Social Proximity and Loan Outcomes: Evidence from an Indian Bank*

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Abstract

We present evidence that social proximity between lenders and borrowers improves loan outcomes. We identify in-group preferential treatment using dyadic data on the religion and caste of bank officers and borrowers from a bank in India, and a rotation policy that induces quasi-random matching between officers and borrowers. Social proximity increases the intensive and extensive margins of lending, and reduces the collateral rate. Ex post, social proximity increases repayment performance, even after the in-group officer is replaced by an out-group one. The results suggest that the information benefits of social proximity may outweigh the misallocation costs of taste-based discrimination.

1 Introduction

In this paper, we analyze the effect of a shared social, cultural, or religious background on the propensity of individuals to discriminate against, or bestow preferential treatment on, one another. In theory, social proximity may improve or hinder the efficiency of transactions. On the one hand, if members of a social or religious group tend to do business with one another for preference-based reasons, social proximity will lead to favoritism and result in the misallocation of resources. Alternatively, if social proximity reduces the costs of gathering or communicating information, or helps to enforce contracts ex post, a shared background can improve efficiency.

Empirically, there are a number of challenges in measuring the extent of preferential in-group treatment, and distinguishing among the various explanations underlying such behavior. First, it requires information on the group membership of both transacting parties. Most studies have relied exclusively on the religion or race of only one side of the market, and have thus been best set up to detect discrimination against minorities rather than dyadic preferences for one's own type.[1] This may bias results against finding any beneficial effect of discrimination, since it is possible that the advantages of in-group interactions operate more effectively within relatively small minority groups. Second, even when dyadic data are available, matching between parties may be driven by the transactions' expected profitability, which is not observed by the econometrician. Unobservable profitability differences —e.g. in the case where minority agents are relatively "unprofitable"— may result in finding no in-group preferences within minority groups even when one exists, or an in-group preference among majority groups even when none exists. Finally, it is difficult to assess the efficiency of outcomes in most economic transactions —the sale price of an automobile (as in Ayres and Siegelman, 1995), for example, largely involves distribution of a fixed pie.

We use data from a large state-owned bank in India that provides a near-ideal setting

[1] For studies with dyadic data see, for example, Ayres and Siegelman, 1995, and Schoar, Iyer and Kumar, 2008, Jackson and Schneider, 2011, and Parsons et al., 2011.

for studying differences in the treatment of in-group and out-group individuals in a market with private information. The data allow us to match all borrowers and branch head officers to their religion and caste. An explicit officer rotation policy among branches provides variation in the matching between lenders and borrowers; we are thus able to control effectively for time-invariant attributes of borrowers and lenders, as well as for time varying credit market conditions. Further, using detailed loan records, we can measure the effect of social proximity on ex ante loan contracting characteristics, such as amount and collateral, as well as ex post loan performance.

We find strong evidence of preferential in-group treatment among both religions and castes. For non-Hindu religions, our estimates imply that total lending to a religious group is 34% higher when the branch is run by an officer of that religion. This preferential treatment holds for all branch head religions (Christian; Muslim; Sikh; Parsi; Buddhist) other than Hindu. These results highlight the importance of using dyadic data to analyze differential in-group preferences: Hindu borrowers represent 89.2% of the population and take out larger loans than those of other religions —presumably because they are wealthier and in other ways better credit risks than others— yet Hindu officers are the only ones in our setting that do not exhibit in-group preferential treatment based on religion. So a naive regression of loan access on borrower religion would indicate discrimination against minorities rather than preferential in-group treatment among minorities.

The religion-level results obscure very strong preferential in-group behavior within the sample of Hindu officers, however. To uncover these effects we further sub-divide Hindu borrowers on the basis of their government-sanctioned caste designations. These group identities have a long and complex history, which we summarize briefly in the section that follows. An interesting feature of our dataset is that we may assess the effect of social proximity inside castes using two independent classifications. Bank records provide detailed information on the government-designated castes of both borrowers and loan officers. In additional analyses, we use surnames to match lenders and borrowers to their respective *Varna*, the religious caste system that prevailed in ancient India.

Among Hindus, we find preferential treatment for own-caste borrowers, particularly for the government-designated "backward" minority castes, where total lending is 19% higher when the branch is run by an officer of that caste (for the non-minority or "general" caste group, the increase is about 5%). We further break down the general caste Hindu borrowers into Brahmin, Kshatriya, and Vaishya subgroups based on surnames, and obtain similar results —an increase in lending of 13% to a caste group when the branch is run by a manager of that group.

We find that in all cases the results are driven more by changes on the intensive (higher loans amounts) rather than the extensive margin (loans to more borrowers), and that the ratio of collateral pledged per amount borrowed is lower when the officer and the borrower belong to the same group.

To fully utilize the religion and caste information in the data, we partition all borrowers and loan officers into religion-caste groupings (i.e., subdividing Hindus into castes) and find a very strong in-group preference in this full-sample regression. Using this parsimonious specification —which imposes equal in-group preferences for each partition— we then attempt to uncover the mechanism that generates preferential in-group treatment by examining the impact of the social proximity on default rates.

Default rates, measured as days late in interest repayment, are lower when the officer and the borrower belong to the same group, despite the increase in lending. Further, we find that defaults remain low a year later, even when the in-group officer has been replaced by one from a different group. Thus, in-group lending improves loan quality, and the effect is persistent even after the direct in-group relationship between the lender and the borrower has been severed. These results suggest that better information on members of one's own community likely accounts for higher in-group lending.

The persistent effect of in-group lending on defaults is also inconsistent with the results being driven by ever-greening —collusion between the officer and the borrower on current loans with the intent of future default. In addition, all the results are robust to the inclusion of branch-time and group-time dummies, which account for all variation in the demand for credit by any group or at any locality, or changes in policy that directs credit differentially to groups or regions over time. Our findings are also unaffected by the inclusion of state-group-time dummies, which strongly suggests that our results are not driven by reverse causality, where each officer is transferred in an area where her group is thriving.

Overall, our results are consistent with social proximity leading to more contracting and better outcomes. They also suggest that the *ex ante* proximity between lender and borrower —at the time of contracting— aligns the borrower's behavior with the interest of the lender *ex post*, despite weaker contractual incentives established through collateral requirements, and even when the in-group lender has departed from a branch and cannot directly monitor the loan. A plausible interpretation for our findings is that in-group preferential treatment is the result of better screening due to advantages in information collection or communication within groups. Under the assumptions that government bank lending in India is characterized by excess loan officer conservatism and that borrowers are credit constrained (Banerjee and Duflo 2008, Banerjee, Cole, and Duflo 2004, 2009), the results imply that social proximity unambiguously increases efficiency in loan contracting.

This paper connects several strands of literature. To start with, our paper relates to a large literature on the role of group identity —defined by religion, race, country-of-birth, or otherwise— in improving economic transactions (see, for example, Banerjee and Munshi 2004, Bandiera, Barankay and Rasul 2005, 2009, Guiso, Sapienza and Zingales 2009, Jackson and Schneider 2011). To our best knowledge, ours is the first study on in-group preferential treatment in credit markets, where the potential distortions in the allocation of resources introduced by discrimination and agency problems have first order welfare consequences. Prior studies on mortgage markets (see Ross et al., 2008 for one recent example, and Ladd, 1998 for a survey of the evidence), small business lending (Blanchflower et al., 2003), trade credit provision (Fafchamps, 2000; Fisman, 2003), and online person-to-person markets (Pope and Sydnor, 2010) identify differential treatment based solely on the identity of the borrower and are thus only able to detect minority discrimination rather than in-group preferences more broadly.

Our paper is also related to a recent and growing literature on social ties in finance. This work finds that past personal direct or indirect interaction, e.g. serving in the board of a public corporation or attending the same school at the same time, affect security market (Cohen, Frazzini and Malloy 2008, 2010), credit market (Engelberg, Gao and Parsons, 2011), corporate policy and governance (Hwang and Kim 2009, Shue 2011), and entrepreneurial (Buchardi and Hassan 2010, Lerner and Malmendier 2011) outcomes, among others. There are two key differences between this research and ours. First, group affiliation in our setting is defined at birth and, thus, not intermediated by personal characteristics or choices. And second, in-group borrowers and lenders have almost surely never met or met the same people in the past. Thus, our results indicate that individuals endowed with a common culture, religion, and codes engage in more and more efficient transactions, even when they are not bound by prior social ties. Moreover, our results indicate that individuals who share such common endowments are more likely to form social ties later in life.

In addition, our work also contributes to the much broader literature on preferential own-group treatment across a range of contexts, which has its roots in Becker's (1957) theoretical analysis on the equilibrium impact of taste-based discrimination in the market, with many empirical applications from marriage markets to consumer purchases, and involving methodologies ranging from audit studies to lab experiments to observational analysis (Goldin and Rouse 2000, List 2004, Charles and Guryan 2008, Norman 2003, Bertrand and Mullainathan 2004). As with the evidence on lending, this larger body of work also fails, by and large, to distinguish between taste-based discrimination versus efficiency-based in-group preferences, resulting in considerable controversy in what they reveal about theories of discrimination and their implications for policy.[2] We view our paper as a first step in filling this gap.

