IJHSR
ijhighschoolresearch.org
RESEARCH ARTICLE

Understanding Financial Inclusion: Patterns and Determinants of Formal Borrowing in India

Aaran Nihalani

Eton College, Windsor, Berkshire, SL4 6DW, UK; aaran.nihalani@gmail.com

ABSTRACT: Financial inclusion plays a major role in household welfare and economic freedom in India, where borrowing is often needed to finance consumption, agriculture, housing, and emergencies like health shocks. The paper examines the household characteristics' association with formal credit access and documents the structural patterns that continue to shape the borrowing landscape across the country. The study exploits the nationally representative All India Debt and Investment Survey (AIDIS), 2019, employing OLS and Logit regression models with fixed effects at the state and district level. MPCE, a proxy for well-being, is positively associated with an increase in formal borrowing by ~1% per thousand rupees. Household size has a small negative effect on formal borrowing. The SCs and STs are less likely to avail credit from formal sources compared to OBCs, whereas the 'Others' caste is more likely to avail credit than OBCs. Muslim and Christian households are also less likely to have access to formal loans. The study highlights the role of loan purpose and relative urgency in shaping borrowing behavior. Addressing structural inequality in the credit market will require policies that explicitly recognize and counteract social disadvantage, rather than assuming that broader financial development will automatically translate into equal access.

KEYWORDS: Economics, Econometrics, Financial Inclusion, Household Credit Behavior, Formal and Informal Borrowing.

Introduction

Financial inclusion plays a major role in household welfare and economic freedom in India, where borrowing is often needed to finance consumption, agriculture, housing, and emergencies like health shocks. Despite significant policy changes over decades, Indian households, across all groups, continue to borrow heavily from informal sources, with the determinants of formal borrowing unclear and varied across regions and socio-economic groups.[1] Understanding why certain households decide to go with formal credit while others choose informal credit is thus essential for identifying long-standing problems in India's financial system.

Existing literature highlights the complexity of credit access in developing economies. Research on microfinance shows that while expanding credit may increase borrowing activity, it does not necessarily translate into sustained or significant improvements in income or consumption. Loan design can constrain productive investment due to short-term repayments and the small volume of these loans.[1-3] Studies specific to India document substantial diversity in borrowing behavior driven by demographic and economic characteristics, including caste, landholding, income, and education.[4] Work on repayment structures further shows that rigid or frequent repayment requirements can discourage entrepreneurship among low-income households, who may not have enough time to deploy the credit before payment deadlines arrive meaningfully.[3,5] Criticisms of the current microfinance model in India include the much higher interest rates that impact the viability of borrowing, continued limited reach to the poorest, adverse selection, and weak infrastructure for expanding businesses.[1-3] A lack of collateral also drives people towards informal borrowing, and despite land being theoretically ideal as collateral, land records are often poorly maintained, impacting whether or not people can use land as collateral. This leads to land being underutilized as collateral, forcing more households to borrow informally.[6] Demand-side analysis indicates small but unimpressive improvements in financial inclusion, with rural households and disadvantaged groups continuing to face persistent frictions.[7]

Earlier empirical evidence highlights the importance of institutional finance for rural development, especially during the mid-20th century, when India made many changes to reduce the share of informal credit in the lending market. Increases in access to formal rural credit have historically supported agricultural productivity and poverty reduction, with the percentage of loans coming from moneylenders declining from 83% in 1951 to 36% in 1971. The AIDIS data used in this study shows that this number has further reduced to 22% in rural areas.[8,9] However, more recent reassessments question the robustness or magnitude of these effects, suggesting that outcomes may depend heavily on data quality, regional variation, and model specification.[10] Complementary research shows that institutional failures, such as corruption in the allocation of formal credit and the relative inconvenience of choosing a formal lender, may push households toward informal lenders even when formal channels are present.[11] Taken together, the literature suggests that both household characteristics and institutional constraints shape borrowing decisions, yet contemporary evidence using detailed, nationally representative microdata remains limited.

Recent contributions in *Economic and Political Weekly* argue that headline gains in financial inclusion, such as expanded banking infrastructure and account ownership, have not necessarily translated into substantively equitable credit access.

© 2026 Terra Science and Education

DOI: 10.36838/IJHSR812.81

Tagade and Reza highlight persistent structural gaps in meaningful participation within the formal financial system, while Chavan emphasizes that aggregate inclusion metrics often obscure disparities in usage patterns and borrower vulnerability across social groups.[12,13] These insights reinforce the need to examine disaggregated patterns of formal borrowing by caste, religion, and region, which the present study undertakes using nationally representative microdata.

