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3000 Years of Discrimination and Counting: How Caste Still Matters in the Indian Credit Sector.

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Abstract

The caste system has dominated the social, political and economic lives of Indian people for over three thousand years. Since independence, the Indian government has introduced a flood of quotas, schemes and affirmative action to tackle caste discrimination. Can seventy years of government policy reverse three thousand years of oppression? Taking a close look at the country's credit system reveals that a new, more subtle, and less overt form of discrimination appears to be emerging, and becoming more widespread. This paper examines whether caste-based differences influence the amount of credit sanctioned to borrowers in India utilising data from the India Human Development Survey collected in 2005 and 2011-12. Using the Blinder–Oaxaca decomposition method, along with the Heckman procedure and the instrumental variable approach to correct for selection and simultaneity bias, I find substantial credit differentials between the general caste and other lower castes. I also show the evidence of caste discrimination against the lower castes. The results of this research have been complemented by qualitative data gathered from interviewing lower caste borrowers in North India to understand the nature of discrimination and obstacles faced by them in the credit sector.

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1. Introduction

Discrimination based on caste is a well-established phenomenon in India. Not that long ago, lower caste people were treated as untouchable, were consistently denied access to public services, and were subject to exploitation, abuse, mistreatment and prejudice. Nowadays, the scale and visibility have changed, but discrimination can still be seen in the form of relatively subtle constraints and restrictions in different areas: education, housing, finance, and employment. Although caste equality has been enshrined in the Indian constitution since 1950, caste-based divisions have continued to dominate - in the economy (Deshpande, 2000; Kijima, 2006), in marriage (Ahuja and Ostermann, 2016), in employment (Agrawal, 2014; Thorat and Attewell, 2007), in access to energy (Saxena and Bhattacharya, 2018), in education (Desai and Kulkarni, 2008) and in general social interaction. These caste divisions are sometimes reinforced through economic boycotts and physical violence (Narula, 1999; Thorat, 2005). Despite various efforts by the government such as reservation policies in educational institutions, and employment in the government and public sector, caste still remains an important indicator of socioeconomic disadvantage (Kumar, 2016). Given the pervasive presence of discrimination, it would be surprising if it did not have a significant influence on credit outcomes.

Credit is one of the most critical constraints in economic development for the lower castes (Thorat, 2009). Variations in access to credit constitute a major source of income inequality (Demirgüç-Kunt and Levine, 2009). Previous research has shown that a lack of access to credit constraints entrepreneurship (Banerjee, Breza, Duflo and Kinnan, 2012), poverty reduction (Chowdhury, Ghosh and Wright, 2005), agricultural investment, and income growth (Kaboski and Townsend, 2012), farm production (Kochar, 1997), and spending on education (Doan, Gibson, and Holmes, 2004). These constraints are even higher for lower caste groups who remain socially excluded from the mainstream and lack access to assets, public facilities and opportunities to improve their plight (Thorat and Neuman, 2012).

I use the definition of discrimination proposed by Becker (1971) which states that discrimination occurs when some individuals complete a market transaction at a higher cost or under more stringent terms than others who share the same characteristics. In credit markets, this translates into differences in loan outcome (approvals, amount, and interest rate) which are based on differences in caste, race, or nationality between groups with otherwise similar human and physical capital. Becker introduced the first model of discrimination which explains discrimination by 'taste for discrimination'. When applied to credit markets, this model implies that lenders may discriminate against minority borrowers to avoid interacting with them, regardless of the borrower's ability to repay, and that they are willing to suffer a financial penalty to do so. Another theory of discrimination, known as 'statistical discrimination' was pioneered by Arrow (1973) and Phelps (1972). The premise of this model - when applied to lending - is that the lenders have limited information about the circumstances of some borrowers - particularly their ability to repay. This gives lenders an incentive to use easily observable characteristics such as caste to assume the expected creditworthiness of borrowers provided that these characteristics are correlated with creditworthiness.

The reasons for credit differentials between castes may originate on both the supply and demand sides of the credit market. On the supply side, some lenders may treat a loan application differently based on whether it comes from a higher caste or a lower caste, notwithstanding similar economic, household, and personal characteristics of the borrower - simply because of preferences or cultural beliefs about castes. Other lenders may discriminate against lower caste borrowers due to an expectation that lower caste clients lack the business acumen to use a loan investment wisely. On the demand side, lower caste borrowers may demonstrate traits such as a cultural reluctance to display entrepreneurship or initiative; a lack of background in negotiation, or a cautious attitude to risk-taking - all of which could affect a loan application. It could also be that a self-fulfilling prophecy was at work: the borrowers themselves anticipated prejudice, felt that the lender would be unfair to them (high-interest rates and unfair collateral requirements), and hence, did not seek large loans.

The qualitative interviews with lower caste borrowers in Northern India demonstrate that modern-day discrimination is rarely in the overt form of denying all loans to the lower castes. More subtle means are used: for example, giving a smaller loan amount, demanding higher collateral, granting inadequate extensions on late repayment, imposing higher interest rates, or denying marginal applications. The qualitative enquiries find evidence of petty discrimination to discourage borrowers: long waiting times for opening bank accounts, lack of help with the completion of paperwork, and intimidating inter-personal contact between higher caste lenders and lower-caste borrowers.

One lower caste entrepreneur expressed his views on business lending from banks:

"….bank lending is not for the poor lower caste businesses. The banks never give us an adequate loan. And it takes many weeks just to start the loan process - they give priority to the higher castes."

Another lower caste borrowers added about his experience in the informal credit market:

"….the loan terms are unfair to us. We get less loan for the same amount and quality of land for collateral compared to upper caste. Lenders always treat it like they are doing us a favour even though we pay such a high-interest rate"

The issue of caste discrimination in credit has largely been ignored in social science research in India. We, therefore, have limited insight on the extent and nature of caste discrimination in credit associated with group identity. This is one of the first studies to analyse the discrimination against lower castes in India in the credit framework using qualitative and decomposition methods.

Using nationally representative data from the India Human Development Survey (IHDS) collected in 2005 and 2011-12 and qualitative interviews with lower caste borrowers, this paper examines and compares loan amount differentials between castes in the Indian credit sector over two periods. Using Blinder–Oaxaca decomposition, I demonstrate to what extent these differences can be 'explained' due to the differences in observable characteristics of the individuals and how much is 'unexplained' - which represents an indication of discrimination. I further decompose the 'explained' component to identify the contribution of each specific characteristic in generating the credit differences. In addition, I use the quantile decomposition technique to analyse the caste gap across the entire credit distribution. Furthermore, I compare the credit outcomes – loan application, approval rate and credit amount sanctioned – in lending from banks, money lenders and social networks.

It is important to acknowledge at the outset that there are genuine statistical differences between castes which affect loan outcomes, regardless of discrimination. There are particular differences in observable characteristics between the general caste (GC) and lower castes - Other Backward Castes (OBC); Schedule Castes (SC); and Schedule Tribes (ST). The former is more urban, better educated, more likely to be self-employed or in regular salaried jobs, have higher income and consumption levels. These disparities inevitably get reflected in the amount of credit sanctioned - such that lower castes on average perform significantly poorly compared to general castes. The differences, however, in the credit amount between the general caste and other lower castes in India are not only because of lower quality attributes of lower caste (in terms of education, income, assets etc) but also because these groups may be facing discrimination in the credit sector.

The findings show three main results. First, there are significant differences in loan amount between the general caste and other lower castes, and a portion of these differences remains unexplained. Second, the credit differentials have decreased between 2005 and 2011-12. Third, loan application and approval rates vary according to caste and lender. Generally, lower castes have a higher loan application and approval rate in lending from informal sector while general caste has a higher loan application and approval from banks.

Another contribution of this paper is highlighting the sticky floor[2] and glass ceiling[3] phenomenon in the credit gaps between the general caste and other lower castes. Using the quantile regression-based decomposition method, I find that the credit gap between the general caste and other lower castes varies across the credit distribution.

This paper is structured as follows: Section 2 draws on literature to give the background of the Indian caste system. Section 3 presents data and uses descriptive evidence to highlight caste differences in India. Section 4 sets out the methodology for the paper. Section 5 presents the results from the selection equation, loan amount equation, decomposition of credit differentials. Section 6 discusses and concludes the paper.

2. Background of the caste system in India

The Indian Constitution identifies three main categories of people for preferential policies that reserve seats in legislatures, public sector enterprises, government jobs, and educational institutions. These are OBC; SC also known as *Dalits*; and ST also known as *Adivasis*. GC (also known as forward class) is a term used in India to classify communities who do not

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[2]Sticky floor refers to the scenario where the gap is higher at the bottom of the distribution and the lower caste at the bottom are at a great disadvantage. In this particular case, it refers to the phenomenon of social rigidity in which a certain group of lower castes fail to or are unable to take advantage of readily available options for improving their social and economic status.

[3] Glass ceiling refers to the scenario where the gap is higher at the top of the distribution and the lower caste at the top at a great disadvantage.

qualify for any affirmative action schemes operated by the Indian government. By default, 'general caste' equates to the higher caste in more traditional categorisations.

In India, caste is associated with socio-economic status with a close relationship with occupation and employment (Thorat and Attewell, 2007), income and expenditure (Deshpande, 2000), and capital (Kijima, 2006) - all which are of course helpful in accessing new lines of credit. General caste groups usually have better economic outcomes than lower castes. There is a great hierarchy among the OBC and generally, many OBC groups are closer to GC than to SC or ST in terms of standard of living, income, education and other characteristics. The SC, ST and OBC comprise about 19.5 percent, 8.6 percent, and 41 percent, respectively, of India's population (National Sample Survey Office, 2011). But seven decades after Independence, 33.6 percent of SC, 44.8 percent of ST and 20.7 percent of OBC live below poverty line.

Table 1: Caste distribution according to population, poverty, expenditure and literacy

Caste	**% of population**	**% below poverty line**	**Average Monthly Expenditure Rural (Rs)**	**Average Monthly Expenditure Urban (Rs)**	**Literacy Rate**
General Castes	25	12.5	1281	2467	79%
Scheduled Castes	19.5	33.6	929	1444	58%
Scheduled Tribes	8.6	44.8	873	1797	50%
Other Backward Classes	41.1	20.7	1036	1679	69%

Source: National Sample Survey Office, 2011. 1 Dollar = Rs 70 in May 2019

Dalits are the most oppressed and marginalised group in India. While Dalits make up around 20% of the total population of India, their control over resources of the country is less than 5% (National Campaign on Dalit Human Rights (NCDHR) report, 2009). Approximately three-quarters of the Dalit workforce are landless or nearly landless agricultural labourers (Census of India, 2011). According to an NCHDR report, the social conditions of Dalits are so deplorable that more than half of the Dalit children are malnourished and less than 10% of Dalit households can afford electricity, safe drinking water, and toilets.

The condition of ST households is no better than their SC counterparts. Even though ST did not face exclusion in the form of untouchability, unlike SC, they have even poorer outcomes in terms of health, education, jobs, and employment. Despite the reservation system, the share of SC and ST in government jobs is 16.99% and 8.55 % respectively (Census, 2011). On the whole, lower castes especially SC and ST perform badly in every development metric - including credit.

3. Data and sample characteristics

The data used in the paper comes from two rounds of the India Human Development Survey (IHDS) - a nationally representative survey of 42,152 households in 2011-12 and 41,554 households in 2005 collected from 1,503 villages and 971 urban neighbourhoods across India. The survey covers a range of questions relating to economic activity, income and consumption expenditure, assets, social capital, education, health, marriage, and fertility. Realising that quantitative secondary data is insufficient to capture most of the social reality of discrimination, this study also makes use of qualitative data using semi-structured interviews and informal discussions with several borrowers in three villages[4] in North India to understand the way caste discrimination exists in the credit sector. 16 men (3 from OBC, 12 from SC, and 1 from ST) and 8 (6 from SC and 2 from ST) women from lower caste communities were randomly selected for the interviews[5]. The interviews followed a semi-structured approach, giving participants the flexibility to discuss issues important to them. Informal discussions were held with political activists and representative of Dalit communities, four junior employees of two rural commercial banks[6] (3 GC and 1 OBC) and six local money lenders (belonging to general caste) operating in the region.

Table 2 presents the descriptive of the variables of the four caste groups used in the analysis. The proportion of caste groups used in IHDS 2011-12 is similar to National Sample Survey Office (2006) where GC are 30 percent, OBC are 41.1, ST are 8.6 percent, SC are

[4] The qualitative work was done in the months of January and February in 2018. The villages demographic are representative of the states in the North India, however, it's difficult to say that it represents nationwide trends since India is such a diverse country. The qualitative analysis are very much in line with the quantitative analysis.
[5] All the clients approached agreed to be interviewed for this study. The interviews were done with women at their houses in the presence of a local social worker who helped with translation and conversations. Consent was taken in verbal form.
[6] Punjab National Bank and State Bank of India.

19.5 percent. The primary dependent variable is the log of loan amount[7]. GC has the highest amount of loan undertaken, followed by OBC, SC and ST. However, only 46 percent of the GC participated in the credit market compared to 60 percent of the OBC, 44 percent of the ST and 56 percent of the SC in 2011-12. Similar trends can be seen in 2005.

