Does financial inclusion mitigate social exclusion? Causal evidence from India

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Abstract

This paper examines whether financial inclusion can reduce social exclusion. We leverage the quasi-experimental setup of a bank branch authorization policy adopted by Reserve Bank of India in 2005, where banks were incentivized to open new branches in the under-banked districts. Using data from three pan-India survey and census datasets, we carry out a regression discontinuity design analysis. Our results show that marginalized castes experience a significant increase in consumption and reduction in poverty compared to the non-marginalized castes, thereby narrowing down the caste-based welfare inequality. Our results also furnish evidence towards an increase in the social inclusion of marginalised castes. We explore three indirect channels that explain why the marginalized castes benefit the most in terms of welfare gain: informal finance channel, business finance channel and labour market channel. Results are robust to all the RD design checks, including pre-policy smoothness, donut hole test, placebo cutoff, second-order polynomial, bandwidth selector and bandwidth multiplier checks. Overall, this paper highlights the importance of strengthening the formal banking sector and making it more inclusive in order to reduce the sticky social norms like caste-based discrimination.

Keywords: Financial Inclusion, Caste Discrimination, Social Exclusion, Bank Expansion Policy, Poverty

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1 Introduction

Access to formal financial services is argued to have a wide range of developmental impacts, both direct and indirect, on household well-being, women's empowerment and accumulation of human capital, especially in underdeveloped and developing countries [Burgess and Pande, 2005; Ashraf et al., 2006; Kochar et al., 2022; Ngo and Wahhaj, 2012; Dupas and Robinson, 2013]. Accordingly, in recent years, countries all around the globe have started to prioritize extending access of financial services to underprivileged and vulnerable groups of the society in their respective policymaking process, which is often termed as financial inclusion. Highlighting its wide range of developmental impacts, financial inclusion has been identified as an enabler for seven out of the seventeen Sustainable Development Goals (SDGs). In India, one of the major barriers to financial access is caste-based discrimination, especially in regions where informal financial sector predominates. Discrimination against marginalized castes, which is often referred to as social exclusion, is also at the core of disparities between marginalized and non-marginalized castes in terms of consumption, wealth and other well-being outcomes [Deshpande, 2000; Banerjee et al., 2013; Munshi and Rosenzweig, 2006; Arunachalam and Shenoy, 2017]. In this paper, we leverage a bank branch expansion policy of the Reserve Bank of India (RBI)[1] to show whether financial inclusion can reduce this caste-based welfare disparity and caste-based discrimination in all spheres of the society.

We contribute to the literature by highlighting financial inclusion as a policy measure to mitigate caste-based social exclusion, which has historically been a sticky norm in India. In a two-step analysis, we first show that financial inclusion improves across all caste categories following the bank branch expansion policy of RBI. Subsequently, we establish that the household welfare indicators, such as consumption and poverty, improve mostly for the marginalized castes, reflecting the reduction in welfare disparity between marginalized and non-marginalized castes. We also

[1] RBI is the central bank of India, responsible for regulating the banking sector in India

emphasize that the results are due to caste disparity and not due to income disparity, by controlling for permanent income of the households, generated using the Least Absolute Shrinkage and Selection Operator (LASSO). This is a pioneering attempt in the literature to disentangle caste and class effects in a causal framework.

Another noteworthy contribution of our study is the explanation of possible channels of impact in a general equilibrium framework. Apart from the direct channel of financial inclusion via formal sector, we analyze informal credit market and labour market. We also investigate how businesses owned by different castes are being able to obtain loans from banks after the policy implementation and link this business finance channel with the labour market. To comprehend the mechanisms more closely, we disaggregate the impacts for agricultural and non-agricultural sectors. The intricacy of the mechanisms helps us to explain our results from all possible angles and weaves a strong message for policymakers.

We also attempt to identify how a reduction in discrimination in one sector of society spills over to other spheres. We show how the expansion of the formal sector reduces discrimination in the informal credit market, indicated by a reduction in interest rates for marginalized castes, and also in the labour market, indicated by an increase in the wages of marginalized castes. We then create a quantitative measure of social inclusion, a dummy variable taking value one if the household is a member of one or more socioeconomic groups in the community and zero otherwise. Results show that social inclusion increases for marginalized castes after the policy in treatment districts.

