DOI:
10.1016/j.worlddev.2012.11.001

Does access to formal agricultural credit depend on caste?

Abstract

This paper analyzes whether caste impedes access to formal agricultural credit in India. Credit is provided mainly through cooperative and commercial banks. Using national data, we find that cooperative banks discriminate against lower caste borrowers, and find weak evidence that commercial banks instead bias lending in their favor in accordance with affirmative action policies. We compare the organizational structures of the two types of bank, and explain discrimination by cooperative banks in terms of interest group capture at the district level by showing that discrimination takes place in those districts where higher castes dominate.

Keywords: Asia, India, caste, formal, credit, discrimination

1. Introduction

Social group identity is intricately related to economic outcomes, particularly in developing countries. In rural India, the historically entrenched caste system wields significant influence on economic outcomes, an indicator of which are the large differences in consumption expenditures between caste-groups (Deshpande 2000). Caste can shape economic outcomes in two inter-linked ways. The first is through socio-political processes and networks that operate largely independent of the State. These can determine cooperation within communities (Drèze & Sen 2002), access to resources such as irrigation water (Anderson 2011) and capital and labour inputs (Banerjee & Munshi 2004), or educational and occupational choices (Munshi & Rosenzweig 2006). The second is through the effect of group-identity on government policy and the provision of services such as public goods (Banerjee et al. 2005; Banerjee & Somanathan 2007). In the second case, government policy might also attempt to alleviate historical disadvantage through affirmative action such as political reservation (Pande 2003; Prakash & Chin 2011), or quotas in government educational institutions (Bertrand et al. 2010) and public-sector jobs (Weisskopf 2004).

Financial inclusion forms an important strand of affirmative action policies in India. Burgess & Pande (2005) examine, for instance, how the large expansion of branch banking services to previously unbanked locations during 1969 to 1990 helped reduce poverty. Yet, the role of caste in determining access to formal credit has not been examined in the literature using national data. In this paper, I use data from 2002-03 and focus on how caste determines access to agricultural production credit. The latter is a crucial determinant of rural incomes, and therefore constitutes an important focus of financial affirmative action. The bulk of formal agricultural credit is disbursed through commercial and cooperative banks. Commercial banks are large and centralized entities under the direct supervision of the Reserve Bank of India[1] (RBI), whose lending is expected to conform to affirmative action policies and targets. Cooperative banks, in contrast, constitute a large network of decentralized, independent entities, many aspects of whose functioning are not directly controlled by the RBI[2].

I first examine how the likelihood of borrowing any formal agricultural credit changes with caste, and find that caste is not a significant determinant of access once other household characteristics are taken into account. I then disaggregate borrowings between commercial and cooperative banks, and use bivariate probit models to analyze the influence of caste. I find that caste is now significant, and that its influence differs radically for the two types of bank. Cooperative banks bias lending in favor of higher castes, indicating the presence of negative discrimination against lower castes, while commercial banks do not. Instead, there is weak evidence that commercial banks bias lending in favor of lower-caste households, in accordance with affirmative action policies for financial inclusion.

A possible explanation for this phenomenon is that cooperative banks' management structures are vulnerable to interest group capture through local political influence. Unlike commercial banks which work with centralized decision-making procedures under the direct supervision of the RBI, cooperative banks are organized in a three-tiered aggregating structure, spanning village, district and state levels. The district-level entities are expected to act as mentors for village-level cooperatives under them. Given the organizational and political significance of the district in Indian administration, any capture by interest groups is likely to take place at this level, and might be reflected in the lending behavior of cooperative banks accordingly.

I test for the possibility of interest-group capture by defining caste dominance in the district in terms of agricultural land ownership, and analyze how the probability of borrowing changes according to the dominant caste. While the notion of dominant caste is multidimensional, Srinivas (1959) points towards land ownership being an important indicator of dominance[3]. I find that the negative discrimination by cooperative banks is visible mainly in those districts where higher caste groups are dominant, and disappears otherwise, lending support to the theory of capture by caste-based interest groups. This is also consistent with several field studies which have studied lending practices in rural India using small samples (Sarap 1990; Jodhka 1995; Drèze et al. 1997). Finally, I also examine whether caste influences the amount of credit borrowed, and whether interest rates and repayment rates differ according to caste.

2. Background

The caste system in India emerged as a hierarchical system of social groupings within Hindus, where occupations were hereditary, and marriages took place only within the same caste. While caste no longer determines occupation, it continues to play an important role through historically-acquired capital, both tangible (land, money and other assets) and intangible—particularly networks. The Indian government categorizes castes into three major groups; the Scheduled Castes (SCs) who are the most disadvantaged (historically these were the Untouchables), the Other Backward Classes[4] (OBCs) who are of middling disadvantage, and Others, the traditionally privileged higher castes. We exclude Scheduled Tribes (STs) from our analysis, an additional category employed to classify tribal peoples, since STs have not, historically, been part of the caste system[5].

Recognizing caste-based socio-economic disadvantage as a major problem, government policies have sought to provide a 'level playing field' through affirmative action in several areas. In financial services, affirmative action is based on caste as well as more generally defined socio-economic disadvantage. The first All India Rural Credit Survey Committee Report (RBI 1954) recognized that access to financial services was strongly dependent on socio-economic status, and policy measures have since aimed to strengthen access in rural areas, particularly for small farmers[6].

The majority of formal credit in rural India is disbursed through cooperative and commercial banks. Beginning from the Indian Cooperative Act of 1904 and the Cooperative Societies Act of 1912, cooperative banks today have 120 million members (GOI, 2005), and are organized in a three-tiered structure: Primary Agricultural Cooperative Societies (PACS) at the village level, (district) Central Cooperative Banks (CCBs) at the district level, and State Cooperative Banks (SCBs) at the state level[7]. Cooperative banks are decentralized, and the district and state units oversee and guide the village-level PACSs, helping them access financial resources and mitigate seasonal patterns in the excess demand and supply of funds by working as clearing centres. As Misra (2010) explains, districts—where CCBs operate—were chosen as the first level of aggregation in view of organisational considerations, since districts form the basic unit for civil administration.

The performance of CCBs and PACSs has been anything but encouraging, and as of 2003 they had large accumulated losses for which poor governance practices have been blamed (Shah et al. 2007). By design, CCBs are expected to mainly have institutional members in the form of PACSs, however individuals have formed an increasing proportion of membership, and constituted 86% of total members in 2007 (Misra 2010). In 2005, the government of India (GOI) set up a committee to review the functioning of cooperative banks and recommend changes. The Vaidyanathan Committee report (GOI 2005) took stock of several structural problems and made recommendations, which included appointing democratically elected managements, board members with 'fit and proper criteria of eligibility' (GOI 2005, 69), and professionally qualified CEOs. The committee noted that governance structures in cooperative banks were impaired "because of politicisation of these institutions, reflected in the fact that directors on Boards of Cooperative Banks are involved in active politics either at the State, District, and Taluka level" (GOI 2005, 27).

Commercial banks, instead, function mainly as centralized institutions with a large network of branches. In 1969, the Indian government nationalized the 14 major commercial banks to bring them under the direct control of the RBI, which enabled these banks to play a major role in pursuit of social objectives (Pande 2007). The need was also felt for a social banking program that involved a major expansion in the number of branches, bringing financial services to nearly 30,000 previously unbanked rural locations between 1969 and 1990 (Burgess & Pande 2005; Burgess et al. 2005). Alongside, 'priority sector' lending has long been a focus of financial inclusion policies. Starting from 1968 when the National Credit Council advised banks to increase their finance to priority sectors, to 1985, when all commercial banks were given a target of 40% finance to this sector from their overall lending portfolio, the RBI has continued to encourage priority sector lending (RBI 2008). The priority sector includes, amongst others, small and marginal farmers and 'weaker sections', where the latter include SC and ST households. As of 2002, the RBI specified that banks extend 10% of Net Bank Credit to weaker sections (RBI 2002a). Policy guidelines urge banks to enable better access to loans for Scheduled Castes, and this includes lending at lower rates of interest (RBI 2002b; 2004; 2006).