Table 2: Summary Statistics

Variables description	2011-2012				2005			
	GC	OBC	ST	SC	GC	OBC	ST	SC
Proportion in the sample	28.57	41.10	8.78	21.74	32.48	39.19	8.28	20.05
Loan Details:								
Loan amount (Rs)	64410	52949	24611	28483	24323	18748	7390	10970
Log of Loan	10.72	10.39	9.60	9.94	10.03	9.56	8.67	9.14
Dummy if loan taken	0.46	0.60	0.44	0.56	0.33	0.47	0.34	0.44
Number of loans taken	1.23	1.87	1.57	1.66	0.96	1.45	1.00	1.42
Household Characteristics:								
Yearly income (Rs)	178309	114354	92998	99492	75420	47279	39268	38676
Yearly consumption (Rs)	148916	114919	83397	94903	68829	49863	32724	43027
Proportion have female head	0.14	0.14	0.15	0.15	.09	.09	.10	.10
Age of the head	51.88	49.53	47.92	47.83	48.51	47.09	45.53	45.46
Education years of the head	7.45	5.46	3.91	4.39	7.30	5.22	3.63	3.99
Size of the Household	4.82	4.92	4.77	4.83	5.12	5.28	5.06	5.19
Amount of land in acres	11.94	11.60	16.52	4.78	22.28	12.97	15.54	3.42
Dummy if own land	0.46	0.46	0.59	0.35	0.41	0.45	0.55	0.33
Dummy if live in urban area	0.44	0.35	0.14	0.30	0.47	0.34	0.15	0.29
House Quality[8]	0.75	0.66	0.35	0.55	0.71	0.57	0.29	0.46
Dummy if have a ration card[9]	0.87	0.87	0.81	0.86	0.85	0.80	0.78	0.86
Market price of rice per kg	23.82	21.64	18.87	20.91	13.06	11.69	10.61	11.59

The general caste has better outcomes in terms of loan amount, income, consumption, and education compared to the other castes. Income, consumption and loan amount increased by

[7] Government policies have invariably seek to tackle the discrimination problem in the credit market by focusing on the access to credit. The assumption is that - having gained access to credit market - the processes and controls within that system will work to ensure equal treatment. This study does not focus on access, instead, it measures how equitably the credit system treats different groups after they have gained access.
[8] A binary variable distinguishing between dwellings that are designed to be solid and include cemented flooring and strong roof compare to houses without a strong floor or roof. (Good = 1, Bad = 0).
[9] Ration card is an identification document issued by state governments in India. It categorises household according to their poverty level and allow the holder of below and extreme poverty households to obtain food and other commodities at a subsidised price.

more than double for all the castes between 2005 and 2012. Caste-based stratification translates into low human capital for lower caste individuals. In 2005, the average number of education years completed by ST (head of the households) in the sample were 3.63 years, 3.99 years for SC, 5.22 years for OBC, followed by 7.30 years for the GC. Generally, the differences at lower levels of education (primary) are less pronounced across social groups but start to diverge widely by middle school and higher. For instance, only 3.5 percent of the SC heads of household have achieved a graduate or post-graduate education compared to 14 percent of GC individuals.

Although the GC are less likely to live in rural areas, they are more likely to own land for agricultural purposes. In 2011-12, 56 percent of GC lived in the rural area, and 46 percent owns land for agricultural purposes. Whereas 65 percent of OBC, 86 percent of ST and 70 percent of SC population live in the rural area, however, 46 of OBC, 59 percent of ST, and 35 percent of SC own land for agricultural purposes. The amount of land owned by SC/ST has increased, while decreased for OBC and GC over this time. The general castes are more likely to live in dwellings that are designed to be solid and include cemented flooring and strong roof (also known as *pukka* houses).

The proportion of those taking a loan has also increased for all the groups. GC has taken the lowest number of loans in the last five years; however, their loan amount is twice as big as SC. However, SC/ST have significantly improved their credit outcomes between 2005 and 2011-12. Figure 1 below plots the kernel density distribution of log loan for all the castes. The distribution of log loan of GC lies to the right of all the other lower castes.

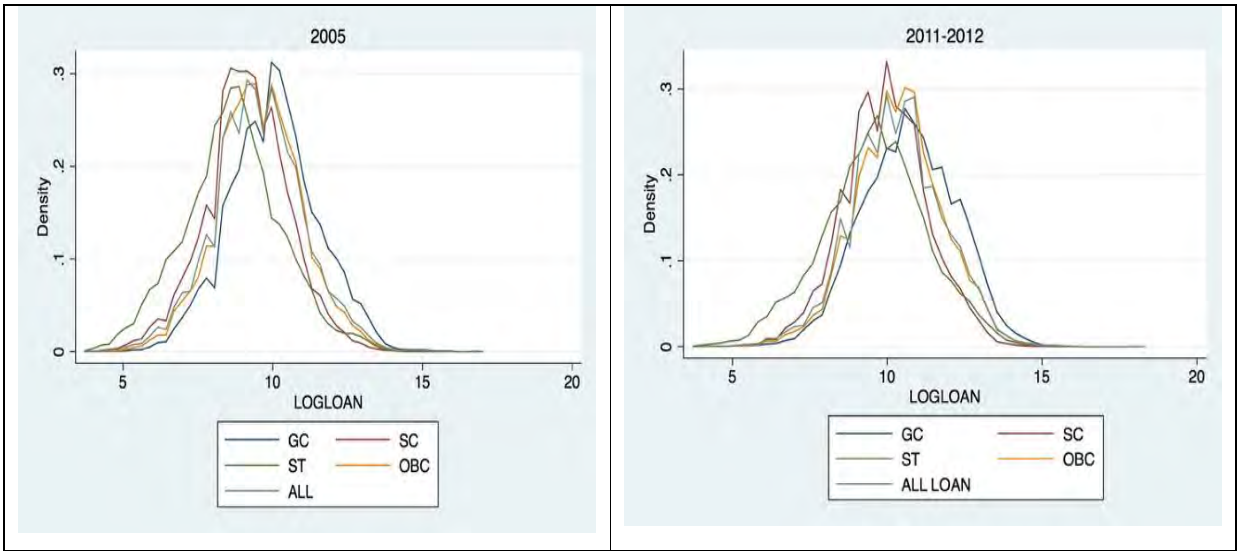

Figure 1: The kernel density distribution of log of amount of loan by various caste groups in 2011-2012 and 2005.

There is a clear distinction in the occupational structure of various castes (see Table 6 in the Appendix). The major source of income for GC and OBC continued to be cultivation, non-agricultural wage labour and salaried employment. Since a large proportion of ST own land, a very significant portion of this caste group derives their income from agricultural activities. The hierarchical nature of the caste system combined with low endowments of human and physical capital implies that major portion of SC's income continues to come from selling their labour and a very small portion derives from cultivation.

The purpose of loans taken varies according to the caste group (see Table 7 in the Appendix). In 2011, around 36.5 percent of the general caste loans are for productive purposes such as buying land, agricultural, business, and education and the rest for non-productive purposes such as marriage, consumption, educational, medical expenses etc. Around a third of the loans by ST and OBC are for productive purposes which are in line with GC. SC mostly comprising of wage labour has only 21 percent of loans for productive purposes and mostly take loans for non-productive purposes.

Compared to 2005, the patterns within the group are more or less the same. Loan for the non-productive purposes has increased for all the caste groups. Since consumption loans do not generate any financial return and are deemed risky, increase in such loans for GCs and OBC shows that lenders favour these castes over SC and ST. Loans for productive purposes such as agriculture and business decreased for all lower castes but the decline in the SC was the sharpest where it reduced to half.

Different castes tend to get their loans from different sources (see Table 8 in the Appendix). The major source of finance for general castes comes from formal lenders such as banks, while social networks and money lenders also play a significant role. OBC have increased their share of lending from banks while reducing their reliance on money lenders between 2005 and 2011-12. SC and ST are majorly dependent on informal sources for their finance, however, these groups have greatly reduced their dependence on money lenders between 2005 and 2011-12.

With the development of formal finance in India in the last decade, all the caste groups have increased their reliance on formal sources such as banks, NGOs and credit groups in 2011-12. With further development in financial services in India specially in microfinance and rural banking, we may see a current trend of a diminishing role for money lenders in Indian society. The data also show an increase in the share of loans from relatives and friends for all the caste groups. Overall, we see a significant convergence of education, income, consumption, loan amount of SC/STs toward non-SC/ST levels (also noted by Hnatkovska, Lahiri and Paul, 2012).

The survey done in 2011-2012 also has information on the breakdown of loan approval and rejection of households from banks, money lenders, and social network (see Table 9 in the Appendix). There is no clear pattern, however, general castes are more likely to borrow from banks, whereas other castes are more likely to borrow from informal sources such as money lenders and friends.

4. Methodology

This paper presents estimates of the mean caste loan amount gap in the Indian credit sector and the extent to which this differential can be explained by differences in observable characteristics or 'endowments' of clients across caste groups. The amount of credit the borrower has arises from the following equation:

$$ln\,Y_{ij} = X_{ij}\beta_j + u_{ij} \qquad (1)$$

Where lnY is the natural logarithm of loan amount of i_{th} individual in j_{th} social group ranging from GC, SC, ST and OBC. X_{ij} is a vector of observed characters, and β_j is a coefficient vector to be estimated for each caste type, and u_{ij} is assumed to be a normally distributed error term with mean zero and positive variance.

The Blinder–Oaxaca decomposition is employed to decompose the credit amount gap in outcomes between various castes[10]. Oaxaca (1973) and Blinder (1973) developed a regression-based decomposition to divide the gap in an outcome of interest between two groups into an 'explained' and an 'unexplained' portion. The 'explained' portion of the gap is the actual difference between the mean values of two castes which could be explained by differences in endowments and personal attributes. The 'unexplained' portion of the gap arises from group differences in the effects of the independent variables (Sen, 2014). This is also known as discrimination function or unexplained residual – a part that cannot be accounted for by differences in characteristics. While the unexplained component is often used as a measure for discrimination, it is very likely that the residual also includes the effects of unobservable or unmeasurable characteristics (Deshpande and Sharma, 2014). All decomposition analyses are subject to this caveat given that it is generally very difficult to control for all the borrower's characteristics that may affect creditworthiness[11].

The difference in the credit amount arise from following equation:

$$\overline{lnY_g} - \overline{lnY_l} = \underbrace{[(\overline{X_g} - \bar{X}_l)\hat{\beta}^*]}_{\text{EXPLAINED}} + \underbrace{[(\hat{\beta}_g - \hat{\beta}^*)\bar{X}_g + (\hat{\beta}^* - \hat{\beta}_l)\bar{X}_l]}_{\text{UNEXPLAINED}} \tag{2}$$

Where lnY is the natural logarithm of loan amount, g and l subscripts stand for general caste and lower castes (SC, ST and OBC) respectively. X_g is a vector of observed characters for general caste, X_l is a vector of observed characters for various lower castes, and β_g is a coefficient vector to be estimated for general caste, β_l is a coefficient vector to be estimated for lower caste and $\hat{\beta}^*$ is the estimate of the non-discriminatory credit coefficient and can be written as:

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[10] Blinder–Oaxaca decomposition has been used to measure differences between castes in health outcomes (Maity, 2018), labour market (Hnatkovska, Lahiri and Paul, 2012), poverty (Borooah, 2005), school enrolment (Borooah and Iyer, 2005), access to energy (Saxena and Bhattacharya, 2018) in Indian context.

[11] It is also possible that pre-market discrimination affects the development of characteristics, and thus, the explained component could also constitute the effects of past discrimination. Considering this, the estimates of the unexplained components should not be taken as precise measurement of discrimination but as rough estimates of its scale (Deshpande and Sharma, 2014).

$$\hat{\beta}^* = D\hat{\beta}_g + (1-D)\hat{\beta}_l$$

The non-discriminatory credit coefficient $\hat{\beta}^*$, can be estimated using the coefficients from the higher caste where (D=1) or the lower caste as the reference coefficients (D=0). However, there is no particular reason to assume that the coefficients of any of the groups are non-discriminating (Jann, 2008). It has been claimed that the undervaluation of one group comes along with an overvaluation of the other (Cotton, 1988). Considering this, I use the method proposed by Neumark (1988) using the coefficients from a pooled regression over both groups as an estimate for $\hat{\beta}^*$.

a. Selectivity and simultaneity bias

Another methodological problem faced in analysing the caste gap is the existence of endogeneity which can be caused by self-selection and simultaneity bias. Selection bias could occur when individuals with similar characteristics (education, assets or consumption level) have different levels of entrepreneurship, perseverance and ability, which may lead to different probabilities of their participating in the credit market. The self-selection is corrected by using the Heckman two-step procedure in the analysis.

Using the Blinder-Oaxaca decomposition, the observed earnings differential can be further decomposed into:

$$\overline{lnY_g} - \overline{lnY_l} + [\gamma_j\bar{\lambda}_j - \gamma_i\bar{\lambda}_j] = \underbrace{[(\overline{X_g} - \bar{X}_l)\hat{\beta}^*]}_{\text{EXPLAINED}} + \underbrace{[(\hat{\beta}_g - \hat{\beta}^*)\bar{X}_g + (\hat{\beta}^* - \hat{\beta}_l)\bar{X}_l]}_{\text{UNEXPLAINED}} \qquad (3)$$

where γ is the coefficient of the inverse Mills ratio (λ).

Simultaneity bias could be caused by the presence of endogenous variable such as consumption expenditure which may cause reverse causality. To remove the simultaneity bias, we require an instrument for consumption expenditure – an exogenous variable that is correlated with consumption expenditure but is not otherwise associated with the loan amount. In this case, the market price of one-kilogram rice in the region satisfies the requirement for use as an instrumental variable[12]**.** Rice is the most consumed food in India,

[12] We also test for the relevance of the instrument in the first-stage regression. Staiger and Stock (1997) proposed a rule of thumb declaring the instruments weak when the first stage F-statistic is less than 10. The F-statistic from the first-stage is sufficiently large in every instance, suggesting that the IV is powerful (see Table 3 in the online appendix). Another approach, by Stock and Yogo (2005) is to reject the null hypothesis of weak

and its price has a significant impact on consumption expenditure. The instrument affects the loan amount through its effect on consumption expenditure only.

b. Specification checks

Identification can be achieved by including at least one independent variable that appears in the selection equation but not in the outcome equation - we need a variable that affects the selection, but not the outcome (Sartori, 2003). In the specification, there are a number of additional identifying restrictions that are described below.

Landownership can affect a household's ability to participate in the credit market as land can be used as collateral, therefore, it appears in the selection model. However, merely having land does not affect the amount of loan a borrower can get and other variables such as size of landholding, quality of land or land titles may be more suitable in the credit amount equation. To check this, I plugged the landownership dummy in the credit amount equation and found it does not have any effect on the amount of loan, whereas it positively affects the probability of participation in credit market. The information regarding the source of loan and purpose of the loan is only available for people who have taken loan, so it appears in the credit amount equation. The rest of the variables appears in both selection and loan amount model.

5. Results

a. Selection equation

I begin the analysis by estimating a model of the probability of participating in the credit market using a probit model[13]. The dependent variable is 1 if the client has taken a loan or 0 otherwise. The estimates of the probit regressions are used to construct the Inverse Mills Ratio (IMR) for the purpose of correcting the credit amount equation for selection bias as reported in the later section.

To facilitate the understanding of the effects of coefficients, I present the marginal effects of the regressors on the probability of participation in the credit market by each caste

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instruments when the Cragg and Donald (1993) F-statistic exceeds a given threshold. In this case, we reject the null hypotheses of the weak instrument since Cragg-Donald F statistic exceeds the threshold of 16.38 at 10%. By these criteria, we have a good instrument in the average market price of one kilogram rice in the region.