Finally, our results also relate to the work on soft information in lending relationships

[2]See, for example, Fryer and Loury (2005), on the debate concerning Affirmative Action policies, and Norman (2003) on the potential efficiency gains from statistical discrimination.

(Petersen and Rajan (1994), Stein (2002)), in which the amount of non-verifiable information collection is affected by the geographical and cultural distance of the borrower from a branch (see, for example, Agarwal and Hauswald (2010), Berger et al., 2001, Mian, 2006).

In the next section, we begin by providing an overview of the data and a description of the Indian bank we study —its organization, the incentives of its officers, and so forth. In Section 3 we present the baseline empirical specification for the analysis. Section 4 presents our results on lending quantity; Section 5 analyzes default patterns to distinguish between taste versus information and enforcement based explanations; Section 6 presents a series of identification and robustness tests. In Section 7 we conclude with some policy implications and directions for future work.

2 Data and Descriptive Statistics

The data for this study are compiled from a range of sources. The main variables in the analysis are obtained from the individual loan portfolio and personnel records of a large state-owned bank in India. The bank operates over 2000 branches across India and the sample starts in 1999 Q2 and ends in 2005 Q1. This section describes in detail the structure and construction of the dataset as well as relevant background information on the organization of the bank itself.

2.1 Loans, Borrowers, and Branch Heads

The individual loan portfolio data include loan-level information for every borrower with a loan outstanding during the sample period (2.92 million individuals), with information about the loan contracts and their repayment status reported on a quarterly basis (1.23 million borrowers per quarter on average). The main variables for the analysis are the amount of debt outstanding, the collateral posted, and the number of days late in interest payment.

The median (mean) amount of debt outstanding in the full borrower-quarter panel is 8,495 (36,086) rupees; excluding borrower-quarter observations with zero balance, the median (mean) is 14,645 (47,924). Outstanding debt is typically secured: the median collateral to loan ratio in the full panel is 1.67. The over-collateralizing reflects that fact that the collateral values remain constant as loans get repaid.

The median borrower's interest payments are current. However, the average days late is 590.5. The skewness in late days results from the stock of past defaulted loans, even those that occurred prior to our sample period, which are never removed from the bank records. Excluding observations with more than 365 days late in repayment (2.76 million borrower-month observations), the average days late is 13.4.[3] [4]

The Bank data also contain information on the religion, official caste classification, and gender of each borrower. Individuals are grouped into seven categories based on the prominent religions in India: Hindu (89.2%), Muslim (6.7%), Christian (1.7%), Sikh (1.8%), Parsi (0.12%), Buddhist (0.24%) and others (0.26%); we drop the last group of borrowers of indeterminate religion from the sample.

Borrowers are classified into four castes according to categories explicitly recognized by the Constitution of India: general caste (GC, 62.6%), Scheduled Castes (SC, 12.8%), Scheduled Tribes (ST, 7.7%) and Other Backward Classes (OBC, 16.9%). The SC category comprises all the castes historically treated as "untouchable" by the upper castes in India. The ST category includes indigenous, typically geographically isolated, tribal groups. The OBC category is a collection of caste groups ranked above untouchables in the ritual hierarchy, but socially and educationally disadvantaged. Individuals belonging to the SC, ST, and OBC categories receive targeted government aid and are beneficiaries positive discrimination policies (subject to means testing) such as reservations in public sector employment and higher education.[5] Although the SC, ST, and OBC categories

[3]Our results are invariant to the sample that is employed in the analysis.

[4]We do not use the interest rate charged on loans in the analysis because, unlike loan amount or collateral, it is not under the discretion of the loan officers or branch managers.

[5]The categories of Scheduled Caste (SC), and Scheduled Tribes (ST) that represented a majority of lower-status castes as well as tribes, were first protected through anti-discrimination laws through the ninth schedule of the Constitution in 1950 (Article 15, 17, and 46). In 1990, the further caste-based categorization of OBC was added for identifying additional communities of socially and economically

include a wide variety of social groups across India, locally they are often relatively homogenous. The cultural and social differences across SC borrowers from two different regions in India are much more pronounced than those between SC borrowers within one region. The GC category is essentially a collection of all the individuals not belonging to the aforementioned backward classes. In some of the analysis that follows, we further subdivide GC borrowers based on religious caste definitions, or *Varna*, based on surname; we postpone discussion of this to later in the paper, where name-based classifications are used in the analysis.

We obtain from the internal personnel records of the Bank information about employees at each branch at a quarterly frequency. Each record has a general job description and the position in the internal hierarchy of the Bank. We use these data to identify the head officer of each branch at each point in time. For each of the 4,270 branch heads we obtain the religion, caste, and gender. Of the 46,233 branch-quarter observations in the sample, 93.8% of head officers are Hindu (1.9% are Muslim, 2.1% Christian, 1.7% Sikh, and the remaining 0.5% classified as Parsi, Buddhist, or other religion); 74.4% belong to the GC category; (15.2% SC, 5.2% ST, and 5.2% OBC), and 2.4% are female.

Loan officers are classified into six grades, with higher grades representing higher seniority, and the ability to approve larger loan amounts. The highest ranked officer in each branch is the branch head. For smaller branches, the branch head may himself have a relatively low grade. This implies that any larger loan request that comes through the branch will have to be approved by a higher grade officer elsewhere in the region. Still, in these cases the decision of whether to submit the loan for approval at the higher level of the hierarchy is under the head officer's discretion, and based on information collected at the branch level.

Branch heads —the focus of our analysis here— are evaluated annually on a range of criteria.[6] These include quantitative measures such as the amount and profitability of

deprived population. A few years thereafter the category of OBC was diversified to include a significant segment of the non-Hindu population, notably Muslims, Christians, and Sikhs.

[6]Information on evaluation and compensation of managers within the bank come primarily from interviews with bank staff.

lending, as well as qualitative considerations such as employee skill development, effective customer communication, and other aspects of "leadership competency." Each officer is ultimately assigned a numerical grade from zero to one hundred based on these criteria.

One specific aspect of officer performance that will be relevant for our analyses that follow is the extent to which officers are responsible for loan defaults after moving branches. Typically, loan officers are responsible for loans they approve for three years following their departure, at which point responsibility is transferred to the officer that has taken charge of the loans.

While there is limited incentive pay, branch heads may be motivated through possible promotion to higher grades or better postings. For example, successful branch heads may be sent to locales with more or better perquisites, such as higher pay (overseas), larger houses, the use of a car, or control over a larger portfolio (large branches). In the results section we evaluate the extent to which such endogenous allocation of officers to branches affects our estimates.

2.2 Descriptive Statistics

The unit of analysis in our initial set of specifications is the branch-group-quarter level (indexed by b, g, and q, respectively) where group refers to the religious or social group of the borrower. We use initially three group definitions: 1) religion, 2) government-sanctioned caste, conditional on religion being Hindu, and 3) a religion-caste partition of the data, which combines the prior two classifications. This leads to one panel per group definition, where each panel has a different size in the cross section, depending on the number of categories in each group definition. The group index g ranges from 1 to 6 for religion, from 1 to 4 for caste, and 1 to 9 for the religion-caste partition (4 caste categories; 5 non-Hindu religious categories). The descriptive statistics of the panels of loan data where groups are formed by religion and caste are shown in Table 1. Consider the religion classification in Panel 1, containing 374,576 branch-group-quarter cells. The average cell has 78.9 borrowers with 59.4 active loans, which aggregate up to a total of just over 2.8 million rupees.[7]

We merge the branch level personnel information to this panel to obtain our main explanatory variable, $SAMEGROUP_{bgq}$, a dummy variable that is equal to one for the branch-group-quarter loan cells where the branch head officer belongs to group g, and zero otherwise. For example, if the head officer of branch b in quarter q is Hindu, then $SAMEGROUP_{bgq} = 1$ for loans from group g, if $g =$ Hindu and zero for the other groups in that branch-quarter.

The Bank follows an explicit policy of geographical officer rotation, with the stated objective of reducing opportunities for corruption, nepotism, or other sources of loan misallocation. As a result, we observe on average 127 head officer reallocations per quarter, and the median branch has two officers during our sample period. The average (median) spell of a head officer in a branch is 8.3 (8) quarters (standard deviation of 4.1).

In Table 2, Panel 1, we report the observed frequency of officer transitions, classified according to the religion of the outgoing and incoming officers, and compare it to the transition probabilities that would result from a random allocation of loan officers. Of the 3,095 officer changes, 87.1% are from a Hindu officer to another Hindu officer (Table 2, Panel 2). This observed frequency is statistically indistinguishable from the expected frequency if officers are randomly allocated to branches at each transition, 87.8% (Table 2, panels 3 and 4). This is true for all the observed religion-based transition rates. These patterns are consistent with officer allocations being orthogonal to religion.