While the policy perspective remains one of improving financial inclusion for socially and economically disadvantaged, a key question is whether formal lenders—mainly banks—*discriminate* between borrowers on the basis of caste, i.e. base their lending decisions on factors which are not 'objective' (Becker 1971). The question of discrimination is distinct from overall issues of access, even as the latter are no doubt important for economic growth and alleviating poverty. Even in the absence of discrimination, profit-maximizing banks can be expected to base their lending decisions on the availability of collateral and past default behavior. Disadvantaged borrowers will have less assets to collateralize, so that even without discrimination, lower-caste borrowers will receive fewer loans on average. The question of discrimination is more serious than that of purely asset-based differences in access to credit, since it implies, if prevalent, that lower castes are less likely to receive credit *even if* they have sufficient assets to collaterialize[8].

Given the crucial role of bank credit in a population largely dependent on agriculture, this has serious implications for the larger policy agenda on reducing poverty. Yet there is relatively little empirical research on household credit transactions and questions of socio-economic disadvantage using quantitative data[9]. What national-level research does exist tends to focus on the role of commercial banks. For example, Burgess & Pande (2005) estimate how access to financial facilities increased for poorer and SC/ST households as a result of the 1969-1990 banking expansion, and Banerjee et al. (2004) examine the functioning of nationalised and private commercial banks, and how their institutional structures relate to their expansion and lending practices.

Other studies on credit in India include Kochar (1997) who examines whether farmers are (formal) credit-constrained using data from Uttar Pradesh, and Pal (2002) who studies the determinants of household credit choices using data from 3 South-Indian villages, and finds that upper-caste households are more likely to borrow from the formal sector. Cole (2009) shows that Indian banks are liable to political capture since there is a marked increase in agricultural lending during election years. Finally, field-studies have analysed borrowers and banks at close quarters and often over long periods of time (mainly in northern India), and concluded that caste-based discrimination does take place alongside questionable or corrupt practices, in certain types of banks (Sarap 1990; Jodhka 1995; Drèze et al. 1997).

3. Data

The data for this study come from the 2002-03 Debt and Investment Survey conducted by the National Sample Survey Organisation, which covered 143,285 households across India[10], of which 91,192 were classified as rural. The main purpose of the survey was to collect information on household borrowings, liabilities and repayments, besides acquisition and loss of assets, consumption expenditure and various demographic details. The survey took place through two visits to each sampled household in the year 2003 which were roughly 6 months apart. The first visit covered all items on the survey questionnaire, while the second visit covered a subset of these: information on loans and assets.

Throughout, means and proportions referred to are estimated statistics for the population rather than the sample, since means and standard deviations are calculated using probability weights and standard errors clustered at the village level, yielding population-level estimates.

I restrict the analysis to 18 states of India[11], excluding the North-Eastern states, Jammu and Kashmir, and Delhi, and use data on Hindu farmer households[12]. In the resulting sample, SCs constitute 15.44% of households, OBCs 52.26%, and Others 32.30%.

The wealth status of households, alongside their land ownership, is likely to play an important role in shaping their access to credit. While the data do not provide direct information on household income, there are at least two ways of obtaining proxies for this. The first is the figure for monthly per capita household consumption expenditure reported in the data, and the second is by constructing an index of asset-ownership. Sahn & Stifel (2003) advocate the latter, since mis-reporting can often jeopardize data on expenditure. I follow this approach, and Appendix A details this argument further and explains the procedure for constructing an assets index based on consumer durables.

Variables on household characteristics include household size, the household head's education level[13] and age, in addition to the proportion of children, adult males and adult females in the household.

71.4% of farmer households in our sample did not have any loan, while 20.8% had a single production loan from a formal source, and 7.8% had two or more such loans. Focusing on the source of these formal production loans, 54.6% came from cooperative banks, 40.8% came from commercial banks, while the remaining 4.6% came from other formal sources[14]. Thus, cooperative and commercial banks together accounted for over 95% of all loans, and we drop households who had loans from formal sources other than these two.

Caste dominance at the district level is calculated using the caste group-wise total ownership of land in a district[15] and specifying the dominant caste to be that which owns the maximum land. Based on this procedure, 7 districts are SC-dominated, 228 are OBC-dominated, and 167 are Others-dominated.

Our final sample covers 402 districts across 18 states, and consists of 18,093 farmer households. Table A.1 summarizes the variables used and provides means and standard deviations for the overall population and according to caste-group.

[Table A.1 about here]

4. Methodology and identification

We model the probability with which a farmer household obtains a production loan from cooperative or commercial banks in two ways. We begin by fitting several specifications of the probit model to analyze the probability that a farmer household has a formal production loan. Next, we break this down into two constituent sources—commercial and cooperative banks—noting that these two categories account for over 95% of all formal loans, and use bivariate probit specifications to model this joint outcome.

The univariate probit model assumes that the binary dependent variable y_i is determined according to whether a latent dependent variable y_i^* is positive or negative, where the latent variable is related to the independent variables $\mathbf{x_i}$ through a linear specification with error term $\epsilon_i \sim N[0,1]$.

$$y_i^* = \mathbf{x_i'}\beta + \epsilon_i$$

$$\text{and} \quad y_i = 1 \quad \text{iff} \quad y_i^* > 0$$

so that

$$\text{Prob}(y_i = 1) = \Phi(\mathbf{x_i'}\beta)$$

The bivariate probit model specifies that there are two latent dependent variables in two linear equations that each determines one of the dependent binary outcomes being modeled (in our case these are whether a household has a cooperative and/or commercial bank loan), as follows.

Allowing y_{1i} (respectively, y_{2i}) to represent the binary outcome corresponding to whether a household has a cooperative (respectively, commercial) bank loan, and $\mathbf{x_1}$ and $\mathbf{x_2}$ to be the corresponding vectors of explanatory variables, we have

$$y_{1i}^* = \mathbf{x_{1i}'}\beta_\mathbf{1} + \epsilon_{1i}$$

$$y_{2i}^* = \mathbf{x_{2i}'}\beta_\mathbf{2} + \epsilon_{2i}$$

where

$$y_{1i} = 1 \quad \text{iff} \quad y_{1i}^* > 0$$

$$y_{2i} = 1 \quad \text{iff} \quad y_{2i}^* > 0$$

and

$$\begin{pmatrix} \epsilon_1 \\ \epsilon_2 \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right]$$

The error terms are assumed to follow a joint, bivariate normal distribution with unit variance and covariance ρ. This allows us to determine the probabilities for all four events of the type $\{y_1, y_2\}$ where $y_1, y_2 \in \{0, 1\}$. For instance

$$\begin{aligned}
\text{Prob}(y_{1i} = 1, y_{2i} = 0) &= \text{Prob}(y^*_{1i} > 0, y^*_{2i} < 0) \\
&= \text{Prob}(\epsilon_{1i} > -\mathbf{x'_{1i}}\beta_{\mathbf{1}}, \epsilon_{2i} < -\mathbf{x'_{2i}}\beta_{\mathbf{2}}) \\
&= \Phi(\mathbf{x'_{1i}}\beta_{\mathbf{1}}) - \Phi_2(\mathbf{x'_{1i}}\beta_{\mathbf{1}}, \mathbf{x'_{2i}}\beta_{\mathbf{2}})
\end{aligned}$$

where Φ_2 represents the cumulative distribution function of the bivariate normal distribution.

4.1. Double hurdle model

In order to examine whether caste influences loan amounts, we model loan amounts together with the probability of obtaining a loan using double hurdle models. This model is originally due to Cragg (1971), and has been applied to household consumption decisions by Deaton & Irish (1984). We use the specification of Moffatt (2005).