[13] I failed to reject the null hypothesis for Wald Test of exogeneity using instrument variable, therefore, a regular probit regression may be appropriate.

in Tables 10 and 11 in the Appendix[14]. The results from both time periods show similar results. One percent increase in consumption increases the probability of taking a loan by 0.1 percent for GC, 0.14 percent for OBC, 0.17 percent for ST and 0.15 percent for SC in 2005 and 0.11 percent for GC, 0.13 percent for OBC, 0.11 percent for ST and 0.14 percent for SC in 2011-2012. The results show that gender exerts an influence on taking a loan. Being a female significantly decreases the probability of taking a loan (except for ST in 2005). The number of education years completed by the head of the households shows a negative relationship with the likelihood of participating in the credit market (except for ST in 2011-12). This implies that highly educated heads are more likely to work in salaried positions and may not require loans. The land ownership has a positive relationship with the probability of participation in credit markets. Households living in a strong and permanent dwelling are less likely to participate in the credit markets (except for SC in 2005 and ST in 2011-12). Households living in rural areas are more likely to participate in the credit market (except for ST in 2011-12) reflecting the cyclical nature of an agricultural economy and the relatively long delay between investment and income. To account for the differences between the sources of income and location, I also controlled for occupation and states dummies.

b. Loan amount equation

I now proceed to estimate regressions for each caste type corrected for selection and endogeneity (see Tables 14 and 15 in the Appendix). The result shows that a single percentage increase in consumption increases the loan amount by 0.68 percent for GC, 0.84 percent for OBC, 1.257 percent for ST and 0.31 percent for SC in 2005 and 0.80 for GC, 0.48 percent for OBC, 0.52 percent for SC, however, no effect for ST in 2011-12. Education has a positive relationship with the loan amount. An additional year of education significantly increases the amount of loan taken by all the castes except for ST in 2005. Age has a quadratic relationship with the volume of loans implying that lenders are more inclined to give higher loans to older borrowers (except for SC in 2005). The size of landholding has a negative relationship with loan amount. This could be due to the following reasons. First, in the absence of land titles, and poorly administered land records, small and marginal farmers, who account for more than half of the total land holding, may not be able to use it as collateral (Reserve Bank of India, 2015). Second, the cost of cultivation per unit of land might decrease with an increase in the size of the land under cultivation (Bhattacharjee &

[14] The coefficients from the probit model are shown in Tables 12 and 13 in the Appendix.

Rajeev, 2014). Third, it's a non-liquid and immovable asset so it's not very suitable for collateral, specially for short term loan for small and marginal farmers. An alternative such as gold rather than land is preferred by the lenders (Sarap, 1991). The quality of borrower's house is a better predictor of loan amount and significantly increases the loan amount (except for ST in 2005). Having a female head of the household and living in urban area increases the loan amount for every caste except for ST in 2005. The estimated models have fairly high explanatory power for all four social groups.

c. Decomposing the differences in participation in the credit market:

To disentangle the role of observable and unobservable factors on the participation level in the credit market among various castes, I extend the Oaxaca-Blinder decomposition to nonlinear methods using Fairlie's (2005) approach. Table 3 below decompose the probability of participation in the credit market into explained and unexplained part using the estimates from the selection equation.

Table 3: Decomposition of the probability of participation in the credit market in 2005 & 2011.

	2005			2011-12		
VARIABLES	GC VS OBC	GC VS ST	GC VS SC	GC VS OBC	GC VS ST	GC VS SC
GC	0.331***	0.331***	0.331***	0.458***	0.458***	0.458***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Others	0.469***	0.337***	0.440***	0.600***	0.440***	0.565***
	(0.004)	(0.008)	(0.005)	(0.004)	(0.008)	(0.005)
Difference	-0.139***	-0.007	-0.109***	-0.142***	0.017*	-0.107***
	(0.006)	(0.009)	(0.007)	(0.006)	(0.009)	(0.007)
Explained	-0.132***	-0.040***	-0.066***	-0.109***	-0.031***	-0.052***
	(0.004)	(0.008)	(0.005)	(0.004)	(0.008)	(0.004)
Unexplained	-0.007	0.033***	-0.044***	-0.032***	0.048***	-0.055***
	(0.006)	(0.011)	(0.007)	(0.006)	(0.011)	(0.007)
Observations	29,714	16,877	21,765	28,444	15,270	20,491

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

For the data collected in 2005, I find that all the lower castes have a higher probability of participating in the credit market compared to the general caste. In 2011-12, I find that the SC and OBC have a higher probability of participation in the credit market compared to GC whereas GC has a small advantage over ST. A considerable proportion of the gap between GC and SC (40 percent in 2005 and 51 percent in 2011-12) remains unexplained. The difference between probability of participation between GC and OBC can largely be explained by characteristics and attributes. A positive unexplained component between GC and ST (45 percent in 2005 and 60 percent in 2011) implies that GC got better return from their characteristics. On average, lower castes are more likely to participate in the credit market compared to general castes after controlling for the selection variables.

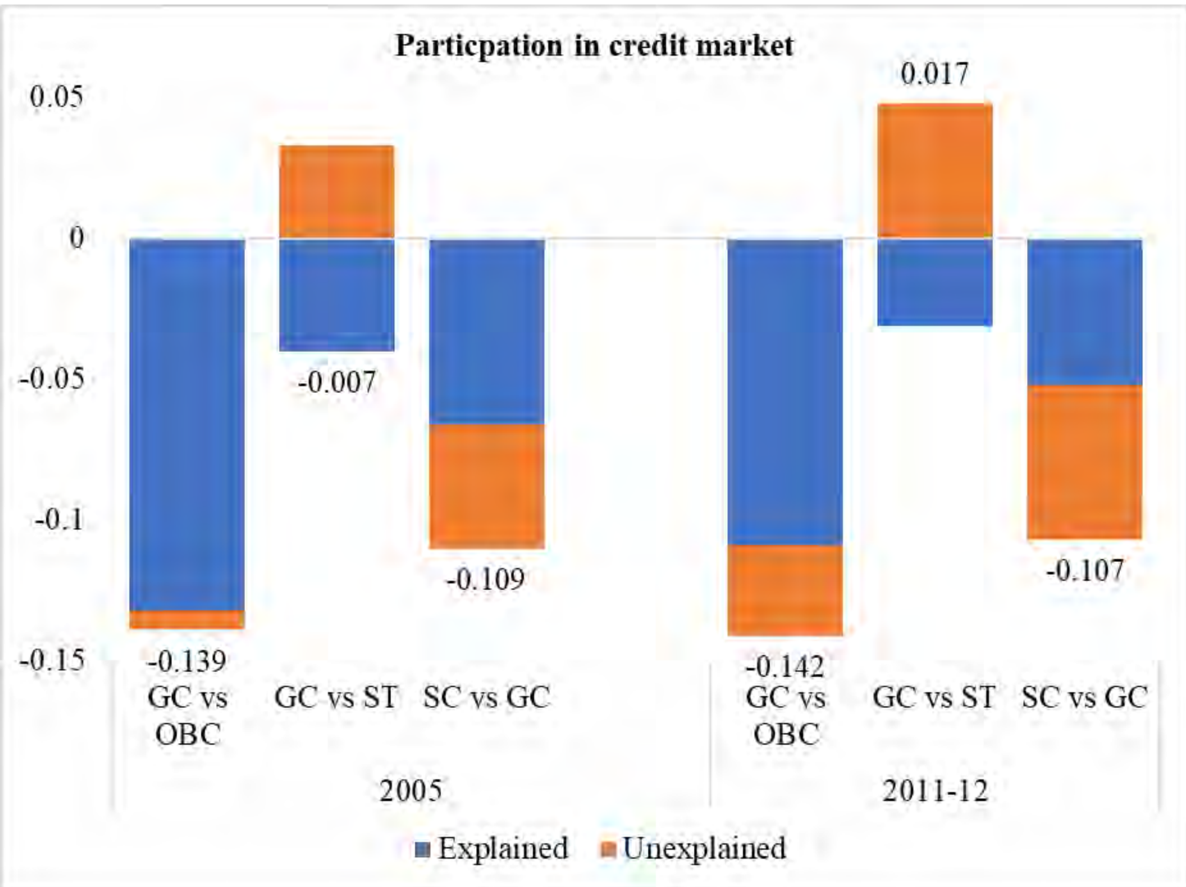

Figure 2: Decomposition of the probability of participation in the credit market. The figure is based on Table 3 comparing caste inequalities between various castes in 2005 and 2011-12.

d. Decomposing credit differential with the selection effect

Tables 4 and 5 present the decomposition of the log credit amount differentials between the general caste and all other castes into explained and unexplained component.

Table 4: Observed credit differentials and selection corrected credit differential in 2005

2005 VARIABLES	Observed credit differential 1 GC vs OBC	Adjusted credit differential 2 GC vs OBC	Observed credit differential 3 GC vs ST	Adjusted credit differential 4 GC vs ST	Observed credit differential 5 GC vs SC	Adjusted credit differential 6 SC vs GC
GC	10.025***	12.368***	10.025***	12.368***	10.025***	12.368***
	(0.022)	(0.125)	(0.022)	(0.125)	(0.022)	(0.125)
Others	9.555***	11.278***	8.667***	10.213***	9.140***	10.695***
	(0.016)	(0.074)	(0.047)	(0.175)	(0.023)	(0.096)
Difference	0.470***	1.090***	1.358***	2.155***	0.885***	1.673***
	(0.027)	(0.146)	(0.052)	(0.215)	(0.032)	(0.158)
Explained	0.470***	0.878***	1.213***	1.405***	0.811***	0.948***
	(0.021)	(0.031)	(0.051)	(0.059)	(0.028)	(0.034)
Unexplained	0.000	0.212	0.140***	0.751***	0.073***	0.725***
	(0.023)	(0.143)	(0.050)	(0.213)	(0.029)	(0.155)
Observations	12,076	12,077	5,600	5,600	8,105	8,105

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table shows decomposition of log of loan into explained and unexplained portion. Columns 1, 3 and 5 show results from equation 2. Columns 2, 4 and 6 show results from equation 3 and are corrected for selection and endogeneity.

Table 5: Observed credit differentials and selection corrected credit differential in 2011-12.

2011-12 VARIABLES	Observed credit differential 1 GC vs OBC	Adjusted credit differential 2 GC vs OBC	Observed credit differential 3 GC vs ST	Adjusted credit differential 4 GC vs ST	Observed credit differential 5 GC vs SC	Adjusted credit differential 6 SC vs GC
GC	10.723***	13.210***	10.723***	13.210***	10.723***	13.210***

	(0.020)	(0.108)	(0.020)	(0.108)	(0.020)	(0.108)
Others	10.386***	12.130***	9.593***	11.614***	9.945***	11.801***
	(0.014)	(0.059)	(0.042)	(0.191)	(0.019)	(0.084)
Difference	0.337***	1.081***	1.130***	1.597***	0.778***	1.409***
	(0.025)	(0.124)	(0.047)	(0.219)	(0.028)	(0.137)
Explained	0.305***	0.726***	1.02***	1.241***	0.649***	0.784***
	(0.016)	(0.027)	(0.046)	(0.051)	(0.025)	(0.029)
Unexplained	0.031***	0.355***	0.103***	0.355	0.128***	0.625***
	(0.002)	(0.122)	(0.045)	(0.218)	(0.025)	(0.135)
Observations	15,328	15,349	6,887	6,897	10,268	10,283

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The table shows the decomposition of log of loan into explained and unexplained portion. Columns 1, 3 and 5 show results from equation 2. Columns 2, 4 and 6 show results from equation 3 and are corrected for selection and endogeneity.

Consistent with earlier results, I find that GC is in a more favourable position in the Indian credit sector. The observed credit differentials show that the GC has 47 percent advantage over OBC, 135.8 percent over ST, and 88.5 percent over SC in 2005 and 33.7 percent advantage over OBC, 113 percent over ST, and 77.8 percent over SC in 2011-12 (see observed credit differentials in Columns 1, 3 and 4 in Tables 4 and 5). Largely these differences can be explained by the endowments and personal characteristics, and a very small portion remains unexplained.

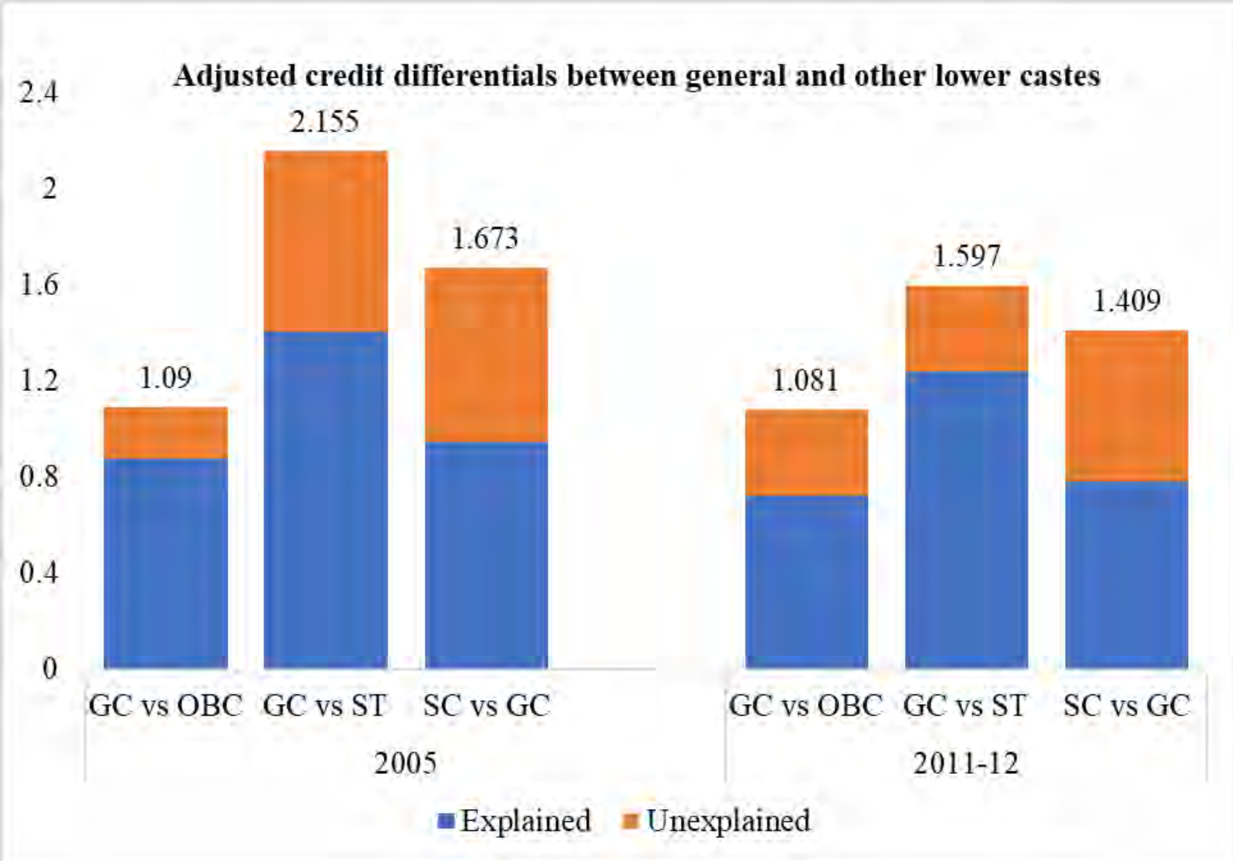

Figure 3: Credit differential between the general caste and other lower castes for 2005 and 2011-12. The figure is based on columns 2, 4 and 6 of Tables 4 and 5 comparing caste inequalities between various castes in 2005 and 2011-12.