This study fills this gap by analyzing borrowing patterns using the 2019 All India Debt and Investment Survey (AIDIS), one of the most comprehensive and recent datasets available on household indebtedness in India. The analysis examines how demographic and economic characteristics (including consumption levels, household structure, land ownership, caste, religion, and location) influence the probability of taking a formal loan as opposed to an informal one. Five econometric models are estimated, using logit and ordinary least squares (OLS) regression with variation of state and district-level fixed effects to control for unobserved regional heterogeneity. Average Marginal Effects are used for interpretability instead of log-odds coefficients. The findings reveal clear differences in borrowing determinants across households and substantial variation in both loan purposes and sources between rural and urban sectors. We find that groups including SC, ST, and Christians are less likely to borrow formally, indicating lower availability of formal sources, showing that structural inequality in India persists through the credit system. Existing literature comparing the propensity of different social groups to borrow formally ranks access to formal credit in agriculture as Others, OBC, SC, and ST.[14] This study finds that Others and OBC are, similarly, the top two, but puts SC below ST in terms of access to formal credit in general, as opposed to just agriculture, supported by average marginal effects (AME) and OLS coefficients.

Structural barriers to formal credit access operate through multiple channels: collateral constraints linked to land titling, historical exclusion from institutional banking networks, informational asymmetries, social discrimination in screening processes, and geographic clustering of financial infrastructure. These mechanisms imply that disparities in formal borrowing are not solely income-driven but embedded within broader institutional arrangements.

By providing updated national evidence, isolating within-region variation, and comparing formal and informal borrowing patterns at a granular level, this study contributes to the literature by offering a contemporary assessment of demand-side financial inclusion in India. It clarifies which household characteristics most strongly predict formal credit access and documents the structural patterns that continue to shape the borrowing landscape across the country.

The paper is structured with Section 2 describing the dataset being used in the study, the All India Debt and Investment Survey, including the details of the survey and the contents of the data. It then looks at the details of the two regression models used, OLS and Logit regression. Next, Section 3 contains the results and analysis of the paper's findings, bringing insights from the data with figures and tables. Finally, there is a conclusion to summarize the points made and the findings of the paper.

Methods and Data

Data:

AIDIS, or the All India Debt and Investment Survey, is a nationally representative survey conducted by India's National Sample Survey Office (NSSO).[15] AIDIS data was collected for the sixth time by the NSSO in 2019, during the National Sample Survey's 77th Round. It was first conducted in 1951, and it has been conducted roughly every 10 years since. AIDIS offers data on asset stock, indebtedness, capital formation, and indicators of rural/urban economies.[16] The survey covered 5,940 villages and 69,455 households in rural sectors and 3,995 blocks and 47,006 households in urban sectors.

The study was sampled through a stratified two-part sample, using simple random sampling without replacement for the villages/blocks in the rural or urban sectors. After this, simple random sampling was used once more for each of the strata based on Monthly Per Capita Consumer Expenditure (MPCE), used as a proxy for well-being in the survey. The survey covers the entirety of the Indian Union, excluding only inaccessible villages in the Andaman and Nicobar Islands. The data was verified post-collection to address errors, and outliers, based on MPCE, were removed from this study, reducing the number of observations by 0.2%.

The data comes with 18 datasets, or 'Levels', all focusing on different areas of the survey. For this study, we use Level 2, which addresses demographic and particulars of household members, Levels 3 and 4, which address household characteristics, and Level 14, which contains the data for loans taken by each household from both formal and informal sources. In this study, we load the datasets into individual R data frames before merging them into one large data frame, with Household ID as the variable being merged upon.

Other datasets, such as the India Human Development Survey (IHDS) from 2012 and the National Bank for Agriculture and Rural Development (NABARD) All-India Rural Financial Inclusion Survey (NAFIS), were considered.17,18 IHDS was not used because its loan data is limited and less detailed for household-level analysis. NAFIS focuses on rural data, so it was not suitable for a study comparing rural and urban borrowing patterns.

Methods:

The study employs OLS regression and Logit regression models with fixed effects at the state and district level, using nationally representative data on Loans in India. OLS regression calculates the response variable using Equation 1, with a closed-form solution for the coefficients given by Equation 2.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_p x_p + \epsilon \quad (1)$$

Equation 1

$$\beta = (X^T X)^{-1} X^T y \quad (2)$$

Equation 2

The first equation shows how response variables are produced during regression, with the β terms being the coefficients that the explanatory variables are multiplied by to arrive at the final response variable, with the ϵ representing the error term, which OLS aims to minimize, taking the sum of the squares of the residuals as its loss function.[19] The second equation offers an analytical solution to find the coefficients. However, as X increases in size, it becomes computationally intensive to invert the matrix, if it even is invertible, with a computational complexity of $O(n^3)$. This study also uses Logit Regression, as OLS has a limitation in that it is purely linear in X, and is not bounded between 0 and 1 like Logit is, which is necessary for a binary response variable. Therefore, Logit Regression is used to output values that are to be interpreted as probabilities. OLS is used for continuous outcomes, while Logit Regression uses Equation 3 to model the log-odds of the event's probability:

$$P(y = 1 \mid x) = \frac{exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ . \ . \ . \ + \beta_p x_p)}{1 + exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ . \ . \ . \ + \beta_p x_p)} \quad (3)$$

Equation 3

This study uses 5 models, shown in Table 1, to analyze different aspects of the AIDIS loan data. Logit Regression is used here to show the probability of borrowers taking a loan based on a certain characteristic, like their expenditure or household size. This allows for comparing how different groups of people borrow. Fixed effects are used at both state and district levels to control for unobserved regionally varying factors.[20] State-level effects control for differences in economic conditions or policies state by state, and district-level effects absorb bias from localized differences, like access to banks. This isolates the within-region variation for more consistent results in the regression. This ensures that the estimated relationships between variables and outcomes reflect variation within regions instead of between them.