For the subsample of Hindu officers, however, the empirical transition rates deviate from the random benchmark when officers are grouped by caste. The observed probability of a GC to GC transition is 61.0%, while the random benchmark is 55.4%, and the difference is statistically significant at the 1% confidence level (Table 3). This indicates that there are some branches that tend to receive general caste officers too often relative to a random assignment policy. Also, the observed transition rate from SC to general caste is 8.4%, while the random benchmark is 11.8% (difference significant at the 10%

[7] The median religion-branch-quarter cell has zero debt because the amount of debt outstanding to minority religions (excluding Muslim) is zero in most branches.

level).

The observed bias in the assignment of officers to branches according to the caste classification may occur if an individual's caste is correlated with her preferences for work location. Alternatively, the bias may result from institutional constraints, such as differential reservation requirements for government employment of SC, ST, and OBC individuals across locations. We discuss the potential consequences of policy-driven distortions in officer allocation in the context of the empirical estimation in the next sections. We also show in Section 4 that the apparent non-randomness disappears once we consider a finer classification of general caste officers based on religious rather than government sanctioned caste definitions.

3 Baseline Specification

Our baseline empirical specification takes the following form:

$$y_{gbq} = \beta SameGroup_{bgq} + \alpha_{gb} + \tau_q + \epsilon_{gbq} \tag{1}$$

The left-hand side variable is a loan outcome (i.e., total lending, number of loans, weighted average of the days late in repayment) at the branch-group-quarter level. As above, g indexes the group —caste, religion, or pooled partition; b indexes the branch; and q indexes the quarter. *SameGroup* is an indicator variable equal to one if the branch head in branch b belongs to group g in quarter q. The two fixed effects —a_{gb} and τ_q— capture time-invariant attributes of each group within each branch (i.e., a group times branch set of fixed effects), and aggregate shocks to all branches. The error term ϵ_{gbq} allows for clustering at the branch level.[8]

The coefficient on *SameGroup* is a difference-in-differences estimate of the effect of

[8]In the robustness section we augment the baseline specification with branch-time dummies, group-time dummies, and state-group-time dummies.

social proximity between a lender and a borrower on loan outcomes. Consider, for example, the regression with log total lending as the dependent variable and a situation where there are only three groups: Hindus, Muslims, and Christians. Suppose that a branch has a Hindu officer during the first half of the sample, and a Muslim officer during the second half. The coefficient on *SameGroup* captures the difference between the log debt of Hindu borrowers in the branch when the officer is a Hindu (in-group) officer relative to when the officer is a Muslim. It also captures the difference between the log debt of Muslim borrowers with a Muslim officer relative to a Hindu officer.

This specification allows us to explore whether there are differential in-group effects across groups. In our initial set of specifications we include the interaction of *SameGroup* and a dummy for group g in order to explore this heterogeneity. However, much of our analysis we will impose equality of the coefficients and focus on the average in-group effect.

4 Results: Loan Amounts

We begin by presenting (unconditional) lending patterns around officer transitions. First we classify borrowers into two categories around officer transitions, based on whether they have the same group identity than the outgoing officer: *in-group* (*out-group*) borrowers are those that belong to the same (a different) group than the officer before the change. For example, in a branch where the outgoing officer is Hindu, then Hindu (minority religion) borrowers are in-group (out-group) borrowers before the officer change. Each of these borrower groups may or may not experience a change in their in-group/out-group status after the officer change. For example, suppose the Hindu officer is replaced by a Muslim one. Then, Hindu borrowers transition from in-group to out-group, Muslim borrowers transition from out-group to in-group, and other (non-Mulsim) minority religions remain being out-group. Alternatively, if the replacement officer is also Hindu, then Hindu (minority religion) borrowers remain being in-group (out-group).

We use these borrower classifications to construct "event study" type plots around officer transitions. The horizontal axis of the plots in Figure 1 measure time in quarters since the officer change in a branch. Time 0 represents the first quarter a new officer appears as the head of the branch in the personnel files. In the vertical axis we plot the average debt of borrowers that experience a change in in-group/out-group status, relative to those that do not. Panel A (Panel B) shows the average debt of out-group (in-group) borrowers that become in-group (out-group) after the officer change, minus the average debt of borrowers that remain out-group (in-group). All averages are taken at the group-branch level using the caste-religion group definition, and both plots include the 95% confidence interval of the mean difference.

The plots indicate a shift in the composition of lending as a function of social, cultural, and religious ties when there is a change in head officer. In Panel 1, the average debt of borrowers that switch from out-group to in-group status increases by approximately 1,500 rupees, relative to borrowers that remain out-group after the officer change. A parallel pattern appears in Panel 2: the average debt of borrowers that switch from in-group to out-group status drops by 4,000 during the four quarters following the change in status, relative to borrowers that remain in-group.

The plots in Figure 1 also suggest that the relationship between cultural proximity and lending may be causal, since the relative debt change occurs immediately around the officer transition and does not appear to be driven by pre-existing differential lending trends across the two groups in each panel. Thus, these plots validate the identification assumptions behind the the difference-in-difference estimator of the in-group effect in specification (1).

There is a small and statistically insignificant increase in the relative amount of lending at time -1 in Panel 1, the quarter prior to the arrival of the new officer. It is likely that this increase is driven by measurement error in the time of arrival of the new officer, since mid-quarter branch head transitions are only reflected in the personnel files at the end of the quarter. Such measurement error will tend to bias downwards our estimates of the in-group effect in specification (1).

4.1 In-Group Effect Estimates

The effect of having an in-group branch head on the level of lending, estimated using specification (1), is presented in Table 4. We use the log of debt by group g in branch b in quarter q, $log(Debt_{bgq})$, as the dependent variable. The log transformation reduces the skewness of the dependent variable, and facilitates an elasticity interpretation of the coefficients. However, it also creates an unbalanced panel, as zero loan cells become missing values. Below, we will also consider the impact of in-group branch officers on an indicator variable denoting non-zero loan observations.[9]

Panel A provides results on the effect of social proximity through religion. In Column (1) we include interactions of the *SameGroup* indicator variable and religion indicator variables. Thus, for example, $SameGroup * Muslim$ captures the difference in loans outstanding to Muslims in a branch when it is headed by a Muslim versus a non-Muslim. The coefficients on all indicator variables aside from $SameGroup * Hindu$ are positive, implying that borrowers of minority religions receive relatively more lending compared to other borrowers in the same branch when the officer belongs to the same religion. For Hindus, the coefficient is negative but not significant. An F-test indicates that the non-Hindu *SameGroup* coefficients are significantly different from zero at the 1% level. As we note in the data section, however, there are very few Sikh, Parsi, or Buddhist branch managers, and further, a relative lack of non-Hindu branch heads in general. We impose equality of coefficients across all non-Hindu *SameGroup* in column (2). That is, we impose that the differential treatment of Muslims by Muslim managers is the same as the differential treatment of Christians by Christian managers (though not that Muslim managers treat Christians and Muslims symmetrically). The coefficient on $SameGroup * non - Hindu$ is significant at the 1% level and its value of 0.34 implies a more than one third increase

[9]We could alternatively use a $ln(1 + x)$ transformation to reduce the skewness of the dependent variable, but this does not allow a ready interpretation of estimated coefficients. Such a transformation generates qualitatively identical results to those reported below.

in lending to borrowers of a (non-Hindu) religious group when the branch is headed by a manager of that religion.

We assess whether the increase in borrowing comes through the intensive (larger loans) or extensive (loans to more borrowers) margin. In column (3), we use the log of the number of borrowers ($log(Borrowers_{bgq})$) as the dependent variable and in (4) the log of average loan size ($log(Debt_{bgq}/Borrowers_{bgq})$) to measure the extensive and intensive margins respectively. These variable definitions are chosen such that the coefficients on *SameGroup* in these specifications add up approximately to the those obtained in column (1). The coefficient in each case is positive and significant at the 1% level, implying a role for both channels. The point estimate on the extensive margin is 0.11 and on the intensive margin is 0.23, indicating that more than two thirds of the in-group effect occurs through an increase in average loan size for existing borrowers.

In columns (5) and (6) we examine the effect of *SameGroup* on collateral. The coefficient on collateral is positive and significant, with a point estimate of 0.24, indicating that borrowers pledge a higher amount of collateral when the branch is run by an officer of their religion. This increase is expected given that borrowers are taking larger loans. However, the ratio of collateral to debt declines as indicated by the negative coefficient on SameGroup in column (6).[10] This will be of particular note when we come to assess the impact of social proximity on ex post loan quality. Finally, in column (7) we use as the outcome an indicator variable that takes on a value of one if $Debt_{bgq} > 0$. This captures the extensive margin: the effect of an in-group officer on the likelihood of a borrower group receiving any debt (switching from zero to non-zero debt). For Hindu officers, the coefficient is a precisely estimated zero; for minority religions, the point estimate is approximately 0.06, implying a six percentage point increase in the probability of receiving any credit. Given that 56.4% of the branch-group-quarter cells for minority religions have zero debt, the point estimate implies a 10.6% increase in the likelihood of receiving credit.