However, these results should be treated with caution due to self-selection in the credit market. The adjusted credit differentials in Tables 4 and 5 show that decomposition results are sensitive to the selection effect. The credit differentials are underestimated without the correction for selectivity. The adjusted credit differential increases to 109 percent for OBC, 215.5 percent for ST, and 167.3 percent for SC in 2005, and 108 percent for OBC, increases to 159.7 percent for ST, and 140.9 percent for SC in 2011-12. The credit differentials are largely explained by the differences in endowments and personal characteristics. Out of the total differences, 19 percent between GC and OBC, 35 percent between GC and ST and 43 percent between GC and SC remains unexplained in 2005; and 32 percent between GC and OBC, 22 percent between GC and ST and 44 percent between GC and SC remains unexplained in 2011. The credit differentials have decreased between the general caste and other lower castes compared to 2005.

Now I will discuss the factors that will explain these sharp differences. Table 16 in the appendix shows the variable decomposition of credit differential.

In 2005, the differences in consumption expenditure is responsible for 28 percent of the explained share of the total difference between GC and OBC. The differences in states contribute to 38 percent, and the differences in source of the loan, purpose of the loan and occupations contribute to 16 percent, and the differences in years of education, age and quality of the house explain the rest. Similarly, 42 percent of the explained portion of the credit differences between GC and ST in 2005 arise from the differences in consumption expenditure; source of the loan, purpose of the loan and occupations explain 19 percent; differences in states contributes to 12 percent and differences in years of education, age and quality of the house explain the rest. In the case of credit differences between GC and SC in 2005, differences in consumption explain around 37 percent; differences in the source of the loan, purpose of the loan and occupations explain 23 percent, and differences in states contribute to 20 percent and differences in years of education, age and house quality explain the rest.

In 2011, 26 percent of the explained portion of the total credit differences between GC and OBC is due to the differences in the level of consumption; differences in states contributes to 12 percent and differences in source of the loan, purpose of the loan and occupations contribute to 37 percent; and differences in age, house quality and education years explain the rest. Similarly, 44 percent of the explained portion of the credit differences between GC and ST in 2005 arise from the differences in consumption expenditure; source of the loan, purpose of the loan and occupations explain 15 percent; differences in states contributes to 18 percent and differences in years of education, age and quality of the house explain the rest. In the case of credit differences between GC and SC in 2011, differences in consumption explain around 37 percent; differences in the source of the loan, purpose of the loan and occupations explain 26 percent, and differences in states contribute to 14 percent and differences in years of education, age and house quality explain the rest.

Differences in states explain a very significant portion of the credit gap[15]. Further investigating the variations in states, I find that states with a significant population of OBC and ST (such as Chhattisgarh, Madhya Pradesh, Orrisa and Karnataka) increase the credit differences between GC and OBC and GC and ST. I also find that living in states such as Himachal Pradesh, West Bengal, Kerala, Punjab and Maharashtra reduces the credit differences between caste. Overall, the characteristics disparity between the general castes

[15] See Tables 1 and 2 in the online appendix.

and lower castes are largely due to differences in consumption, location (state), years of education, house quality, source of the loan, purpose of the loan, and occupations.

e. Quantile decomposition

In this section, I apply a quantile regression-based decomposition method proposed by Firpo, Fortin, and Lemieux (2009) to evaluate caste-based differences in the Indian credit sector[16]. Their methodology relies on an extension of the Oaxaca-Blinder decomposition which introduces a two-stage procedure; first, carry out the decomposition based on unconditional quantile regressions (UQR) techniques using a reweighting approach dividing the distributional changes into structure effect and a composition effect; second, the two components are further divided into the contribution of each explanatory variable using recentred influence function (RIF) regressions[17].

Figures 4 and 5 (based on Tables 23 and 24 in the Appendix) report the quantile regression decompositions obtained for three quantiles (10th, 50th, and 90th). The quantile decomposition suggests that credit gaps between GC and OBC are higher at lower (10th) deciles compared to upper (90th) and middle (50th) deciles for both time period. The share of the unexplained component of the gap is also higher at the lower end of the credit distribution, demonstrating the evidence of sticky floor effect. This suggests that borrowers from the OBC group may be facing greater discrimination at the lower end of credit distribution. However, this effect reverses in the higher decile where borrowers from lower castes experience negative discrimination – credit markets favours OBC at the higher end of the distribution.

The credit differences between GC and ST are higher at lower and middle deciles in 2005. The unexplained component of the gap is also higher at the lower and middle deciles suggesting sticky floor effect. However, this effect reverses in 2011-12, where the credit differences and the unexplained gap are higher at the higher quantile. The credit differences between GC and SC and unexplained component is higher at higher quantile in 2005 suggesting a glass ceiling effect. However, this effect reverses in 2011-12, where the credit differences and unexplained component is higher at lower deciles suggesting a sticky floor effect.

[16] I used the Stata program rifreg to estimate the unconditional quantiles. The programme can be downloaded from here: http://faculty.arts.ubc.ca/nfortin/datahead.html.
[17] The Firpo et al. method allows us to decompose the caste gap into the contribution of each individual variable. However due to the space constraint, I haven’t shown this in the paper.

In 2011, sticky floor effect for prevails for OBC and SC borrowers suggesting that the credit market only favours them at the higher end of the distribution. After correcting for selection, we see that the credit differences and the unexplained component reduced at upper quantiles implying that OBC and SC borrowers at higher quantiles who self-selected in the credit market got a better return for their characteristics. These borrowers at the upper end of the distribution are more likely to possess higher levels of entrepreneurial ability, perseverance and drive which improve their creditworthiness. They are also aware of their rights and might be in a better position to take action against perceived discrimination. Lenders aware of these possibilities may not be able to discriminate at the upper end of credit distribution. Moreover, the credit market at the higher end would be far more structured and rigidly defined, making it harder to discriminate across caste. Glass ceiling effect for the ST borrowers in 2011 suggest that borrowers from this caste group may face higher discrimination at the higher end of the distribution. In 2005, we see sticky floor effect for OBC and ST borrowers and glass ceiling effect for SC borrowers.

It is generally very difficult to disentangle taste-based discrimination and statistical discrimination. Both kinds of discrimination can easily coexist in the credit market. The quantile decomposition shows significant variations in the unexplained component across the distribution. This suggests that a statistical discrimination effect prevails. If the discrimination was largely due to taste, it would have been constant across the entire credit distribution.

A possible reason for the sticky floor effect for OBC and SC borrowers in 2011 and OBC and ST borrowers in 2005 could be due to the statistical discrimination practised in the credit market. In India, division of labour according to the caste system has frequently prevented individuals from starting businesses (Iyer, Khanna, Varshney, 2013) and hence, the lack of business experience at the lower end of credit distribution hurts their credit prospects. Even when Dalits become entrepreneurs, their businesses could suffer due to discrimination present in most domestic markets and the lack of suitable social and business networks. Because of this, lower castes are perceived as less creditworthy and riskier to lend to than upper castes. As a lower caste borrower moves up the economic ladder, lenders are less like to discriminate against them and; even favour them.

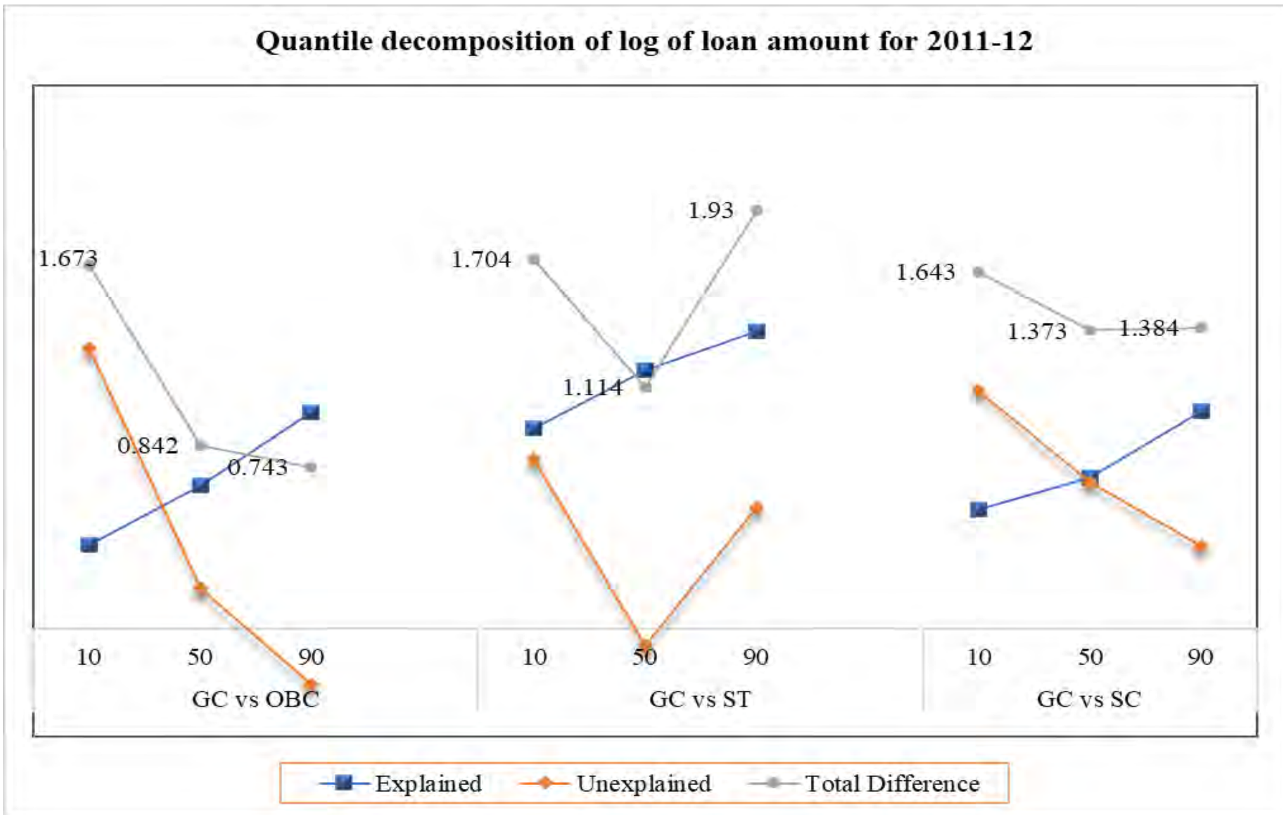

Figure 4: Quantile decomposition of log of loan amount for 2011-12. The figure plots the result from quantile regression decompositions obtained at 10th, 50th, and 90th percentile.

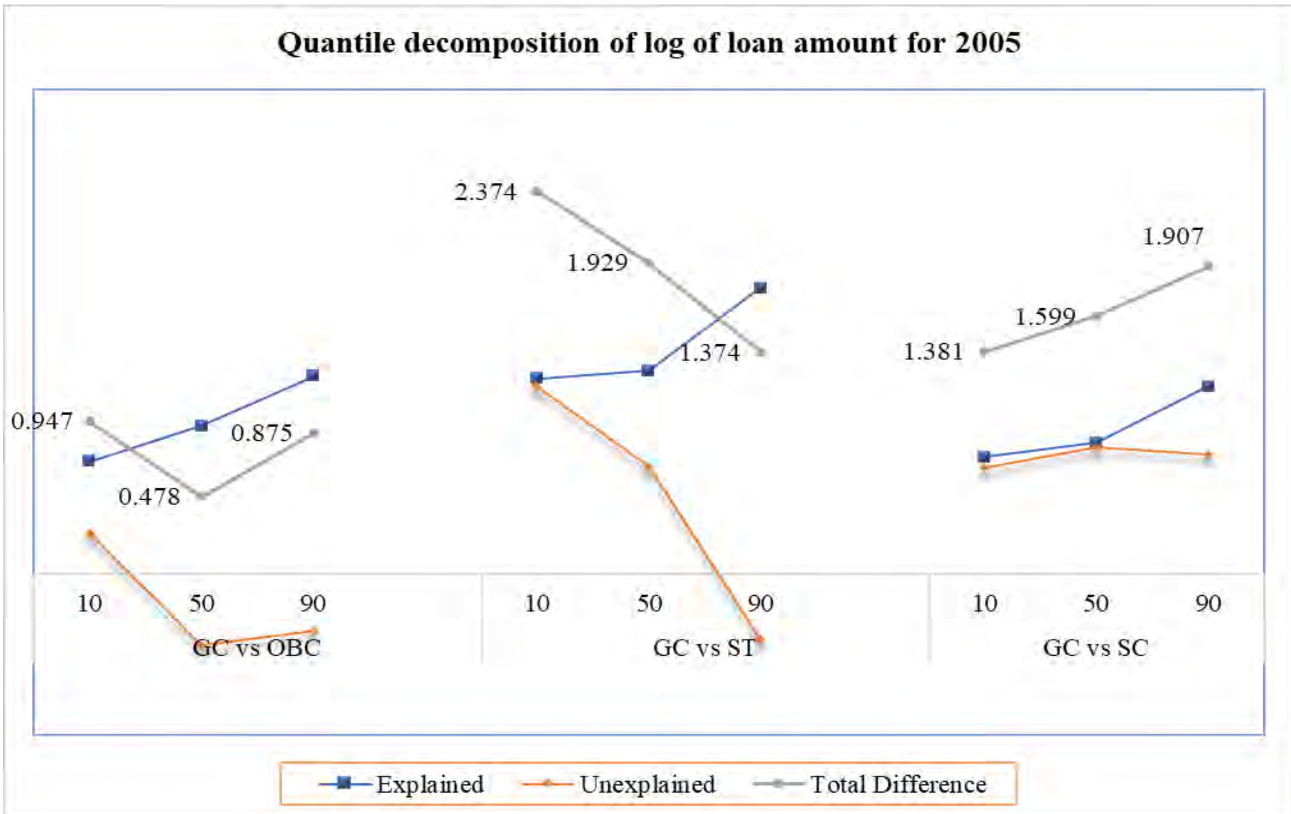

Figure 5: Quantile decomposition of log of loan amount 2005. The figure plots the result from quantile regression decompositions obtained at 10th, 50th, and 90th percentile.

f. Decomposing credit outcomes differences by lenders:

Since we have data regarding loan applications and approvals from various sources in the IHDS (II) 2011-12 survey data, we are able to decompose the caste differences in the probability of loan application and approval from banks, moneylenders, and social networks. The decomposition analysis reveals that GC has a lower probability of applying but a higher approval rate on their loan application in lending from banks compared to OBC (Panel A, Table 17 in the Appendix). However, GC has a higher probability of applying and approval rate in lending from the bank compared to SC and ST (Panel A, Table 17 in the Appendix). Contrary to that, all lower castes have a higher probability of applying and approval in lending from money lenders (Panel B, Table 17 in the Appendix). In lending from social networks, OBC and SC have a higher probability of applying but lower probability of approval compared to GC, whereas GC has a higher probability and approval compared to ST (Panel C, Table 17 in the Appendix).