Table 1: List of models being used in the study.

Model 1	Logit Regression on MPCE (Monthly Per-Capita Consumer Expenditure)
Model 2	Logit Regression on all characteristics, e.g., household size, land owned, caste
Model 3	Logit Regression on all characteristics with state-level fixed effects
Model 4	OLS Regression on all characteristics with district-level fixed effects
Model 5	Logit Regression on all characteristics with district-level fixed effects

While log odds offer a comparative measure of likelihood for borrowing characteristics, they are not intuitive and are difficult to interpret. A more understandable alternative is using Average Marginal Effects.[21] AME tells us what the expected impact on the outcome is when an independent variable is increased by one unit, averaged over all observations. This gives us an idea of how much of an impact each variable has on the final probability of borrowing, to see which factors are the most significant for identifying borrowing trends.

Replication/Reproducibility:

Replication code and data for this paper can be found at https://github.com/AaranNihalani/AIDIS.

Results and Discussion

Sample Characteristics:

Table 2: Summary of sample characteristics in AIDIS data. We see an even gender distribution and a majority of Hindus. Most respondents are located in rural areas, and loans are evenly distributed between formal and informal.

Summary Characteristics (AIDIS 2019)	
Variable	Value
Gender	
Male (%)	51.1
Female (%)	48.9
Religion	
Hinduism (%)	78.5
Islam (%)	12.6
Christianity (%)	4.9
Other religion (%)	4.0
Caste	
OBC (%)	44.2
Other caste (%)	27.8
SC (%)	16.7
ST (%)	11.4
Sector	
Rural (%)	62.9
Urban (%)	37.1
Loan Type	
Formal Loan (%)	49.8
Informal Loan (%)	50.2
Household Attributes	
Avg age (years)	30.6
Avg HH size (people)	5.5
Avg land owned (acres)	0.2
Avg MPCE (₹)	13,571.0
No. of Observations	480,687.0
Source: Author's Calculations from AIDIS, 2019	

Table 2 provides a summary of the observations made in the AIDIS data, where each observation is a loan. There is a very even distribution between male and female borrowers, ensuring we get representative data. The religion of borrowers is mostly Hindu, as is to be expected, with the next major groups being Islam and Christianity, with proportions consistent with official census numbers. With regards to caste, the largest portion is OBC (Other Backward Class), and the proportions of each caste are representative of the entire population. There are more rural respondents than urban respondents, but this is due to 63% of India's population being rural, consistent with AIDIS data.

Loan Characteristics:

Table 3: Loan data characteristics, by lender type. Formal loans are larger on average than informal loans. Interest for informal loans is almost twice as much, on average, as the interest rate of formal loans.

Loan Characteristics by Lender Type (AIDIS 2019)

Weighted using survey multiplier (MLT.x/100)

Lender Type	Number of Loans	% of Total Loans	Mean Amount (₹)	Median Amount (₹)	Mean Interest (%)	Median Interest (%)	Mean Outstanding (₹)	Median Outstanding (₹)
Formal	237,757	49.9%	225,774.39	70,000.00	10.52	10.00	203,430	55,120
Informal	238,483	50.1%	73,755.89	32,000.00	18.65	16.00	71,824	29,000

Source: Author's Calculations from AIDIS, 2019

DOI: 10.36838/IJHSR812.81

Table 3 offers a comparison of formal and informal loans. We have an even number of formal and informal loans available to us in the dataset, and the mean amount of each loan is much higher for formal loans, as would be expected. With the average formal loan over 250% greater than the average informal loan, borrower behavior for larger loans is very clear, with farm loans typically going through formal sources. Informal loans also have much higher interest rates, which is another reason why borrowers prefer formal sources of lending when larger amounts or less urgent matters are at hand.

Seeing the differences between the two loan types raises questions about other differences there may be between borrowers, in particular, their characteristics. To compare borrowers with and without a given characteristic, this study uses two-sample t-tests to evaluate whether the mean value of the characteristic differs across the two groups. The null hypothesis is that the true group means are equal. Rejecting this hypothesis indicates that the characteristic is statistically associated with formal borrowing and that the difference in the means isn't due to pure chance within the sampling methods. Regression is another way to investigate the characteristics that pertain to formal borrowing, using coefficients to see expected impacts on chosen borrowing source based on changes in relevant characteristics, which this study uses to understand the precise effect that each characteristic has on the choice of formal or informal borrowing sources.

Loan Distributions:

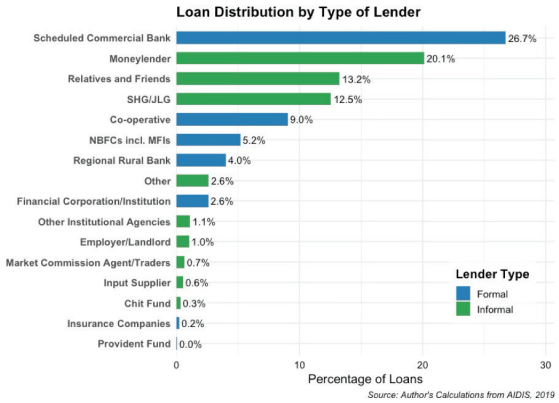

Figure 1: Distribution of loans by type of lender - both formal and informal sources. Scheduled commercial banks are the most common formal source, and moneylenders are the most common informal source.