The double hurdle model is similar to the tobit model but extends it, by dividing households into two types: those who would never borrower, and those who might borrow given the appropriate circumstances—the potential borrowers. The first hurdle determines household type, while the second hurdle models loan amounts for potential-borrower households[16]. In the following, the latent variable d_i^* represents the first hurdle: a loan is observed to be taken if and only if $d_i^* > 0$, i.e. if a household is a potential borrower. For potential-borrowers, the latent variable y_i^{**} in the second hurdle models whether the loan amount is zero (no loan taken) or positive. The equation that determines y_i^{**} is similar to a tobit model: if we define y_i^* to be the observed loan amount (where positive) and also include 'no loan' cases by taking on the value zero, then $y_i^* = \max\{y_i^{**}, 0\}$. Finally, since our data contain loan amount observations only when the amounts are positive, then representing this by y_i, we can take into account both the probability of crossing the first hurdle and, conditional on this, the second hurdle, so that $y_i = d_i \times y_i^*$.

$$d_i^* = z_i'\gamma + \epsilon_i \qquad \text{(First hurdle)}$$

$$y_i^{**} = x_i'\beta + \mu_i \qquad \text{(Second hurdle)}$$

where

$$\begin{pmatrix} \epsilon \\ \mu \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & \sigma^2 \end{pmatrix}\right]$$

The two error terms are assumed to be independently distributed; the variance of the first term is normalized to one while that of the second term is estimated as part of the model. We specify vectors of explanatory variables **x** and **z** for, respectively, the first and second hurdles. The model is then estimated by maximizing the log-likelihood that obtains from the model to estimate the parameters γ, β and σ:

$$ln(L) = \sum_0 ln\left[1 - \Phi(z_i'\gamma)\Phi\left(\frac{x_i'\beta}{\sigma}\right)\right] + \sum_1 ln\left[\Phi(z_i'\gamma)\frac{1}{\sigma}\phi\left(\frac{y_i - x_i'\beta}{\sigma}\right)\right]$$

4.2. Identification

We are able to identify the influence of caste on loan outcomes due to ample household and district-level variation in caste. However the data tell us household credit *outcomes*, that result from two events which we do not observe independently: an application for credit, and the lender granting a loan. Therefore, our analysis is valid subject to the assumption that caste-based differences in the realized outcomes are attributable to the lender's decisions, and not to systematic differences in household demand and applications for credit. The assumption seems plausible, since demand for credit is likely to depend on occupation and household characteristics that determine productivity, such as the availability of manpower and the ownership of assets—the latter especially, since most loans need to be collaterialized. It is unlikely that caste would play any *residual* role, i.e. beyond its role as a correlate of characteristics which we control for. We discuss this issue further in section 6.4.

We must also assume that any differences in loan outcomes between co-operative and commercial banks are not based on an underlying process of caste-based sorting[17]. Otherwise, if commercial banks lend overwhelmingly to SCs for instance due to affirmative action policies, crowding out OBCs and Others who then turn to cooperative banks, caste-based discrimination would not be identified. We present supporting evidence for our view and discuss this issue further in section 6.3.

Household caste is almost completely invariant across time, since individuals cannot change their caste. In addition, to be able to identify the effect of caste, it is necessary to assume that loan outcomes do not influence where a household resides; i.e., households should not have migrated in search of credit. Indeed, caste-based migration is very low in India (Munshi & Rosenzweig 2009), and, as Anderson (2011) argues using historical census data, caste proportions in villages and by implication districts have remained largely unchanged and are thus assumed to be exogenous.

For the explanatory variables relating to ownership of land and assets, identification requires that access to credit does not determine ownership; vice-versa, if current loans allowed borrowers to purchase land, then the relationship between land ownership and credit outcomes would not be identified. We assume that production credit is used for its stated purpose—agricultural production—and not for purchasing consumer durables or land. Even so, in order to guard against the possibility that these assets were purchased using loans, we use data on loan outcomes from the second visit, and data on land and consumer durable assets from the first visit that took place approximately 6 months earlier, so that the observed, current loan outcomes are unlikely to have aided the acquisition of these assets[18].

Land ownership is also unlikely to be related with current loan outcomes since very little land gets traded in India, so that land ownership is likely a function of intra-family land partitioning over successive generations rather than the result of sales and purchases[19]. An additional issue could be that of land reforms, which were aimed at reducing inequality in land ownership and allowing cultivators to own land, and have historically focused on implementing ownership ceilings (Besley & Burgess 2000) and redistributing holdings, but there is no indication that these efforts implemented redistribution by encouraging access to credit.

5. Results

We start by analyzing the probability that a household obtains a formal production loan given a vector of characteristics $\mathbf{x}$ that include caste group, using probit models, and table A.2 reports the results from using different specifications. These, and all subsequent estimations are carried out by weighting the observations using given probability weights, and standard errors reported are clustered at the village level[20].

All five models pass the Ramsey RESET specification test (Ramalho & Ramalho 2011). Model 1 includes only caste group and state dummies as explanatory variables. Model 2 adds ownership of irrigated and non-irrigated land and respective squared terms as explanatory variables to those of model 1, while model 3 adds the (log) assets index to model 2. Finally, models 4 and 5 add household characteristics as explanatory variables. These include the household head's age and education (model 4), household size and its square, and the respective proportions of children, adult females and adult males (model 5). These household characteristics are jointly significant in, respectively, models 4 and 5, while the coefficients for land ownership and the assets index are positive and significant in models 3, 4 and 5. The latter is as expected, since both types of land can act as collateral, enabling a household to obtain a loan, and the assets index, similar to long-run income, captures the fact that richer households are more likely to obtain a loan.

Household caste is significant only in models 1 and 2, and once assets have been accounted for in model 3, this significance disappears. This indicates that caste is correlated with the ownership of assets, and appears as significant only if the latter is omitted. We conclude that while assets and land ownership positively influence the probability of obtaining a formal production loan, household caste does not have any significant influence on borrowings if we do not distinguish between the sources of loans.

[Table A.2 about here]

5.1. Disaggregating borrowing by bank type and examining caste dominance

We now use bivariate probit models to disaggregate formal borrowing by bank type, and study the bivariate probability of a household obtaining a loan from either a cooperative or commercial bank or both. Over two thirds of households (12,569) in our sample do not have a loan from either type of bank. Of the remainder, just over half (2,824) have loans from cooperative banks only, while 2,392 households have loans from commercial banks only, and a small number (308) have loans from both types of bank.

Table A.3 presents results from three specifications of the bivariate probit model, using two columns for each model that correspond, respectively, to cooperative and commercial bank borrowings. Model 1 uses state dummies, household caste, characteristics of the household head, land ownership and assets as explanatory variables. Unlike the corresponding univariate probit model 4 in table A.2, household caste is now significant, and remains significant with the introduction of other household characteristics as explanatory variables—the proportion of children, adult males and adult females—in model 2. And, as with the univariate probit models, land ownership and assets exert a positive influence on the probability of having either type of loan, and are statistically significant in all models.

[Table A.3 about here]

That the influence of caste is very different for the two types of bank can be deduced from the signs and significance of the respective caste coefficients. The base category is Others, so that both models 1 and 2 indicate that SCs and OBCs are less likely to have a loan from a cooperative bank compared to Others. For commercial bank loans, SCs are most likely to have a loan, followed by Others and finally OBCs, in agreement, it would appear, with affirmative action policies. Models 1 and 2 thus show that cooperative banks might discriminate between borrowers on the basis of caste, since, even after controlling for the most apparent criteria of loan-worthiness, namely assets and land ownership alongside other household characteristics, caste continues to be statistically significant, and lower-caste SCs have a lower probability of having a cooperative bank loan compared to higher-caste Others. A central task of this paper is to explain why this may be.

We therefore test whether district-level caste dominance, as defined by caste-aggregate land ownership, plays a role in explaining loan outcomes. Model 3 introduces a categorical variable for district-level caste dominance, and interaction terms between this caste dominance variable and household caste[21]. Together with household head characteristics and other household characteristics, Wald tests show that the caste-based interaction terms are strongly significant, and hence we base our analysis and conclusions on model 3.

