WORKING PAPER 306/2026

Financing the Fields: An Empirical Analysis to Understand the Access to Formal Credit in Indian Agriculture

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June 2026

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Price : Rs. 35

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Abstract

Access to formal credit plays a crucial role in enhancing agricultural productivity and mitigating risks in rural India. Despite sustained policy interventions, a significant share of agricultural households continues to rely on informal credit sources, often under unfavorable terms. This study investigates the determinants of formal credit access in Indian agriculture using unit-level data from the 77th Round of the National Sample Survey (NSS) on the Situation Assessment of Agricultural Households, covering the 2018–19 agricultural year and comprising around 58,000 rural households. The analysis addresses three core dimensions: (i) household-level determinants of the percentage share of formal loans, (ii) factors influencing the likelihood of obtaining a loan for agricultural purposes, and (iii) the elasticity of credit demand with respect to interest rates. Ordinary Least Squares (OLS), logistic regression, and log-log models are employed to analyze the demand side factors influencing the above dimensions. OLS results indicate that institutional linkages such as access to Kisan Credit Cards (KCC), crop insurance, and membership in farmer organizations substantially increase the share of formal loans. Higher consumption expenditure and larger landholdings are also positively associated. The logistic regression model reveals that households engaged in crop production are significantly more likely to access agricultural loans, especially when supported by KCC and insurance coverage. The log-log model shows credit demand to be inelastic with respect to interest rates, reflecting structural constraints. These findings underscore the critical role of institutional inclusion and economic capacity in enabling formal credit access, while highlighting the persistent limitations in expanding credit demand in rural India.

Keywords: *Agriculture, Access to Credit, Farm Households, Interest Sensitivity*

JEL Codes: *Q1, Q12, Q14*

Acknowledgement

We would like to thank the discussant and other participants for their valuable comments received at the Second International Conference on Finance for Development at the National Institute of Bank Management in Pune Maharashtra and the MSE faculty members and PhD students for their valuable inputs when this work was presented at the Faculty Seminar in March 2026.

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INTRODUCTION

In a developing and agrarian country like India, the agriculture sector plays a crucial role in shaping economic growth, ensuring price stability, and driving poverty reduction (see Chand, 2012). With its deep-rooted interconnectedness with other industries through the provision of raw materials, agriculture serves as a foundation for industrial and economic development (see Basu, 1995; Sarap, 1991). Beyond its economic impact, the sector also holds immense social significance by uplifting rural communities and enhancing the livelihoods of millions dependent on farming. Given this, the expansion and modernization of India's agriculture sector are inextricably linked to the availability and accessibility of formal credit.

Agricultural credit is one of the fundamental prerequisites for increasing productivity and promoting sustainable agricultural development (see Mohan, 2006; Narayanan, 2016). Access to timely and adequate credit enables farmers to invest in high-quality seeds, fertilizers, irrigation systems, and modern machinery, thereby enhancing farm output and overall efficiency. However, financial constraints often hinder farmers' ability to adopt these advancements, as their limited incomes make it challenging to bear additional costs. Institutional financing, therefore, plays a transformative role in improving farmers' financial conditions and promoting agricultural growth (see Basu, 2006; Ramakumar et al, 2007).

Institutional credit influences agricultural outcomes through three primary channels. First, it facilitates the purchase of essential inputs during the cropping season, ensuring that farmers have access to necessary resources at critical times. Second, it supports long-term investments in capital assets such as mechanization, irrigation facilities, and storage infrastructure, key to enhancing productivity and resilience. Third, it reduces reliance on informal credit sources that often charge exorbitant interest rates, trapping farmers in cycles of debt and financial distress. Thus, a robust and well-functioning institutional credit system is indispensable for fostering agricultural sustainability and rural prosperity[1].

Recognizing the importance of formal credit in agriculture, the Indian government has undertaken several policy measures to expand institutional credit access. Key initiatives include the nationalization of major commercial banks in 1969 and 1980, the establishment of Regional Rural Banks (RRBs) in 1975, and the creation of the National Bank for Agriculture and Rural Development (NABARD) in 1982. The introduction of the Kisan Credit Card (KCC) scheme in 1998–99 was a significant step toward providing flexible and hassle-free credit to farmers. Further, the Agricultural Credit Plan was doubled in 2004 to enhance financial inclusion, and the Agricultural Debt Waiver and Debt Relief Scheme was launched in 2008 to alleviate farmers' debt burdens. These measures have significantly increased the share of direct agricultural credit in agricultural GDP, from 10% in FY1971 to 63% in FY2022.

Despite these advancements, a considerable gap remains in ensuring full financial inclusion of agricultural households. According to the National Sample Survey Office's (NSSO) All-India Debt and Investment Survey (AIDIS) for 2018–19, non-institutional sources still account for approximately 33% of the total outstanding credit for agricultural households (National Statistical Office, 2021). This persistent reliance on high-interest informal loans highlights the inadequacies of the institutional credit system in fully addressing farmers' financial needs. Structural challenges such as cumbersome loan application procedures, collateral requirements, and the limited reach of formal banking services in remote rural areas continue to hinder seamless credit access.
The productive use of credit, particularly for agricultural purposes, is essential for translating financial access into tangible improvements in

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[1] See Braverman et al (1986) for a detailed exposition on efficacy of rural credit on productivity. However, Basu (1997) provides theoretical exposition explaining problems faced by institutional credit lending agencies for rural India.

farm productivity. Merely extending credit does not guarantee effective utilization in inputs like seeds, irrigation, or equipment. Empirical insights from the current study show that while a large share of credit is indeed availed for agricultural purposes, its alignment with productive outcomes remains uneven, particularly in the absence of risk-mitigation tools like crop insurance and low penetration of institutional instruments like the Kisan Credit Card. In a study of agricultural credit in Pakistan by Chandio, A. A., Jiang, Y., & Rehman, A. (2018), it was observed that access to credit alone is insufficient when agricultural loans are fungible and not aligned with farmers' production needs, an observation echoed in our findings, which underscore the importance of channeling credit toward productive agricultural uses rather than merely increasing access. Understanding the drivers of agricultural-purpose borrowing is thus critical for improving the targeting and efficacy of institutional credit.

Estimating the elasticity of credit demand provides critical insight into how rural households respond to changes in interest rates, income, consumption, or credit cost. A low elasticity suggests that credit is a basic necessity, relatively unresponsive to economic shifts, while a higher elasticity indicates more flexible or precautionary borrowing behavior. Turvey (2010) highlights that credit demand is closely linked to income volatility and household-level savings capacity in risk-prone agrarian economies. Similarly, Razzaq et al. (2019) demonstrate that credit elasticity in rural Pakistan is shaped by education, income, and transaction costs. In the Indian context, measuring credit elasticity can inform interest rate policy, subsidy effectiveness, and the design of responsive credit programs.

Addressing the persistent challenges in agricultural credit access, therefore, requires a multi-pronged approach that goes beyond increasing credit volume. It necessitates enhancing the reach and functionality of formal credit systems, ensuring that loans are tailored to both productive agricultural purposes and household-specific economic constraints. Financial literacy programs, simplification of loan processes, and the promotion of digital and fintech-led models can play a transformative role. Most critically, aligning credit delivery with the actual borrowing patterns and responsiveness of rural households, as revealed in this study, can enable more inclusive and impactful agricultural financing, driving both productivity and rural welfare.

It is in this context the present study makes an attempt to contribute to the existing literature. First, it tries to identify the key socio-economic and institutional factors influencing the share of formal loans among rural agricultural households. Second, it tries to examine the primary drivers affecting the acquisition of loans specifically for agricultural purposes, with a focus on institutional, demographic, and economic determinants. Finally, we try to estimate the interest rate elasticity of credit demand, providing insights into how fluctuations in interest rates, alongside income and consumption patterns, influence borrowing behavior in rural agricultural settings.

The rest of the paper is organized as follows. Section 2 provides a brief review of literature. Section 3 describes the data sources and methodologies employed. Section 4 presents the results and interpretations. Section 5 concludes.

A BRIEF REVIEW OF LITERATURE

Access to formal credit continues to be a linchpin for agricultural growth in developing economies, where farmers' reliance on financing is critical for procuring inputs, investing in infrastructure, and mitigating financial risks. Yet, despite ongoing policy efforts, the landscape of rural credit remains riddled with disparities and inefficiencies. Socio-economic characteristics, institutional barriers, and market dynamics collectively shape borrowing behaviors (Kishore & Sequeira, 2016; kumar et al., 2021). Financial literacy, or the lack thereof, often becomes the first hurdle: complex loan application processes deter smallholder farmers, driving them toward informal moneylenders despite the high costs and exploitative conditions associated with such borrowing (Ullah et al., 2024; Osabohien et al., 2019). Improvements in financial literacy have been shown to significantly enhance farmers' access to formal agricultural credit by improving awareness of loan products, repayment capacity, and engagement with financial institutions (Raza et al., 2023; Aqsa Tabbasum et al., 2025).

Farm productivity, household income levels, and market linkages further determine not only the accessibility but also the utilization of formal loans (Chauke et al., 2013; Kumar et al., 2021). Land ownership status is another pivotal factor; secure tenure boosts credit eligibility, while farmers with informal or insecure titles face considerable barriers (Yadav & Rao, 2024; Giang & Hang, 2019). Institutional inefficiencies such as bureaucratic hurdles, collateral requirements, and poor outreach compound these challenges. Integration of mobile banking technologies has been highlighted as a potential means of improving access to formal financial services and reducing transaction-related frictions for marginalized rural populations (Kishore & Sequeira, 2016).

Socio-demographic attributes including farm size, age, gender, education, and cooperative membership have emerged as strong predictors of credit access. Larger farms and households with diversified income sources are favored by lenders, whereas youth, women, and marginal farmers often struggle due to systemic biases and weaker bargaining power (Odhiambo et al., 2023; Ullah et al., 2024). Business development services, such as training and advisory support, positively influence farmers' ability to navigate financial systems, improving both credit uptake and loan performance (Masoud & Mwirigi, 2013). Moreover, studies consistently emphasize that digital credit assessment models have begun to erode the traditional reliance on collateral-based lending, democratizing credit access for smaller farmers (Osabohien et al., 2019).