Loans are distributed relatively evenly between formal and informal sources, as shown by Figure 1, where the formal lenders (shown in blue) make up 44.7% of loans taken (the sum of the blue formal bars), dominated by scheduled commercial banks, which have more capital on hand than many of the other sources, therefore attracting borrowers looking for larger loans, for businesses or farms. Moneylenders are the most common informal source of loans, as they are often the most accessible, through personal relations or just by being based in the same village as many borrowers. As expected, relatives and friends are common informal lenders, while SHGs (self-help groups) and JLGs (joint liability groups) facilitate small-scale credit through group responsibility. It is clear from Figure 1 that many Indians choose to borrow from community-based sources for credit access.

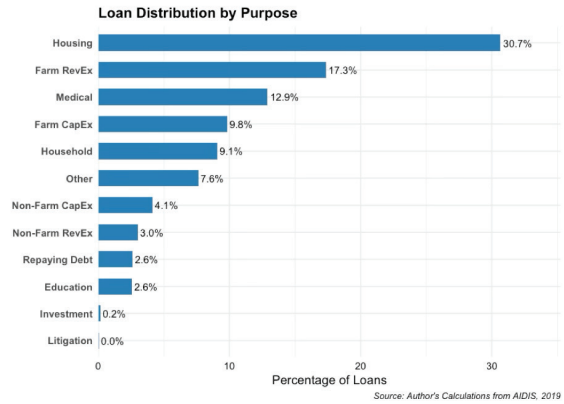

Figure 2: Distribution of loans by purpose. Housing is the largest cited purpose of loans, and farm-related loans form over a quarter of all loans.

Understanding the reason for loans being taken out allows us to draw conclusions about the behavior of borrowers in India and identify trends. To that end, Figure 2 gives us information about the purpose for each loan, weighted with the multipliers provided by NSS. Housing makes up the largest share of loan purposes, with Farm Revenue Expenditure and Medical expenses being the 2nd and 3rd most common loan purposes. The high proportion of Farm-related expenditure shows the scale of the rural population taking loans, as Farm expenditure forms over a quarter of all loans. This highlights the Indian economy's dependency on agriculture and the scale of the enterprise that leads to so many loans being taken.

T-Tests:

Table 4: T-test results table. Land ownership, household size, and MPCE exhibit statistically significant differences in mean values between households that borrow formally and those that borrow informally.

Independent-Samples *t*-Test Results by Formal Lending Status

Outcome Variable	*M* (No formal lending)	*M* (Formal lending)	*t*	*df*	*p*	95% CI
Land ownership	0.217	0.225	−5.916	437,546	3.304e-09	[-0.00954, -0.00479]
Household size	5.448	5.687	−30.671	421,707	< 2.2e-16	[-0.25452, -0.22394]
Monthly per-capita expenditure (MPCE)	11,897.740	15,831.670	−134.550	329,388	< 2.2e-16	[-3991.24, -3876.62]

Note. Group 0 = households without formal lending; Group 1 = households with formal lending.

Table 4 shows the results of statistical t-tests, used to evaluate the null hypothesis, which states that, in this case, the characteristics we evaluate don't have any association with formal borrowing. All three of the t-tests have a p-value less than 0.05, by many orders of magnitude, which allows us to reject the null hypothesis and deduce that the means of the groups of formal and informal borrowers differ.

Formal loan borrowers own more land on average than informal loan borrowers, with 0.217 acres for informal as compared to 0.225 acres for formal, $t(427536) = -5.9$, $p = 3.3e-9$. Formal borrowers also tend to have larger household size, with an average of 5.69 people, while informal borrowers have 5.45, $t(421707) = 30.6$, $p < 2.2e16$. Formal borrowers also have higher Monthly Per Capita Expenditure, a proxy for wellbeing, at 15832 rupees, while informal borrowers have 11898, 33% higher among formal borrowers, $t(329388) = -134.6$, $p < 2.2e-16$.

Land ownership has $p < 0.01$, indicating that there is a statistically significant difference between land ownership of

borrowers who borrow formally compared with informal borrowers. Since the mean in the informal borrowing group is less than the mean of the formal borrowing group, we can deduce that formal borrowers have higher land ownership than informal borrowers, although the magnitude of the difference is small. This t-test tells us that formal loan borrowers have more land holdings than informal loan borrowers. Landholding also facilitates loans, as it can be used as a form of collateral.

Household size, again $p < 0.01$, has a statistically significant difference in household size between formal and informal borrowers. However, with a difference of 0.2 people per household on average between each group, while statistically significant, it may not be economically significant. While household size is slightly larger on average for formal borrowers, the difference is minimal and likely doesn't have a major effect on borrowing decisions.