In Table 5, we repeat the exercise on the sample of Hindu borrowers, and use the

[10]This is also implied by the larger effect on loan size relative to collateral, i.e., column (2) versus column (5).

government-sanctioned caste definitions to measure for preferential treatment of own-caste borrowers by branch managers. In these specifications, we use the government caste classifications: SC, ST, OBC, and GC. In column (1), we see that the insignificant point estimate of the coefficient on $SameGroup * Hindu$ in our religion results (Panel A) masks a strong caste in-group preference within the Hindu sub-sample of borrowers and loan officers. The coefficients on the *SameGroup* variable interacted with SC, ST, and OBC dummies are in the range of 0.16 to 0.27, and all individually significant at least at the 10% level. An F-test for equality of coefficients implies a p-value of 1.04, so in column (2) we impose equality of coefficients for the *SameGroup* variable across backward castes, yielding a coefficient of 0.19. This implies that SC, ST, and OBC borrowers receive on average 19% more credit when the branch head officer is a member of their caste.

The in-group effect for general caste (GC) borrowers is much smaller in magnitude. The point estimate indicates that the average debt of GC borrowers increases by 4.7% when the branch has a GC officer. However, as with the Hindu classification above, this result conceals a substantial heterogeneity and preferential treatment within sub-groups of the GC classification. In the last section of the paper we report results using the religious caste classification of GC borrowers (based on surname matching) and find estimates that are close in magnitude to the one obtained for the SC,ST, and OBC borrowers.

As with religion, we find that while both average loan size and number of borrowers contribute to the increase, nearly 80% of the increase comes from an increase in the amount of debt per borrower. Also, the level of collateral increases with *SameGroup*, while the collateral rate (collateral/debt) declines with *SameGroup*. Parallel to the results based on religion, *SameGroup* has no effect on the likelihood of of obtaining any debt for the majority caste (GC) borrowers, but increases the probability of obtaining any debt for backward castes by 1.1 percentage points (a 6% increase relative to the 18.6% of backward caste branch-group-quarter cells with zero debt in our sample). However, this effect is only significant at the 10% level.

In Table 6 we present the pooled results with a full caste-religion partition of the data.

In column (1), we allow the in-group coefficient to differ by caste (conditional on Hindu) and minority religions. The coefficients are nearly three times larger for same religion relative to same caste lending —unsurprising given the patterns in Panels A and B.[11] When we constrain the coefficients to be equal, the coefficient on *SameGroup* is 0.15. In columns (3) and (4) —as with previous (unpooled) specifications— we find that the effect is a combination of intensive (loan size) and extensive (number of loans) margins; similarly, the results on collateral mirror these earlier findings: the positive in-group effect on lending is accompanied by a positive effect in collateral, but a negative effect in the collateral to debt ratio. To simplify the exposition of the results, in what follows we focus on pooled samples, with a parsimonious specification that imposes equality of coefficients across groups.

Finally, in Table 7 we repeat the estimation of the parameters in Table 6 on two different subsamples of borrowers, depending on whether borrower had already established a credit relationship with the bank prior to the arrival of the current officer, or the borrower is receiving credit from the bank for the first time.

The results on the existing borrower subsample parallel those above. Having an in-group officer has a positive effect on the amount of lending and collateral, and a negative effect on the collateral to loan ratio. Mechanically, the effect on the number of borrowers is zero on this sample, so the increase in lending occurs exclusively through the intensive margin. The direction of the effect on the subsample of new borrowers is the same for all variables except the collateral to loan ratio. Collateral seems to increase in lock-step with the size of loans for first time borrowers. Most of the in-group effect on lending for first time borrowers comes from the extensive margin: of the total 16.9% effect, 13.2 percentage points are due to an increase in the number of borrowers.

The results on the existing borrower subsample are obtained holding the set of borrowers in each branch-group constant over time, and thus characterize the in-group effect

[11] If we allow for a separate coefficient for $SameGroup * GC$ and $SameGroup * SC/ST/OBC$, splitting general caste members off from other Hindus, the coefficient on the GC interaction is 0.047, while the coefficient on $SameGroup * SC/ST/OBC$ is 0.187, consistent with the Hindu-only analyses in Panel (B).

conditional on borrower selection. The results on the new borrower sample combine this conditional effect with the potential effect that an in-group officer may have on the composition of new borrowers. Borrower composition may change, for example, if Muslim borrowers with a larger need for credit approach a branch when a Muslim officer is heading it. We do not observe loan applications, which prevents further exploration of the selection dimension. Since the main effect on the amount of lending is consistently positive across the two samples, we continue to present the aggregate effects in what follows.

We reiterate the two main conclusions that can be derived from the results in this section. First, social proximity between lenders and borrowers leads to more credit. And second, social proximity reduces the cost of borrowing as reflected in the value of collateral per rupee borrowed. We investigate the potential mechanisms behind such in-group preferential treatment in the next section. In Section 6 we perform several identification tests to corroborate the causal interpretation of the results.

5 Ex Post Loan Quality

The key identification challenge in understanding the causes and consequences of preferential in-group treatment is whether it is due to better information and/or enforcement, or the result of taste-based preferences. While it will be virtually impossible to test definitively between these alternatives, by carefully considering the impact of in-group lending on ex post loan quality —default or repayment— we can shed light on whether in-group transactions lead to a better or worse use of information and allocation of resources.

Any supply-driven lending expansion will lead, at least weakly, to lower quality loan portfolios, since marginal borrowers tend to be of lower credit quality than infra-marginal ones. If the observed increase in own-group lending derives primarily from taste-based preferences, a deterioration of lending quality will result. If own-group preferential treatment is based on, or results in, better information or enforcement, loan portfolio quality may remain the same or even improve after the lending expansion. Although these two effects are not mutually exclusive, by probing the impact of in-group lending on loan quality we can assess which one dominates and provide strong suggestive evidence on the underlying causes of preferential in-group lending.

We examine the impact of *SameGroup* on loan repayment in Table 8. In the first set of results (columns 1 through 3), we use the average number of days that debt is overdue, weighted by loan size (i.e., $log(Days\_Late\_Wt_{bgq})$, as the dependent variable. As noted above, we focus for simplicity of exposition on the pooled caste-religion partition of the full data, and present the average *SameGroup* effect across all groups. In column (1), we present our main result: the coefficient on *SameGroup* is negative and significant at the 1% level. Its magnitude implies a reduction of about 14% in days late, on average, for a loan issued to borrowers from the branch head's group.[12]

These findings indicate that branch officers are better at screening of, or enforcing repayment by, in-group borrowers. There are several potential rationales for the source of the information and/or enforcement advantage. One possibility is that shared codes and language aid communication and information gathering, both ex ante and ex post. Another is that a common background allow the officer to implement social sanctions ex post in case of default. There are is also an interpretation that relies also on taste-based preferences. For example, officers may spend more time with borrowers of their own group due solely to preferences and, as a by-product, collect better information about them. Alternatively, social norms or altruism may increase the borrowers' utility cost of defaulting when the issuing officer belongs to their own group. All these interpretations lead to the same conclusion: social proximity between officers and borrowers reduces the cost of improving ex post loan quality.

The main alternate theory that leads ultimately to higher default in the long run, but can still provide a rationale for the immediate increase in repayment is *ever-greening*, or the rollover of loans to delay default until after the loan officer has moved on to a different branch. We note, first of all, a loan officer is responsible for loans issued during his tenure

[12] If we allow the coefficient to differ for caste and religion, we find that the impact is negative and significant at the 1% level for both coefficients.

in a branch even after his departure (see the discussion of officer career concerns in Section 1), so ever-greening would be costly to the officer's career progression. Further, if ever-greening were a significant concern, we would expect to see *SameGroup* loans' defaults increase in the future. In columns (2) and (3) we examine the impact of *SameGroup* on the one year lead of $log(Days\_Late\_Wt)$. The coefficient on *SameGroup* is nearly identical to the point estimate in the contemporaneous specification.

A sharper test for ever-greening is to check whether the positive effect of *SameGroup* on loan quality reverts when the in-group officer is replaced with an out-group one since incoming, self-interested, officers will tend to uncover any bad quality loans that the departing officer kept alive through ever-greening. We implement this test by augmenting specification in column (2) with the one-year lead of *SameGroup*. The coefficient on this variable represents the difference in future default across borrowers that still have an officer from the same group relative to those that experienced a change. We find that the one year lead of *SameGroup* is a precisely estimated zero, implying that the increase in loan quality persists even after the in-group officer is replaced by out-group one.

The only scenario in which this result is consistent with ever-greening is one where branch managers of different groups ever-green one another's loans. Although such behavior could arise from collusion between loan officers, sustaining such collusion is unlikely given that negative career consequences of adding what would be near-certain delinquent loans to one's records would give strong incentives to deviate. (In a different setting, Andrew Hertzberg et al. (2010) provide evidence that loan officer career concerns provide incentives to the incoming officer to uncover any bad news withheld by the incumbent officer upon arrival.)

