).

Discussion. As mentioned, the coefficients of only four variables from the list of determinants are statistically significant in the present study. A literature review shows mixed results while considering the sign and significance level of the coefficient estimates. As per the results from this study, the coefficient of the age of the head of the household is negative, which indicates that chance of getting a higher amount of credit decreases with the age of the head. On the part of the lenders, the level of risk increases with age. Many other studies also reported a negative coefficient (Ali and Awade, 2019; Sekyi et al., 2017; Akhtar et al., 2019).

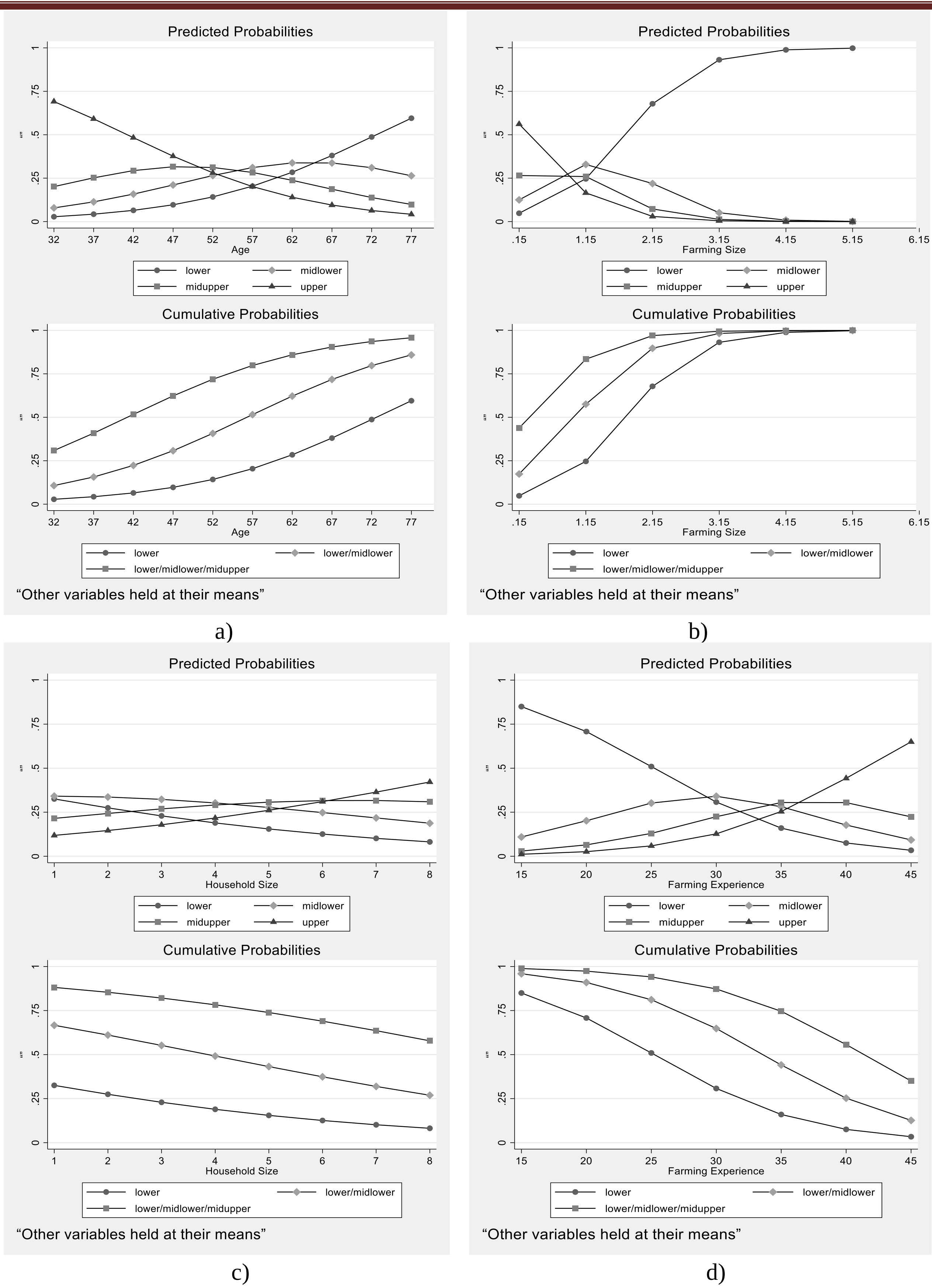

Figure 2. Predicted probability of credit category across: a) age, b) farm size, c) household size, d) farming experience

Source: developed by the authors.