MPCE has another sufficiently small p-value of $p < 0.01$, meaning that there is a statistically significant difference in Monthly Per Capita Consumer Expenditure (MPCE) between formal and informal borrowers. Here we see the largest difference in the groups, with the difference between the two groups' means at around 4000 rupees. This tells us that formal borrowers tend to spend a significant 33% more than informal borrowers. We can conclude that households accessing formal credit have higher consumption levels, suggesting higher income or wealth.

While the statistical significance is clear, the economic magnitude differs across variables. The difference in land ownership, although statistically significant, is small in absolute terms (0.008 acres). This suggests that land ownership alone may not explain formal borrowing access, but could operate through collateral constraints. In contrast, the 33% higher MPCE among formal borrowers represents a substantively large gap, indicating that income-related screening mechanisms may play a central role in formal credit allocation. These unconditional differences motivate the multivariate regression analysis that follows, where confounding factors are jointly controlled.

Loan Distributions for Urban and Rural:

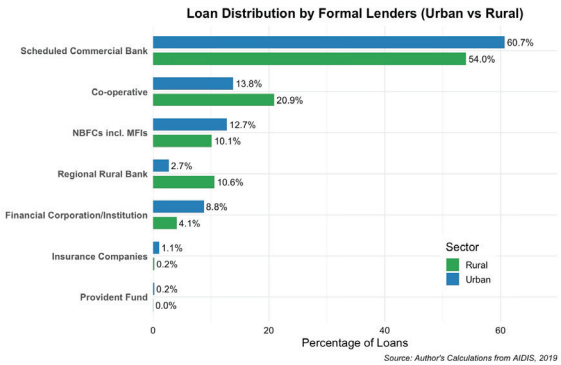

Figure 3: Distribution of loans from formal sources, comparing rural and urban borrowers. Scheduled Commercial Banks provide over half of all loans. Co-operative lending is more present in rural areas, which is reflected in borrower behavior.

Figure 3 shows us how rural and urban communities borrow when they choose to borrow from a formal source. Looking at the population as a whole, Scheduled Commercial Banks are clearly the most popular option, providing over 50% of the loans for both rural and urban populations. Co-operative lending is more popular among rural borrowers than urban borrowers, due to its stronger rural presence. Microfinance institutions are one of the more popular sources among both populations, with over 10% of formal loans going through Non-Bank Financial Corporations (NBFCs).

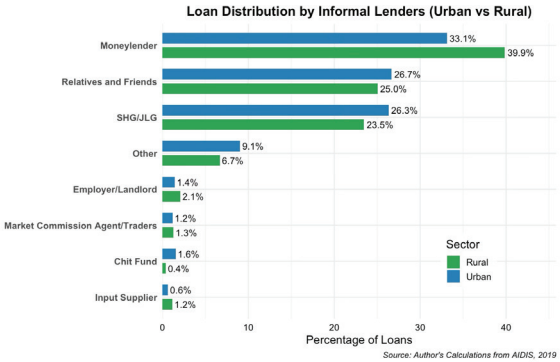

Figure 4: Distribution of loans from informal sources, comparing rural and urban borrowers. The distribution between informal lending sources is consistent between rural and urban borrowers, and moneylenders are the most popular choice.

Figure 4 shows us the differences between the sources of rural and urban borrowers when choosing an informal loan source. We see that the differences between rural and urban borrowing for each of the sources are much smaller than for formal borrowing, with all sources having less than a 3% difference between rural and urban borrowers, except for moneylenders, the most common choice. Rural borrowers are more likely to choose a moneylender by about 7 percentage points, attributed to moneylenders, who usually operate in villages or rural areas, accounting for the larger difference between the two populations for moneylenders.

Loan Purpose for Urban and Rural:

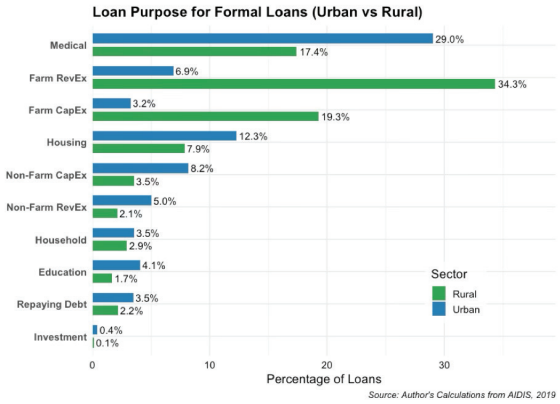

Figure 5: Distribution of loan purposes from formal sources, comparing rural and urban borrowers. The most common urban formal loan purpose is medical, while the most common rural formal loan purpose is farm revenue expenditure.

DOI: 10.36838/IJHSR812.81

Medical reasons are the most cited reason for borrowing, according to Figure 5, mainly from urban sources. One possible explanation for this is that when there is an urgent medical emergency and a loan has to be taken, urban communities have an easier time getting a formal loan than rural communities. Farm-related expenditure forms the next two largest purposes named for formal borrowing, showing the agricultural reliance in modern Indian society. As would be expected, the vast majority of borrowers for farm expenditure are rural, with over half of all rural formal loans being for farm revenue expenditure (RevEx) or capital expenditure (CapEx).