In columns (4) through (6) of Table 8, we repeat these analyses using unweighted loan defaults as the outcome variable. In contrast to our findings on amount-weighted defaults, the *SameGroup* coefficient is close to zero, and its t-statistic not significant at conventional levels. This implies that the positive effect of social proximity on repayment performance is also operating mostly through the intensive margin: it is the result of giving larger loans to borrowers that default less ex post. In Appendix Table A.1 we show that the larger loans were not given to borrowers of an observable high quality ex ante: the coefficient on *SameGroup* in a specification that uses the ex ante credit rating of the borrower, amount-weighted or unweighted, is always statistically insignificant. Together with the positive in-group lending results, the findings suggest that branch managers increase the amount of lending to ex ante seemingly indistinct borrowers from their own group that display a better repayment performance ex post.

Overall, our results indicate that the lower in-group default rates are likely due to improved loan quality. The improved quality persists even after the originating in-group officer has been replaced by an out-group one. This suggests that the improvement in loan repayment results from better ex ante screening, as opposed to better ex post monitoring or enforcement. The cost of direct ex post monitoring or application of social sanctions should increase with communication and transportation costs. The fact that we do not observe any decline in the likelihood of repayment after the officer has reallocated to a different branch and replaced by an officer of a different group is suggestive that the in-group effect on loan repayment has an ex ante, rather than an ex post, explanation.

Improved in-group lending quality also implies that the observed decline in the collateral to loan ratio is not due to an unwarranted relaxation of lending standards to in-group borrowers. On the contrary, the findings are consistent with officers correctly anticipating the improved quality of same-group borrowers. Overall, the findings are consistent with an interpretation in which contracts between individuals of the same group have better outcomes because of reduced ex ante information asymmetries.

6 Identification Tests

In this section we address two important concerns with the interpretation of our results. The first is the possibility of confounding credit demand or supply factors that differentially affect certain locations or groups. Specifically, we are concerned that officer rotation is implemented so as to place an officer in areas where prospects from borrowers of her group —religion or caste— are growing. We address this possibility by verifying that our estimates are robust to saturating all the branch-time, group-time, and state-group-time variation in the empirical specification.

The second concern arises from the use of government-based caste definitions. The SC, ST, OBC, and GC categorizations not only encompass a very broad range of cultures, languages, and backgrounds, but also are used for affirmative action policies regarding both government positions and lending. We demonstrate below that the estimated in-group effects are robust to a group categorization based on religious caste definitions (Varnas).

6.1 Saturated Model

We consider the robustness of the results to augmented specifications that account for branch specific shocks, group specific shocks, and state-group specific shocks:

$$y_{gbq} = \beta SameGroup_{bgq} + \alpha_{gb} + \tau_{bq}^{Branch} + \tau_{gq}^{Group} + \delta_{bgq}^{State\text{-}Group} + \epsilon_{gbq} \tag{2}$$

Branch-time dummies, τ_{bq}^{Branch}, account for all changes in the demand for credit in a particular location, as well as changes in directed credit policies aimed at certain localities. Since there is one head loan officer per branch at any time, the branch-time dummies also account for all unobserved branch head heterogeneity, whether time invariant or time varying, and for any effect that the change of an officer may have on average lending in a branch. The group-time dummies, τ_{gq}^{Group}, account for aggregate changes in the credit demand from, or supply to, specific social groups. The state-group-time dummies, $\delta_{bgq}^{State\text{-}Group}$, absorb any changes in the demand or supply of credit that are specific to a group in any given region, such as secular borrowing trends affecting particular groups in a location.

In Table 9 we report the estimated coefficients of the augmented specification (2) using the log of total debt as the left-hand side variable. Column (1) includes branch-quarter dummies; column (2) includes both branch-quarter and group-quarter dummies; and column (3) includes state-group-quarter dummies. To reduce the number of nuisance parameters to be estimated in these specifications, we remove the branch-group means from all variables in the panel rather than including branch-group fixed effects, and adjust the standard error estimation accordingly. The magnitudes of the estimated coefficients using debt (columns (1) through (3)) and weighted days late (columns (4) through (6)) as dependent variables remain consistent across specifications, and the point estimates are statistically indistinguishable from those reported in Tables 6 and 8 respectively.

The overall results argue against our findings being driven by confounding factors, rather than social proximity. The primary concern with the baseline results is one of reverse causality: an officer may be placed in areas where the demand for credit and the general economic prospects of potential borrowers from his group are improving. For example, a trend in relatively increasing wealth amongst Muslims in a particular locale could plausibly lead the bank to appoint a Muslim branch head. This possibility is largely accounted for in the saturated specification and has relatively little impact on our results, which is itself a form of validation of the bank's claim that officer rotation is independent of religion and caste.

6.2 Alternative Caste Definition

Just as religion is too coarse a classification to measure differential Hindu in-group treatment, our government caste classifications may be too coarse to properly assess caste in-group preferences, given the many caste subgroups not captured by the government definitions. In this section, we present results from name-based caste classifications that further disaggregate —albeit in a noisy way— the general caste loan officers and borrowers in our sample.

According to religious texts such as Manusmriti, Hindu society is broadly divided into four Varnas: the Brahmins (priests and scholars), Kshatriyas (warriors), Vaishyas (merchants and traders) and Shudras (laborers and artisans). Each Varna is a unification of several Jatis, or communities (see Buhler 1886), and a person's surname typically reflects the Jati she belongs to. We exploit this link with surnames to classify each individual into her Varna.[13]

Since the association between individual names and their borrowing and employment records is proprietary and cannot be disclosed outside the Bank, the process of assigning individuals to the Brahmins, Kshatriya, and Vaishya groups followed four steps. First, the Bank provided us with a list of all the surnames—both borrowers and officers—present in Bank records. Second, we searched Google and the Anthropological Survey of India (Singh, et al., 1998, 2003, 2004) to establish a community association for each name. Third, we searched Google, Wikipedia, matrimonial websites, and other references (Dahiya 1980, Dudhane 2007, UNP, Marathas 2010, Maheshwari Samaj 2006, Bindu 2008) to establish the link between communities and Varnas. Finally, the Bank linked community and Varna information to bank records by surname, before removing the borrower and manager identifiers from the data.

The following are examples of the name matching and search process using three common surnames in India:

- Example 1. Surname: Birla. A Google search of the surname was found listed in one of the matrimonial sites of the Maheshwari Samaj community (Maheshwari Samaj 2006). In the Maheshwari Samaj we find information that they belong to the Vaishya Varna.

- Example 2. Surname: Rathod. The name Rathod was found in the Anthropological survey of India to be commonly used by the Rajput community (K. S. Singh et al., 2004). Following up with K. S. Singh et al. (2004) we find that the Rajputs are Kshatriyas according to the Varna system.

[13]See Banerjee, Bertrand, Datta, and Mullainathan 2009 for a further discussion of the link between surnames and castes in India

- Example 3. Surname: Deshpande. The Google search showed the surname listed under the Deshastha community.[14] A search in Kamat.com showed this community belongs to the Brahmin Varna.

There were various sources of noise and imprecision in the name matching approach to classifying borrowers and officers by religious caste. First, many surnames could be classified into two or more Varnas. For example Saxena is grouped under both Brahmins and Kshatriyas. Similarly Desai is grouped under both Brahmins and Vaishyas. We created three special categories for individuals for whom this ambiguity arises (Kshatriya-Brahmin, Kshatriya-Brahmin-Vaishya, and Kshatriyas-Vaishyas). Second, it was unclear how to categorize individuals into the Shudra Varna according to their community affiliations, which precluded using surnames for individuals outside of the general castes. Finally, in a large fraction of cases, the surname-based classification conflicted with the bank classifications assigned to loan officers and borrowers. For example, many bank-classified Muslims had "Hindu" surnames, and vice-versa. It is for these reasons that we have primarily left analyses based on the Varna classification as a robustness check, but note that our main results all hold with a finer partition that takes account of this further disaggregation.[15]

At the end of the matching process, 502,723 borrowers (18.7% Brahmin, 65.0% Kshatriya, 6.2% Vaishya, 3.2% mixed categories) and 1,689 officers (24.6% Brahmin, 46.4% Kshatriya, 12.4% Vaishya, 16.6% mixed categories) had a Varna assigned, all of them drawn from the general caste. Using these classifications, we repeat the analyses from earlier sections to verify that they are robust to this alternative definition of group affiliation.

In Table 10 we report the comparison between the actual and theoretical officer transition rates. In contrast to the caste transition rates in Table 3, the observed frequency of officer transitions classified by the Varna of the outgoing and incoming officers is sta-

[14] http://en.wikipedia.org/wiki/List_of_Deshastha_Brahmin_surnames.

[15] Note, however, that the partition will depend on the prioritizing of bank and name-based classifications.

tistically indistinguishable at the standard confidence levels from the expected frequency if officers are randomly allocated to branches at each transition. This hints at the possibility that the apparent non-random rotation of officers by caste may have been masking heterogeneity in Varnas across regions.