Our task now is to explain how caste and district-dominant caste influence loan outcomes. To do so, we calculate the marginal probabilities predicted by model 3 for each type of bank loan. So, given the probability function estimated using model 3, we calculate Prob(Household has cooperative bank loan | $\mathbf{x}$) for a given vector $\mathbf{x}$ of household characteristics, and likewise for commercial bank loans. We repeat this calculation several times, replacing the values for the assets index, household, and subsequently dominant caste by, respectively, deciles of the assets index and all combinations of caste, to obtain the mean predicted probability for each combination of (asset decile, household caste) or (asset decile, household caste, dominant caste). Finally, mean predicted probabilities are plotted to enable comparison across castes and asset levels (and subsequently dominant caste). Following this procedure, we first quantify the influence of household caste by calculating the marginal probabilities for each type of bank. The results from this are shown in figure A.1.

[Figure A.1 about here]

As expected, the probability of borrowing from either type of bank increases with asset decile. The influence of caste is opposite between the two types of banks. Higher-caste Others are more likely to have a loan from a cooperative bank compared to both OBCs and SCs (the latter are least likely to have a loan). The reverse holds for commercial banks, where SCs are most likely to have a loan, followed by Others and finally OBCs. A possible explanation for the latter low probability is that OBCs emerge as the 'squeezed middle' category: while the upper castes are historically well-endowed and SCs benefit from affirmative-action in the targeting of commercial bank credit, there are no such allowances for OBCs. Indeed, unlike admissions to educational institutions or job quotas in government employment where OBCs do benefit from affirmative-action policies, there is no counterpart to this in agricultural credit. However, as the confidence intervals in figure A.1b show, few of the between-caste differences in predicted probabilities for commercial banks are statistically significant.

To examine the influence of district level caste dominance, we likewise calculate the predicted probabilities for combinations of asset decile, household caste, and dominant caste. This yields 90 categories because there are ten asset deciles and nine combinations of household and dominant caste. However, since only seven (out of 402) districts are dominated by SC households, we restrict the discussion to OBC and Others-dominated districts[22].

[Figure A.2 about here]

Figure A.2 shows how the probabilities for cooperative bank loans change with dominant and household caste, and summarizes an important finding of the paper. In districts dominated by higher-caste Others, it is Others who have the highest probability of having a cooperative bank loan. OBCs and SCs have lower probabilities for all asset levels, and the majority of these differences are statistically significant. Indeed, SCs have the lowest probability of having a cooperative bank loan, and the differences between Others and SCs are significant at all asset levels. The magnitude of the difference is also large: for the third to seventh asset deciles, Others have a cooperative bank loan with probability at least 0.2, while the same probability for SCs is at most 0.1.

In contrast, for districts dominated by the OBC group, there are no statistically significant between-caste differences. While Others have higher probability at lower asset levels, OBCs have the highest loan probability at higher asset levels, but none of these differences are significant. SCs continue to have the lowest loan probability even in OBC dominated districts, but again, the difference between SCs and other caste groups are not statistically significant.

The significant influence of district level caste dominance on the functioning of cooperative banks is a central finding of this paper. It lends support to the hypothesis that interest group capture at the district level is the reason why cooperative banks discriminate against lower caste households. This takes place in districts where traditionally empowered higher-castes dominate, but not where the traditionally backward OBC or SC caste groups are dominant. As our discussion of the cooperative bank structure explained, the district plays an important role in how village level cooperatives function throughout the district, and the likely path through which dominant interest-groups influence the functioning of district CCBs is through the profile of personnel who run CCBs. Further, since CCBs are independent entities, there would be no procedure of transferring employees between locations unlike commercial bank branches, further strengthening the influence of entrenched interests.

An associated question could be why OBC-dominated districts do not witness discrimination in favour of OBCs at the cost of Others or SCs. The answer to this would lie in the manner in which influence between caste groups has been devolved over the past few decades. It is only recently that

OBCs (and to a lesser extent SCs) have seen their influence rise and become comparable to Others. The non-high castes, even when the dominant economic group in the district, are unlikely to see their influence spanning multiple channels and institutions simply because the traditional power structures which survive at least partially today, would not allow for this. An OBC-dominant district is thus unlikely to have OBCs occupying entrenched positions of power in society and government or semi-government institutions, in contrast to the influence of Others in an Others-dominated district.

While our finding of caste-dominance is consistent with field studies, it is important that we have established this using national data. Drèze et al. (1997) highlighted the role of bias (caste and otherwise) using data from a single village in northern India[23]. Likewise, Shah et al. (2007) point out in their review of cooperative bank credit that cooperative societies were prone to capture because they "were embroiled in local power politics and were a source of rural patronage and influence" (Shah et al. 2007, 1352). And, Ambewadikar (1991) reports that casteism and politics are major reasons why members of weaker sections of society[24] fail to obtain loans from cooperative credit societies in rural Maharashtra.

Figure A.3 shows that the interactions between district caste dominance and household caste do not have a significant influence on the probability of obtaining a commercial bank loan. This suggests that commercial banks are unlikely to be susceptible to interest group capture, which is probably a result of their centralized structures, routine staff transfer policies, and professional management practices.

[Figure A.3 about here]

5.2. Double-hurdle model for loan amounts

In order to examine whether discrimination extends to the loan amounts provided by banks, we employ double-hurdle models for borrowings from cooperative and commercial banks separately. The dependent variable in each case is the log total loan amount whenever that amount is positive, and zero otherwise[25]. This total includes all respective loans a household might have. Table A.4 shows the population and caste-wise mean loan amounts, and indeed, all the between-caste differences are statistically significant. Our aim in this section is to deduce whether these differences persist, and if so their pattern, even after accounting for plausible explanatory variables.

[Table A.4 about here]

The results from double hurdle models for loan amounts from cooperative and commercial banks (separately) are presented in table A.5. We show results for the most general specification, including state, household caste and dominant caste, household characteristics, land ownership and assets. Wald tests for both 'decision' equations are strongly significant, implying that the double hurdle model is preferred over the simple tobit. Similar to the results from the bivariate probit model, caste terms are significant in the decision equation for cooperative banks only, but they are insignificant in the equation for loan amount. Hence, cooperative loan amounts do not differ significantly by caste conditional on obtaining a loan. However, caste and district dominance interaction terms are also significant in the amount equation for cooperative banks, indicating that loan *amounts* from cooperative banks depend on the combination of household and district dominant caste.

[Table A.5 about here]

To examine how caste and dominant caste influence cooperative bank amounts, we use a similar procedure as before and calculate the (log) loan amounts predicted by the amount equation for subpopulations defined by asset decile, household caste, and dominant caste. The resulting predictions are plotted in figure A.4. The influence of caste is similar to that on the probability of obtaining cooperative bank loans, in that for Others-dominated districts, households in the Others caste group are likely to receive larger loans compared to OBCs and SCs, conditional on receiving a loan. However, none of the between-caste differences are significant at different asset deciles, in either OBC or Others-dominated districts. We conclude that while the data indicate that interest-group capture of cooperative banks in Others-dominated districts potentially extends to the amount of loan sanctioned, this pattern is not statistically significant.

Since neither household caste nor interaction terms with dominant caste are significant in either equation for commercial banks, we conclude that caste does not influence the size of loans obtained from commercial banks.

[Figure A.4 about here]

6. Alternative explanations

In this section we explore alternative explanations for the caste-based differences in the loan outcomes, which we have so far explained in terms of the lending decisions of banks.

6.1. Interest rates

Caste-based differences in interest rates could lead to differences in demand for loans, which in turn might drive loan outcomes. For example, if SCs were offered higher interest rates than Others by a certain type of bank, this would lead to fewer SC households taking loans. The analysis so far would explain the latter outcome in terms of the banks' reduced willingness to sanction a loan to an SC household, whereas in fact the correct explanation would then be that a higher interest rate leads to reduced demand from SCs.