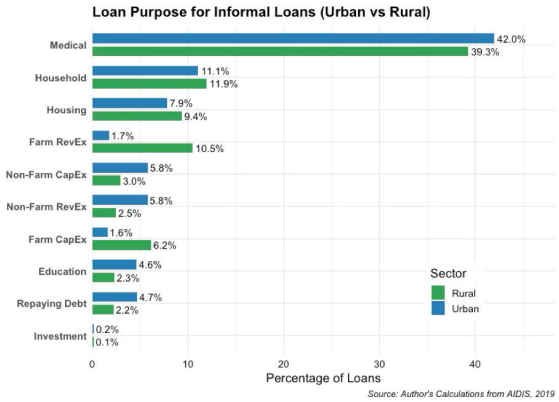

Figure 6: Distribution of loan purposes from informal sources, comparing rural and urban borrowers. For informal loans, both rural and urban borrowers cite medical purposes as the dominant purpose.

Just as with formal loans, Figure 6 tells us that medical reasons are the most common reason for borrowing from informal sources, with much more even numbers than with formal loans and a much higher proportion. This can be explained as borrowers needing medical loans urgently, in the event of a sudden emergency that requires money as soon as possible. Since informal loans are easier and generally quicker to obtain, more borrowers go to informal sources. Farm-related expenditure is much lower here, as farm loans are usually much larger than normal informal loans, so going to a formal source offers more competitive interest rates and the potential for much larger loans.

Loan Purpose for Formal and Informal:

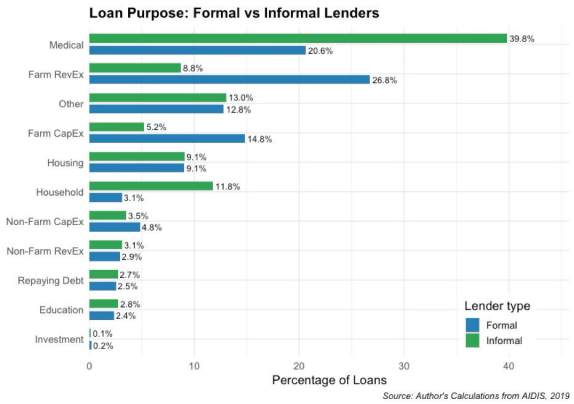

Figure 7: Distribution of loan purposes for formal and informal lenders. The largest share of informal loans is medical, and the largest share of formal loans is farm revenue expenditure. Loan purposes that are typically more urgent, like medical, are more likely to be informal.

Figure 7 displays the distribution of each loan purpose for formal and informal sources. Most medical loans are informal, due to the relative urgency of the loan and the increased accessibility of informal lending, particularly for rural communities. Farm-related expenditure is dominated by formal loans, due to the higher interest rates for informal loans and the higher formal loan size. We notice that urgent loan purposes, like medical and household, have a higher proportion of informal borrowing, detailing the behavior of borrowers when faced with an urgent situation, leaning away from formal loan sources.

The dominance of informal credit for medical purposes suggests that time-to-disbursement and procedural requirements act as binding constraints in formal markets. Formal lenders typically require documentation, collateral assessment, and processing delays, which are incompatible with emergency expenditure. This complements the t-test and regression findings, where income and land ownership increase formal access, suggesting that formal borrowing is structured around verifiable and planned financial needs rather than liquidity shocks.

Loan Distribution by Sector:

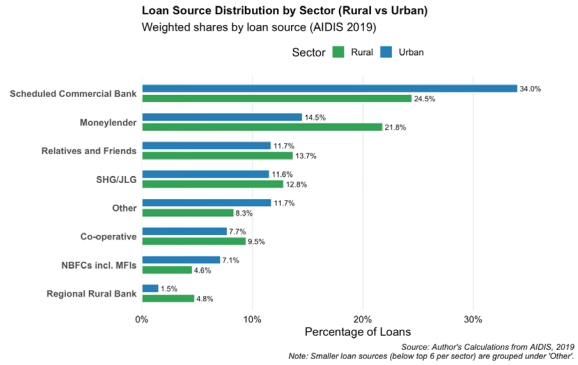

Figure 8: Distribution of loan sources by sector. Both rural and urban borrowers use SCBs the most. As would be expected, moneylenders are more common in rural communities, with other values relatively consistent between the two groups.

To compare where borrowers in rural and urban communities get their loans from, Figure 8 illustrates the top 6 sources, with the rest falling under the category of 'Other'. Scheduled Commercial Banks are the most common, once again, with both sectors having SCBs as the preferred source. Moneylenders, which are often considered much more common in rural sectors, are also the second major choice for urban borrowers, although there is a higher proportion of rural loans than urban loans from moneylenders. Relatives and Friends, as well as SHGs and JLGs, persist with similar rates across both sectors, as borrowing from people you already know makes sense for many borrowers who seek smaller-scale credit, and is much more convenient.