We report in Table 11 the estimated coefficient on *SameGroup* using the Varna classification, estimated over the sample of general caste borrowers and branch heads. The effect on each of debt, average loan size, and collateral is positive and significant at the 1% level. This indicates that our results based on the general caste classification, reported in Table 5, conceal a strong in-group preference within the general caste (GC) sub-sample of borrowers and loan officers (that is, among individuals not classified as SC, ST and OBC according to the government categorization). Notably, the point estimate of the coefficient on *SameGroup* using the Varna classification for general caste individuals is of the same order of magnitude as that found for *SameGroup* among the SC, ST, and OBC individuals. For example, in the debt regression, the same group effect is 0.13 for general caste individuals classified by Varna, and 0.19 for SC, ST, and OBC individuals. The coefficient on the default specifications are also of similar magnitude as those obtained before, and also significant at the 5% level.

These results further confirm our overall conclusion that it is social proximity that drives the observed preferential in-group lending and improved loan repayment. In particular, they rule out that the estimated in-group effect is due to reservation policies for minority or backward groups, since there are no affirmative action policies targeting higher caste individuals. Also, since the Varna classification is independent of the Bank's internal records on religion and caste, these results also indicate that our main findings are not due to systematic misclassification of officers and borrowers.

7 Conclusion

In this paper, we have measured the extent of differential treatment of those that share one's social, cultural, or religious background in the loan market. Our empirical context provides a near-ideal setting for assessing differential in-group treatment: since we have data on both lender and borrower affiliations, we may distinguish between own-group preferences versus differential treatment of minorities. Further, quasi-random officer rotation allows us to identify in-group preferences from changes in officer branch assignments. Finally, since we focus on credit markets we may distinguish between information, enforcement, and collusion explanations by analyzing loan outcomes. Overall, our findings indicate that better information explains in-group preferential treatment.

Our findings have a number of implications for theories of discrimination as well as economic policy. First, we note that the information-based preferential treatment we uncover can itself perpetuate income inequality among minorities. In our context, 74.4% of the officers belong to the general caste category. This implies that the probability that a backward caste borrower (SC, ST, or OBC) will face unfavorable loan conditions is nearly 75%, for reasons related only to the social group they belong to.

Further, our findings suggest one possible mechanism through which statistical discrimination against minorities can arise. Minorities will be infrequently "matched" with a loan officer of their own group and hence have inferior loan outcomes on average. As a result lenders may form what are ultimately self-confirmatory beliefs about the creditworthiness of minorities, assuming lenders use average default rates to generate lending rules (Kim and Loury, 2009).

Finally, our findings have several policy implications. In the India context, targeted reservation policies that impose a larger proportion of backward caste officers in regions with high concentration of backward caste borrowers have the potential to improve efficiency and reduce inequality of loan allocation. The reason, however, is different than the preference-based rationales for political reservations (see, for example, Chattopadhyay and Duflo, 2004). Our findings suggest that reservations may improve contracting outcomes because they reduce information asymmetries between bureaucrats and their communities. Further, polices aimed at reducing social and cultural differences across groups - for example, by teaching a common language - may lead to improvements in cross-group contracting. However, further research is required to identify which dimensions of cultural, social, and religious differences have a first-order effect on reducing the the ability to exchange information across group boundaries.

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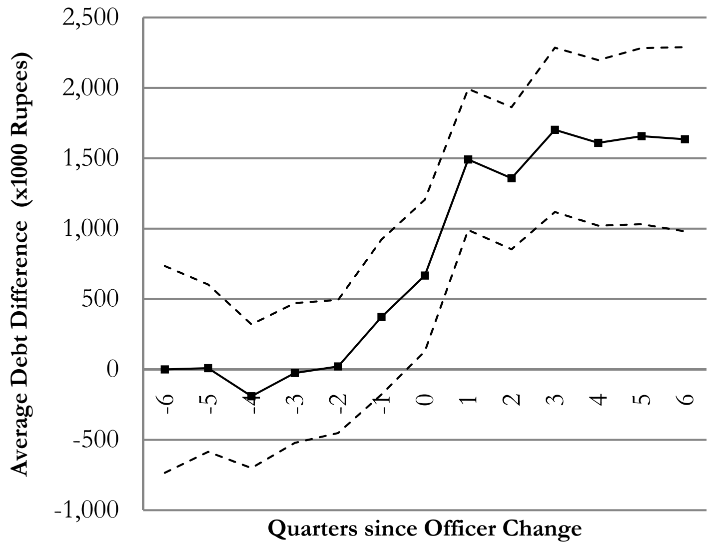
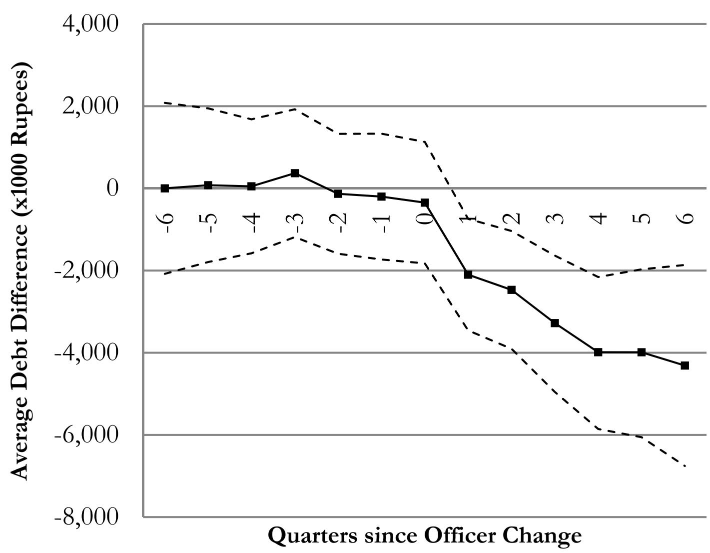
Figure 1: Average (Relative) Debt by Time since Officer Change

(a) Borrowers that Transition from *Out-Group* to *In-Group* Officer, Relative to *Out-Group* to *Out-Group* Transition Borrowers



(b) Borrowers that Transition from *In-Group* to *Out-Group* Officer, Relative to *In-Group* to *In-Group* Transition Borrowers



The horizontal axis measures time, in quarters, since the officer transition (0 represent the first quarter of the new officer). The vertical axis measures the average debt difference calculated based on a classification of borrowers and officers into five minority religions and four government sanctioned castes (conditional on Hindu). The dashed lines indicate the 95% confidence interval of the mean differences by quarter.

Table 1: Summary Statistics, Branch-Group-Quarter Panel

Group refers to the religion and/or caste conditional on Hindu religion the borrower belongs to. Each panel reports statistics for a different group definition (Panel 1: six religions, Panel 2: four government sanctioned castes, conditional on Hindu religion, Panel 3: five minority religions and, conditional on Hindu religion, government sanctioned caste). We report, the mean, standard deviation, 1st percentile, median and the 99th percentile for all the variables.

	Mean	Std. Dev.	p1	p50	p99
Panel 1: Group Defined by Religion (N=374,576)					
Sum of Debt (1,000s of rupees)	2,847	9,896	0	0	44,135
Sum of Collateral Posted (1,000s of rupees)	18,621	1,075,316	0	0	165,808
Number of Borrowers	78.9	254.6	0	0	1175
Number of Loans	59.4	183.8	0	0	867
Average Days Late, Weighted by Loan Amount	112.5	2,631.4	0.0	0.6	2,141.0
Panel 2: Group Defined by Government-Sanctioned Caste, conditional on Hindu (N=165,256)					
Sum of Debt (1,000s of rupees)	4,996	11,579	0	1,082	51,960
Sum of Collateral Posted (1,000s of rupees)	28,823	1,472,526	0	2,345	194,739
Number of Borrowers	139.3	245.3	0	47	1069
Number of Loans	104.7	172.4	0	37	748
Average Days Late, Weighted by Loan Amount	27.7	172.0	0.0	1.2	652.3
Panel 3: Group Defined by Minority Religions and Government-Sanctioned Caste (N=446,188)					
Sum of Debt (1,000s of rupees)	2,126	7,550	0	25	32,872
Sum of Collateral (1,000s of rupees)	13,621	956,154	0	60	121,881
Number of Borrowers	58.9	166.3	0	1	733
Number of Loans	44.3	118.8	0	1	532
Average Days Late, Weighted by Loan Amount	84.9	2,073.8	0.0	1.4	1,829.0

Table 2: Empirical versus Random Officer Transition Probabilities, by Religion

In this table we report the branch officer transition probabilities, by officer religion. Panel A: actual transition frequencies in our sample. Panel 2: transition probability distribution based on actual frequencies. Panel 3, expected transition probabilities under the assumption of random assignment. Panel 4: p-values obtained from the χ^2 test of equality between empirical and the random transition probabilities.