Table A.6 shows the population and caste-wise mean interest rates on loans. For households with more than one loan from a given type of bank, the interest rate is calculated as the weighted mean across all loans using the loan amounts as weights. There are 16 households with cooperative bank loans for whom interest rate information is missing. In addition, there are also some outliers in the data. Table A.6 retains households up to the 95$^{\text{th}}$ percentile of interest rate in order to remove the outliers. Wald tests for the equality of interest rates across caste groups show that there are no significant between-caste differences for cooperative bank loans[26]. Interest rates are thus unlikely to explain the finding that cooperative banks discriminate against lower-caste borrowers.

For commercial bank loans, the interest rates charged from SCs are significantly lower than those charged from OBCs and Others. These findings are consistent with the affirmative-action policy guidelines of the Central Bank, since preferential lending for SC/ST households also includes lending at lower rates of interest under the Differential Rate of Interest (DRI) Scheme according to which "(I)t should be ensured that not less than 40 per cent of the total advances granted under DRI scheme go to scheduled caste/scheduled tribes. At least two third of DRI advances should be granted through rural and semi-urban branches" (RBI 2006, 4).

[Table A.6 about here]

6.2. Repayment rates

In the event that banks maintain and exchange information on the credit histories of potential borrowers, a household's loan outcomes would depend on their past repayment behavior. In the US context, Becker (1993) argues that past repayment and default behavior must be taken into account to determine whether banks discriminate between borrowers on the basis of race, since lending patterns which we might otherwise conclude indicate racial discrimination might actually reflect repayment histories. Our analysis has presented strong evidence in favor of the view that cooperative banks discriminate negatively against SC households, and weak evidence that commercial banks discriminate positively. These conclusions would remain valid even if loan outcomes did depend on repayment behavior, but they might not, if there exist caste-based differences in repayment rates.

In the Indian context, it is unlikely that Indian banks base lending decisions on credit ratings given that credit bureaus and the associated processes have only recently begun to expand. The data, however, do provide information on the recent credit histories of borrowers, and we use this to examine whether there are systematic caste-based differences in repayment rates using the ratio of total repayment to total loan amount.

The data provide information on the repayments made by households in, approximately, the year prior to the date of survey[27]. Out of 2,700 households with a commercial bank loan, 202 did not make any repayments, while out of 3,132 households with cooperative bank loans, 2,041—a far higher number—did not make any repayments during this period. We calculate the ratio of total repayments during this period to total loan amounts, for those households who had outstanding loans on the date of survey, as shown in table A.7. However, Wald tests for equality of mean repayment ratios across caste groups show that most between-caste differences in repayment ratios are insignificant, whether we consider all households together or only those who made positive repayments.

The only exception to this is in the case of households with commercial bank loans, where the repayments made by SCs are significantly lower than those of Others, for households who made positive repayments. This implies that if commercial banks do base their lending decisions on repayment behavior, then all else being equal, they should lend less often to SCs. That commercial banks bias borrowing *towards* SCs would then imply that affirmative action policies favor SCs sufficiently strongly to ensure that they receive loans at least, if not more often, than their non-SC counterparts, despite potentially poorer repayment behavior.

[Table A.7 about here]

6.3. Caste-based sorting

There is also the possibility that the observed patterns of lending reflect a sorting process between cooperative and commercial banks. That is, given that commercial banks are encouraged to lend to SCs, this might crowd out higher castes who then approach cooperative banks. While this possibility cannot be ruled out entirely using the data at hand, it is unlikely that such sorting is responsible for the observed loan outcomes given the cultural and political context of India. Commercial banks account for the majority of agricultural credit in India (GOI 2007), and thus have greater funds available for lending compared to cooperative banks[28], making it doubtful that their commitments to weaker sections of society crowd out lending to OBCs and Others. And, since the interest rates reported in table A.6 show that cooperative banks charge somewhat higher rates than do commercial banks, a commercial bank loan should be, on this basis, the first preference of all borrowers irrespective of caste.

Moreover, were a sorting process at play, we might expect the caste-based lending patterns for cooperative and commercial banks to be an opposing, mirror image of each other. Instead, as figure A.1 shows, caste-based differences in the probability of obtaining a loan are significant only for cooperative banks. This supports the view that affirmative action has, in the case of commercial banks, succeeded in overcoming any caste-based differences that might otherwise disadvantage lower caste borrowers, but not at the *cost* of higher caste borrowers. But since no such affirmative action has taken place for cooperative banks, their lending remains vulnerable to caste-based interest group capture.

Finally, it is unlikely that district-level caste dominance would be a significant influence on the caste-wise probabilities of obtaining loans, were in fact a sorting process responsible for the caste-wise differences in loan outcomes. Instead, caste-wise differences are significant only for cooperative banks, and only in districts where Others are dominant (figure A.2). This lends support to the view that interest-group capture by higher-caste groups results in lower castes facing discrimination in these districts.

6.4. Differences in demand

As discussed in Section 4.2, the identification of caste-based differences in banks' willingness to lend depends on the assumption that household demand for credit does not depend systematically on caste once we have controlled for other household characteristics. While this assumption cannot be tested with the current data, there are at least two arguments in favor. First, we argued that households' own perceptions of the ease with which credit might be granted by a bank, and thus their propensity to apply for such, will almost certainly vary according to wealth, land-ownership and education levels, but not, *once these factors have been accounted for*, with caste. Jodhka (1995) quotes poor farmers on their (very negative) perceptions of certain formal lenders, as a result of which they have been very hesitant to apply for credit. Such borrowers are often also of lower caste, but it would be spurious to argue that their perception of formal lenders' unwillingness to lend are a result of their caste *even after* taking into account other characteristics, i.e. beyond the fact that they are poor and marginalized. Indeed, a convincing counter-argument could be made only if we observed instances where poor and marginalized *higher* caste farmers had positive perceptions of formal lenders, but the latter is a rather unrealistic possibility.

Second, it is important to note the view of Drèze et al. (1997, 24) on this issue (authors' emphasis):

> The question remains as to whether poor households are <u>unable</u> or <u>unwilling</u> to borrow substantial amounts from other institu-

> tional sources. It would be pointless to seek a general answer to this question. We have met several poor individuals who emphatically stated that they would never dare to borrow from a public lending institution (for fear of being cheated or of not being able to repay); we also know others who have made repeated but unsuccessful attempts to persuade a bank manager to give them a loan. The point is that, in <u>both</u> cases, (1) there is a failure of public provision of credit services to poor borrowers, and (2) the root of the problem lies in the discriminatory practices of public lending institutions.

This clearly supports the view that differences in demand and discriminatory practices can both be expected to move together, implying that the identifying assumption made earlier is indeed plausible for the rural Indian context.

7. Conclusion

Using national data on household borrowings, our main finding is that banks do discriminate between borrowers on the basis of caste in the provision of agricultural credit. For commercial banks, we find weak evidence of positive discrimination that favors lower-caste SC households, but for cooperative banks, we find strong evidence that discrimination is negative and favors higher caste Others households.

The explanations for the two patterns are very different. For commercial banks, the observed lending behavior is consistent with affirmative action policies aimed at improving financial inclusion for SC households through increased lending and lower rates of interest. For cooperative banks on the other hand, we test the hypothesis that capture at the district level by locally dominant interest groups leads to discrimination. We find that negative discrimination is most visible in districts where higher castes dominate, and is insignificant in districts where OBCs dominate. Given the organization and structure of cooperative banks in India, District Central Cooperative Banks play a key role in overseeing the lending of village cooperatives in each district. We thus find support for the hypothesis that capture at the district level takes place through entrenched interests gaining hold of cooperative bank management which in turn shapes the latter's lending decisions. This is also consistent with several field studies which examine the functioning of cooperative banks, even as our conclusions are based on national data.

We also analyze how loan amounts are influenced by borrowers' castes, and find weak evidence that discrimination by cooperative banks extends to loan amounts as well. Finally, interest rates and repayment rates do not, in general, depend on borrowers' castes, but in the few cases where they do, they do so in ways that lend support to our findings.

Notes

[1]India's central bank.