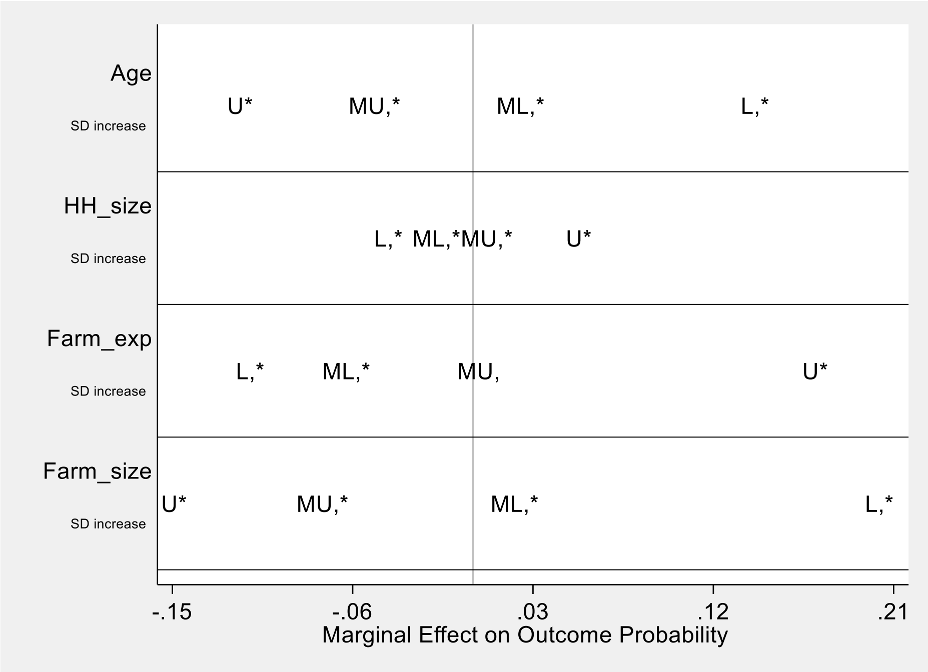

Figure 3. Marginal effect on outcome probability

Note. *Indicate that the effects are significant at a 5 % level.

Source: developed by the authors.

Generally, larger households are more capable of producing more compared to smaller ones. Larger families can easily manage diverse farming activities because of the availability of human resources. They have added advantages regarding larger social networks and information sharing. The coefficient estimate from the study is positive, as expected. Tang and Guo (2017) and Chandio et al. (2017) also reported a positive coefficient for household size, and a significant positive coefficient for household size indicates the possibility of making income from alternative sources and a lower dependency ratio.

Agricultural experience is vital as a farmer must deal with many uncertain events like climate change. So, more extended experience is considered a significant contributing factor in agriculture. Most of the studies explicitly included separate variables for age and farming experience. As a result, mixed results are reported for both variables in many studies (Chandio et al., 2017; Akhtar et al., 2019). As in this study, many of them yielded positive coefficients for farming experience. Saqib et al. (2018) mentioned that with more experience, farmers enhance their networks and association with other farmers and formal credit institutions. It could help influence getting higher credit levels in many ways. Farming experience, especially while using extension services, positively and significantly affects the loan repayment rate of small-scale farmers. More extended farming experience and participation in extension services help farmers identify and employ more productive farming techniques. It enables them to make more income and achieve a better repayment rate. So, creditors may perceive the farming experience as a positive factor while deploying the credit.

Generally, larger farms will be able to get more credit than small ones. However, recent experiences show that scale economies are not working as expected in the cases of farms in many parts of the world. Primarily, statutory ceilings (credit limits) favor small farms. The estimated coefficient for the farm size is negative. We observe this as the impact of the statutory ceiling on agricultural credit delivery and the influence of unobserved factors. We consider this to be the effect of the legal ceiling on agricultural lending and the effect of unobservable factors. We cannot find a reason to say why relatively large farmers do not get as much credit as others. Nepotism could be a reason in some cases, but it cannot be a reason to generalize. We used the Heckman model to ensure that no selection bias happened with particular reference to this context. Sebopetji and Belete (2009) also reported a negative coefficient for farm size, but the reasons are different for both studies.

Policy Recommendation. The estimated model coefficients are statistically significant, and based on test statistics, the estimated model and its predicted probability pattern can be readily accepted. The study's results indicate the probability of a farmer falling into a specific credit category based on his characteristics or background. The inverse relationship between age and the probability of getting higher credit levels shows suggests a need for government policy intervention. It will be hard for farmers to continue farming while aging if they do not get sufficient credit. The government has to develop policies to counter age's impact on credit availability, like special schemes for old age groups.