Loan characteristics such as interest rates, repayment structures, loan tenures, and associated risk-mitigation tools exert a profound influence on farmers' borrowing decisions. High-interest rates, in particular, act as a significant deterrent to formal credit uptake, especially among liquidity-constrained and risk-averse households (Chauke et al., 2013; Argaw, 2017; Ullah et al., 2024). Interest rate sensitivity reflects not only the cost of credit but also the perceived value of investing borrowed funds into agricultural production under volatile market conditions. Thorat (2006) emphasizes that for credit to be developmentally effective, its terms must align with farmers' repayment capacities and seasonal income flows. In this context, subsidized interest rates and concessional credit lines have proven instrumental in incentivizing credit participation among smallholders (Masoud & Mwirigi, 2013; Reyes Duarte et al., 2024).

In the context of rural households, credit is often used for consumption smoothing, particularly in response to income shocks or seasonal fluctuations in agricultural production. The elasticity of credit demand is influenced by households' need for access to formal loans to stabilize consumption during periods of financial stress, thereby making credit uptake more sensitive to interest rate changes and other economic factors. The concept of credit demand elasticity specifically with respect to interest rates has gained traction as a critical tool in understanding rural borrowing behavior. It helps isolate the extent to which farmers adjust their demand for credit in response to changes in the cost of borrowing. Turvey (2010) asserts that interest rate responsiveness in rural settings is often muted due to the necessity-driven nature of agricultural credit, where urgent seasonal expenditures limit the flexibility of borrowing decisions. Similarly, Giang and Hang (2019) find that interest rate elasticity varies across farm types and regions, influenced by the availability of substitutes like informal lending and the presence of risk-mitigation instruments. Reyes Duarte et al. (2024) further argue that even modest reductions in interest rates can significantly enhance uptake if coupled with simplified lending procedures and better information access. While income and consumption elasticity of credit demand have been widely studied, interest rate elasticity remains relatively underexplored in the Indian context, particularly in the case of loans taken for agricultural purposes.

Despite the positive effects of policy interventions such as the Kisan Credit Card (KCC) in India and cooperative lending programs in Ethiopia, significant gaps persist in bridging formal credit access with actual financial needs at the farm level. Farmers continue to prefer informal lenders for their accessibility and flexibility, even though this often leads to exploitative debt cycles (Kumar et al., 2021; Ullah et al., 2024; Shkodra et al., 2018). Strengthening rural credit cooperatives, expanding the use of mobile financial services, and enhancing digital financial literacy are increasingly seen as viable solutions to these enduring challenges.

While significant advancements have been made in expanding rural financial access, a comprehensive review of the literature reveals enduring and multifaceted gaps. Although several studies emphasize the importance of socio-economic characteristics, institutional barriers, and market conditions, gaps persist in how these factors interact dynamically to influence credit behavior. Financial literacy initiatives, land tenure reforms, and digital banking solutions have improved access, but disparities in credit uptake based on gender, farm size, and market connectivity remain inadequately addressed. Moreover, while much attention has been paid to factors enabling general access to credit, there is a notable scarcity of research examining the differentiated challenges faced by farmers seeking loans specifically for agricultural investment purposes. Understanding how purpose-specific credit demand for input purchases, infrastructure development, or risk management varies across general household borrowing behavior remains an underexplored area that demands closer scrutiny.

Additionally, the dimension of credit demand elasticity relative to interest rates present another critical research gap. While several international studies have examined how borrowing behavior shifts with changes in credit cost, systematic evidence within the Indian rural context particularly with respect to agricultural-purpose loans remains limited. Bridging this gap will require more nuanced, disaggregated, and context-sensitive research that captures how changes in interest rates affect farm households with different resource endowments. Ultimately, addressing these intertwined deficits in purpose-based credit analysis and interest rate elasticity is essential for designing more inclusive, responsive, and farmer-centric financial systems capable of supporting sustainable agricultural development.

Hence, the present study makes a modest attempt to address all the three issues raised. First, it tries to identify the key socio-economic and institutional factors influencing the share of formal loans among rural agricultural households. Second, it makes an attempt to examine the primary drivers affecting the acquisition of loans specifically for agricultural purposes, with a focus on institutional, demographic, and economic determinants. Finally we try to estimate the interest rate elasticity of credit demand, providing insights into how fluctuations in interest rates, alongside income and consumption patterns, influence borrowing behavior in rural agricultural settings.

DATA AND METHODOLOGY

Data

The present study utilizes cross-sectional unit-level data from Visit 1 of the 77th Round of the National Sample Survey (NSS), conducted by the National Statistical Office (NSO) of India under the survey titled *"Land and Livestock Holdings of Households and Situation Assessment of Agricultural Households."* This extensive survey covered rural areas across India, except the Andaman and Nicobar Islands, and focused on the agricultural year 2018–19. A total of 58,035 agricultural households across rural India were surveyed, providing a robust and nationally representative dataset.

The dataset comprises socio-economic characteristics of households such as household size, religion, social group (Scheduled Caste, Scheduled Tribe, Other Backward Class, or Others), consumption expenditure, banking access, possession of MGNREGS job cards, membership in farmers' organizations, ownership of Kisan Credit Cards, possession of soil health cards, and enrollment under crop insurance schemes like the Pradhan Mantri Fasal Bima Yojana (PMFBY). It also included demographic particulars of household members, including age, gender, education level, and economic activities, which are crucial for analyzing socio-economic factors influencing credit access. Details of landholding including data on the total area of land owned is also provided which is essential for assessing the relationship between land size and credit behavior. Detailed information on agricultural production, such as the types of crops grown along with the land size holdings provide a comprehensive understanding of agricultural output and farm-level dynamics.

Finally, a separate section in the data focuses on household indebtedness, capturing vital data on the nature and purpose of loans, credit sources, interest rates, loan tenures, and outstanding liabilities. This block serves as the foundation for analyzing factors affecting formal loan uptake, purposes of borrowing, and estimating credit demand elasticity. It is important to note that each household in the sample was visited only once during Visit 1, and the loan-related data, including details on loan sources, purposes, and other characteristics, reflects information from this single visit.

The data for bank density comprises the number of commercial bank branches per district and the geographical area of each district. The number of banks was obtained from the Reserve Bank of India (RBI) publication titled District-Wise Number of Functioning Offices of Commercial Banks as at End of the Quarter – June 2018. The area of each district was sourced from the Census of India 2011 and respective state government sources.

The present research primarily utilizes Visit 1 data, corresponding to the Kharif season, providing a focused analysis on household-level determinants of formal loan shares, agricultural credit uptake, and the responsiveness of credit demand to economic characteristics in rural India.

METHODOLOGY

The empirical strategy of this study is designed to address three principal research objectives: (i) identifying household-level factors influencing the percentage share of formal loans, (ii) examining determinants affecting the purpose of obtaining agricultural loans, and (iii) estimating the elasticity of credit demand concerning interest rate sensitivity.

All models assume independence of observations and random sampling. Robust standard errors are utilized to address potential heteroskedasticity. Empirical estimations are conducted using STATA, ensuring consistency and robustness of results.

Model 1: Determinants of Formal Credit Share (OLS Model)

The first objective of this study is to model the percentage share of formal loans in total household borrowing. This is achieved through an Ordinary Least Squares (OLS) regression model, where the dependent variable is the percentage share of formal loans in the total borrowing of the household.

The equation for this model is specified as:

$$
\begin{aligned}
PercenategeofFormalLoans \\
= \beta_0 + \beta_1 Gender + \beta_2 HouseholdSize + \beta_3 Education \\
+ \beta_4 Religion + \beta_5 SocialGroup \\
+ \beta_6 HouseholdClassification + \beta_7 log(Expenditure) \\
+ \beta_8 DwellingType + \beta_9 LandSize \\
+ \beta_{10} BankAccountAccess + \beta_{11} KCCAccess \\
+ \beta_{12} InsuredCrop + \beta_{13} FarmersOrganisation \\
+ \beta_{14} MGNREGCardAccess + \beta_{15} bankDensity \\
+ \beta_{16} CropType + \beta_{17} SoilHealthCardAccess \\
+ \beta_{18} StateFixedEffects + \epsilon
\end{aligned}
$$

where, $PercenategeofFormalLoans$ represents the percentage share of formal loans in total household borrowing. β_0 is the constant term, while all other variables are explanatory, representing demographic, economic, and institutional factors influencing formal credit uptake. State Fixed Effects are included to account for unobserved heterogeneity across states. ε represents the error term.

This model seeks to identify how various household and institutional characteristics, including gender, education, access to financial services, and state-level fixed effects, influence the share of formal loans in total borrowing among rural households.

Estimation Procedure

The model is estimated using Ordinary Least Squares (OLS) regression. OLS is chosen for this analysis due to its simplicity, interpretability, and ability to estimate the linear relationship between household characteristics and the percentage share of formal loans. Given that the data is based on a multi-stage sampling design, where villages in rural areas serve as the first-stage sampling units (FSUs), the standard errors are clustered at the FSU level. This adjustment accounts for potential intra-cluster correlation of error terms, as observations within the same village or urban block may not be independent of each other.

Robust standard errors are employed to further account for heteroskedasticity in the error term. All statistical tests are conducted at the 5% significance level, and the results are interpreted for both statistical significance and practical significance. This ensures that the conclusions drawn from the regression analysis are both statistically reliable and practically meaningful.

Model 2: Determinants of Access to Agricultural Loans (Logistic Regression Model)

The second objective of this study is to assess the likelihood of a household obtaining a loan for agricultural purposes. To model this binary outcome, a Logistic Regression model is employed, where the dependent variable is a binary indicator taking the value 1 if the household obtained a loan for agricultural purposes and 0 otherwise.

The equation for this model is specified as:

$$
\begin{aligned}
P(AgricultureLoan = 1 \mid X) \\
&= 1 / [1 + exp(-(\beta_0 + \beta_1 Gender + \beta_2 HouseholdSize \\
&+ \beta_3 Education + \beta_4 Religion + \beta_5 SocialGroup \\
&+ \beta_6 HouseholdOccupation + \beta_7 log(Expenditure) \\
&+ \beta_8 Dwelling\ Type + \beta_9 Land\ Size \\
&+ \beta_{10} BankAccount\ Access + \beta_{11} KCC\ Access \\
&+ \beta_{12} Crop\ Insurance \\
&+ \beta_{13} FarmerOrganisationMembership \\
&+ \beta_{14} MGNREG\ Card\ Access + \beta_{15} Bank\ Density \\
&+ \beta_{16} Crop\ Type + \beta_{17} Soil\ Health\ Card \\
&+ \beta_{18} State\ Fixed\ Effects))]
\end{aligned}
$$

$P(AgricultureLoan = 1 \mid X)$ represents the probability that a household has taken a loan for agricultural purposes given its characteristics X. β_0 is the constant term, and the other β coefficients correspond to the explanatory variables that represent demographic, economic, and institutional characteristics. State Fixed Effects are included to capture unobserved heterogeneity across states.