[2]See Sen (2005) for a detailed discussion of the latter issue.

[3]The land-ownership based definition of dominance has been used by Anderson (2011) who analyzes the market for irrigation water in northern India. Using this to define village-level caste dominance, she finds that lower castes are less likely to participate in the market for irrigation water in villages dominated by higher castes, and thus, have lower agricultural incomes in such villages.

[4]As Weisskopf (2004) explains, the definition of OBCs is complex, since this category includes lower-caste Hindus as well as other sub-groups from other religious and ethnic minorities. We restrict our analysis to households classified as Hindu.

[5]A second reason for excluding STs from the analysis is that areas where tribal populations are dominant are likely to be systematically different, and possibly have fewer financial institutions, making it difficult to identify discrimination.

[6]In the absence of formal financial services, particularly credit, poor borrowers usually turn to informal lenders who are known to charge unreasonably high interest rates. Informal credit transactions, such as those between sharecroppers and landlords or moneylenders, have also been explained in the literature in terms of interlinkages with other factor markets (Bardhan & Rudra 1978; Bardhan 1980; Basu 1983, 2000)

[7]This structure is, however, not uniformly implemented across all states. See Sen (2005).

[8]A substantial literature has analyzed whether banks in the US discriminate between borrowers applying for mortgages on the basis of race, since home ownership is a decisive economic outcome in the American context. While the evidence is mixed, several researchers have concluded that discrimination does indeed take place (Charles & Hurst 2002; Cavalluzzo 2002; Cavalluzzo & Cavalluzzo 1998; Blanchflower et al. 2003).

[9]Indian government reports such as that by the National Sample Survey Organisation (2005) provide summary statistics from household surveys but do not, as such, analyze the data.

[10]With the exception of certain areas in Jammu and Kashmir, Nagaland, and the Andaman and Nicobar Islands

[11]Andhra Pradesh, Bihar, Chhattisgarh, Gujarat, Himachal Pradesh, Haryana, Jharkhand, Karnataka, Kerala, MP, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, Uttarakhand and West Bengal.

[12]The data classify a household head's occupation using 16 categories and also classify each household into one of four *types*: self-employed in non-agriculture, agricultural labour, other labour, self-employed in agriculture, and others. 'Farmer households' are those classified as 'self-employed in agriculture' and the occupation of whose household head is 'agriculture'. Households classified as agricultural labour are excluded since such households are likely to form a distinct category who are poorer than farmers and unlikely to own land or rent it for cultivation. I also drop Scheduled Tribes (ST) households, since as mentioned, they are not usually considered as part of the caste system.

[13]Classified in the following categories: illiterate, literate without formal schooling, literate but below primary, primary schooling, middle schooling, secondary schooling, higher secondary schooling, diploma/certificate course, graduate, post graduate and above.

[14]These include government schemes, insurance providers, provident funds, (non-bank) financial institutions and companies.

[15]For this step, ST, non-Hindu and non-farmer households are included in the calculations. ST-dominated districts are then dropped.

[16]Whereas, the tobit specification assumes that all households belong to the second category. The double-hurdle model is therefore more general.

[17]I am grateful to a referee for highlighting this issue.

[18]Identification would be compromised only if there are unobservables correlated with both assets-ownership and loan outcomes. To this end, covariates that are likely to play this role have been controlled for.

[19]In their study of a the Palanpur village in Northern India, Drèze et al. (1997) document that a very small proportion of land in the village was traded.

[20]We must note that the use of probability weights implies that the probit models are estimated by maximizing the pseudo log-likelihood and the resulting maximized value of such cannot be used to compare between specifications of the model, nor can it be used to generate likelihood-based statistics such as the Akaike Information Criteria (or Likelihood ratio tests). As such, the only valid criteria for selecting between models is by using Wald tests to judge the significance of (different sets of) variables (Korn & Graubard 1990). The significance of individual coefficients in all the estimations are, for the same reason, reported as based on Wald tests instead of t-tests.

[21]Household caste and district-dominant caste are both categorical variables with three categories each, corresponding to SC, OBC and Others. Interacting these yields nine categories. Since both household caste and district-dominant caste also appear in the equation individually, only four of the nine interaction terms are entered in the estimation: these are SC*SC-dominant, SC*OBC-dominant, OBC*SC-dominant, OBC*OBC-dominant.

[22]The predicted probabilities for SC-dominated districts have wide confidence intervals and do not have significant between-caste differences.

[23]While comparisons based on caste-dominance was not the focus of the Drèze et al. (1997) study, the village where data was collected – Palanpur – would qualify as an Others-dominated village in view of the land-ownership patterns they document. The authors detail how caste (and privilege) based biases influenced loans made by a certain cooperative bank (the 'Farmers Service Society').

[24]'Weaker sections' refers here to SC, ST and small farmers (Ambewadikar 1991).

[25]Since all loans are at least Re. 1, there are no negative log loan amounts.

[26]If we include the outliers, then interest rates do differ between castes, but the interest rates for SCs are on average *lower* than those of OBCs and Others. This would then add support to our previous analysis: if at all, it would appear that SC households should have higher demand for cooperative bank loans if indeed they are offered lower interest rates. The fact that we observe fewer SC households with cooperative bank loans in Others-dominated districts would imply that negative discrimination is then even stronger than

we have estimated, and were interest rates to be the same, then SC households would have even fewer cooperative bank loans.

[27]Repayment amounts are detailed for each of three periods: July 2002-Sept 2002, Oct 2002-Dec 2002, Jan 2003 to the date of survey.

[28]In 2002-03, commercial banks provided Rs. 397,740 million of agricultural credit compared to Rs. 236,360 million from cooperative banks (GOI 2007, 36) .

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Appendix A. Calculating the assets-based wealth index

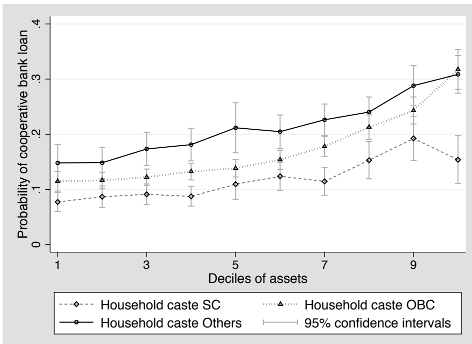
Sahn & Stifel (2003) argue that information elicited about consumption expenditure during surveys is likely to be both inaccurate because of recall or truth-telling problems, as well as unrepresentative of long-run household wealth since poor households' consumption exhibits substantial seasonal or other variation, while that of rich households may not allow for effectively differentiating between levels of wealth or income. As an alternative, they suggest calculating an index based on assets that the household owns, and using this as a proxy for income or wealth. Such an index can be calculated using principal components analysis, that seeks to find a linear combination of assets that maximizes variance across the sample (Filmer & Pritchett 2001). We calculate such an index based on consumer durable assets.

Principal components analysis is used to construct this wealth index as follows: The data are arranged into column vectors, each of which correspond to a particular type of asset, and each entry of which gives the number of that asset owned a given household. Principal components analysis then creates linear combinations of column vectors by determining suitable weights such that these combinations are a) orthogonal to each other, and b) account for the maximum amount of the variance across households. The weighting attaches minimum importance to features common across households and vice versa: if most households own a single bed for instance, then this column will receive a small weight. The first principal component contains the maximum variance and can thus be used as an index of asset ownership. While the data provide information on ownership of several categories of assets including transport and business equipment, residential buildings and consumer durables, we use only the last category since it is the only category common across all households. And, certain types of consumer durables such as bullion have very few observations. Dropping such categories, the types of consumer durables considered for principal components analysis are:

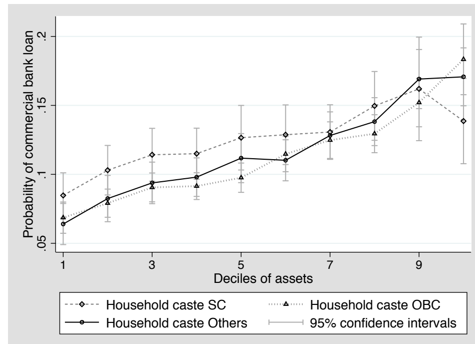
1. Bedstead
2. Steel / wooden almirah / dressing table
3. Radio, record player/tape recorder/stereo/ musical instruments for household use
4. Television, VCR/VCP/VCD, DVD Player, home theatre, multimedia PC
5. Pressure cooker/ household utensils
6. Gas/electric oven/cooking range/ microwave oven
7. Electric fan, clock/ watch, water filter / electric iron/ sewing machine
8. Refrigerator/ air cooler/ air conditioner/ washing machine

The first principal component captures 34.7% of the total variance in durable assets across households. The resulting assets index takes on values in the interval (-1.71, 17.36) and we calculate its log by adding 2 to each observation.