Regression Results:

Table 5: Logit and OLS regression table, with AME for interpretability. MPCE increases the likelihood of borrowing formally. OBCs and 'Others' are the most likely castes for formal borrowing, while Muslim and Christian households are less likely to borrow formally as compared to Hindu households.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Model description	Logit: MPCE only	Logit: Full controls	Logit + State FE	OLS + District FE	Logit + District FE
Monthly Per Capita Expenditure (MPCE per 1000 units)	1.36	1.25	1.08	0.72	1.13
Household Size	–	-0.48	-0.46	-0.06	-0.59
Land Owned (acres)	–	2.62	2.55	2.58	2.52
Urban (1 = Urban, 0 = Rural)	–	3.36	2.58	4.08	2.26
Caste: SC (ref = OBC)	–	-4.71	-5.72	-6.80	-6.24
Caste: ST (ref = OBC)	–	2.09	-2.32	-4.20	-3.69
Caste: Others (ref = OBC)	–	10.78	7.53	6.68	6.16
Religion: Christianity (ref = Hinduism)	–	-7.92	-3.90	-2.57	-3.23
Religion: Islam (ref = Hinduism)	–	-8.53	-9.49	-11.42	-10.67
Religion: Others (ref = Hinduism)	–	-0.16	1.98	3.10	2.67

AMEs expressed as percentage-point changes. Computed on a 10% subsample for efficiency. Models with fixed effects (3 & 5) computed without standard errors due to memory and package limitations. Source: Author's calculations from AIDIS, 2019.

Table 5 displays the results of the 5 regression models used in this study, with descriptions of each model in the top row. The inclusion of caste and religion indicators allows for comparison between different groups and shows how differences in characteristics impact accessibility of formal borrowing. Instead of log-odds, Average Marginal Effects have been chosen, as they provide changes in predicted probability, which are easier to interpret than log-odds coefficients. It shows how much a one-unit change in the explanatory variable will affect the outcome variable, in percentage points. It is worth noting that Model 4 uses OLS regression instead of logit regression, but the coefficients offer similar interpretations to the AME values.

MPCE, as would be expected, is positively associated with an increase in formal borrowing, by about 1% per thousand rupees, as borrowers with higher income can take larger loans out from banks. Household size has a small negative effect on formal borrowing, possibly explained by larger households implying lower income, needing to fit more people under a single roof. Increased land ownership is associated with an increase in the chance of formal borrowing by about 2.5 percentage points per acre, and the large proportion of farm-related formal loans offers qualification for this trend. Urban residence also increases the likelihood of formal borrowing, reflecting better access to formal financial institutions.

Caste is compared to the reference category of OBC, and relative to this, AME coefficients show a reduction in the likelihood of formal borrowing for SC households of between -4.71 and -6.80 percentage points, showing how inequality in socioeconomic groups persists through the credit market, where fewer SC households can borrow formally. We see a mixed range for ST households, from a positive coefficient in the baseline model to negative coefficients in the fixed effects models, highlighting the importance of adjusting for micro-variations that are unseen in the data. The large increase in the probability of formal borrowing for the 'Others' caste category, between 6.16 and 10.78 percentage points, reflects how socially advantaged groups have much more access to formal borrowing.

We see similar results with religion, where Muslims are consistently less likely to borrow formally relative to Hindus, showing persistent inequality in access to credit. Christians also show a lower likelihood of formal borrowing, while the 'Others' religion group displays smaller and mixed effects. This further demonstrates that disparities in formal borrowing are not only driven by economic characteristics but also by social and religious group identity.

The OLS coefficients indicate how a one-unit change in each explanatory variable affects the predicted value of the outcome, holding all other variables constant. Negative coefficients for SC, ST, as well as Christian and Muslim households, imply a lower predicted likelihood of formal borrowing relative to their respective reference groups (OBC for caste and Hindu for religion). Positive coefficients for land ownership, urban residence, and the 'Others' caste and religion categories indicate higher predicted likelihoods of formal borrowing.

These disparities persist even after controlling for income, land ownership, and fixed regional effects, suggesting that differences are not fully explained by observable economic characteristics. This raises the possibility of structural exclusion mechanisms operating within credit screening processes or through differential access to documentation and financial networks.

■ Conclusion

This study provides updated, nationally representative evidence on the determinants of formal borrowing in India, using the 2019 All India Debt and Investment Survey (AIDIS). The results show that, while formal and informal borrowing coexist at comparable levels, access to formal credit is highly uneven across households, often associated with particular characteristics of the borrowers. Higher consumption, land ownership, and urban location significantly increase the likelihood of formal borrowing, reflecting the importance of income and proximity to financial institutions when it comes to credit accessibility. In contrast, socially disadvantaged groups - particularly Scheduled Caste households, Muslims, and Christians - remain systematically less likely to access formal credit, even after controlling for state and district-level variations through fixed effects. These findings indicate that inequalities in India's credit market closely mirror broader social and structural inequalities, rather than being driven solely by economic characteristics or rural-urban differences.

The study also highlights the role of loan purpose and relative urgency in shaping borrowing behavior. Formal credit dominates larger, planned expenditure, such as agricultural investment, while informal credit is the primary source for urgent needs, especially medical and household expenses. This suggests that barriers to formal borrowing are institutional as well as situation-dependent, with speed and accessibility playing an important role in household decision-making when it comes to borrowing.