For our analysis, we combine data from RBI Master Office File (MOF) with three pan-India survey and census datasets: Indian Human Development Survey (IHDS), All India Debt and Investment Survey (AIDIS) and Economic Census (EC). The novelty of these datasets lies in the fact that they have one survey round before the policy and one after the policy, which allows us to carry out the standard pre-policy smoothness checks for each post-policy results in a regression discontinuity setup and helps us to claim causality for our results. To set up a regression discontinuity design framework, we leverage the 2005 bank branch authorization policy of RBI. The policy classifies the districts into banked and underbanked categories and incentivizes the banks to open branches in the underbanked districts by increasing their chances of obtaining licenses in favoured locations. Our results show that marginalized castes experience a significant increase in consumption and reduction in poverty in treatment districts after the implementation of the policy, whereas no such significant impact is observed for non-marginalized castes. As a direct channel of welfare enhancement, we find an increase in financial inclusion of marginalized castes after the policy in treatment districts. As an indirect channel, in the informal credit market, lenders face competition after the formal sector expansion and are compelled to reduce discrimination against marginalized castes in the form of lower interest rates, allowing them to take out more informal loans for consumption purposes. On the other hand, the non-discriminatory nature of formal loans allows the marginalized castes to take out more agricultural loans, which increases their agricultural productivity as well as crop income. We find that non-marginalized groups prefer formal loans for business expansion, which creates additional labour demand in the market and raises the wages of marginalized groups, thereby acting as an additional welfare-enhancing channel for them.

Our results are robust to all the standard RD design checks. We start by showing the pre-policy smoothness of the outcome variables, which rules out the possibility of any manipulation near the cutoff. Then, we use six placebo cutoffs to show that the results are only valid for the cutoff specified in the policy. To emphasize the strength of our results, we re-estimate our RD coefficients using second-order polynomial in the model and show that our results hold still. Furthermore, we establish the robustness of our results to four alternative bandwidth selection methods and four different bandwidth multipliers in the RD framework. Lastly, following the latest RD literature, we carry out a donut hole test to discard any sensibility of the results to the observations closest to the cutoff.

The rest of the paper is organized in the following sections. Section 2 outlines the existing literature, and section 3 lays out a conceptual framework for our study. Section 4 describes all the datasets we use for our study. Section 5 outlines the regression discontinuity framework and provides evidence of its validity. Section 6 and 7 discuss the main results and mechanisms, respectively. Section 8 furnishes the robustness checks and finally, section 9 concludes.

2 Literature Review

Caste has historically been a major source of discrimination in Indian societies [Deshpande, 2011]. The caste system originated from the occupation-based classification or *varna* system[2], which dates back to 1500-500 BCE, with hundreds of *jatis* within each *varna* [Munshi, 2019]. There are four major caste groups in India, the Scheduled Castes (SCs), Scheduled Tribes (STs), Other Backward Castes (OBCs) and Unreserved Castes, who are often referred to as General Castes. The SCs were historically the *untouchables* and hence encountered the highest level of discrimination [Munshi, 2019; Bagde et al., 2016]. STs, the indigenous ethnic groups (tribals), are also economically and socially marginalised [Munshi, 2019]. OBCs, described as 'Socially and Educationally Backward Classes' (SEBC) in Article 340 of the Indian constitution, stand higher than the SCs but lower than the general castes in the social hierarchy [Deshpande, 2011]. In this paper, we refer to the non-general castes as marginalised castes, but the level of marginalisation and discrimination is not the same for all.

The caste identity of an individual has always been a determining factor in education [Munshi and Rosenzweig, 2006; Hanna and Linden, 2012; Hoff and Pandey, 2014], access to healthcare services [Luke and Munshi, 2007], access to public goods [Anderson, 2011] and marital choices [Munshi and Rosenzweig, 2009]. The Government of India has undertaken world's largest affirmative action program to eliminate caste-based discrimination and social exclusion, but caste

[2]Brahmins (priests), Kshatriyas (warriors), Vaishyas (merchants), and Shudras (menial workers) were the four major *varnas* in India. One other group (the so-called *Dalits*) fell outside the caste system, and they were considered "untouchables" [Bidner and Eswaran, 2015].

continues to play a significant role in all facets of Indian society, even among the ostensibly progressive educated urban population [Banerjee et al., 2013].

In the labour market, the caste identity often restricts occupational mobility [Munshi and Rosenzweig, 2006] and gives rise to caste-based wage discrimination where marginalised workers systematically get lower wages compared to their non-marginalised counterparts [Banerjee and Knight, 1985; Ito, 2009; Das and Dutta, 2007]. Furthermore, workers from marginalised castes often get assigned to less prestigious jobs [Das and Dutta, 2007; Deshpande and Sharma, 2016]. The implication of caste in the labour market is so intense that workers often decline higher wages to avoid employments that do not fit with their caste identity [Oh, 2023].