Figures



(a) Cooperative bank loans



(b) Commercial bank loans

Figure A.1: Influence of household caste on predicted loan probabilities
(*Source*: Calculations based on model 3 in table A.3)

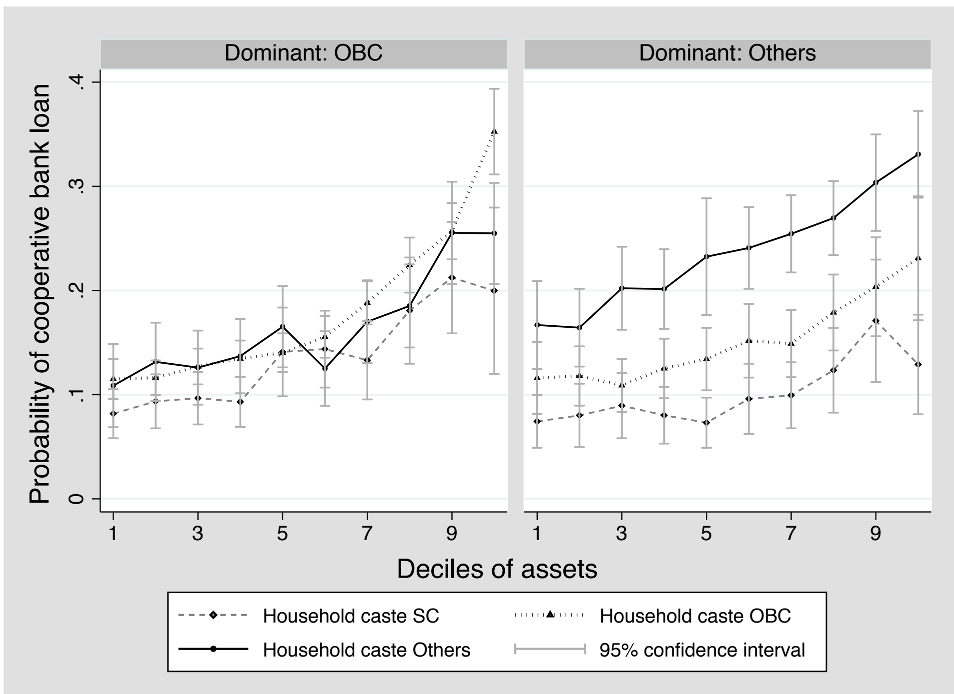


Figure A.2: Influence of dominant and household caste on the probability of borrowing from a cooperative bank
(*Source*: Calculations based on model 3 in table A.3)

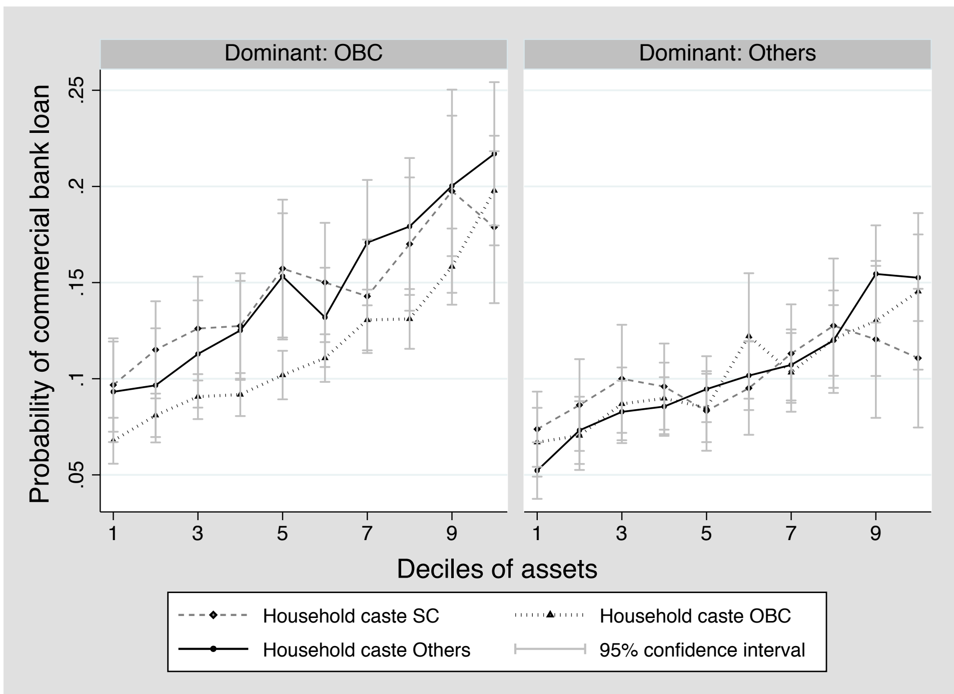


Figure A.3: Influence of dominant and household caste on the probability of borrowing from a commercial bank
(*Source*: Calculations based on model 3 in table A.3)

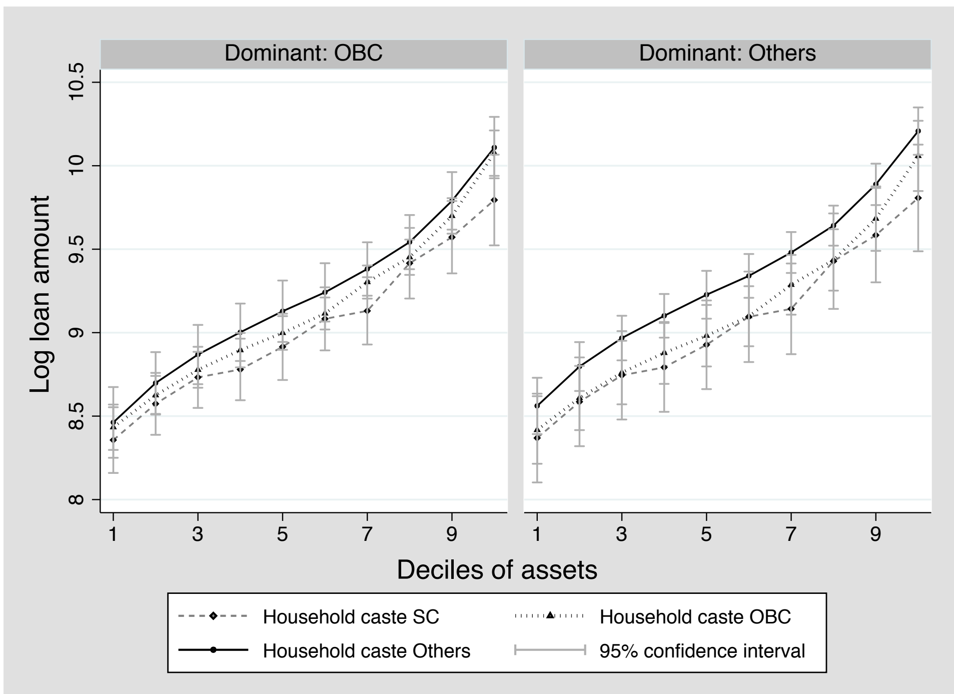


Figure A.4: Influence of dominant and household caste on predicted log loan amounts from cooperative banks
(*Source*: Calculations based on results from table A.5)

Tables

Table A.1: Means and standard deviations of variables for population and caste groups

	Population		**SC**		**OBC**		**Others**	
Variable	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Irrigated land owned (Ha)	0.863	1.556	0.500	0.905	0.829	1.550	1.091	1.740
Unrrigated land owned (Ha)	0.603	1.641	0.269	0.797	0.593	1.639	0.779	1.873
Log assets index	0.382	0.725	0.078	0.658	0.312	0.695	0.640	0.719
Age of household head	47.803	14.117	46.363	14.331	47.236	13.739	49.407	14.448
Household size	5.700	2.875	5.559	2.856	5.811	2.894	5.589	2.841
Proportion of children	0.368	0.229	0.386	0.242	0.383	0.230	0.333	0.216
Proportion of adult males	0.320	0.175	0.319	0.191	0.313	0.172	0.330	0.170
Proportion of adult females	0.310	0.150	0.294	0.158	0.300	0.145	0.335	0.152
Median education level of household head	literate but below primary		illiterate		literate but below primary		primary schooling	

Source: Author's calculations.