Estimation Procedure

This model is estimated using a binary logistic regression technique. Logistic regression is suitable here as the dependent variable is binary, and the model estimates the log-odds of a household receiving agricultural credit. As the data follows a multi-stage sampling framework, standard errors are clustered at the First Stage Unit (FSU) level to adjust for intra-cluster correlation. Robust standard errors are used to handle potential heteroskedasticity. All inferences are based on a 5% significance level, ensuring both statistical validity and interpretability of the model results.

Model 3: Elasticity of Credit Demand (Log-Log Regression Model)

The third objective of this study is to estimate the interest rate elasticity of credit demand among rural households. For this purpose, a log-log regression model is applied where both the dependent variable (loan amount) and the key independent variable (interest rate) are transformed into natural logarithms. This specification allows the coefficients to be interpreted as elasticities, thereby measuring the responsiveness of credit demand to percentage changes in explanatory factors, especially interest rates.

Model 3a: Formal Credit Demand

$$\begin{aligned} log(FormalLoanAmount) &\\ &= \beta_0 + \beta_1 log(FormalInterestRate) + \beta_2 X_{2\mathrm{i}} \\ &+ \beta_3 X_{3\mathrm{i}} + \ldots + \beta_{\mathrm{k}} X_{\mathrm{ki}} + \varepsilon_{\mathrm{i}} \end{aligned}$$

Model 3b: Informal Credit Demand

$$\begin{aligned} log(InformalLoanAmount) &\\ &= \beta_0 + \beta_1 log(InformalInterestRate) + \beta_2 X_2 \\ &+ \beta_3 X_3 + \ldots + \beta_{\mathrm{k}} X_{\mathrm{k}} + \varepsilon \end{aligned}$$

Where $log(FormalLoanAmount)$ and $log(InformalLoanAmount)$ are the natural logarithms of the loan amount obtained from formal and informal sources, respectively. $log(FormalInterestRate)$ is the natural logarithm of the average interest rate faced by the households from formal sources. $log(InformalInterestRate)$ is the natural logarithm of the average interest rate faced by the households from informal sources. X_2 to X_k represent other explanatory variables, representing demographic, economic, and institutional characteristics. β_1 represents the elasticity of credit demand with respect to interest rate. ε is the error term.

Estimation Procedure

A log-log regression framework is appropriate for estimating elasticity as it directly provides the percentage change in loan demand resulting from a 1% change in interest rates. Ordinary Least Squares (OLS) is used to estimate the coefficients. Given the clustered survey design, standard errors are clustered at the FSU level. Robust standard errors are used to mitigate heteroskedasticity concerns, and statistical tests are carried out at a 5% level of significance. This specification provides an interpretable and theoretically consistent estimation of credit demand elasticity.

RESULTS AND ANALYSIS

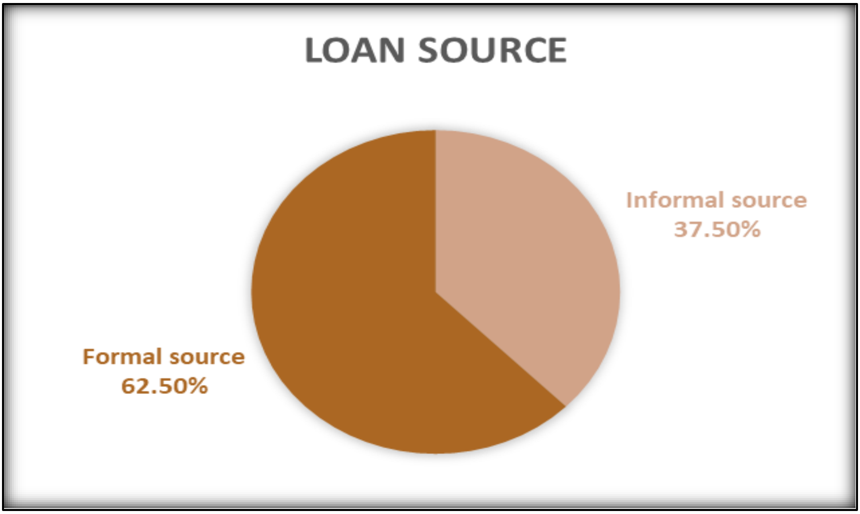
This section presents the empirical findings of the study. It begins by analyzing the determinants of the percentage share of formal loans in total household borrowing using descriptive statistics and an Ordinary Least Squares (OLS) regression framework. To ensure the robustness of the results, standard errors are clustered at the First Stage Sampling Unit (FSU) level, accounting for the complex survey design. It further investigates the factors influencing the likelihood of a household obtaining a loan for agricultural purposes through a logistic regression model. Lastly, a log-log regression model is employed to estimate the elasticity of credit demand with respect to interest rates, separately for formal and informal credit sources, providing key insights into household credit behavior.

Loan Source - Formal and Informal Divide

Formal sector loans comprise of 62.5 percent of total loans while the rest 37.5percent are from informal sources (Figure 1). Scheduled commercial banks turn out to be the most common source (29.28percent) followed by professional moneylenders (13.13percent). The least common source is provident fund (0.02percent)[2]. Distribution of loans across formal and informal sources with respect to socio-economic and demographic characteristics like bank account access, consumption expenditure, crop insurance, crop type, education level of the head of the household, gender of the head of the household, Kisan credit card, land size, membership of farmer's organization and social groups are provided in Figures 3 – 12 in the appendix.

Table 1 below provides the results of mean difference test across the formal and informal sources with respect to various socio-economic, demographic and financial indicators.

Figure 1: Formal and Informal Source Division



Source: Authors' calculations using NSSO 77th Round data (2018).

[2] See Figure 2 in the appendix.

Table 1: Mean Difference Test across Formal & Informal Source of Loan

Variable Name	Mean if Formal Loans	Mean if Informal Loans	Mean Difference
Social Group			
Scheduled Caste (SC)	0.2626	0.1971	0.0654***
Scheduled Tribe (ST)	0.1602	0.1243	0.0359***
Other Backward Classes (OBC)	0.3481	0.2321	0.1161***
Other Social Groups	0.368	0.1718	0.1962***
Gender			
Female Household Head	0.1928	0.1314	0.0614***
Male Household Head	0.3164	0.1984	0.118***
Religion			
Hindu	0.3232	0.203	0.1202***
Muslim	0.2499	0.167	0.0829***
Christian	0.1433	0.0962	0.047***
Other Religions	0.2806	0.1636	0.117***
Household Classification			
Self-employed: Crop	0.3898	0.2353	0.1545***
Self-employed: Animals	0.367	0.2939	0.0731***
Self-employed: Agri (Mixed)	0.2048	0.1222	0.0826***
Regular Wage: Agri	0.2064	0.1138	0.0926***
Casual Labour: Agri	0.149	0.1397	0.0093
Dwelling			
Owned	0.3848	0.2408	0.144***
Hired	0.4441	0.3706	0.0734**
No Dwelling	0.3889	0.2778	0.1111
Other	0.2994	0.2853	0.0141
Land Category			
Landless	0.0059	0.0156	-0.0098
Marginal	0.217	0.1614	0.0556***
Small	0.4248	0.2433	0.1815***
Semi-medium	0.5221	0.2623	0.2597***
Medium	0.6662	0.2802	0.386***
Large	0.5443	0.2743	0.27***

Education Level of Household Head			
Illiterate	0.2667	0.2165	0.0502***
Primary	0.3109	0.1919	0.1190***
Primary to Secondary	0.3250	0.1730	0.1520***
Above Secondary	0.3541	0.1511	0.2030***
Household Size			
Small (1–3)	0.2675	0.1662	0.1012***
Medium (4–6)	0.3102	0.1967	0.1136***
Large (7+)	0.3403	0.2158	0.1246***
Crop Type			
Both Food & Cash	0.5469	0.2854	0.2614***
Only Cash Crop	0.5182	0.2727	0.2454***
Only Food Crop	0.3316	0.2226	0.1091***
Financial Access			
Bank Account Access	0.390	0.245	0.145***
Kisan Credit Card Access	0.699	0.261	0.439***
Soil Health Card Access	0.618	0.306	0.311***
Crop Insurance	0.775	0.367	0.408***
Member of Farmer's Organisation	0.552	0.222	0.33***
MGNREG Job Card	0.398	0.281	0.116***
Continuous Variables			
Monthly Consumption Expenditure (Log)	9.1273	9.0459	-0.0814***
Bank Density (Branches/km²)	0.0759	0.0667	-0.0092***

Source: Authors' calculations using NSSO 77th Round data (2018).
Note: *p < 0.10, **p < 0.05, ***p < 0.01

Loan Purpose – Agriculture & Non-Agriculture Purpose

When it comes to analyzing the purpose for which loan has been taken, it turns out that 52.54 percent avail the loan for agriculture purpose while 47.46 percent take loans for non-agricultural purpose[3]. The major purpose for taking loans is revenue expenditure for firm business (30.96percent) followed by capital expenditure in farm business

[3] See Figure 13 in the appendix.

(21.58percent). The least proportion of loans taken are for education purpose (1.66percent)[4]. Distribution of loans according to purpose (agricultural vis-à-vis non-agricultural) based on different parameter like bank account access, consumption expenditure, crop insurance, education level of the head of the household, gender of the head of the household and land size are provided in Figures 15 – 21 in the appendix.

Table 2 below provides the results of mean difference test between agriculture and non-agriculture purpose of loan across various socio-economic, demographic and financial variables

Table 2: Mean Difference Test across Agriculture & Non-Agriculture Purpose of Loan

Variable Name	Mean if Agriculture Purpose	Mean if Non-Agriculture Purpose	Mean Difference
Social Group			
Scheduled Caste (SC)	0.1945	0.2287	-0.0343***
Scheduled Tribe (ST)	0.1198	0.1474	-0.0276***
Other Backward Classes(OBC)	0.2814	0.2551	0.0263***
Other Social Groups	0.3102	0.2002	0.1100***
Gender			
Female Household Head	0.1346	0.1687	-0.0341***
Male Household Head	0.2564	0.2228	0.0337***
Religion			
Hindu	0.2635	0.2253	0.0382***
Muslim	0.1748	0.2241	-0.0493***
Christian	0.0910	0.1380	-0.0470***
Other Religions	0.2419	0.1590	0.0828***

[4] See Figure 14 in the appendix.