In the following subsection, I will decompose the credit amount differences between castes in lending from banks, moneylenders and social networks.

Banks: Banks are one of the major sources of credit for Indian borrowers. 27 percent and 32 percent of all the borrowers in the sample in 2005 and 2011, respectively, took their loan from banks (see Table 13 in the Appendix). With the development of the banking system in India in the last decade, all the caste groups have increased their lending from banks. Figure 6 (based on Table 18 in the Appendix) shows that there are large credit differentials between the general caste and lower castes. However, the credit differentials between GC and OBC have increased, whereas the credit differentials between GC and SC and GC and ST have decreased over the period considered. The share of the unexplained portion of the total differences between GC and lower castes have increased from 2005. A large portion of the differences between GC and SC remains unexplained suggesting that banks may be discriminating against the SC borrowers.

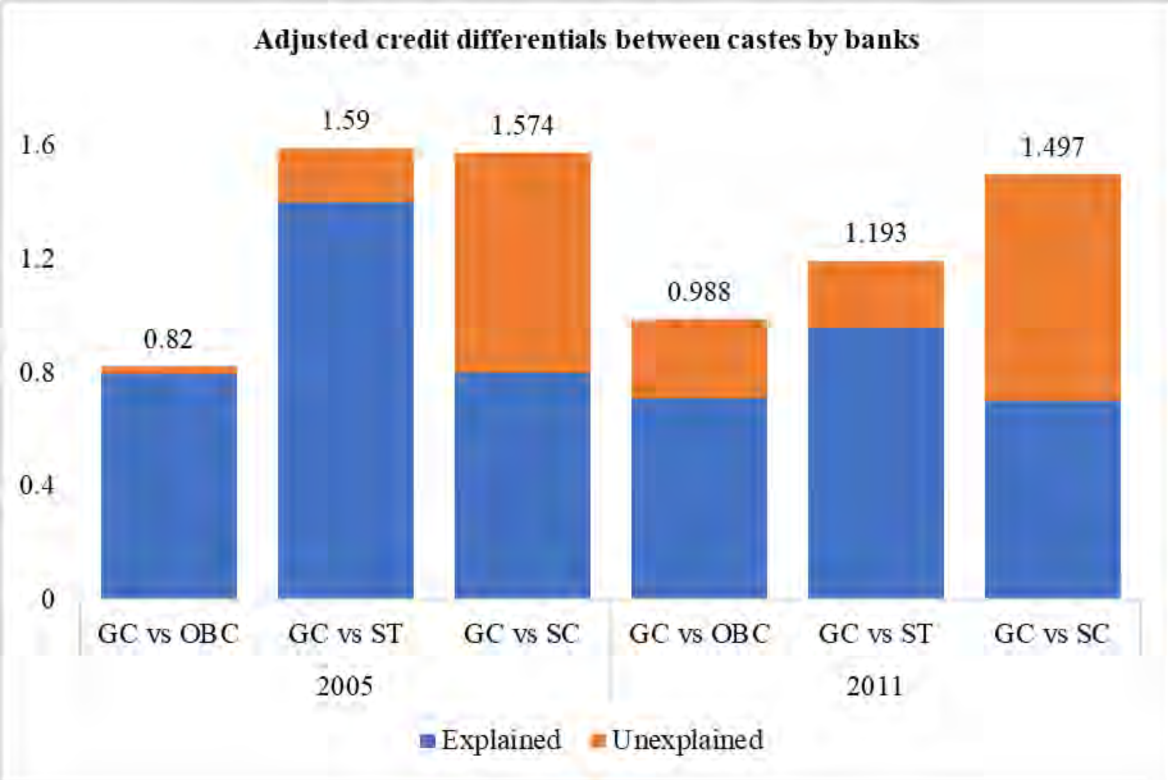

Figure 6: Adjusted credit differentials between castes in 2005 and 2011-12 in credit taken from banks.

One ST borrower described the process of bank lending as humiliating:

"...they (the bank) keep sending back our documents for the loan. While the loan officer collects the documents for the Jaats (upper caste) from their houses, we are not even allowed to sit on the chairs in the bank or offered any help to fill the complicated forms. While they photocopy the documents of upper castes in the bank, we are asked to get the photocopies from outside"

One female Dalit interviewee said:

"....even though my documents were complete, I was asked to sweep the bank floor in return for opening a bank account. This was despite the bank having a cleaning staff. This is degrading..."

Some of the credit differences between castes in banking lending could also arise from repayment enforceability of the financial contract (as shown by Rubin and Kuran, 2018). Successive Indian governments have passed reforms to ensure a substantial flow of credit to SC/ST for self-employment at concessional interest rates through priority lending and other special banking schemes. In some cases, loans to SC and ST entrepreneurs are given interest-free[18] and waiving the loan all together is in the process[19]. Reserve Bank of India (RBI) updated its guidelines on credit facilities to Scheduled Castes and Scheduled Tribes in 2016 giving extra support to these communities in the formal banking sector[20]. However, schemes like these may have made the lower caste borrower riskier to lend to and less profitable. In this setting where lending is biased in favour of SC/ST, banks may resort to minimising the risk by giving less amount of loans to these communities, imposing an intended cost on them. Hence, these large credit differences may be echoing inherent conflict between allowing the banking system to be driven by market forces and expecting greater inclusion from the system.

In the absence of credit history or information regarding borrowers' creditworthiness, the unexplained gap is more likely to be due to statistical discrimination[21]. In such cases, banks may be holding lower caste loan applications to higher standards of creditworthiness than upper castes. For example, lower caste borrowers are more likely to come from poor areas with a higher risk of default leading a bank loan officer to grade their loan application strictly. When a substantial part of statistical discrimination is influenced by profit-maximising actors, market forces are less likely to eliminate it.

Our qualitative enquiries suggest that bank loan officers (largely belonging to general caste as observed by Fisman, Paravisini, and Rig, 2017) provide more assistance to higher caste borrowers in loan applications engaging in a subtle form of statistical discrimination, referred to as the "thick file" phenomenon. This means that the loan application file of a marginal higher caste borrower us more likely to be thicker with extra documents than those of a marginal lower caste borrower. The idea here is that upper caste loan officers may have

[18] Under Chief Minister Scheduled Caste and Scheduled Tribes Entrepreneur Scheme, Bihar government will provide interest free loans to eligible entrepreneurs from scheduled caste and scheduled tribes category.

[19] In the state of Karnataka, the state president has requested to the state government to waive education loans of the SC/ST students.

[20] Under new recommendations, banks are responsible for increasing awareness about new credit facilities among SC/ST borrowers and helping the borrowers in filling out forms and completing other formalities. Loan proposals from these communities are encouraged to be considered with utmost sympathy and understanding. To ensure these policies are followed, a special department has been set up for monitoring the flow of credit to SC/ST beneficiaries. Under the same guidelines, the Ministry of Rural Development, Government of India has launched Deendayal Antyodaya Yojana-National Rural Livelihood Mission (DAY-NRLM), which would seek to ensure adequate coverage of vulnerable sections of the society such that 50% of these beneficiaries are SC/ST. Under Differential Rate of Interest Scheme, banks will provide finance up to Rs 15,000 at a concessionary rate of interest of 4 percent per annum to the lower castes for engaging in productive and gainful activities.

[21] Bertrand and Mullainathan (2004) show that more information regarding minority applicants' skills does not always reduce discrimination in the labour market.

less cultural affinities with and less knowledge of lower caste applicants. They are more likely to be strict with lower caste applications, relying on the group characteristics rather than investing resources in gathering more information on the creditworthiness of lower caste borrowers. In such a situation, extra documentation providing mitigating information could positively affect the credit outcome of marginal upper caste applications. Although this phenomenon has some credibility, further investigation is needed to documents its relevance and occurrence.

Money lenders: Although the share of money lenders has reduced significantly over this time, they still play a major role in financing lower caste borrowers (see Table 13 in the Appendix). However, Figure 7 (based on Table 19 in the Appendix) shows that there are large credit differentials between the general caste and other lower castes, and a significant portion of the gap is unexplained. The credit differences have actually increased between 2005 and 2011-12. Since money lenders provide credit to people in regions where formal finance has not reached; or to borrowers who are not creditworthy for banks and MFIs, the increase in the credit differentials and unexplained component is worrying.

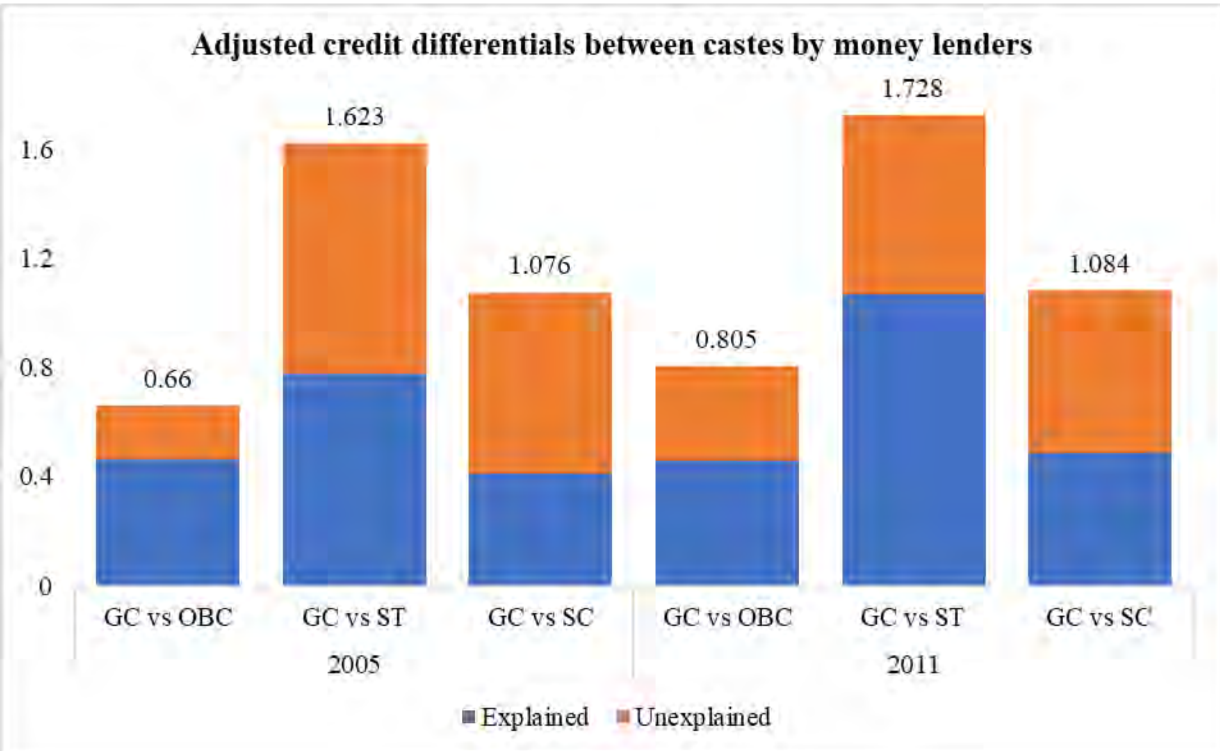

Figure 7: Adjusted credit differentials between castes in 2005 and 2011-12 in credit taken from money lenders

The qualitative interviews confirm the discriminatory attitude practised by informal money lenders towards lower castes.

One respondent said:

"… my local money lender always says that people from my caste cannot be trusted, even though I have never defaulted on a loan in my life. The conditions they set are always discriminatory. Upper caste lenders think that if they give loans to lower castes, we might become rich and less dependent on them."

One Dalit entrepreneur said:

"The bayaj (interest rate) varies depending on your caste. Dalits are also expected to offer collateral (security) far in excess of the loan amount, and far in excess of other castes".

These informal money lenders, generally belonging to upper castes, have historically been the main source of financial credit for lower castes. In this sector of the credit market, discrimination is frequently overt and extreme. The informal lender I interviewed didn't dispute the fact that they discriminate, and based their arguments on old-fashioned prejudice.

One money lender feared loss of face in dealing with lower castes:
"…….if a Dalit dared to default on my loan, people would laugh at me "

Another questioned the whole idea of Dalit entrepreneurs:
"…if they all have businesses, who will work in our fields or clean our toilets?"

In informal lending, money lenders can force repayments through *panchayats* (village councils usually consist of upper caste men whose verdicts are largely partial to the money lenders) or by keeping the collateral given as a security for the credit. Therefore, the approval rate of lower caste is higher than general caste in lending from money lenders. Logically, the credit differentials between general and other lower castes and the unexplained portion of these differentials should be lower since lower castes are less risky, however, this is not the case here. Moneylenders are sometimes the last resort of credit for poor and lower caste households. The qualitative enquiries suggest the informal lenders practice an extreme form of discrimination against lower caste and are reluctant to fund lower caste entrepreneurs. Hence, low risk of giving credit to lower caste reduces the credit differences, while discrimination practised by moneylenders increases it. The results suggest that the latter effect prevails.

The qualitative enquiries also suggest that taste-based discrimination is more likely to be present in lending from money lenders. In the case of better information regarding the borrower's creditworthiness, as usually in informal lending, the unexplained or discriminatory component in the total gap is more likely to be due to taste-based discrimination. Berkovec et al (1994) suggest that taste-based discrimination is likely to be higher when the lenders have higher market power.