Table A.2: Probit models

	Model 1	Model 2	Model 3	Model 4	Model 5
SC	-0.238***	-0.0689	-0.0155	0.0407	0.0187
	(0.0532)	(0.0564)	(0.0567)	(0.0568)	(0.0576)
OBC	-0.185***	-0.0979*	-0.0670	-0.0420	-0.0593
	(0.0462)	(0.0495)	(0.0494)	(0.0493)	(0.0501)
Others (base)	-	-	-	-	-
Irrig land owned		0.266***	0.235***	0.231***	0.223***
		(0.0187)	(0.0192)	(0.0190)	(0.0190)
Irrig land owned square		-0.00833***	-0.00745***	-0.00722***	-0.00680***
		(0.00147)	(0.00142)	(0.00133)	(0.00132)
Nonirrig land owned		0.170***	0.158***	0.155***	0.152***
		(0.0203)	(0.0201)	(0.0201)	(0.0201)
Nonirrig land owned square		-0.00666***	-0.00631***	-0.00608***	-0.00596***
		(0.00163)	(0.00156)	(0.00156)	(0.00155)
Log assets index			0.152***	0.108***	0.0737**
			(0.0242)	(0.0256)	(0.0270)
Household head characteristics[a]				yes	yes
Other household characteristics[b]					yes
State dummies	yes	yes	yes	yes	yes
N	18093	18093	18093	18093	18093
Significance (p-values under Wald tests)					
Household caste	0.000	0.142	0.318	0.219	0.214

Notes

Dependent variable: Household has formal production loan

Standard errors clustered by village in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[a] Age, age-squared, and education level of household head

[b] Household size and its square, proportions of children, adult males and adult females

Source: Author's calculations.

Table A.3: Bivariate Probit models

	Model 1		Model 2		Model 3	
	Coop	Comm	Coop	Comm	Coop	Comm
SC	-0.167*	0.154**	-0.189**	0.140*	-0.336***	0.0731
	(0.0674)	(0.0557)	(0.0686)	(0.0562)	(0.0935)	(0.0766)
OBC	-0.0870	-0.0135	-0.104	-0.0249	-0.247**	-0.0380
	(0.0546)	(0.0431)	(0.0555)	(0.0434)	(0.0889)	(0.0629)
Others (base)	-	-	-	-	-	-
Irrig land owned	0.0954***	0.0916***	0.0916***	0.0894***	0.0905***	0.0903***
	(0.0177)	(0.0136)	(0.0176)	(0.0137)	(0.0178)	(0.0138)
Nonirrig land owned	0.0487***	0.0564***	0.0462***	0.0554***	0.0456***	0.0561***
	(0.0115)	(0.0127)	(0.0115)	(0.0128)	(0.0115)	(0.0128)
Log assets index	0.102***	0.125***	0.0652*	0.0981**	0.0667*	0.0995**
	(0.0291)	(0.0296)	(0.0310)	(0.0317)	(0.0312)	(0.0318)
SC*SC-dominated					1.940***	0.271
					(0.454)	(0.479)
SC*OBC-dominated					0.326*	0.0326
					(0.129)	(0.108)
OBC*SC-dominated					1.144*	0.928
					(0.567)	(0.545)
OBC*OBC-dominated					0.254*	-0.0712
					(0.109)	(0.0855)
State dummies	yes		yes		yes	
Household head[a] characteristics	yes		yes		yes	
Other household[b] characteristics			yes		yes	
$\hat{\rho}$	-0.096		-0.099		-0.099	
	(0.030)		(0.030)		(0.030)	
N	18093		18093		18093	
Significance (p-values under Wald tests)						
Household caste	0.002		0.001		0.002	
Household and dominant caste interaction terms					0.000	

Notes
Bivariate dependent variable: (cooperative loan, commercial loan).
Standard errors clustered by village in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Age, age-squared, and education level of household head.
[b] Household size and its square, proportions of children, adult males and adult females.
Source: Author's calculations.

Table A.4: Total loan amounts[a] (in Rupees)

	Population		SC		OBC		Others	
Bank	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Cooperative	30,561	57,654	14,328	23,135	27,332	52,338	37,798	64,923
Commercial	43,374	72,492	22,499	42,669	42,041	66,171	54,113	85,179

[a] Calculated using those households who have a loan from the respective type of bank.
Source: Author's calculations.

Table A.5: Double hurdle models for loan amounts

	Cooperative		Commercial	
	Decision	Amount	Decision	Amount
SC	-0.336***	-0.0775	0.0739	-0.128
	(0.0934)	(0.138)	(0.0763)	(0.136)
OBC	-0.248**	-0.126	-0.0380	-0.121
	(0.0890)	(0.0945)	(0.0630)	(0.101)
Others (base)	-	-	-	-
Irrig land owned	0.0905***	0.0991***	0.0911***	0.112***
	(0.0176)	(0.0211)	(0.0138)	(0.0180)
Nonirrig land owned	0.0455***	0.0602***	0.0565***	0.0603***
	(0.0113)	(0.0138)	(0.0128)	(0.0167)
Log assets index	0.0667*	0.402***	0.0986**	0.307***
	(0.0312)	(0.0460)	(0.0318)	(0.0486)
SC*SC-dominated	1.905***	1.302**	0.275	-0.756
	(0.457)	(0.486)	(0.482)	(0.432)
SC*OBC-dominated	0.330*	0.0865	0.0342	-0.0139
	(0.129)	(0.176)	(0.108)	(0.164)
OBC*SC-dominated	1.107	0.0508	0.936	-1.698**
	(0.574)	(0.535)	(0.548)	(0.586)
OBC*OBC-dominated	0.257*	0.115	-0.0686	0.0905
	(0.109)	(0.129)	(0.0855)	(0.141)
State dummies	yes		yes	
Household head characteristics[a]	yes		yes	
Other household characteristics[b]	yes		yes	
N	18093		18093	
Significance (p-values under Wald tests)				
Household caste	0.001	0.385	0.356	0.394
Household and dominant caste interaction terms	0.000	0.048	0.684	0.303

Notes
Dependent variable is log total loan amount from the respective bank type.
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
[a] Age, age-squared, and education level of household head.
[b] Household size and its square, proportions of children, adult males and adult females.
Source: Author's calculations.

Table A.6: Interest rates from cooperative and commercial banks (in percent)

	Population		SC		OBC		Others	
Bank	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Cooperative	12.97	2.61	12.66	3.26	12.98	2.79	13.03	2.23
Commercial	12.15	2.87	11.49	3.90	12.19	2.82	12.38	2.41

Source: Author's calculations.

Table A.7: Ratios of total repayment to total loan amounts

	Population		SC		OBC		Others	
Bank	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Cooperative	0.173	0.328	0.149	0.333	0.166	0.333	0.185	0.318
Commercial	0.152	0.303	0.130	0.266	0.155	0.311	0.157	0.299

Source: Author's calculations.