From a policy perspective, the findings imply that expanding financial inclusion requires more than a narrow focus on rural outreach. Existing policies mandate that a fixed share of lending must be supplied to priority sectors (like the 40% sector requirement for rural credit through the Priority Sector Lending scheme), but these regulations are insufficient on their own. Disparities by caste and religion hint towards the need for more targeted interventions within both rural and urban credit markets. These interventions could include improved access to

DOI: 10.36838/IJHSR812.81

collateral through better land record systems, simplified loan procedures for urgent credit needs, and continued and explicit monitoring of credit allocation across social groups to mitigate exclusion.

Overall, the evidence suggests that formal financial expansion in India has been uneven in terms of its inclusivity. Addressing structural inequality in the credit market will require policies that explicitly recognize and counteract social disadvantage, rather than assuming that broader financial development will automatically translate into equal access.

Acknowledgments

I would like to extend my sincere appreciation to Atif Anwar for his guidance and mentorship throughout the study.

References

1. Banerjee, A. V.; Duflo, E. *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty*; PublicAffairs: New York, 2011; Chapter 7.
2. Banerjee, A. V.; Duflo, E. Giving Credit Where It Is Due. *J. Econ. Perspect*. 2010, *24* (3), 61–80. https://doi.org/10.1257/jep.24.3.61
3. Bateman, M.; Chang, H.-J. Microfinance and the Illusion of Development. *World Econ. Rev*. 2012, 1, 13–36.
4. Prakash, A.; Kumar, A.; Singh, D. Determinants of Household Borrowing in India: Evidence from National Microdata. *Indian J. Econ. Dev*. 2019, *15* (3), 512–522.
5. Field, E.; Pande, R.; Papp, J.; Rigol, N. Does the Classic Microfinance Model Discourage Entrepreneurship among the Poor? *Am. Econ. Rev*. 2013, *103* (6), 2196–2226. https://doi.org/10.1257/aer.103.6.2196
6. Narayanan, S.; Chakraborty, J. *Land as collateral in India*; IGIDR Working Paper 2019-006, Indira Gandhi Institute of Development Research: Mumbai, 2019.
7. Venumuddala, V. R. Patterns in Demand Side Financial Inclusion in India — An Inquiry Using IHDS Panel Data. arXiv. 2020, arXiv:2005.08961. https://arxiv.org/abs/2005.08961
8. Binswanger, H. P.; Khandker, S. R. The Impact of Formal Finance on the Rural Economy of India. *J. Dev. Stud*. 1995, *32* (2), 234–262. https://doi.org/10.1080/00220389508422413
9. Burgess, R.; Pande, R. Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment. *Am. Econ. Rev*. 2005, *95* (3), 780–795. https://doi.org/10.1257/0002828054201242 aeaweb.org+1
10. Buliskeria, N.; Baxa, J. Do Rural Banks Matter That Much? Burgess and Pande (2005) Reconsidered. *J. Appl. Econ*. 2022, DOI: 10.1002/jae.2922 library.utia.cas.cz+1
11. Ghosh, P. Formal Credit, Corruption and Informal Credit. *J. Dev. Econ*. 2013, *104*, 47–58. https://doi.org/10.1016/j.jdeveco.2013.05.001
12. Tagade, N.; Reza, M. S. *Financial Inclusion in India*; Economic and Political Weekly 2025, *60* (22).
13. Chavan, P. *How Inclusive Is Financial Inclusion in India?*; Economic and Political Weekly 2025, *60* (40).
14. Karthick, V., and Madheswaran, S. (2018). Access to formal credit in the Indian agriculture: Does caste matter? *Journal of Social Inclusion Studies*, 4(2). https://doi.org/10.1177/2394481118814064
15. National Sample Survey Office. *All India Debt and Investment Survey (AIDIS), NSS 77th Round*; Government of India: New Delhi, 2019.
16. National Data Archive (NADA). *AIDIS 2019 Microdata Catalogue Entry*. https://microdata.gov.in/NADA/index.php/catalog/156.
17. Desai, S.; Vanneman, R.; NCAER India Human Development Survey (IHDS) Team. *India Human Development Survey-II (IHDS-II), 2011–12*; University of Maryland & NCAER: New Delhi, 2015.
18. NABARD. *NABARD All India Rural Financial Inclusion Survey 2016–17 (NAFIS)*; National Bank for Agriculture and Rural Development: Mumbai, 2018.
19. Wooldridge, J. M. *Introductory Econometrics: A Modern Approach*, 5th ed.; South-Western Cengage Learning: Mason, OH, 2013.
20. Allison, P. D. *Fixed Effects Regression Models*; SAGE Publications: Thousand Oaks, CA, 2009.
21. UVA Library. *A Beginner's Guide to Marginal Effects*. UVA Library StatLab. https://library.virginia.edu/data/articles/a-beginners-guide-to-marginal-effects

Author

Aaran Nihalani is a Year 12 Student at Eton College with interests in Computer Science, Machine Learning, Maths, Statistics, and Economics. He finds applied Machine Learning particularly interesting in the context of Finance and Econometrics, and plans to study Computer Science with a focus on Finance and Machine Learning at university.