Similarly, special schemes should be made available to relatively large farmers needing more mechanization or modernization credit. Relative to the area under plantations or cash crops like tea and rubber, large paddy farms are small (the largest in the sample is 6 acres) in the Kerala context. Mechanization and modernization are required for sustainable agriculture, suitable for larger paddy farms. The government has to develop new credit policies ideal for relatively large paddy farmers to modernize their farms and enhance overall productivity.

Conclusions. Agricultural credit helps rural communities in multiple ways. Most importantly, it enhances the capability of small and medium farmers by allowing them to accommodate new farming techniques. However, in rural areas, people, especially farmers, struggle with significant credit shortages because of the difficulties in accessing credit from commercial banks. Under such circumstances, cooperative banks are crucial in agricultural credit disbursement, especially in rural areas. Only a few studies have explored the factors affecting credit availability from these notable organizations and related issues. Based on a primary survey, the present study tries to identify the determinants of the availability of agricultural credit to paddy farmers from the cooperative banks in Kerala.

The study shows that farming experience and household size positively contribute to credit availability. However, results show that aged farmers will need help getting more significant amounts of credit. Similarly, relatively larger farms will need more credit than small farms. Because of land reforms, the size of private paddy farms is already restricted by law in Kerala, and there are very limited scale economies. Under such circumstances, credit constraints faced by relatively large farms and aged people must be resolved by policy intervention.

We acknowledge some limitations, as some essential variables are excluded from the model due to the unavailability of the relevant data. Especially supply-side variables are not considered in the model. Similarly, political, social, and institutional affiliations and associations (connections or cooperative links between people or organizations) can play a vital role in these scenarios but are not incorporated into the model. Moreover, the survey is geographically binding, and the sample size is relatively small. A detailed study could address these limitations better in the future.

In many developing countries like India, the governments heavily support agricultural credit for cereals like paddy to achieve self-sufficiency and ensure food security. In some states like Kerala, the average size of the individual agricultural farms is relatively small due to the land reforms. The political and social lineages highly influence the operations of the cooperatives in many countries. Under such circumstances, future studies should focus on the cooperatives and farmers' political, social, and institutional lineages to understand the dynamics of credit deployment in more detail. As other supply-side factors are mostly limited, the relationship between customers and cooperative management could explain the variations in the amount of credit available to farmers.

References

1. Adjognon, S., G., Liverpool-Tasie, L. S. O., & Reardon, T. A. (2017). Agricultural input credit in Sub-Saharan Africa: telling myth from facts. *Food Policy*, 67, 93–105. https://doi.org/10.1016/j.foodpol.2016.09.014.

2. Afande, F. O. (2015). The factors that affect access to credit services by small-scale sugarcane farmers in Kenya: a case of Bungoma County, Kenya. *Developing Country Studies*, 5(5), 99–114.

3. Akerlof, G. (1970). The market for lemons: qualitative uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3), 488–500. Available at: https://viterbi-web.usc.edu/~shaddin/cs590fa13/papers/AkerlofMarketforLemons.pdf.

4. Akhtar, S., Li, G., Nazir, A., Razzaq, A., Ullah, R., Faisal, M., Naseer, M. A. U. R., & Raza, M. H. (2019). Maize production under risk: the simultaneous adoption of off-farm income diversification and agricultural credit to manage risk. *Journal of Integrative Agriculture*, 18(2), 460–470. https://doi.org/10.1016/S2095-3119(18)61968-9.

5. Ali, E., & Awade, N. E. (2019). Credit constraints and soybean farmers' welfare in subsistence agriculture in Togo. *Heliyon*, 5(4), E01550. https://doi.org/10.1016/j.heliyon.2019.e01550.

6. Asante-Addo, C., Mockshell, J., Zeller, M., Siddig, K., & Egyir, I. S. (2017). Agricultural credit provision: what really determines farmers' participation and credit rationing? *Agricultural Finance Review*, 77(2), 239–256. https://doi.org/10.1108/AFR-02-2016-0010.

7. Baltensperger, E., & Devinney, T. M. (1985). Credit rationing theory: a survey and synthesis. *Journal of Institutional and Theoretical Economics*, 141(4), 475–502. http://www.jstor.org/stable/40750797.

8. Chanda, A. (2020). Evaluating the Kisan credit card scheme: some results for Bihar and India. *Journal of Economic Theory and Practice*, 19(1), 68–107. https://doi.org/10.1177/097674791987.