Social networks such as friends and relatives: Credit in the informal sector is highly segmented, and is based around people of the same caste, religion and kinship (Gupta and Mitra 2002). Hence, poor and lower castes are significantly disadvantaged due to a lack of networks, income, land, and education in obtaining loans from friends and relatives. The proportion of those taking loans from friends and relatives have marginally changed over the years. Figure 8 (based on Table 20 in the Appendix) shows that the credit differentials in lending from social networks such as friends and family have decreased significantly between GC and other lower castes.

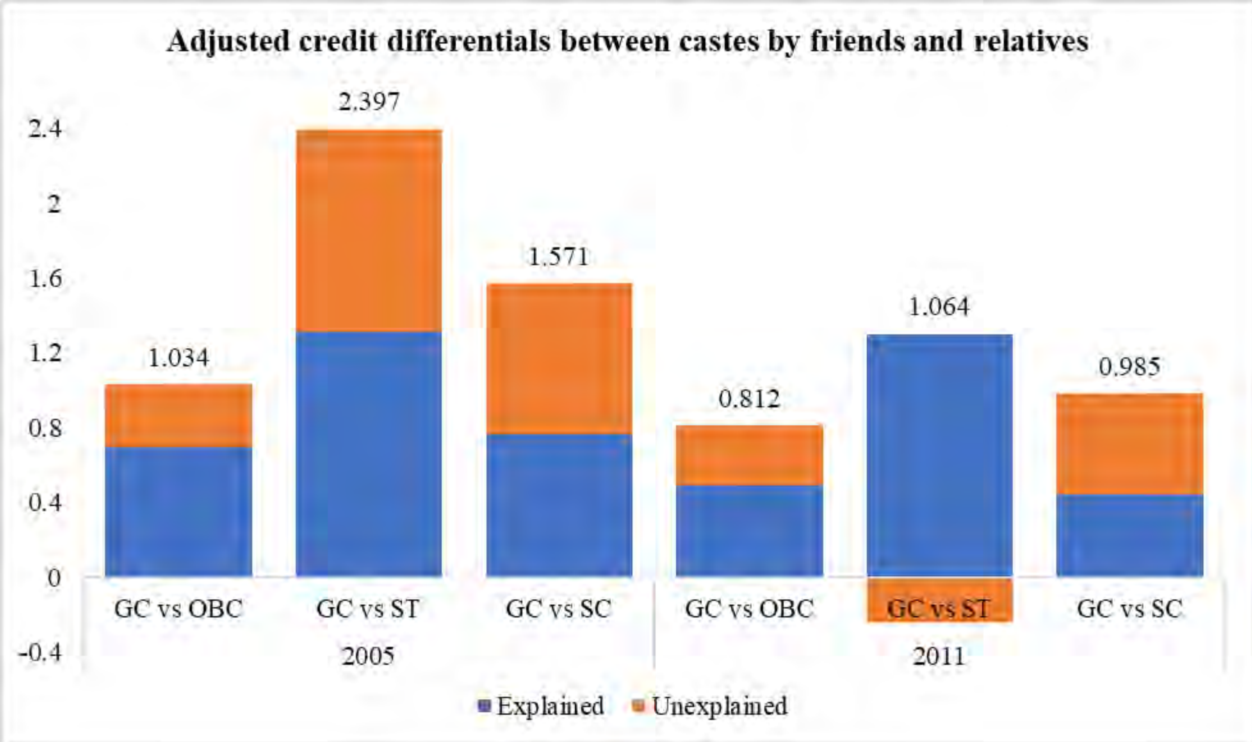

Figure 8: Adjusted credit differentials between castes by credit taken from friends and relatives

However, these changes in credit differentials above are not easy to explain without significant additional research. The individual results from each year are perhaps easier to interpret: if lower caste borrowers seek credit from lower caste friends, while general caste borrowers seek credit from general caste friends, then it is logical that there would be a wide differential in the availability and ease of credit – in this scenario, the general caste 'lenders' simply have more credit available to give. It is, though, difficult to explain why this differential has changed so dramatically over the time period unless the overall level of wealth within the pool of lower caste lenders has increased at a greater rate than that of their general caste equivalents – and there is little evidence to suggest that this is the case. This could also be due to the lower caste abandoning formal channels of finance because of the poor treatment and discouragement, thereby increasing their reliance on their own caste.

In terms of this study, however, the reasons for the change are not directly relevant. What is relevant is that this is the only category of lending in which both borrower and lender are likely to share the same caste, and it is also the only category which shows improvement in the credit differentials between the general caste and all three lower castes. Clearly, this represents a positive development, but it also indicates that caste-based discrimination may be a significant factor in driving the credit differentials in other types of lending. In other words, caste-based differences may be decreasing, but only if lower caste borrowers are borrowing from lower caste lenders.

g. Decomposing credit differences by residence:

Figure 9 (based on Tables 21 and 22 in the Appendix) presents the caste differences in the credit amount by place of residence – urban and rural areas. There are stark differences between credit differentials in rural and urban areas. Compared to 2005, the credit differences between GC and other lower castes have increased in the urban area and decreased in the rural area. The credit differences between GC and OBC and GC and ST are larger in the rural compared to the urban area in 2005 while the credit differences between GC and other lower castes are higher in urban area in 2011.

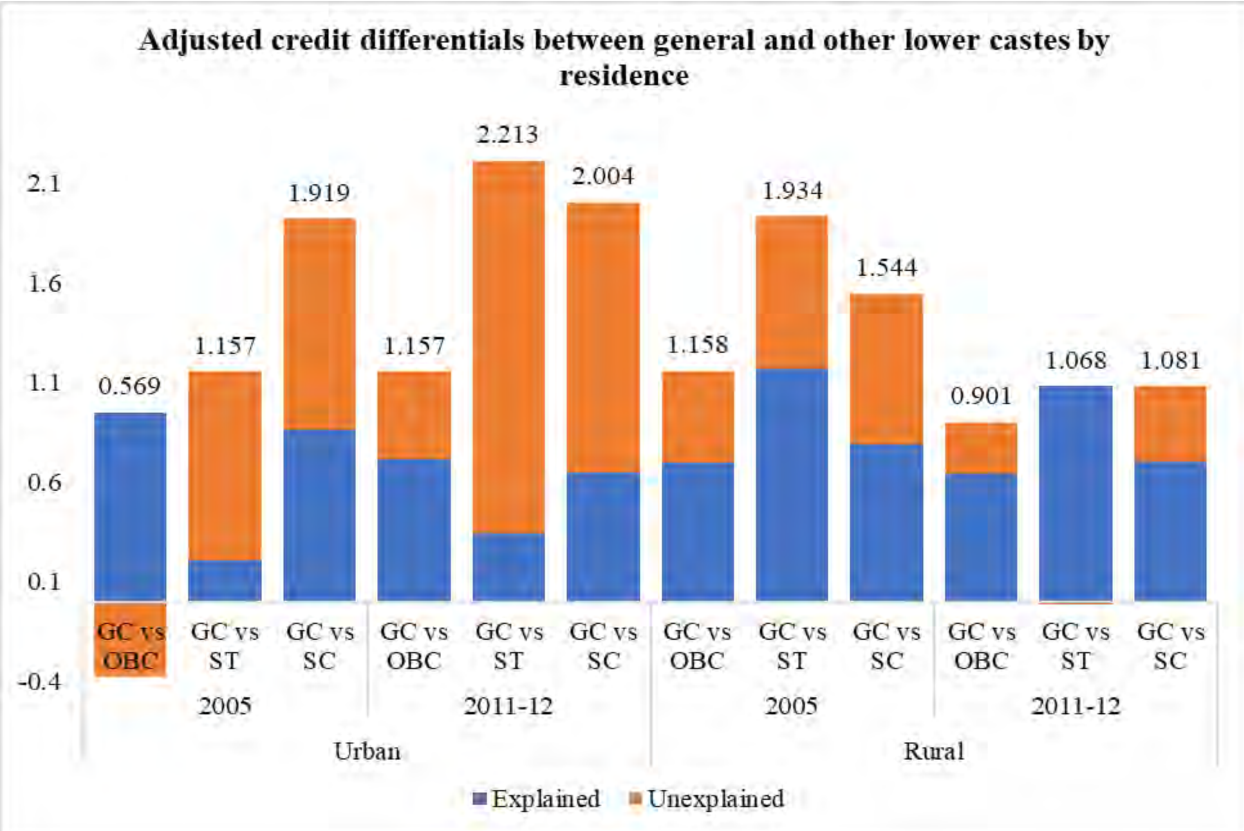

Figure 9: The figure compares credit inequalities between various caste in urban and rural areas in 2011-12 and 2005.

While caste may be losing its relevance in traditional custom in urban areas, caste differences and prejudices are being reinforced by high gaps in credit amount. The credit gap has increased over this time suggesting that situation of lower caste has actually worsened in urban areas. A greater proportion of the lower castes live in rural areas, and the credit differentials between upper castes and lower castes, although decreased over the years, are overwhelmingly high. Successive Indian governments have failed to improve the village banking infrastructure in India. Even though 70 percent of India's population lives in rural areas, they only have 37 percent of the total number of bank branches of the country (Reserve Bank of India, 2015). Thus, a significant proportion of rural households, especially lower castes, are still outside the formal fold of the banking system.

6. Discussion and conclusion

The study of discrimination in economics is motivated both by the moral case for equality and the consequent loss of efficiency in the market. Advances in research methods and designs have produced a significant interest in the field which has generated new insights into the nature of discrimination. Guryan and Charles (2013) argue that a deeper understanding of the sources and causes of discrimination is needed in order to formulate policies to reduce its incidence and effects; however, in order to do this, it is first necessary to identify the nature and scale of discrimination clearly. That is the focus of our study.

The empirical evidence in this paper suggests that caste is still a worryingly potent determinant of lending outcomes in India. There are substantial credit differences between the general caste and other lower castes and these differences have decreased over the years. A portion of the credit differences between general caste and other lower castes (specially SC) remains unexplained. Hence, it can be argued that the disparities between the loans granted to general castes and other lower castes in India are not only because lower castes possess less human and physical capital than general castes, but also because these groups may be facing extensive and persistent discrimination in the credit sector. I also find that the loan application and approval rates are higher for general caste in the formal sector whereas lower castes are generally more likely to participate and have a higher approval on their loans in informal sector. However, the differences in the amount of credit granted is still a cause of apprehension, and in some cases, the situation appears to be growing worse, not better.

Using a quantile regression-based decomposition method I analysed the caste gap across the entire credit distribution. I found the evidence of sticky floor effect in lending to OBC (for both time period), ST (in 2005) and SC (in 2011-12), whereas glass ceiling effect prevails in lending to SC (in 2005) and ST (in 2011-12). It's also important to note that there are large credit differentials between the general caste and lower castes in almost every instance in question: this includes rural and urban areas, credit taken from banks, money lenders and social network. In many instances, the credit differentials have actually increased over the time period considered in this research.

In attempting to explain the results, I recognise that the unexplained portion may include unmeasurable or unobservable characteristics, for instance, drive, determination or other attitudes which are likely to affect the credit outcomes and thus, it does not necessarily mean explicit discrimination against lower castes. It is worth noting that the analysis seeks to measure the effects of a social variable named 'caste' which is itself composed of a number of ill-defined and unquantifiable elements. For instance, lower castes may possess higher levels of unmeasured characteristics like perseverance and determination which improve their creditworthiness but display more traits such as humility and lowered expectations which limit their credit requests. Hence, the issue of the unexplained components including the effects of unobservable or unmeasurable characteristics is a standard limitation in the decomposition analysis.

Altogether, the evidence is consistent that lower caste individuals are disadvantaged in the credit sector. Recognising this, the Indian government has launched various programmes to improve the provision of financial services to the lower castes. However, the government can only play a direct role in the formal sector. Since banks and other government programmes have become the major source of finance for borrowers in India, a broader intervention from the government is much needed. Furthermore, the differences in credit amount sanctioned and loan approval rates between the general caste and other lower castes in lending from banks are high. Schemes to promote the economic empowerment of lower castes through finance have been implemented on a large scale since the 1990s, but if we take anything from the results in this research, they have not been very effective.

A large endowments difference between social groups indicates that there is a need to promote educational and training opportunities for the lower castes. The government should also ensure that the disadvantaged sections of society get full participation in schooling, employment, health programmes to reduce pre-market discrimination. Policy-makers need to adopt a broader range of strategies to tackle the deep-seated and multi-faceted challenge of systemic discrimination. Initiatives need to include the improvement of financial literacy across lower castes, encouragement of positive discrimination, improving the functioning and competitiveness of the financial sector, active monitoring of caste bias, and more focused social research into the causes and nature of caste discrimination.

7. References

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8. Appendix: Tables

Table 6: Primary income generating occupational activities of various caste by percentage

	2011-12				**2005**			
Occupational activities	GC	OBC	ST	SC	GC	OBC	ST	SC
Cultivation	25.89	26.52	36.48	13.63	23.24	26.97	35	12.84
Allied agriculture	0.77	1.27	0.85	0.63	1.02	0.98	0.44	0.76
Agricultural wage labour	4.06	8.99	15.48	18.08	5.76	12.61	22	24.76
Non-agricultural wage labour	12.51	23.38	22.87	33.82	10.81	17.7	17	28.45
Artisan/Independent	1.58	1.91	0.8	1.35	5.26	8.01	2	4.9
Petty shop/Small business	13.72	12.87	4.39	6.87	5.68	5.03	2.44	2.54
Organized Trade/Business	2.4	1.32	0.41	0.4	9.02	5.58	2.06	2.92
Salaried employment	26.67	15.81	14.69	18.45	28.56	16.25	15	17.38
Other Professions	1.04	0.45	0.22	0.39	1.41	0.98	0.44	0.64
Pension/Rent/Dividend	8.23	4.28	2.72	3.7	6.05	3.25	2.27	2.51
Others	3.14	3.2	1.1	2.67	3.19	2.63	1.37	2.32

Table 7: Purpose of the loan in 2011-2012 and 2005

Purpose	**GC**	**OBC**	**ST**	**SC**	**Purpose**	**GC**	**OBC**	**ST**	**SC**
	2011-12					2005			
House	15.56	14.24	12.96	16.46	House	19	15.21	14.16	14.16
Land*	1.97	1.53	1.45	1.05	Land*	1.21	0.94	0.52	0.52
Marriage	13.92	17.07	18.68	19.76	Marriage	13.05	15.58	12.78	12.78
Agriculture*	18.38	18.21	23.14	9.8	Agri/business*	35.13	32.88	33.33	33.33
Business*	10.25	7.77	4.47	5.35	Consumption	8.38	12.29	18.05	18.05
Consumption	13.16	13.8	16.6	15.65	Car/appliance	2.76	1.1	0.78	0.78
Car/Jeep	3.34	1.22	1.01	0.95	Education*	2.88	2.44	1.81	1.81
Two-wheeler	1.23	1.02	0.44	0.97	Medical	10.89	13.83	12.09	12.09
Truck/Bus*	0.56	0.3	0.38	0.1	Other	6.69	5.73	6.48	6.48
Educational*	5.61	4.91	3.77	4.69					
Medical Exp	12.21	15.71	13.77	19.76					

Others	3.82	4.22	3.33	5.45

* Loans for productive purposes

Table 8: Source of the loan in 2011-12 and 2005

Source	GC	OBC	ST	SC	GC	OBC	ST	SC
	2011-12				2005			
Employer	2.36	2.06	2.45	3.64	2.00	1.65	1.81	1.91
Money Lender	10.22	20.19	20.57	24.81	19.47	33.58	32.9	42.17
Friend	10.91	10.3	11.19	11.71	8.86	9.13	13.21	10.32
Relative	19.85	21.45	23.77	21.23	18.39	19.19	19.78	17.41
Bank*	43.81	32.31	26.42	22.9	37.36	26.28	21.07	19.62
NGO*	0.91	0.78	1.45	1.39	0.13	0.17	0.26	0.14
Credit Group*	3.28	2.29	2.39	3.12	2.61	2.06	3.97	1.83
Govt. Program*	1.02	0.48	0.38	0.64	1.44	0.8	1.64	1.12
Self-help group*	3.45	6.04	6.92	7.83	9.76	7.15	5.35	5.49
Kisan Credit*	2.06	2.53	2.58	0.85				
Prov Funds*	0.3	0.19	0.13	0.02				
Suppliers*	0.26	0.22	0.31	0.4				
Others	1.58	1.16	1.45	1.47				

* Loan from formal sources.