Household Classification			
Self-employed: Crop	0.3422	0.2395	0.1027***
Self-employed: Animals	0.2779	0.3265	-0.0485***
Self-employed: Agri (mixed)	0.1274	0.1790	-0.0516**
Regular Wage: Agri	0.1106	0.1851	-0.0745***
Casual Labour: Agri	0.1040	0.1603	-0.0564***
Dwelling			
Owned	0.3086	0.2743	0.0343***
Hired	0.3881	0.3462	0.0420
No dwelling	0.4444	0.2778	0.1667
Other	0.2260	0.3079	-0.0819**
Land Category			
Landless	0.0039	0.0137	-0.0098
Marginal	0.1500	0.2033	-0.0534***
Small	0.3730	0.2509	0.1221***
Semi-medium	0.4784	0.2482	0.2303***
Medium	0.6316	0.2315	0.4001***
Large	0.5316	0.1899	0.3418***
Education Level of Household Head			
Illiterate	0.2207	0.2197	0.0010
Primary	0.2458	0.2232	0.0226***
Primary to Secondary	0.2580	0.2113	0.0467***
Above Secondary	0.2788	0.2091	0.0697***
Household Size			
Small Household (1–3)	0.2235	0.1812	0.0423***
Medium Household (4–6)	0.2421	0.2291	0.0129***
Large Household (7+)	0.2807	0.2382	0.0425***

Crop			
Both Food & Cash	0.4806	0.3054	0.1753***
Only Cash Crop	0.4471	0.2844	0.1627***
Only Food Crop	0.2620	0.2563	0.0057
Access Variables			
Has Bank Account	0.3128	0.2783	0.0345***
Has KCC	0.6227	0.2795	0.3432***
Has Soil Health Card	0.5707	0.2804	0.2903***
Has Crop Insurance	0.7374	0.3231	0.4142***
MGNREG Job Card	0.3094	0.3158	-0.0065
Farmer Org. Membership	0.4441	0.2967	0.1474***
Other Variables			
Monthly Consumption Expenditure (Log)	9.1128	8.9279	-0.2010***
Bank Density (branches per sq km)	0.0632	0.0757	0.0125***

Source: Authors' calculations using NSSO 77th Round data (2018).

Note: *p < 0.10, **p < 0.05, ***p < 0.01

Model 1: OLS Regression - Factors Affecting Access to Formal Loans

The results of the OLS Regression employed to identify the factors affecting access to loans from formal sources are shown below in Table 3.

Table 3: OLS Regression Results – Factors Affecting Access to Formal Loans

Variable	Coefficient (SE)
Gender (Base: Male) Female	0.985(1.079)
Household Size (Base: Small Household (1-3 members))	
Medium Household (4–6)	-0.727 (0.718)
Large Household (7+)	-0.851 (1.046)
Education (Base: Illiterate)	
Primary	2.179 (0.761) ***
Primary to Secondary	4.566 (0.740) ***
Above Secondary	6.965 (1.157) ***
Religion (Base: Other Religion)	
Hindu	-1.627 (2.639)
Muslim	-5.157 (2.899) *
Christian	-3.829 (3.382)
Social Group (Base: General)	
SC	-3.314 (1.088) ***
ST	-3.083 (1.486) **
OBC	-3.115 (0.834) ***
Occupation (Base: Others)	
Self-employed in Crop	-0.962 (0.817)
Self-employed in Animal	-4.834 (1.833) ***
Casual Agricultural Labour	-5.874 (1.545) ***
Regular Wage Agricultural Labour	2.309 (2.508)
Economic Variables	
Log Monthly Consumption Expenditure	2.846 (0.834) ***
Dwelling Unit (Base: Other)	
Dwelling Unit Owned	6.059 (3.203) *
Dwelling Unit Hired	-1.334 (3.883)
No Dwelling Unit	6.496 (14.203)
Land Size (Base: Landless)	
Marginal	28.747 (9.346) ***
Small	32.006 (9.355) ***
Semi-medium	34.522 (9.369) ***
Medium	38.572 (9.421) ***
Large	31.254 (9.781) ***

Access to Financial Services	
Bank Account Access	8.557 (2.818) ***
Kisan Credit Card Access	26.532 (0.865) ***
Crop Insurance	1.408 (0.956)
Soil Health Card Access	-2.034 (1.816)
Member of Farmers' Org.	0.963 (1.111)
MGNREG Job Card Access	-3.281 (0.723) ***
Banking Infrastructure	
Bank Density	17.440 (5.219) ***
Type of Crop (Base: Food Crop)	
Both Food and Cash Crops	1.132 (0.844)
Cash Crop Only	3.164 (1.096) ***
State Fixed Effects	Yes
Constant	-27.994 (13.680) **

Source: Authors' calculations using NSSO 77th Round data (2018).
Note: *p < 0.10, **p < 0.05, ***p < 0.01

Education stands out as one of the strongest predictors of formal credit access. Compared to illiterate households, those with primary education are 2.179 units more likely to access formal credit, while those with education up to secondary and above secondary levels are 4.566 and 6.965 units more likely, respectively. This clearly reflects the role of education in improving financial literacy, reducing informational barriers, and enhancing the confidence and ability of households to engage with formal credit institutions findings supported by Ayuub et al. (2024) and Ullah et al. (2024), who emphasize education as a critical enabler of financial inclusion.

Social group identity significantly affects credit access. Scheduled Castes (SC), Scheduled Tribes (ST), and Other Backward Classes (OBC) are 3.314, 3.083, and 3.115 units less likely, respectively, to obtain formal loans than General category households. These results suggest that deep-rooted social inequalities, historical exclusion, and limited access to networks and documentation continue to hamper the ability of marginalized groups to participate in formal financial systems concerns similarly noted in studies by Kumar et al. (2021) and Odhiambo et al. (2024).

In terms of occupation, households engaged in self-employment in animal farming and casual agricultural labour are significantly less likely to access formal loans, by 4.834 and 5.874 units respectively, compared to the reference group. These groups often face volatile and uncertain incomes, which likely diminish their perceived creditworthiness. This supports the arguments made by Kishore (2024), who highlights the precarious economic conditions of informal rural workers as a barrier to credit access.

From an economic standpoint, monthly household consumption expenditure used as a proxy for permanent income is positively associated with formal credit access. A one-unit increase in the logarithm of monthly consumption leads to a 2.846-unit increase in the likelihood of obtaining formal loans, suggesting that wealthier or more economically stable households are more capable of meeting eligibility criteria and servicing debt.

The role of landholding is especially pronounced. Compared to landless households, those owning even marginal land see a 28.747-unit higher likelihood of accessing formal loans. This effect strengthens with land size, peaking at 38.572 units for medium landholders. Land serves as both collateral and a marker of agricultural productivity, making these households more attractive to banks and cooperatives, as emphasized in the findings of Yadav & Rao (2024) and Giang & Hang (2024).

Access to financial services and infrastructure plays a pivotal role. Having a bank account increases the likelihood of accessing formal loans by 8.557 units, while possession of a Kisan Credit Card (KCC) raises it by a striking 26.532 units. Furthermore, bank density, representing the number of banks per population or area, is positively associated with formal credit access each unit increase boosts credit access by 17.440

units. These results affirm the importance of physical and financial connectivity in improving credit outreach and reducing access costs.

Importantly, the presence of a MGNREG job card is associated with a 3.281-unit decrease in the probability of accessing formal credit. This could suggest that households reliant on such public employment programs may be economically more vulnerable and perceived as less creditworthy by formal lenders, or it may reflect a substitution effect where government transfers reduce reliance on formal credit a hypothesis that merits further investigation.

Access to financial infrastructure, represented by the number of banks per district, was positively related to formal loan share. This underscores the importance of physical banking outreach in enhancing credit availability in rural areas.

Lastly, households engaged in exclusive cash crop cultivation are 3.164 units more likely to access formal loans compared to those cultivating only food crops. This is likely due to the commercial nature of cash crops, which may require higher capital investment but also offer greater returns, encouraging both demand for and supply of formal credit. With state fixed effects accounted for, the results point to both structural inequalities and policy-sensitive levers that can be targeted to enhance inclusive access to credit in India’s agrarian landscape.

Model 2: Logistic Regression - Factors Affecting Agricultural Loan Access

Table 4 below presents the results of the Logistic Regression employed to identify the factors affecting access to agricultural loan.

Table 4: Logistic Regression Results for Factors Affecting Agricultural Loan Access

Variable	Coefficient (SE)
Net Expenditure on Farm	0.000(0.000) ***
Gender (Base: Male)	
Female	-0.321 (0.072) ***
Household Size (Base: Small Household (1–3))	
Medium Household (4–6)	0.031 (0.054)
Large Household (7+)	-0.045 (0.075)
Education (Base: Illiterate)	
Primary Education	0.078 (0.052)
Primary to Secondary Education	0.092 (0.051) *
Above Secondary Education	0.003 (0.082)
Religion (Base: Other)	
Hindu	-0.299 (0.176) *
Muslim	-0.500 (0.195) **
Christian	-0.283 (0.232)
Social Group (Base: Other)	
Scheduled Caste (SC)	-0.047 (0.077)
Scheduled Tribe (ST)	-0.593 (0.094) ***
Other Backward Class (OBC)	-0.002 (0.058)
Household Classification (Base: Other)	
Self-employed in Crop Production	0.387 (0.058) ***
Self-employed in Animal Husbandry	0.571 (0.137) ***
Casual Agricultural Employment	0.173 (0.116)
Regular Agricultural Employment	-0.122 (0.236)
Log of Expenditure	0.282 (0.059) ***
Dwelling Unit (Base: Other Dwelling)	
Owned	0.063 (0.228)
Hired	0.297 (0.286)
No Dwelling	-0.119 (0.924)
Land Size (Base: Landless)	
Marginal Land	-0.748 (0.424) *
Small Land	-0.331 (0.422)
Semi-medium Land	-0.202 (0.421)

Medium Land	0.214 (0.424)
Access to Financial Services	
Bank Account Access	0.385 (0.168) **
Kisan Credit Card (KCC) Access	1.757 (0.064) ***
Crop Insurance	0.968 (0.097) ***
Farmers' Organization Membership	-0.066 (0.098)
MGNREG Job Card Access	0.245 (0.051) ***
Soil Health Card Access	-0.053 (0.178)
Bank Density	-0.466 (0.412)
Type of Crop (Base: Food Crop)	
Both Crops	0.442 (0.061) ***
Cash Crops	0.367 (0.083) ***
State Fixed Effects	Yes
Constant	-4.998 (0.790) ***

Source: Authors' calculations using NSSO 77th Round data (2018).
Note: *p < 0.10, **p < 0.05, ***p < 0.01

Households with higher net farm expenditure are significantly more likely to have an agricultural loan suggesting that as farm spending increases, so does the likelihood of loan uptake.