9. Chandio, A. A., Jiang, Y., Wei, F., Rehman, A., Liu, D., & Aye, G. (2017). Famers' access to credit: does collateral matter or cash flow matter? – Evidence from Sindh, Pakistan. *Cogent Economics and Finance*, 5(1), 1369383. https://doi.org/10.1080/23322039.2017.1369383.

10. Denkyirah, E. K., Okoffo, E. D., Adu, D. T., Aziz, A. A., Ofori, A., & Denkyirah, E. K. (2016). Modeling Ghanaian cocoa farmers decision to use pesticide and frequency of application: the case of Brong Ahafo Region. *SpringerPlus*, 5, 1113. https://doi.org/10.1186/s40064-016-2779-z.

11. Elahi, E., Abid, M., Zhang, L, Haq, S., & Sahito, J. G. M. (2018). Agricultural advisory and financial services; farm level access, outreach and impact in a mixed cropping district of Punjab, Pakistan. *Land Use Policy*, 71, 249–260. https://doi.org/10.1016/j.landusepol.2017.12.006.

12. Enimu, S., Eyo, E. O., & Ajah, E. A. (2017). Determinants of loan repayment among agricultural microcredit finance group members in Delta state, Nigeria. *Financial Innovation*, 3, 21. https://doi.org/10.1186/s40854-017-0072-y.

13. FAO (2015). Country fact sheet on food and agriculture policy trends – Ghana. FAO, Rome. Available at: www.fao.org/3/a-i4490e.pdf.

14. Flannery, M. (1983). Enforcing implicit contracts: an application to the theory of banking. *Working Paper*. The Wharton School, University of Pennsylvania.

15. Grohmann, A., Klühs, T., & Menkhoff, L. (2018). Does financial literacy improve financial inclusion? Cross country evidence. *World Development*, 111, 84–96. https://doi.org/10.1016/j.worlddev.2018.06.020.

16. Hodgman, D. (1960). Credit risk and credit rationing. *Quarterly Journal of Economics*, 74(2), 258–278. https://doi.org/10.2307/1884253.

17. Jaffee, D. M. (1971). Credit rationing and the commercial-loan market. Wiley, New York.

18. Jaffee, D. M., & Modigliani, F. (1969). A theory and test of credit rationing. *American Economic Review*, 59(5), 850–872.

19. Jaffee, D., & Rüssel, T. (1976). Imperfect information, uncertainty, and credit rationing. *Quarterly Journal of Economics*, 90(4), 651–666. https://doi.org/10.2307/1885327.

20. Kaur, S., & Kapuria, C. (2000). Determinants of financial inclusion in rural India: does gender matter? *International Journal of Social Economics*, 47(6), 747–767. https://doi.org/10.1108/IJSE-07-2019-0439.

21. Keeton, W. (1979). Equilibrium credit rationing, 1 st ed. London, Routledge. https://doi.org/10.4324/9781315207223.

22. Koskela, E. (1976). A study of bank behaviour and credit rationing. Helsinki, Suomalainen Tiedeakatemia.

23. Kumar, C. S., Turvey, C. G., & Kropp, J. D. (2013). The impact of credit constraints on farm households: survey results from India and China. *Applied Economic*

Perspectives and Policy, 35(3), 508–527. https://doi.org/10.1093/aepp/ppt002.

24. Kumar, A., Mishra, A. K., Saroj, S., & Joshi, P. K. (2017). Institutional versus non-institutional credit to agricultural households in India: evidence on impact from a national farmers survey. *Economic Systems*, 41(3), 420–432. https://doi.org/10.1016/j.ecosys.2016.10.005.

25. Linh, T. N., Long, H. T., Chi, L. V., Tam, L. T., & Lebailly, P. (2019). Access to rural credit markets in developing countries, the case of Vietnam: a literature review. *Sustainability*, 11(5), 1468. https://doi.org/10.3390/su11051468.

26. Long, J. S., & Freese, J. (2014). Regression models for categorical dependent variables using stata, 3rd ed. College Station, Stata Press.

27. Manig, W. (1990). Formal and informal credit markets for agricultural development in developing countries – the example of Pakistan. *Journal of Rural Studies*, 6(2), 209–215. https://doi.org/10.1016/0743-0167(90)90007-U.

28. Mohamed, K. (2003). Access to formal and quasi-formal credit by smallholder farmers and artisanal fishermen: a case of Zanzibar. Research report No. 03.6. Research on Poverty Alleviation. Mkuki na Nyota Publishers, Dar es Salaam, Tanzania.

29. Mushinski, D. W. (1999). An analysis of offer functions of banks and credit unions in Guatemala. *Journal of Development Studies*, 36(2), 88–112. https://doi.org/10.1080/00220389908422622.