Table 9: Application for loans from various sources

		All	GC	OBC	SC	ST
Banks	Didn't apply	75	75	72	81	82
	Rejected	3	3	3	3	4
	Approved	22	22	25	16	15
Money Lenders	Didn't apply	81.5	89	77.5	78	84
	Rejected	3.5	3.5	4	3	3
	Approved	15	8	18.5	19	13
Relative and friends	Didn't apply	70.5	76.5	66.5	70	71.5
	Rejected	3.5	3.5	4	3.5	4
	Approved	26	20	29.5	26.5	24.5

Note: Numbers in percentages

Table 10: The marginal effect of participation in the credit market by various castes in 2005.

	(1)	(2)	(3)	(4)
VARIABLES	GC	OBC	ST	SC

CONSUMPTION	0.105***	0.142***	0.170***	0.155***
	(0.008)	(0.008)	(0.018)	(0.011)
AGE	0.005***	0.007***	0.006	0.001
	(0.002)	(0.002)	(0.004)	(0.003)
AGESQ	-0.000***	-0.000***	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
EDUCATION	-0.007***	-0.008***	-0.008***	-0.007***
	(0.001)	(0.001)	(0.003)	(0.002)
LAND	0.065***	0.080***	0.070***	0.104***
	(0.014)	(0.013)	(0.025)	(0.016)
SEX	-0.054***	-0.060***	0.010	-0.042**
	(0.015)	(0.015)	(0.032)	(0.020)
URBAN RURAL	-0.076***	-0.083***	-0.122***	-0.035**
	(0.013)	(0.012)	(0.034)	(0.017)
HOUSE QUALITY	-0.037***	-0.044***	0.053**	-0.009
	(0.012)	(0.011)	(0.026)	(0.015)
STATE DUMMIES	YES	YES	YES	YES
OCCUPATIONAL DUMMIES	YES	YES	YES	YES
Observations	13,332	16,213	3,270	8,304

Delta standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is 1 if the client has taken a loan or 0 otherwise. All predictors at their mean value. The independent variables are: log of consumption, age, sex of the head of the household, size of the household, number of education years completed by the head, log of amount of land, dummy whether the household has a ration card, dummy for quality of the house (good/bad), dummy whether household is in urban area, and various dummies for occupation and the state where the household is located.

Table 11: The marginal effect of participation in the credit market by various castes in 2011-12

	(1)	(2)	(3)	(4)
VARIABLES	GC	OBC	ST	SC
CONSUMPTION	0.119***	0.132***	0.113***	0.141***
	(0.009)	(0.007)	(0.018)	(0.010)
AGE	0.009***	0.013***	0.021***	0.013***
	(0.002)	(0.002)	(0.005)	(0.003)
AGESQ	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)

EDUCATION	-0.009***	-0.009***	0.004	-0.007***
	(0.001)	(0.001)	(0.003)	(0.001)
LAND	0.078***	0.078***	0.092***	0.062***
	(0.015)	(0.012)	(0.025)	(0.016)
SEX	-0.048***	-0.057***	-0.109***	-0.033*
	(0.015)	(0.012)	(0.029)	(0.017)
URBAN RURAL	-0.083***	-0.093***	-0.024	-0.058***
	(0.015)	(0.011)	(0.035)	(0.016)
HOUSE QUALITY	-0.034**	-0.031***	0.003	-0.035**
	(0.014)	(0.011)	(0.026)	(0.014)
STATE DUMMIES	YES	YES	YES	YES
OCCUPATIONAL DUMMIES	YES	YES	YES	YES
Observations	11,680	16,763	3,590	8,807

Delta standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Same as Table 3

Table 12: Probit model for 2005

VARIABLES	(1) GC	(2) OBC	(3) ST	(4) SC
CONSUMPTION	0.304***	0.358***	0.482***	0.397***
	(0.022)	(0.019)	(0.050)	(0.029)
AGE	0.016***	0.018***	0.017	0.002
	(0.006)	(0.005)	(0.012)	(0.007)
AGE SQ	-0.000***	-0.000***	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
EDUCATION	-0.021***	-0.021***	-0.023***	-0.017***
	(0.003)	(0.003)	(0.008)	(0.004)
LAND OWN	0.187***	0.201***	0.200***	0.266***
	(0.040)	(0.032)	(0.071)	(0.042)
SEX HEAD	-0.156***	-0.151***	0.027	-0.108**
	(0.044)	(0.038)	(0.092)	(0.052)
URBAN	-0.218***	-0.209***	-0.348***	-0.091**
	(0.037)	(0.030)	(0.096)	(0.043)
HOUSE QUALITY	-0.107***	-0.112***	0.151**	-0.023
	(0.034)	(0.028)	(0.073)	(0.038)
STATE DUMMIES	YES	YES	YES	YES
OCCUPATIONAL DUMMIES	YES	YES	YES	YES
Constant	-3.673***	-3.047***	-4.932***	-3.314***
	(0.517)	(0.276)	(0.629)	(0.501)

Observations	13,332	16,213	3,270	8,304

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is 1 if the client has taken a loan or 0 otherwise. The independent variables are: log of consumption, age, sex of the head of the household, size of the household, number of education years completed by the head, log of amount of land, dummy whether the household has a ration card, dummy for quality of the house (good/bad), dummy whether household is in urban area, and various dummies for occupation and the state where the household is located.

Table 13: Probit Model for 2011-12

VARIABLES	(1) GC	(2) OBC	(3) ST	(4) SC
CONSUMPTION	0.301***	0.345***	0.290***	0.360***
	(0.022)	(0.018)	(0.046)	(0.027)
AGE	0.024***	0.034***	0.053***	0.032***
	(0.006)	(0.005)	(0.012)	(0.007)
AGE SQ	-0.000***	-0.000***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
EDUCATION	-0.022***	-0.023***	0.010	-0.017***
	(0.003)	(0.003)	(0.007)	(0.004)
LAND OWN	0.198***	0.203***	0.235***	0.157***
	(0.038)	(0.030)	(0.064)	(0.040)
SEX HEAD	-0.122***	-0.148***	-0.279***	-0.084*
	(0.039)	(0.033)	(0.074)	(0.043)
URBAN	-0.208***	-0.242***	-0.062	-0.147***
	(0.037)	(0.029)	(0.090)	(0.040)
HOUSE QUALITY	-0.087**	-0.080***	0.007	-0.090**
	(0.036)	(0.028)	(0.066)	(0.035)
STATE DUMMIES	YES	YES	YES	YES
OCCUPATIONAL DUMMIES	YES	YES	YES	YES
Constant	-3.872***	-3.393***	-3.306***	-4.127***
	(0.862)	(0.267)	(0.605)	(0.503)
Observations	11,680	16,763	3,590	8,807

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Same as Table 15.

Table 14: Selection corrected loan amount equation estimates for 2005

VARIABLES	(1) GC	(2) OBC	(3) ST	(4) SC

CONSUMPTION	0.684***	0.848***	1.257***	0.318*
	(0.152)	(0.129)	(0.331)	(0.177)
AGE	-0.022**	-0.038***	-0.014	0.026**
	(0.009)	(0.007)	(0.018)	(0.011)
AGESQ	0.000***	0.000***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
EDUCATION	0.047***	0.041***	0.026**	0.037***
	(0.006)	(0.004)	(0.011)	(0.006)
LAND UNIT	-0.084***	-0.063***	-0.082*	-0.031
	(0.022)	(0.017)	(0.042)	(0.024)
SEX	0.322***	0.486***	0.277**	0.183***
	(0.067)	(0.050)	(0.138)	(0.071)
URBAN	0.454***	0.291***	0.056	0.338***
	(0.060)	(0.047)	(0.189)	(0.057)
HOUSE QUALITY	0.198***	0.188***	-0.042	0.176***
	(0.058)	(0.042)	(0.116)	(0.058)
MILLS	-2.589***	-2.414***	-1.837***	-2.095***
	(0.136)	(0.101)	(0.206)	(0.125)
Constant	6.948***	2.913*	-5.794	9.958***
	(1.687)	(1.491)	(3.792)	(1.949)
LOAN PURPOSE	YES	YES	YES	YES
LOAN SOURCE	YES	YES	YES	YES
OCCUPATIONAL DUMMIES	YES	YES	YES	YES
STATE DUMMIES	YES	YES	YES	YES
Observations	4,444	7,633	1,156	3,661
R-squared	0.511	0.460	0.628	0.496
Cragg-Donald Wald F statistic)	164.83	261.90	48.76	114.99

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of amount of loan. The independent variables are age, age square, number of education years completed, unit of land owned, predicted values of the first stage regression replacing the original value of log of consumption, and various dummies for loan source, its purpose and the state where the household is located.

Table 15: Selection corrected loan amount equation estimates for 2011-12

VARIABLES	(1) GC	(2) OBC	(3) ST	(4) SC
CONSUMPTION	0.809***	0.484***	-0.225	0.528***
	(0.160)	(0.102)	(0.500)	(0.148)
AGE	-0.047***	-0.049***	-0.074***	-0.044***
	(0.008)	(0.007)	(0.025)	(0.009)
AGESQ	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
EDUCATION	0.050***	0.044***	0.013	0.028***
	(0.005)	(0.003)	(0.013)	(0.005)
LAND UNIT	-0.085***	-0.034***	-0.059**	-0.055***
	(0.017)	(0.011)	(0.026)	(0.017)
SEX	0.381***	0.372***	0.453***	0.295***
	(0.053)	(0.038)	(0.120)	(0.056)
URBAN	0.483***	0.468***	0.519***	0.223***
	(0.055)	(0.036)	(0.157)	(0.052)
HOUSE QUALITY	0.206***	0.267***	0.342***	0.257***
	(0.053)	(0.037)	(0.115)	(0.043)
MILLS	-3.273***	-3.121***	-3.050***	-3.012***
	(0.140)	(0.103)	(0.287)	(0.134)
Constant	3.688**	8.339***	17.829***	7.108***
	(1.870)	(1.319)	(5.562)	(1.634)
LOAN SOURCE DUMMIES	YES	YES	YES	YES
LOAN PURPOSE DUMMIES	YES	YES	YES	YES
OCCUPATIONAL DUMMIES	YES	YES	YES	YES
STATE DUMMIES	YES	YES	YES	YES
Observations	5,316	10,012	1,571	4,952
R-squared	0.447	0.47	0.630	0.473

	158.20	333.48	167.50	166.17

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Same as Table 6

Table 16: Decomposition of the log of credit amount differential for a selection corrected equation in 2005 and 2011-12

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	GC VS OBC	GC VS ST	GC VS SC	GC vs OBC	GC vs ST	GC vs SC
	2005			2011-12		
CONSUMPTION	0.249***	0.592***	0.353***	0.190***	0.554***	0.292***
	(0.027)	(0.077)	(0.047)	(0.019)	(0.070)	(0.036)
AGE	-0.038***	-0.037	0.002	-0.091***	-0.119***	-0.117***
	(0.010)	(0.025)	(0.022)	(0.014)	(0.027)	(0.024)
AGE SQ	0.048***	0.074***	0.029	0.112***	0.140***	0.154***
	(0.012)	(0.026)	(0.021)	(0.016)	(0.028)	(0.024)
EDUCATION	0.081***	0.162***	0.109***	0.074***	0.104***	0.103***
	(0.007)	(0.019)	(0.012)	(0.006)	(0.015)	(0.010)
LAND UNIT	-0.008***	0.004	-0.023***	-0.007***	0.003	-0.034***
	(0.002)	(0.003)	(0.007)	(0.002)	(0.003)	(0.007)
URBANRURAL	0.027***	0.094***	0.037***	0.025***	0.073***	0.027***
	(0.004)	(0.014)	(0.006)	(0.004)	(0.011)	(0.004)
SEX	-0.001	0.001	-0.002	0.001	0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
HOUSE QUALITY	0.022***	0.059***	0.028***	0.017***	0.060***	0.040***
	(0.004)	(0.018)	(0.009)	(0.003)	(0.016)	(0.006)
PURPOSE OF LOAN	0.028***	0.050***	0.041***	0.015***	0.024***	-0.003
	(0.005)	(0.009)	(0.008)	(0.005)	(0.009)	(0.007)
SOURCE OF LOAN	0.061***	0.113***	0.102***	0.051***	0.115***	0.143***
	(0.007)	(0.013)	(0.011)	(0.007)	(0.014)	(0.010)
OCCUPATION	0.065***	0.116***	0.079***	0.063***	0.050***	0.067***
	(0.007)	(0.016)	(0.014)	(0.006)	(0.014)	(0.012)
STATES	0.342***	0.178***	0.194***	0.275***	0.233***	0.113***
	(0.023)	(0.035)	(0.019)	(0.017)	(0.030)	(0.015)
Observations	12,077	5,600	8,105	15349	6897	10,283

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table decomposes the explained component from the equation 3 to identify the contribution of each specific characteristic in generating credit differences.