Panel 1: Number of Officer Changes, by Outgoing/Incoming Officer Religion

	Outgoing Officer Religion:						
	Hindu	Muslim	Christian	Sikh	Parsi	Buddist	Others
Incoming Officer Religion:							
Hindu	2,698	53	75	45	1	9	4
Muslim	57	3	1	0	0	0	1
Christian	62	2	14	0	1	0	0
Sikh	43	0	0	10	1	0	0
Parsi	1	0	0	0	0	0	0
Buddist	6	0	0	0	0	0	1
Others	5	0	0	0	0	0	2

Panel 2: Empirical Transition Probabilities

	Outgoing Officer Religion:						
	Hindu	Muslim	Christian	Sikh	Parsi	Buddist	Others
Incoming Officer Religion:							
Hindu	87.173%	1.712%	2.423%	1.454%	0.032%	0.291%	0.129%
Muslim	1.842%	0.097%	0.032%				0.032%
Christian	2.003%	0.065%	0.452%		0.032%		
Sikh	1.389%			0.323%	0.032%		
Parsi	0.032%						
Buddist	0.194%						0.032%
Others	0.162%						0.065%

Panel 3: Expected Transition Probabilities under Random Assignment

	Outgoing Officer Religion:						
	Hindu	Muslim	Christian	Sikh	Parsi	Buddist	Others
Incoming Officer Religion:							
Hindu	87.841%	1.697%	2.023%	1.651%	0.047%	0.233%	0.233%
Muslim	1.697%	0.033%	0.039%	0.032%	0.001%	0.004%	0.004%
Christian	2.023%	0.039%	0.047%	0.038%	0.001%	0.005%	0.005%
Sikh	1.651%	0.032%	0.038%	0.031%	0.001%	0.004%	0.004%
Parsi	0.047%	0.001%	0.001%	0.001%	0.000%	0.000%	0.000%
Buddist	0.233%	0.004%	0.005%	0.004%	0.000%	0.001%	0.001%
Others	0.233%	0.004%	0.005%	0.004%	0.000%	0.001%	0.001%

Panel 4: p-value from χ^2 test of equality

	Outgoing Officer Religion:						
	Hindu	Muslim	Christian	Sikh	Parsi	Buddist	Others
Incoming Officer Religion:							
Hindu	0.71	0.99	0.82	0.91	0.99	0.97	0.95
Muslim	0.94	0.97	1.00				0.99
Christian	0.99	0.99	0.82		0.99		
Sikh	0.88			0.87	0.99		
Parsi	0.99						
Buddist	0.98						0.99
Others	0.97						0.97

Table 3: Empirical versus Random Officer Transition Probabilities, by Caste

In this table we report the branch officer transition probabilities, by officer caste (conditional on Hindu religion). Panel A: actual transition frequencies in our sample. Panel 2: transition probability distribution based on actual frequencies. Panel 3, expected transition probabilities under the assumption of random assignment. Panel 4: p-values obtained from the χ^2 test of equality between empirical and the random transition probabilities.

Panel 1: Number of Officer Changes, by Outgoing/Incoming Officer Caste

	Outgoing Officer Caste:			
	SC	ST	OBC	General
Incoming Officer Caste:				
SC	106	20	21	283
ST	18	23	10	71
OBC	21	9	20	101
General	240	67	107	1,750

Panel 2: Empirical Transition Probabilities

	Outgoing Officer Caste:			
	SC	ST	OBC	General
Incoming Officer Caste:				
SC	3.70%	0.70%	0.73%	9.87%
ST	0.63%	0.80%	0.35%	2.48%
OBC	0.73%	0.31%	0.70%	3.52%
General	**8.37%**	2.34%	3.73%	**61.04%**

Panel 3: Expected Transition Probabilities under Random Assignment

	Outgoing Officer Caste:			
	SC	ST	OBC	General
Incoming Officer Caste:				
SC	2.52%	0.78%	0.76%	11.82%
ST	0.78%	0.24%	0.23%	3.64%
OBC	0.76%	0.23%	0.23%	3.56%
General	**11.82%**	3.64%	3.56%	**55.44%**

Panel 4: p-value from χ^2 test of equality

	Outgoing Officer Caste:			
	SC	ST	OBC	General
Incoming Officer Caste:				
SC	0.529	0.967	0.989	0.296
ST	0.937	0.763	0.951	0.534
OBC	0.989	0.966	0.802	0.985
General	**0.065**	0.486	0.926	**0.003**

Table 4: Effect of Social Proximity on Loan Contracts – Religion

In this table we report the estimated effect of social proximity (religion) on lending patterns using specification (1). The unit of analysis is a branch-group-quarter, where group is defined by religion (Hindu, Muslim, Christian, Sikh, Parsi, and Buddhist). The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same religion. The variables Hindu, Muslim, Christian, Sikh, Parsi, Buddhist, and Non-Hindu are dummies equal to one if the borrower is of the corresponding religion. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	log of Sum Debt		log of # Borrowers	log of Sum Debt/ # Borrowers	log of Sum Collateral	log of Average Collateral/Debt	Dummy=1 if Sum Debt>0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SameGroup × Hindu	0.0168	0.0168	-0.0006	0.0177	-0.0233	-0.0314*	-0.0017
	(0.024)	(0.024)	(0.024)	(0.020)	(0.031)	(0.019)	(0.002)
SameGroup × Muslim	0.4069***						
	(0.114)						
SameGroup × Christian	0.2527***						
	(0.088)						
SameGroup × Sikh	0.3346***						
	(0.115)						
SameGroup × Parsi	0.7751***						
	(0.186)						
SameGroup × Buddhist	0.5185**						
	(0.213)						
SameGroup × Non-Hindu		0.3414***	0.1105***	0.2294***	0.2361***	-0.0553**	0.0593***
		(0.059)	(0.037)	(0.050)	(0.058)	(0.024)	(0.014)
Branch-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	139,736	139,736	146,753	139,736	143,654	139,736	264,804
R-squared	0.939	0.939	0.981	0.751	0.956	0.600	0.832

Table 5: Effect of Social Proximity on Loan Contracts – Government Sanctioned Castes (Hindu Borrowers Only)

In this table we report the estimated effect of social proximity (caste) on lending patterns using specification (1). The unit of analysis is a branch-group-quarter, where group is defined by government designated caste, and conditioning on Hindu borrowers (General Caste/SC/ST/OBC). The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same caste. The variables General Caste, SC, ST, OBC, and SC/ST/OBC are dummies equal to one if the borrower belongs to the corresponding caste. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	log of Sum Debt		log of # Borrowers	log of Sum Debt/ # Borrowers	log of Sum Collateral	log of Average Collateral/Debt	Dummy=1 if Sum Debt>0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SameGroup × General Caste	0.0471**	0.0471**	0.0104	0.0364***	0.0215	-0.0181*	0.0015
	(0.020)	(0.020)	(0.018)	(0.013)	(0.022)	(0.010)	(0.001)
SameGroup × SC	0.1612***						
	(0.036)						
SameGroup × ST	0.1589*						
	(0.090)						
SameGroup × OBC	0.2729***						
	(0.069)						
SameGroup × SC/ST/OBC		0.1868***	0.0398*	0.1507***	0.1317***	-0.0399**	0.0115*
		(0.030)	(0.021)	(0.024)	(0.032)	(0.016)	(0.006)
Branch-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,163	142,163	144,431	142,163	143,105	142,163	165,256
R-squared	0.914	0.914	0.954	0.785	0.931	0.628	0.773

Table 6: Effect of Social Proximity on Loan Contracts – Religion and Caste

In this table we report the estimated effect of social proximity (caste and religion) on lending patterns using specification (1). The unit of analysis is a branch-group-quarter, where group is defined by combining religion and caste based measures of social proximity (five minority religions and four government designated castes conditional on Hindu religion). The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same group. The variable Hindu - Same Caste is an indicator denoting that borrowers and the branch manager are both Hindu and belong to the same caste. The variable Minority Religion is a dummy equal to one if the borrower is non-Hindu. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	log of Sum Debt		log of # Borrowers	log of Sum Debt/ # Borrowers	log of Sum Collateral	log of Average Collateral/Debt	Dummy=1 if Sum Debt>0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SameGroup × Hindu - Same Caste	0.1197***						
	(0.018)						
SameGroup × Minority Religion	0.3407***						
	(0.059)						
SameGroup		0.1511***	0.0379***	0.1147***	0.1013***	-0.0455***	0.0148***
		(0.018)	(0.012)	(0.013)	(0.018)	(0.011)	(0.004)
Branch-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	237,810	237,810	247,053	237,810	242,657	234,577	385,926
R-squared	0.912	0.911	0.965	0.750	0.935	0.629	0.830