30. Narayanan, S. (2016). The productivity of agricultural credit in India. *Agricultural Economics*, 47(4), 399–409. https://doi.org/10.1111/agec.12239.

31. Nkegbe, P. K. (2018). Credit access and technical efficiency of smallholder farmers in Northern Ghana: double bootstrap DEA approach. *Agricultural Finance Review*, 78(5), 626–639. https://doi.org/10.1108/AFR-03-2018-0018.

32. Nouman, M., Siddiqi, M. F., Asim, S. M., & Hussain, Z. (2013). Impact of socio-economic characteristics of farmers on access to agricultural credit. *Sarhad Journal of Agriculture*, 29(3), 469–476. Available at: https://ssrn.com/abstract=2336223.

33. Ojo, T. O., & Baiyegunhi, L. J. S. (2020) Determinants of credit constraints and its impact on the adoption of climate change adaptation strategies among rice farmers in South-West Nigeria. *Journal of Economic Structures*, 9, 28. https://doi.org/10.1186/s40008-020-00204-6.

34. Ouattara, N., Xueping, X., BI, T. B. A. Y., Traoré, L., Ahiakpa, J. K., & Olounlade, O. A. (2020). Determinants of smallholder farmers' access to microfinance credits: a case study in Sassandra-Marahoué District, Côte d'Ivoire. *Agricultural Finance Review*, 80(3), 401–419. https://doi.org/10.1108/AFR-07-2019-0075.

35. Panda, R. K. (1985). Agricultural indebtedness and institutional finance. Ashish Publishing House, New Delhi.

36. Petrick, M. (2005). Empirical measurement of credit rationing in agriculture: a methodological survey. *Agricultural Economics*, 33(2), 191–203. https://doi.org/10.1111/j.1574-0862.2005.00384.x.

37. Rajeev, M., & Deb, S. (1998). Institutional and non-institutional credit in agriculture: case study of Hugli district of West Bengal. *Economic and Political*

Weekly, 33(47/48), 2997–3002. Available at: https://www.jstor.org/stable/4407410.

38. Reyes, A., & Lensink, R. (2011). The credit constraints of market-oriented farmers in Chile. *Journal of Development Studies*, 47(12), 1851–1868. https://doi.org/10.1080/00220388.2011.579111.

39. Saqib, S. E., Kuwornu, J. K. M., Panezia, S., & Ali, U. (2018). Factors determining subsistence farmers access to agricultural credit in flood-prone areas of Pakistan. *Kasetsart Journal of Social Sciences*, 39(2), 262–268. https://doi.org/10.1016/j.kjss.2017.06.001.

40. Sebopetji, T. O., & Belete, A. (2009). An application of probit analysis to factors affecting small-scale farmers decision to take credit: a case study of the greater letaba local municipality in South Africa. *African Journal of Agricultural Research*, 4(8), 718–723.

41. Seefeldt, K. S. (2015). Constant consumption smoothing, limited investments, and few repayments: the role of debt in the financial lives of economically vulnerable families. *Social Service Review*, 89(2), 263–300.

42. Sekyi, S., Abu, B. M., & Nkegbe, P. K. (2017). Farm credit access, credit constraint and productivity in Ghana: empirical evidence from Northern Savannah ecological zone. *Agricultural Finance Review*, 77(4), 446–462. https://doi.org/10.1108/AFR-10-2016-0078.

43. Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *American Economic Review*, 71, 393–410. Available at: https://www.jstor.org/stable/1802787.

44. Tang, S., & Guo, S. (2017). Formal and informal credit markets and rural credit demand in China. *4th International Conference on Industrial Economics System and Industrial Security Engineering (IEIS)*, (pp. 1–7). Kyoto, Japan. https://doi.org/10.1109/IEIS.2017.8078663.

45. Ullah, A., Mahmood, N., Zeb, A., & Kächele, H. (2020). Factors determining farmers' access to and sources of credit: evidence from the Rain-Fed Zone of Pakistan. *Agriculture*, 10(12), 586. https://doi.org/10.3390/agriculture10120586.

Citation:

Стиль – ДСТУ:

Jisha K. K., Palakkeel P. Availability of agricultural credit: determinants, marginal effect, and predicted probability. *Agricultural and Resource Economics*. 2023. Vol. 9. No. 4. Pp. 5–25. https://doi.org/10.51599/are.2023.09.04.01.

Style – APA:

Jisha, K. K., & Palakkeel, P. (2023). Availability of agricultural credit: determinants, marginal effect, and predicted probability. *Agricultural and Resource Economics*, 9(4), 5–25. https://doi.org/10.51599/are.2023.09.04.01.