Caste also acts as a barrier to access to credit in many parts of India, majorly in informal credit markets where the rate of interest charged can be heavily impacted by the caste-biasedness of the informal lender [Kumar, 2013; Mosse, 2018]. A vast range of literature suggests that credit constraint can induce income inequality [Demirgüç-Kunt and Levine, 2009], hinder agricultural investment and income growth [Kaboski and Townsend, 2012] and limit entrepreneurial opportunities [Banerjee et al., 2017]. Credit constraints stemming from caste discrimination, which typically manifest in a wide gap in the rate of interest faced by marginalised and non-marginalised caste borrowers, act as a significant channel of caste disparity.

Our paper also connects with the literature that attempted to examine the impacts of bank presence in developing countries. Leveraging the exogenous branch expansion policy of RBI during 1977 and 1990 in rural unbanked districts[3], Burgess and Pande [2005] establish the effectiveness of formal banking sector expansion in reducing rural poverty. In this paper, we leverage the exogenous bank branch authorization policy (2005) of RBI, which earmarked some districts as 'underbanked' based on a random cutoff and incentivised the commercial banks (except regional rural banks) to open branches in those districts in order to increase their chance of obtaining

[3]This policy is often termed as Social Banking Policy of India. For more details, see Burgess et al. [2005]; Burgess and Pande [2005]

licenses for favoured locations[4]. Existing literature by Young [2017] and Cramer [2021] have already established that this particular policy has indeed led to the expansion of bank branches in the treatment (underbanked) districts. Young [2017] shows that this policy has led to an increase in both agricultural and manufacturing outputs and, thereby, an increase in the local GDP proxied by night-time luminosity. Cramer [2021] further investigated the impact of this policy on health outcomes and found positive health impacts resulting from higher institutional loan, better offering of health insurance and better health infrastructure. Gupta and Sedai [2023] found that the impact of the policy on overall household well-being has been more prominent in urban areas. Our present study focuses broadly on the distributional impacts of the policy on the financial inclusion and welfare of different caste groups in India and shows that marginalised caste groups gain significantly more compared to their non-marginalised counterparts. In other words, the policy induces marginalised caste groups to catch up with non-marginalised groups.

3 Conceptual Framework

The discussion in section 2 outlines the existing literature on caste-based discrimination and social exclusion in India, which is argued to have resulted in a significant welfare disparity between marginalised and non-marginalised castes in India [Deshpande, 2000; Kijima, 2006]. For our study, apart from the social exclusion induced by caste-based discrimination, we focus on two sectors, informal credit market and labour market, where discrimination against marginalized castes has led them to significantly fall behind their non-marginalized counterparts in terms of overall household welfare. In panel A of figure 1, we depict this pre-policy status quo.

Our main findings from this study suggest that the banking expansion policy of 2005 has led to a significant reduction in caste-based welfare disparity because the benefits of the policy mainly accrued to the marginalised castes. Why did marginalised castes benefit more from the bank

[4] For details of the policy framework, please refer to section 5.1

expansion policy? We seek the answer in a general equilibrium framework, which is depicted in panel B of figure 1. Our analysis again focuses on the informal credit market and the labour market and we try to unravel what happens in those two sectors after the implementation of the policy. As an immediate impact of the policy, the entry of banks into the market raises competition for informal lenders. They may also borrow from the formal sector and distribute the funds as informal loans [Conning and Udry, 2007; Sagrario Floro and Ray, 1997]. Increased competition and higher availability of funds to lend out induce the informal lenders to mitigate discriminatory practices towards borrowers from marginalised castes, manifesting in a reduced interest rate.

On the other hand, the establishment of a bank branch enhances the accessibility to business loans and thereby fosters overall productive activity in the locality. This results in higher labour demand, contributing to reduced labour market discrimination [Becker, 2010]. With the additional labour demand, business owners find it rational to hire workers from marginalised castes, whose wages are cheaper compared to non-marginalised workers. Furthermore, the diminished prevalence of discrimination in the informal credit market and labour market has a cascading effect on other spheres of the society, ultimately resulting in the broader social integration of marginalized castes. In a nutshell, reduced interest rates, increased wages and overall social inclusion lead to the extra welfare gain of marginalised castes and enable them to catch up with their non-marginalised counterparts in terms of overall household welfare.

Insert Figure 1 about here

4 Data

For our analysis, we use data from the following four sources: (a) Reserve Bank of India's (RBI) Master Office File (MOF), (b) Indian Human Development Survey (IHDS), (c) All India Debt and

Investment Survey (AIDIS) and (d) Economic Census. In figure 2, we provide a brief timeline of all the datasets. Below is a detailed discussion of how we use these datasets for our analysis.