A key result is the negative and statistically significant effect of gender, indicating that female-headed households are less likely to obtain loans for agricultural purposes than male-headed households. This highlights persistent gender disparities in agricultural credit allocation, consistent with earlier findings on the limited role of women in accessing productive resources in rural areas.

In terms of education, households where the head has attained primary education are more likely to use credit for agriculture compared to illiterate households. Though moderate in effect size, the relationship is statistically significant, suggesting that even basic literacy enhances a household's capacity to seek and utilize credit for farming-related activities.

The effect of religion is notable. Relative to households of other religious backgrounds, Hindu, Muslim, and Christian households show lower odds of taking loans for agricultural purposes. This pattern may be influenced by cultural preferences in loan usage or institutional biases that affect loan categorization and targeting. The result underscores the importance of investigating whether religious identity intersects with financial inclusion or sectoral loan allocation.

Social identity, particularly belonging to a Scheduled Tribe (ST) group, significantly reduces the probability of accessing credit for agriculture. This reflects the broader exclusion of tribal households from formal financial systems, especially in the domain of productive credit, due to geographic isolation and administrative neglect.

Occupational category also plays a central role. Households primarily engaged in crop production are significantly more likely to utilize loans for agricultural purposes, aligning with the policy focus of most institutional lenders on crop-based credit. Households involved in animal farming also show increased likelihood, although the effect is slightly smaller, suggesting that livestock-related credit is less prioritized but still significant.

Households with higher monthly consumption expenditure (log-transformed) are more likely to use loans for agriculture. This supports the notion that better-off households are more likely to be considered creditworthy and may have greater knowledge of available agricultural loan products.

Landholding size emerges as a critical determinant. Households with semi-medium, medium, and large landholdings are substantially more likely to take loans for agricultural purposes than landless households. This underlines the role of land as both a productive asset and a proxy for collateral in accessing sector-specific credit.

Indicators of financial inclusion are strongly associated with agricultural credit access. Possession of a bank account, Kisan Credit Card (KCC), or crop insurance under PMFBY significantly increases the likelihood of a household using credit for agriculture. The effect of the KCC is particularly strong, underscoring its central role in channeling institutional credit toward crop-related needs. Additionally, owning an MGNREG job card also increases the probability of agricultural loan access, possibly by stabilizing household income and enhancing repayment capacity in the eyes of lenders.

An unexpected finding is that higher district-level bank density is associated with a lower probability of agricultural loan access. While bank density typically suggests better financial infrastructure, the negative effect here could reflect a mismatch in spatial distribution i.e., banks may be concentrated in semi-urban areas or may not prioritize agricultural lending.

Households cultivating cash crops or a combination of food and cash crops are significantly more likely to use loans for agricultural purposes. This supports the idea that lenders are more inclined to support households engaged in commercial farming, due to their higher expected returns and clearer income cycles.

Significant regional disparities are also observed. These disparities likely stem from weaker financial infrastructure, limited outreach of institutional credit, and topographical barriers.

Model 3: Log-Log Regression - Elasticity of Credit Demand (Formal vs Informal)

In this section we present the results for the Log-Log Regression analyses done for determining the elasticities of credit demand – for both formal (Table 5) and informal (Table 6) credit.

Table 5: Log-Log Regression Results – Interest rate elasticity of Formal Credit Demand

Variable	Coefficient (Std. Error)
Log of Formal Interest Rate	0.073*** (0.019)

Source: Authors' calculations using NSSO 77th Round data (2018).
Note: *p < 0.10, **p < 0.05, ***p < 0.01

Dependent Variable: Logarithm of the Amount of Formal Credit
Key Independent Variable: Logarithm of the Formal Interest Rate

Table 6: Log-Log Regression – Interest rate elasticity of Informal Credit Demand

Variable	Coefficient (Std. Error)
Log of Informal Interest Rate	0.049 (0.038)

Source: Authors' calculations using NSSO 77th Round data (2018).
Note: *p < 0.10, **p < 0.05, ***p < 0.01; No statistical significance at conventional levels (p = 0.201)

Dependent Variable: Logarithm of the Amount of Informal Credit
Key Independent Variable: Logarithm of the Informal Interest Rate

The analyses of formal and informal credit demand using log-log regression models reveals notable contrasts in borrower responsiveness to interest rate changes.

The log-log regression results for formal credit demand indicate a positive and statistically significant relationship between the amount of formal credit accessed and the formal interest rate. Specifically, a 1% increase in the interest rate is associated with a 0.073% increase in the demand for formal credit, significant at the 1% level. This positive elasticity is counterintuitive, as standard economic theory suggests that higher interest rates should discourage borrowing. However, this result may reflect credit rationing or supply-side constraints in rural credit markets where households with better collateral or higher repayment capacity still access loans despite higher rates. It may also imply that borrowers who manage to secure formal loans are less price-sensitive, prioritizing access over cost due to the lack of suitable alternatives.

In contrast, the relationship between informal credit demand and the informal interest rate is positive but statistically insignificant, with a coefficient of 0.049 and a p-value of 0.201. This suggests that changes in the interest rate do not have a meaningful effect on the amount of informal credit borrowed. The insignificance of this relationship may reflect the informal sector's flexibility and reliance on social ties, where loan terms are negotiated based on relationships rather than market rates. It also indicates that informal lenders may be less sensitive to interest rate changes, and borrowers may continue to rely on these sources regardless of cost, possibly due to limited access to formal credit. This divergence in elasticity highlights the segmented nature of rural credit markets and the need for targeted policy interventions to improve financial inclusion.

CONCLUSION

This study has successfully investigated the key socio-economic and institutional factors that influence the access to formal agricultural loans and the demand for credit in rural India, using data from the 77th round of the National Sample Survey (NSS). The findings reveal that socio-economic factors such as gender, education, land ownership, household occupation, and financial inclusion play significant roles in determining access to formal credit. Female-headed households and Scheduled Tribe (ST) households were found to have lower chances of accessing formal credit, underlining the persistence of gender and social disparities in rural finance. On the other hand, households with primary education, larger landholdings, and higher consumption expenditure are more likely to obtain loans, emphasizing the importance of financial awareness and economic status in facilitating access to credit.

The study also highlights the crucial role of financial inclusion in improving access to formal credit. Households with access to banking services, Kisan Credit Cards (KCCs), crop insurance under PMFBY, and MGNREG job cards were significantly more likely to access formal loans. This demonstrates the importance of financial products in expanding formal credit access, particularly in rural areas. Furthermore, the study examined the primary drivers affecting the acquisition of loans for agricultural purposes and found that financial inclusion and institutional access are key determinants.

In terms of demand, the results show that formal credit demand is positively related to formal interest rates, indicating that rural households are willing to access formal loans even at higher interest rates. This finding suggests that credit rationing or supply-side constraints in rural markets may contribute to borrowers' willingness to prioritize access to formal credit over cost considerations. On the other hand, informal credit demand exhibited less sensitivity to interest rate changes, highlighting the social nature of informal credit markets, where loan terms are often negotiated based on relationships rather than economic factors.

The study also estimated the interest rate elasticity of credit demand, revealing that formal credit demand is positively responsive to interest rates, albeit with a small elasticity coefficient of 0.073 for formal credit, suggesting that formal borrowers are less price-sensitive. In contrast, informal credit demand showed no significant relationship with interest rate fluctuations, further emphasizing the distinct characteristics of informal credit systems in rural areas.

Despite its contributions, the study has limitations. The cross-sectional nature of the data restricts causal inference and limits the ability to analyze long-term trends in credit access. Future research could benefit from panel data to explore the dynamic nature of credit access and demand. Additionally, the exclusion of informal credit systems, such as community lending, restricts the scope, and further exploration of these systems could provide deeper insights into rural credit dynamics.

Furthermore, understanding institutional barriers to loan approval and examining the role of financial institutions could enrich the analysis of credit access in rural India.

From a practical standpoint, the study suggests that promoting financial literacy, particularly for women and marginalized groups, could improve access to formal credit. Financial education campaigns could enhance understanding of the benefits of formal credit and build trust in using these services. Expanding the availability of Kisan Credit Cards (KCCs) and crop insurance would strengthen rural farmers' access to financial resources. Additionally, enhancing banking infrastructure, including mobile banking and digital platforms, would facilitate easier access to formal credit, particularly in remote areas. Policymakers should also address regional disparities, ensuring that loan access is improved in underserved regions.

In conclusion, this study provides valuable insights into the socio-economic factors that influence access to formal agricultural loans and the demand for credit in rural India. While the findings emphasize the importance of financial inclusion and institutional access, further research is needed to explore informal credit systems and institutional barriers. By addressing these factors, promoting financial literacy, and enhancing access to formal financial products, policymakers can foster greater financial inclusion, support marginalized rural households, and promote the sustainable growth of rural economies in India.