Table 7: Heterogeneity – Existing and First Time Borrowers

In this table we report the estimated effect of social proximity on lending patterns (specification (1)) separately for existing borrowers (Panel 1) and first time borrowers (Panel 2). Existing borrowers are those that obtained credit at any time in our sample prior to the arrival of the current officer in charge of the branch. First time borrowers receive their first credit from the Bank under the current officer. The unit of analysis is a branch-group-quarter, where group is defined by combining religion and caste based measures of social proximity. The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same group. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	log of Sum Debt (1)	log of # Borrowers (2)	log of Sum Debt/ # Borrowers (3)	log of Sum Collateral (4)	log of Average Collateral/Debt (5)	Dummy=1 if Sum Debt>0 (6)
Panel 1: Subsample of borrowers that had obtained credit from a previous officer						
SameGroup	0.0966***	-0.0067	0.1065***	0.0483**	-0.0463***	0.0135***
	(0.022)	(0.015)	(0.017)	(0.022)	(0.013)	(0.005)
Branch-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218,232	229,914	218,232	224,338	214,488	398,871
R-squared	0.893	0.955	0.754	0.927	0.651	0.855
Panel 2: Subsample of borrowers that had never obtained credit from the Bank						
SameGroup	0.1695***	0.1324***	0.0380**	0.1874***	0.0162	0.0109
	(0.030)	(0.023)	(0.019)	(0.033)	(0.014)	(0.007)
Branch-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185,783	191,480	185,783	188,729	183,424	397,116
R-squared	0.793	0.844	0.628	0.814	0.509	0.737

Table 8: Effect of Social Proximity on Loan Repayment

In this table we report the estimated effect of social proximity on loan repayment using specification (1). The unit of analysis is a branch-group-quarter, where group is defined by combining religion and caste based measures of social proximity. Repayment is measured as average number of days late in interest repayment weighted (not weighted) by debt amount in columns 1 through 3 (4 through 6). The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same group. Average repayment performance is included as the dependent variable contemporaneously in columns 1 and 4, and with a one-year lead in the rest. Columns 5 and 6 include the one year lead of the *SameGroup* variable in the regression. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	log of (Value Weighted) Average Days Late			log of (Unweighted) Average Days Late		
	Contemporaneous	One Year Lead		Contemporaneous	One Year Lead	
	(1)	(2)	(3)	(4)	(5)	(6)
SameGroup, Contemporaneous	-0.1401***	-0.1326***	-0.1288***	-0.0241	-0.0227	-0.0258
	(0.030)	(0.029)	(0.028)	(0.018)	(0.018)	(0.018)
SameGroup, One Year Lead			-0.0063			0.0132
			(0.027)			(0.018)
Branch-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	183,494	143,478	142,035	183,494	143,478	142,035
R-squared	0.815	0.850	0.851	0.721	0.745	0.745

Table 9: Identification Test – Saturated Model

In this table we report the estimated effect of social proximity on lending outcomes using the saturated specification (2). The unit of analysis is a branch-group-quarter, where group is defined by combining religion and caste based measures of social proximity. The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same group. The Branch-Quarter and Group-Quarter dummies absorb branch-specific and group-specific shocks, respectively. The State-Group-Quarter dummies absorb shocks that are specific to any given group in a particular location. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	log of Sum Debt			log of Average (Value Weighted) Days Late		
	(1)	(2)	(3)	(4)	(5)	(6)
SameGroup	0.1429***	0.1465***	0.1494***	-0.1371***	-0.1431***	-0.1422***
	(0.019)	(0.019)	(0.017)	(0.031)	(0.031)	(0.029)
Branch-Group Means Removed	Yes	Yes	Yes	Yes	Yes	Yes
Branch-Quarter Dummies	Yes	Yes		Yes	Yes	
Group-Quarter Dummies		Yes			Yes	
State-Group-Quarter Dummies			Yes			Yes
Observations	237,810	237,810	232,947	183,494	183,494	180,148
R-squared	0.299	0.306	0.106	0.410	0.421	0.088

Table 10: Empirical versus Random Officer Transition Probabilities, by Varna (Surname Match)

In this table we report the branch officer transition probabilities, by officer religious caste —Varna (Brahmin, Kshatriya and Vaishya). Individuals are assigned to a Varna using a surname-matching algorithm. Individuals that were classified by the algorithm into more than one Varna were grouped into one category (Multiple Matches) for the purposes of constructing this table. The algorithm failed in matching individuals to the Shudra Varna, son individuals that do not belong to the General Caste are classified into the Other category. Panel A: actual transition frequencies in our sample. Panel 2: transition probability distribution based on actual frequencies. Panel 3, expected transition probabilities under the assumption of random assignment. Panel 4: p-values obtained from the χ^2 test of equality between empirical and the random transition probabilities.

Panel 1: Number of Officer Changes, by Outgoing/Incoming Officer Varna

	Outgoing Officer Varna:				
	Brahmin	Kshatriya	Vaishya	Multiple Matches	Other
Incoming Officer Varna:					
Brahmin	29	52	11	19	45
Kshatriya	53	127	34	42	84
Vaishya	18	27	18	8	17
Kshatriya/Brahmin/Vaishya	24	39	7	23	33
Other	38	81	14	23	96

Panel 2: Empirical Transition Probabilities

	Outgoing Officer Varna:				
	Brahmin	Kshatriya	Vaishya	Multiple Matches	Other
Incoming Officer Varna:					
Brahmin	3.01%	5.41%	1.14%	1.98%	4.68%
Kshatriya	5.51%	13.20%	3.53%	4.37%	8.73%
Vaishya	1.87%	2.81%	1.87%	0.83%	1.77%
Kshatriya/Brahmin/Vaishya	2.49%	4.05%	0.73%	2.39%	3.43%
Other	3.95%	8.42%	1.46%	2.39%	9.98%

Panel 3: Expected Transition Probabilities under Random Assignment

	Outgoing Officer Varna:				
	Brahmin	Kshatriya	Vaishya	Multiple Matches	Other
Incoming Officer Varna:					
Brahmin	3.01%	5.37%	1.55%	2.03%	5.40%
Kshatriya	5.37%	9.57%	2.76%	3.62%	9.62%
Vaishya	1.55%	2.76%	0.79%	1.04%	2.77%
Kshatriya/Brahmin/Vaishya	2.03%	3.62%	1.04%	1.37%	3.64%
Other	5.40%	9.62%	2.77%	3.64%	9.68%

Panel 4: p-value from χ^2 test of equality

	Outgoing Officer Varna:				
	Brahmin	Kshatriya	Vaishya	Multiple Matches	Other
Incoming Officer Varna:					
Brahmin	1.00	0.99	0.90	0.99	0.82
Kshatriya	0.96	0.26	0.81	0.82	0.78
Vaishya	0.92	0.99	0.74	0.95	0.76
Kshatriya/Brahmin/Vaishya	0.89	0.89	0.92	0.75	0.95
Other	0.65	0.71	0.68	0.70	0.93

Table 11: Effect of Social Proximity on Loan Contracts – Varna (Surname Match)

In this table we report the estimated effect of social proximity on loan outcomes using specification (1). The unit of analysis is a branch-group-quarter, where group is defined by Varna, the caste system that was prevalent in ancient India. Individuals are assigned to Varnas using a surname-matching algorithm. Individuals classified by the algorithm into more than one Varna are allocated to three mixed groups: Kshatriya-Brahmin, Kshatriya-Brahmin-Vaishya, and Kshatriyas-Vaishyas. Individuals that are not in the General Caste category are excluded, because the algorithm cannot correctly identify individuals from the Shudra Varna. The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same group. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%

Dependent Variable	log of Sum Debt	log of # Borrowers	log of Sum Debt/ # Borrowers	log of Sum Collateral	log of Average Collateral/Debt	Dummy=1 if Sum Debt>0	log of Average (Weighted) Days Late	
							Contemporaneous	One Year Lead
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SameGroup (Varna)	0.1347***	0.0149	0.1224***	0.1152***	-0.0186	0.0149*	-0.1511**	-0.1503**
	(0.034)	(0.014)	(0.031)	(0.030)	(0.020)	(0.008)	(0.075)	(0.066)
Branch-Group Fixed Effects	Yes		Yes	Yes		Yes	Yes	Yes
Quarter Dummies	Yes		Yes	Yes		Yes	Yes	Yes
Observations	67,996	71,134	67,996	70,064	67,996	104,854	46,810	36,222
R-squared	0.894	0.965	0.759	0.928	0.621	0.858	0.797	0.824

Table A.1: Effect of Social Proximity on Ex Ante Borrower Credit Rating

To verify whether officers reallocate credit to borrowers of a better observable ex ante credit quality, we report in this table the estimated effect of social proximity on the credit rating of loan recipients using specification (1). The unit of analysis is a branch-group-quarter, where group is defined by combining religion and caste based measures of social proximity. The credit rating is a score between 0 and 100 that is increasing with the default probability of the borrower, weighted (not weighted) by debt amount in column 1 (column 2). The variable SameGroup is an indicator denoting that borrowers and the branch manager are of the same group. Standard errors are clustered at the branch level. * significant at 10%; ** significant at 5%; *** significant at 1%. The precisely estimated zeroes in both specification indicate that officers do not shift credit towards *observably* better borrowers of their own group.

Dependent Variable	Credit Rating	
	Value Weigthed	Unweighted
	(1)	(2)
SameGroup	-0.0655	-0.1553
	(0.049)	(0.108)
Branch-Group Fixed Effects	Yes	Yes
Quarter Dummies	Yes	Yes
Observations	183,494	183,494
R-squared	0.774	0.806