Table 17: Decomposition of loan application and loan approval rates.

VARIABLES	(1) GC vs OBC	(2) GC vs ST	(3) GC vs SC	(4) GC vs OBC	(5) GC vs ST	(6) GC vs SC
	Loan application rate			Loan approval rate		
Panel A: Banks						
GC	0.257***	0.257***	0.257***	0.963***	0.963***	0.963***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Others	0.274***	0.187***	0.192***	0.937***	0.909***	0.898***
	(0.003)	(0.007)	(0.004)	(0.004)	(0.012)	(0.008)
Difference	-0.017***	0.070***	0.065***	0.026***	0.054***	0.065***
	(0.005)	(0.008)	(0.006)	(0.005)	(0.012)	(0.008)
Explained	-0.015***	0.044***	0.069***	0.020***	0.030***	0.050***
	(0.004)	(0.007)	(0.004)	(0.003)	(0.008)	(0.006)
Unexplained	-0.002	0.026**	-0.003	0.006	0.024*	0.015
	(0.006)	(0.010)	(0.007)	(0.005)	(0.013)	(0.009)
Observations	27,988	15,050	20,240	7,256	3,431	4,421
Panel B: Money Lenders						
GC	0.112***	0.112***	0.112***	0.806***	0.806***	0.806***
	(0.003)	(0.003)	(0.003)	(0.012)	(0.012)	(0.012)
Others	0.223***	0.164***	0.221***	0.878***	0.894***	0.900***
	(0.003)	(0.006)	(0.004)	(0.006)	(0.013)	(0.007)
Difference	-0.111***	-0.052***	-0.109***	-0.072***	-0.088***	-0.095***
	(0.004)	(0.007)	(0.005)	(0.013)	(0.018)	(0.014)
Explained	-0.088***	-0.036***	-0.063***	-0.048***	-0.107***	-0.066***
	(0.003)	(0.005)	(0.004)	(0.008)	(0.016)	(0.010)
Unexplained	-0.023***	-0.016*	-0.047***	-0.024*	0.019	-0.029*
	(0.005)	(0.009)	(0.006)	(0.013)	(0.020)	(0.015)
Observations	27,988	15,050	20,240	4,655	1,670	2,991
Panel B: Social Networks						
GC	0.233***	0.233***	0.233***	0.926***	0.926***	0.926***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Others	0.336***	0.287***	0.302***	0.922***	0.940***	0.925***
	(0.004)	(0.008)	(0.005)	(0.004)	(0.008)	(0.005)
Difference	-0.102***	-0.053***	-0.068***	0.004	-0.014	0.001
	(0.005)	(0.009)	(0.006)	(0.006)	(0.009)	(0.007)
Explained	-0.073***	-0.061***	-0.056***	0.002	-0.022***	-0.014***
	(0.003)	(0.007)	(0.004)	(0.004)	(0.008)	(0.005)
Unexplained	-0.029***	0.008	-0.012*	0.002	0.008	0.015**
	(0.006)	(0.011)	(0.007)	(0.007)	(0.011)	(0.007)
Observations	27,988	15,050	20,240	7,883	3,457	5,070

Robust standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. The dependent variable is 1 if applied for a loan at a bank, from money lender or in social network, 0 otherwise (Columns 1-3). The independent variable is 1 if approved by bank, money lender or in social network (Columns 4-6). The dependent variables are same as used in selection model.

Table 18: Adjusted differences between castes by banks

	2005			2011		
VARIABLES	GC vs OBC	GC vs ST	GC vs SC	GC vs OBC	GC vs ST	GC vs SC
GC	12.918***	12.918***	12.918***	13.674***	13.674***	13.674***
	(0.205)	(0.205)	(0.205)	(0.160)	(0.160)	(0.160)
Others	12.097***	11.328***	11.344***	12.686***	12.481***	12.177***
	(0.133)	(0.341)	(0.219)	(0.096)	(0.424)	(0.165)
Difference	0.820***	1.590***	1.574***	0.988***	1.193***	1.497***
	(0.244)	(0.398)	(0.300)	(0.187)	(0.453)	(0.230)
Explained	0.794***	1.401***	0.802***	0.710***	0.960***	0.702***
	(0.050)	(0.119)	(0.062)	(0.038)	(0.084)	(0.048)
Unexplained	0.027	0.189	0.772***	0.278	0.232	0.795***
	(0.239)	(0.391)	(0.296)	(0.183)	(0.449)	(0.228)
Observations	3,664	1,900	2,377	5,541	2,743	3,460

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table shows the decomposition results corrected for selection and endogeneity for sample of borrowers from banks.

Table 19: Credit differences between castes by money lenders

	2005			2011		
VARIABLES	GC vs OBC	GC vs ST	GC vs SC	GC vs OBC	GC vs ST	GC vs SC
GC	11.553***	11.553***	11.553***	12.752***	12.752***	12.752***
	(0.254)	(0.254)	(0.254)	(0.317)	(0.317)	(0.317)
Others	10.893***	9.930***	10.478***	11.947***	11.024***	11.667***
	(0.126)	(0.303)	(0.140)	(0.128)	(0.373)	(0.166)
Difference	0.660**	1.623***	1.076***	0.805**	1.728***	1.084***
	(0.284)	(0.395)	(0.290)	(0.342)	(0.490)	(0.358)
Explained	0.465***	0.778***	0.413***	0.457***	1.068***	0.487***
	(0.052)	(0.083)	(0.050)	(0.058)	(0.106)	(0.062)
Unexplained	0.195	0.845**	0.663**	0.348	0.659	0.597*
	(0.282)	(0.394)	(0.287)	(0.340)	(0.487)	(0.354)
Observations	3,430	1,246	2,409	2,579	871	1,775

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table shows the decomposition results corrected for selection and endogeneity for sample of borrowers from money lenders.

Table 20: Credit differences in social networks

	2005			2011		
VARIABLES	GC vs OBC	GC vs ST	GC vs SC	GC vs OBC	GC vs ST	GC vs SC
GC	11.933***	11.933***	11.933***	12.699***	12.699***	12.699***
	(0.236)	(0.236)	(0.236)	(0.207)	(0.207)	(0.207)
Others	10.899***	9.536***	10.362***	11.886***	11.635***	11.714***
	(0.148)	(0.274)	(0.175)	(0.115)	(0.348)	(0.157)
Difference	1.034***	2.397***	1.571***	0.812***	1.064***	0.985***
	(0.279)	(0.362)	(0.294)	(0.237)	(0.405)	(0.260)
Explained	0.696***	1.312***	0.766***	0.489***	1.302***	0.443***
	(0.050)	(0.101)	(0.054)	(0.043)	(0.085)	(0.043)
Unexplained	0.338	1.085***	0.805***	0.323	-0.238	0.542**
	(0.277)	(0.360)	(0.292)	(0.235)	(0.403)	(0.258)
Observations	3,374	1,594	2,228	4,836	2,186	3,272

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table shows the decomposition results corrected for selection and endogeneity for sample of borrowers from social networks.

Table 21: Adjusted credit differential between castes in urban areas.

	2005			2011		
VARIABLES	GC vs OBC	GC vs ST	GC vs SC	GC vs OBC	GC vs ST	GC vs SC
GC	13.225***	13.225***	13.225***	14.493***	14.493***	14.493***
	(0.250)	(0.250)	(0.250)	(0.230)	(0.230)	(0.230)
Others	12.656***	12.068***	11.306***	13.336***	12.280***	12.490***
	(0.187)	(0.651)	(0.205)	(0.156)	(0.596)	(0.166)
Difference	0.569*	1.157*	1.919***	1.157***	2.213***	2.004***
	(0.313)	(0.698)	(0.323)	(0.277)	(0.639)	(0.283)
Explained	0.949***	0.204	0.861***	0.712***	0.338**	0.646***
	(0.061)	(0.179)	(0.063)	(0.054)	(0.136)	(0.052)
Unexplained	-0.380	0.953	1.059***	0.445	1.875***	1.358***
	(0.306)	(0.680)	(0.315)	(0.274)	(0.626)	(0.277)
Observations	3,815	1,754	2,534	4,877	2,082	3,213

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table shows the decomposition results corrected for selection and endogeneity for sample of borrowers from urban area only.

Table 22: Adjusted credit differential between castes in rural areas.

	2005			2011		
VARIABLES	GC vs OBC	GC vs ST	GC vs SC	GC vs OBC	GC vs ST	GC vs SC
GC	11.970***	11.970***	11.970***	12.549***	12.549***	12.549***
	(0.136)	(0.136)	(0.136)	(0.117)	(0.117)	(0.117)
Others	10.812***	10.036***	10.426***	11.647***	11.481***	11.468***
	(0.076)	(0.192)	(0.105)	(0.058)	(0.191)	(0.093)
Difference	1.158***	1.934***	1.544***	0.901***	1.068***	1.081***
	(0.156)	(0.235)	(0.172)	(0.131)	(0.224)	(0.149)
Explained	0.697***	1.170***	0.787***	0.639***	1.083***	0.701***
	(0.033)	(0.062)	(0.039)	(0.028)	(0.054)	(0.034)
Unexplained	0.461***	0.765***	0.757***	0.262**	-0.015	0.380**
	(0.153)	(0.234)	(0.170)	(0.129)	(0.225)	(0.150)
Observations	8,262	3,845	5,571	10,472	4,805	7,068

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table shows the decomposition results corrected for selection and endogeneity for sample of rural area only.

Table 23: Quantile decomposition of log of loan amount for 2011-12

VARIABLE	GC VS OBC					GC VS ST					GC VS SC				
Percentiles	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
GC	11.467***	12.471***	12.961***	14.552***	15.385***	11.467***	12.471***	12.961***	14.552***	15.385***	11.467***	12.471***	12.961***	14.552***	15.385***
	(0.019)	(0.021)	(0.018)	(0.023)	(0.021)	(0.213)	(0.173)	(0.135)	(0.205)	(0.236)	(0.213)	(0.173)	(0.135)	(0.205)	(0.236)
Others	9.794***	10.995***	12.119***	13.285***	14.642***	9.762***	11.711***	11.847***	12.220***	13.455***	9.824***	10.430***	11.589***	12.649***	14.001***
	(0.007)	(0.011)	(0.012)	(0.014)	(0.016)	(0.428)	(0.342)	(0.267)	(0.320)	(0.425)	(0.111)	(0.089)	(0.101)	(0.118)	(0.198)
Difference	1.673***	1.476***	0.842***	1.267***	0.743***	1.704***	0.760**	1.114***	2.332***	1.930***	1.643***	2.041***	1.373***	1.904***	1.384***
	(0.020)	(0.024)	(0.021)	(0.027)	(0.027)	(0.478)	(0.383)	(0.299)	(0.380)	(0.486)	(0.240)	(0.195)	(0.168)	(0.236)	(0.308)
Explained	0.384***	0.581***	0.659***	0.937***	0.997***	0.925***	1.109***	1.193***	1.532***	1.369***	0.547***	0.679***	0.698***	0.891***	1.003***
	(0.016)	(0.021)	(0.020)	(0.026)	(0.026)	(0.081)	(0.070)	(0.056)	(0.074)	(0.096)	(0.037)	(0.034)	(0.031)	(0.039)	(0.049)
Unexplained	1.289***	0.895***	0.183***	0.330***	-0.255***	0.779	-0.350	-0.079	0.801**	0.561	1.096***	1.361***	0.674***	1.012***	0.381
	(0.007)	(0.005)	(0.004)	(0.005)	(0.006)	(0.484)	(0.385)	(0.299)	(0.379)	(0.492)	(0.237)	(0.194)	(0.168)	(0.232)	(0.307)
Observation	15,361	15,361	15,361	15,361	15,361	6,904	6,904	6,904	6,904	6,904	10,295	10,295	10,295	10,295	10,295

Robust standard errors in parentheses. p<0.01, ** p<0.05, * p<0.1. The table shows the result from quantile regression decompositions of log of loan amount obtained at 10%, 25%, 50%, 75%, and 90%

Table 24: Quantile decomposition of log of loan amount for 2005

VARIABLE	GC VS OBC					GC VS ST					GC VS SC				
Percentiles	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
GC	10.264***	10.93***	12.086***	13.425***	14.628***	10.264***	10.92***	12.086***	13.425***	14.628***	10.264***	10.93***	12.086***	13.425***	14.62***
	(0.019)	(0.017)	(0.020)	(0.024)	(0.029)	(0.202)	(0.135)	(0.150)	(0.188)	(0.355)	(0.202)	(0.135)	(0.150)	(0.188)	(0.355)
Others	9.318***	9.682***	11.607***	12.730***	13.752***	7.891***	9.162***	10.157***	11.502***	13.254***	8.884***	9.681***	10.487***	11.559***	12.720***
	(0.015)	(0.009)	(0.017)	(0.017)	(0.019)	(0.367)	(0.276)	(0.212)	(0.340)	(0.450)	(0.154)	(0.121)	(0.109)	(0.135)	(0.206)
Difference	0.947***	1.250***	0.478***	0.695***	0.875***	2.374***	1.770***	1.929***	1.923***	1.374**	1.381***	1.251***	1.599***	1.866***	1.907***
	(0.024)	(0.019)	(0.026)	(0.029)	(0.035)	(0.419)	(0.307)	(0.259)	(0.389)	(0.573)	(0.254)	(0.182)	(0.185)	(0.231)	(0.410)
Explained	0.698***	0.512***	0.920***	1.032***	1.226***	1.211***	1.146***	1.262***	1.589***	1.774***	0.724***	0.680***	0.813***	0.957***	1.162***
	(0.023)	(0.016)	(0.027)	(0.029)	(0.033)	(0.091)	(0.065)	(0.059)	(0.077)	(0.124)	(0.041)	(0.032)	(0.032)	(0.039)	(0.060)
Unexplained	0.249***	0.739***	-0.442***	-0.337***	-0.351***	1.162***	0.623**	0.666**	0.334	-0.401	0.657***	0.571***	0.786***	0.909***	0.745*
	(0.005)	(0.005)	(0.004)	(0.004)	(0.007)	(0.422)	(0.308)	(0.259)	(0.393)	(0.582)	(0.254)	(0.182)	(0.184)	(0.229)	(0.404)
Observation	12,081	12,081	12,081	12,081	12,081	5,602	5,602	5,602	5,602	5,602	8,108	8,108	8,108	8,108	8,108

Robust standard errors in parentheses. p<0.01, ** p<0.05, * p<0.1. The table shows the result from quantile regression decompositions of log of loan amount obtained at 10%, 25%, 50%, 75%, and 90%.