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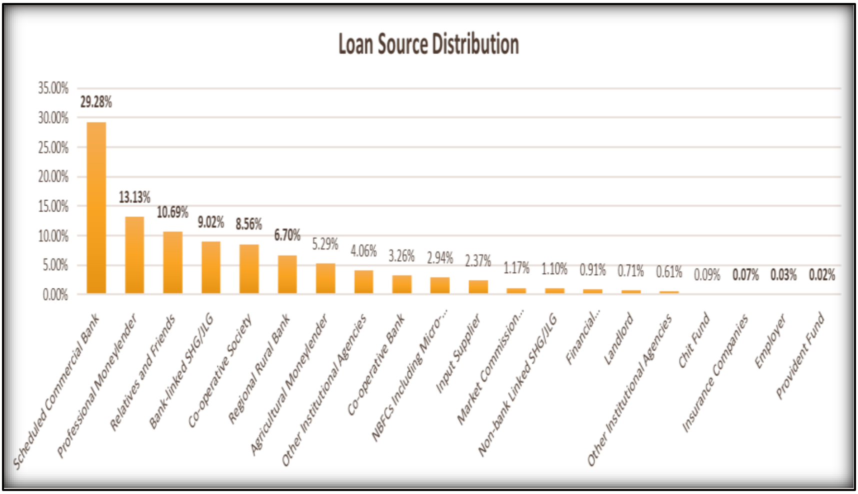
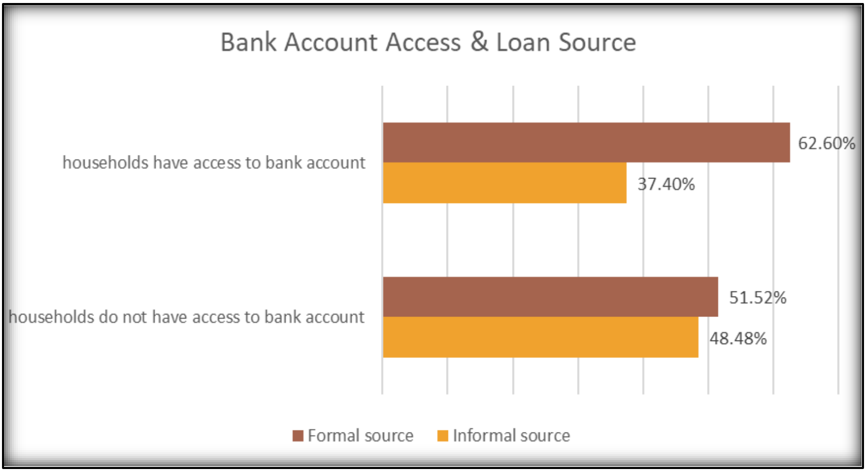
APPENDIX

Figure 2: Loan Source Distribution: Most to Least Common



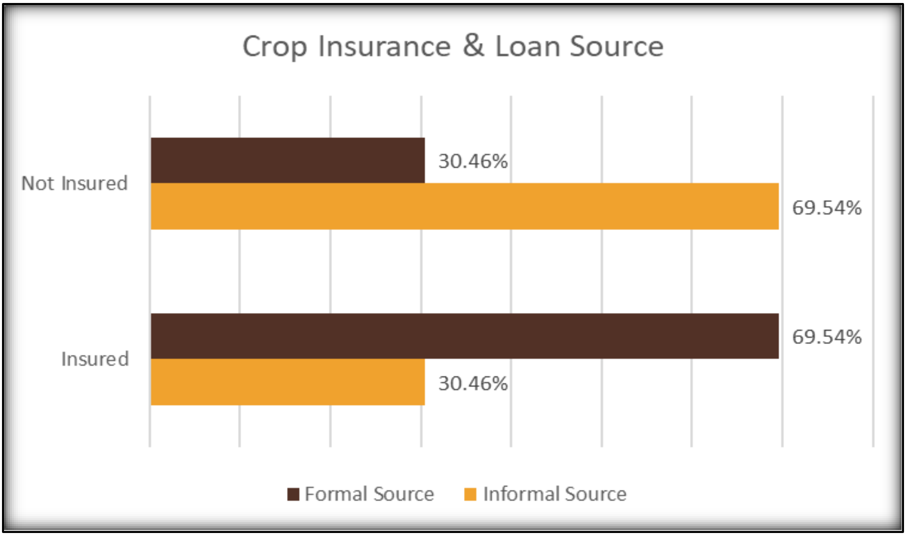
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 3: Distribution of Loan Sources based on Bank Account Access



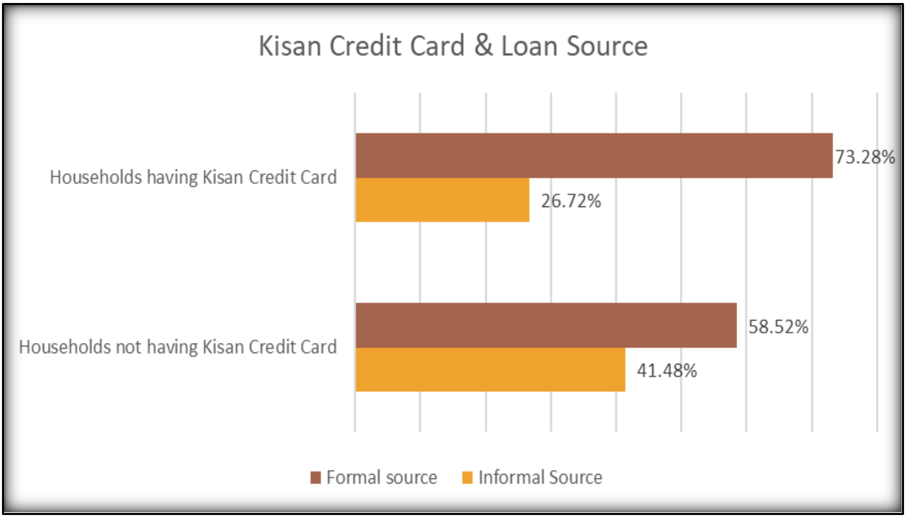
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 4: Distribution of Loan Sources based on Crop Insurance



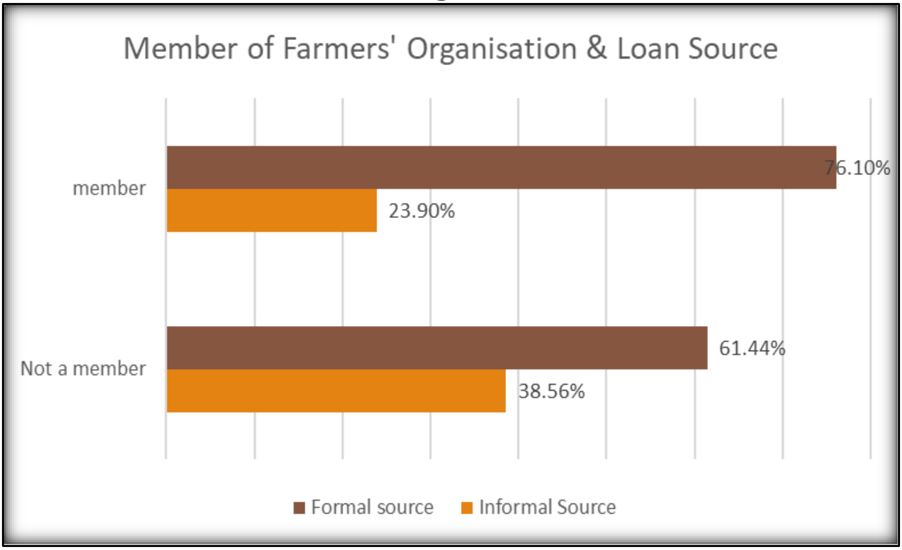
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 5: Distribution of Loan Sources based on Kisan Credit Card



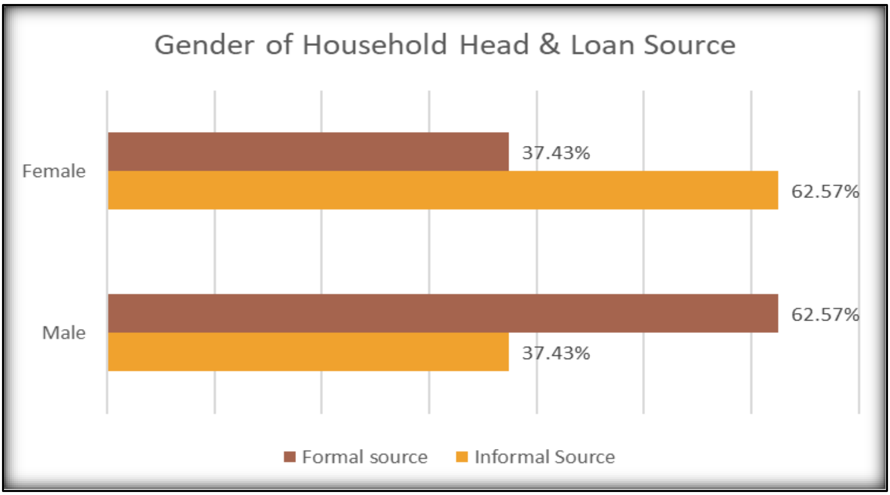
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 6: Distribution of Loan Sources based on Membership of Farmer's Organisation



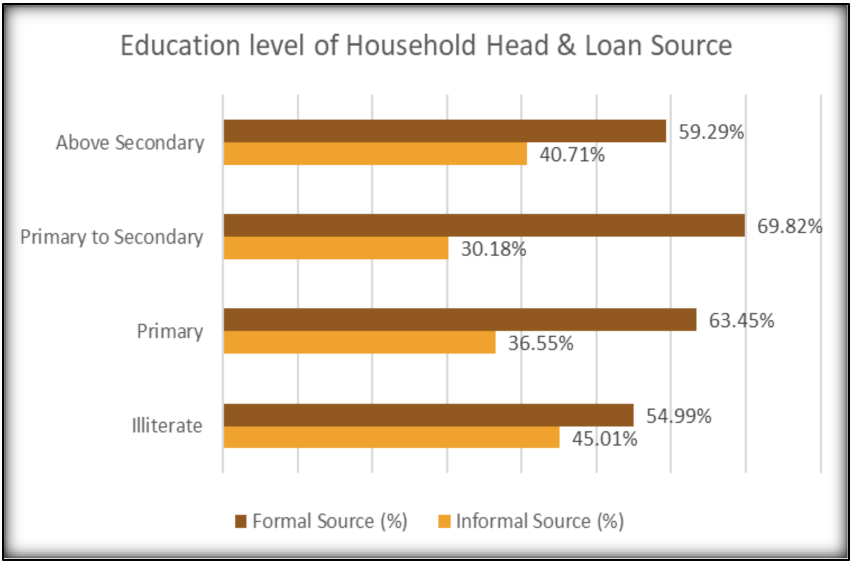
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 7: Distribution of Loan Sources based on Gender of Household Head



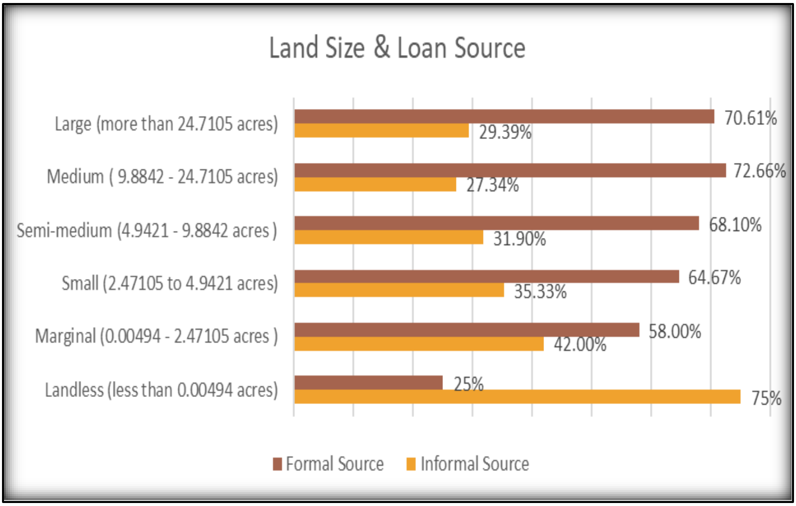
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 8: Distribution of Loan Sources based on Education Level of Household Head



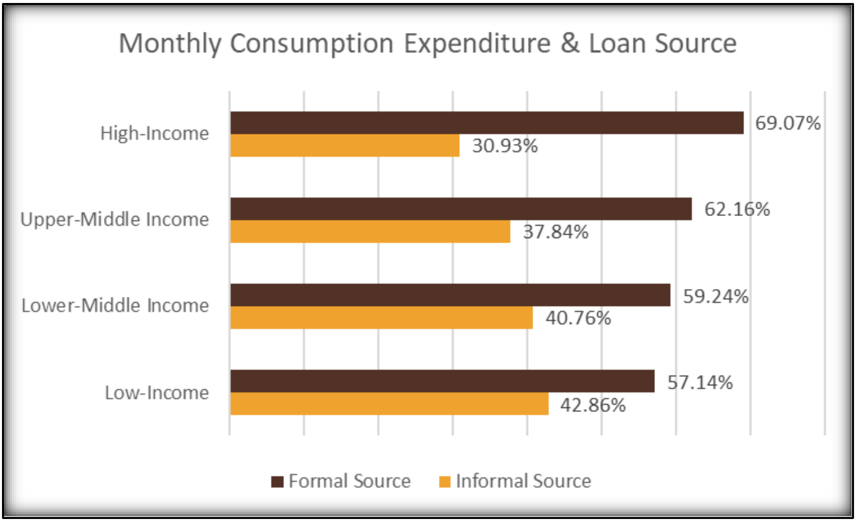
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 9: Distribution of Loan Sources based on Land Size



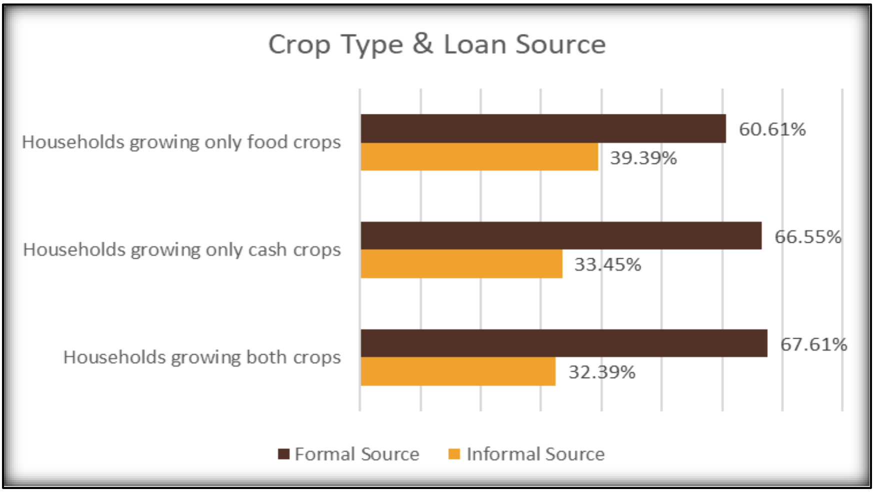
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 10: Distribution of Loan Sources based on Consumption Expenditure



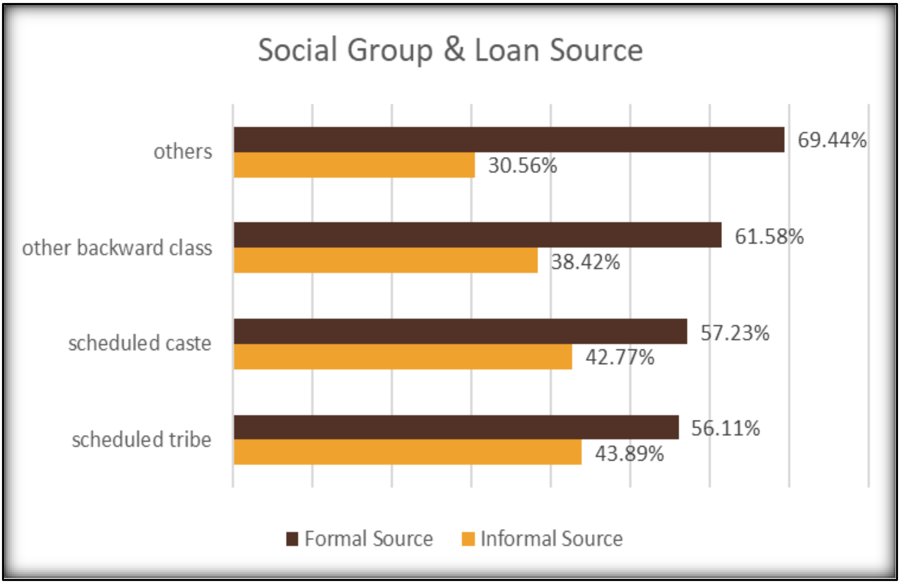
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 11: Distribution of Loan Sources based on Crop Type



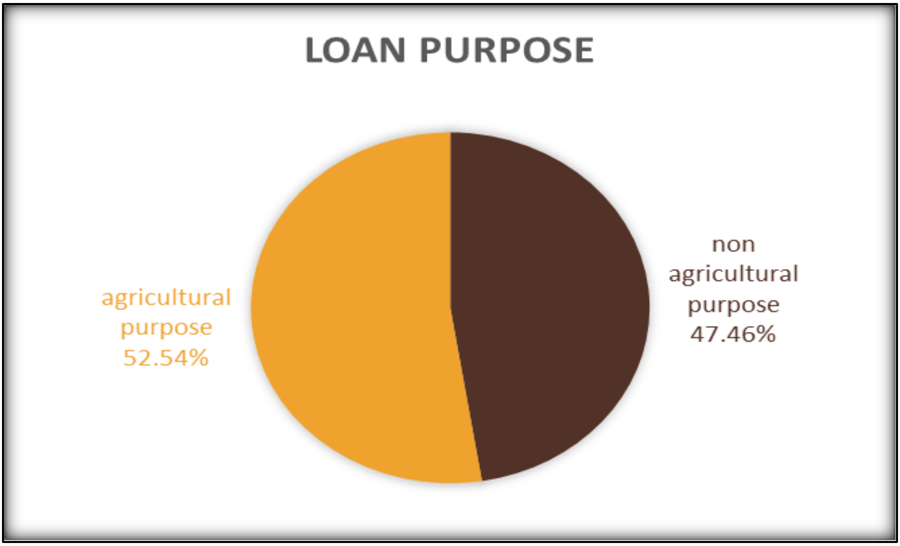
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 12: Distribution of Loan Sources based on Social Groups



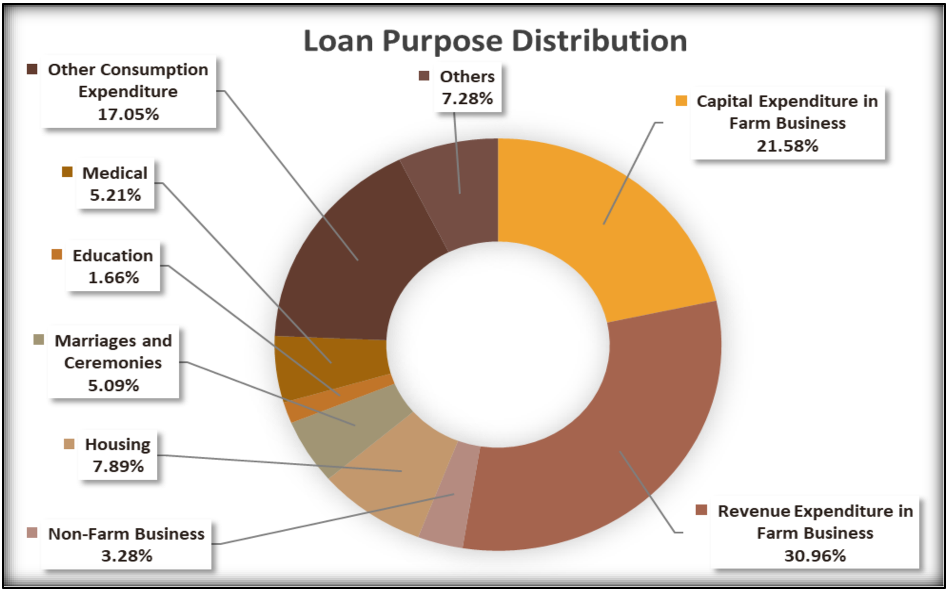
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure13: Distribution of Loans based on Purpose



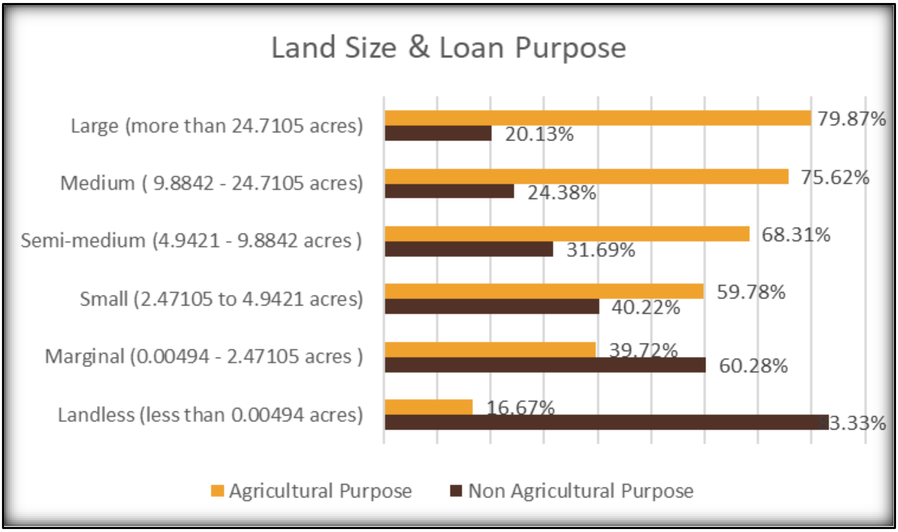
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 14: Distribution of Loans according to Purpose



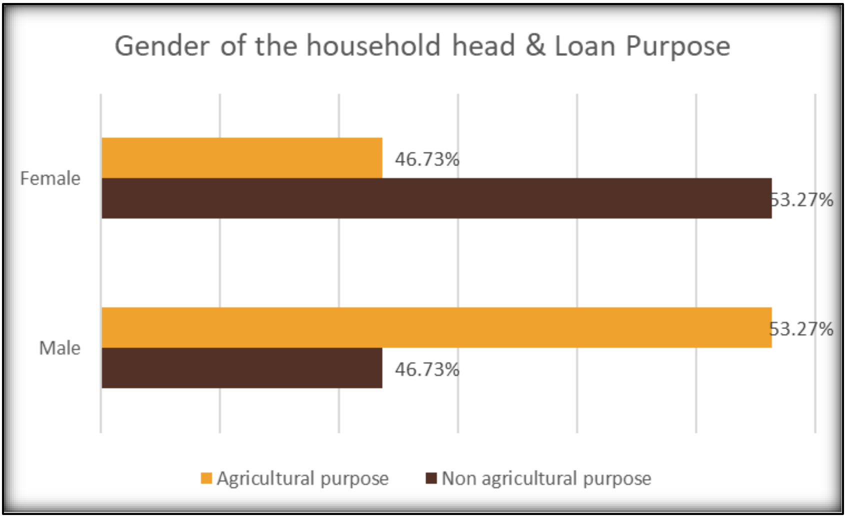
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 15: Distribution of Loan Purpose based on Land Size



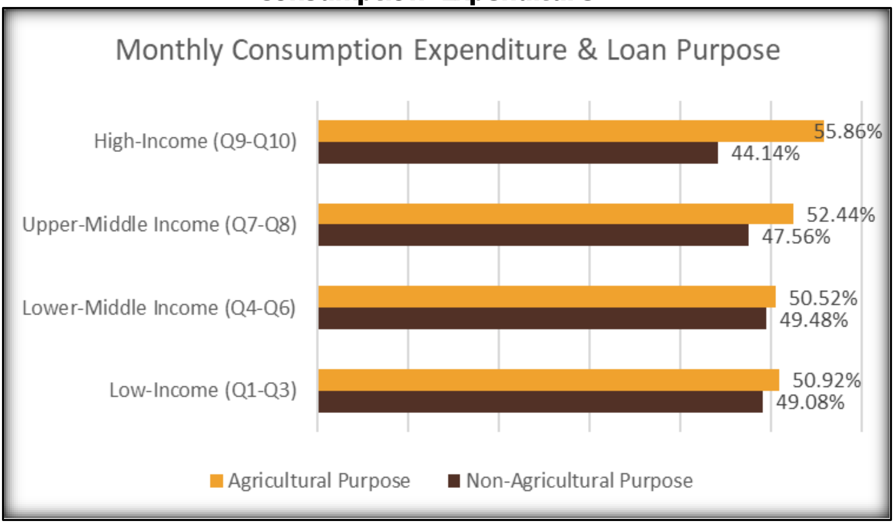
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 16: Distribution of Loan Purpose based on Gender of the Household Head



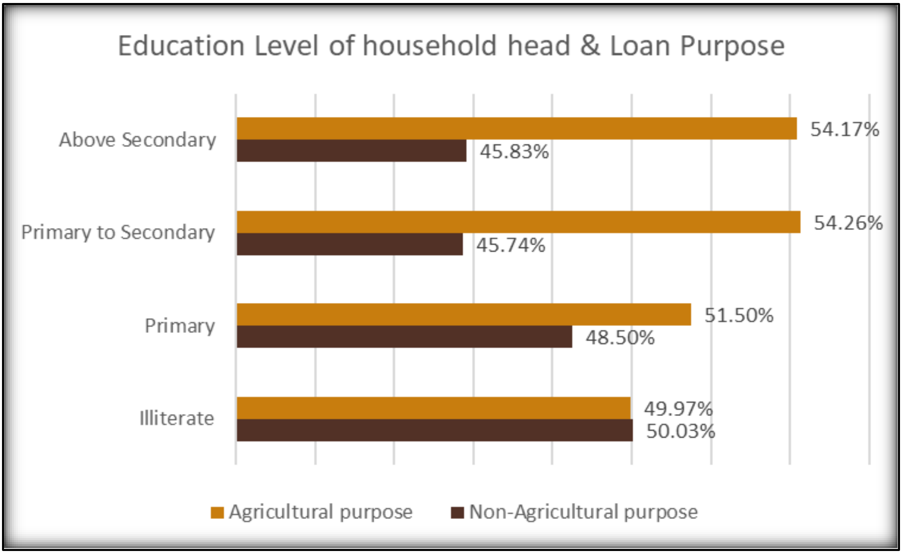
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 17: Distribution of Loan Purpose based on Monthly Consumption Expenditure



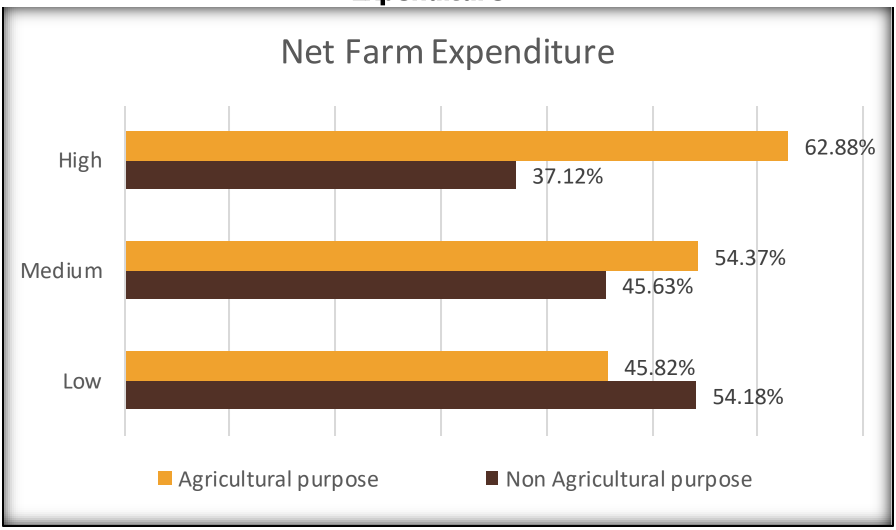
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 18: Distribution of Loan Purpose based on Education level of Household Head



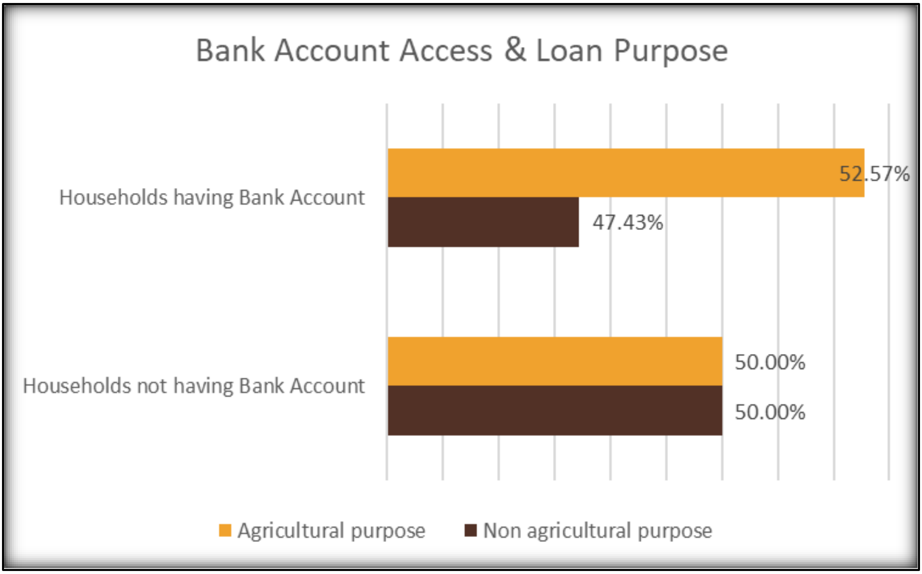
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 19: Distribution of Loan Purpose based on Net Farm Expenditure



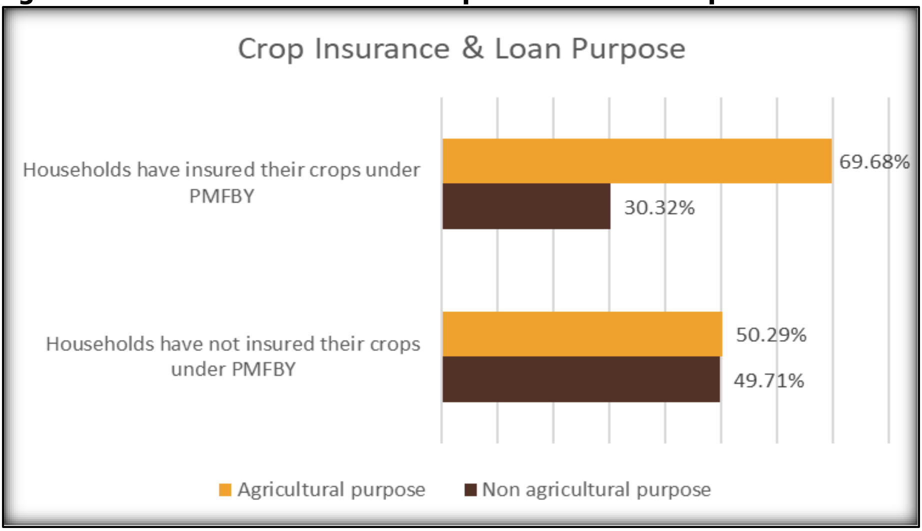
Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 20: Distribution of Loan Purpose based on Bank Account Access



Source: Authors' calculations using NSSO 77th Round data (2018).

Figure 21: Distribution of Loan Purpose based on Crop Insurance



Source: Authors' calculations using NSSO 77th Round data (2018).

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