Insert Figure 2 about here

4.1 Master Office File of RBI

The Master Office File (MOF) of RBI contains detailed information about all the bank branches operating in India. The file is maintained separately for commercial banks and cooperative banks. Within commercial banks, there are five main classifications: (a) State Bank of India (SBI) and its associates, (b) Nationalised Banks, (c) Private Sector Banks, (d) Foreign Banks, and (e) Regional Rural Banks (RRBs). The policy was aimed at all commercial banks excluding RRBs. Hence our focus is also on the same. From the MOF file, we get the number of bank branches in 581 districts in India, which helps us to construct the running variable for RD design.

4.2 Indian Human Development Survey (IHDS)

IHDS is the largest panel survey in India, conducted in two waves, 2004-05 and 2011-12. Since wave 2 was conducted six years after the policy introduction, we use it for the main results and wave 1 data for the pre-policy smoothness check. We first merge the IHDS data with the RBI MOF data to carry out the RD analysis. A total of 371 districts from 581 districts in MOF data are merged with IHDS panel. However, this does not threaten our study because the IHDS dataset is nationally representative. In table A1, we compare the distribution of different caste categories in IHDS with other nationally representative and contemporary datasets like NFHS-3, NSS and population census, and show that the percentage shares of four caste categories are similar for all these surveys. Furthermore, in table A8, we furnish evidence that IHDS subsample is random and does not bias the data-generating process.

From IHDS, we use the outcome variables related to financial inclusion and household welfare. Financial inclusion is measured by five indicators: having a savings/current account with a bank, taking a loan from bank, having a long-term fixed deposit in the bank, investing in a financial market security (mutual fund/bonds/shares/unit trust) and purchasing life/health insurance. Household welfare is measured by another set of five variables: household consumption, household food consumption, poverty, multidimensional poverty and social inclusion. Consumption is represented by quintiles of total annual household consumption, whereas food consumption is measured by quintiles of total monthly food consumption of the household. Poverty is a dummy variable; takes value 1 if the household falls below the poverty line defined by the Tendulkar cut-off [5]. Multidimensional poverty is another indicator of poverty in a broader sense, which takes into account three dimensions of overall household welfare: education, health and living standards[6]. Following Alkire and Foster [2011], we calculate a multidimensional deprivation score of the household, ranging from 0 to 1, where a higher score implies that the household is more multidimensionally poor. Our outcome variable, multidimensional poverty, is a dummy variable that takes the value 1 if the multidimensional poverty score is above or equal to 0.33 (the standard cutoff defined by Alkire and Foster [2011]). Lastly, social inclusion is a dummy variable, which takes the value 1 if the household is a member of more than one social group in the community[7]. In table 1, we provide summary statistics of all the outcomes we use from IHDS[8].

[5]Tendulkar Committee was formed in 2009 with Suresh Tendulkar as the chairperson. This is a consumption-based poverty line, which has been used by the Planning Commission of India [Thorat et al., 2017]. Instead of using the Universal Reference period, the Committee used the Mixed Reference period and recommended new poverty lines for urban and rural areas.

[6]For the education dimension, we use two indicators: school enrolment of children, years of education of adult members. Indicators for the health dimension are infant mortality and malnutrition of the members. Indicators for living standards are clean cooking fuel, electricity, safe drinking water, proper sanitation, pucca flooring and possession of household durables like TV, motorcycle, refrigerator etc.

[7]From IHDS, we get information on whether the household is a member of different social groups, like religious groups, caste associations, cooperatives, unions, ROSCAs, self-help groups, Panchayet, and NGOs. We contend that membership in these groups can be an indicator of social inclusion.

[8]All these outcome variables are drawn from IHDS household file, except multidimensional poverty, which is drawn from the individual data. This is because we need education and health data of each household member to calculate the multidimensional poverty

4.3 All India Debt and Investment Survey (AIDIS)

AIDIS is a nationally representative survey containing detailed information on credit access, asset holding and indebtedness of Indian households. RBI started this survey under the name of 'All India Rural Credit Survey' in 1951-52 with a broad objective of using the collected data for designing banking policies. In 1971, RBI entrusted the data collection process for this survey to National Sample Survey Organization (NSSO) and since then, NSSO has been conducting this survey every ten years. For our current analysis, we choose two rounds of this survey: AIDIS 2003 (NSS 59th round) and AIDIS 2013 (NSS 70th round), and we merge both these datasets separately with the MOF data. AIDIS 2013 is used for the main results, and AIDIS 2003 for the pre-policy smoothness check.

AIDIS has a wide set of information on the loans taken by the households, including source of loan (credit agency), amount of loan, year of taking the loan, type of mortgage, purpose of loan, interest rate etc. This set of information allows us to study the impact of banking expansion policy on the credit market more closely and in more detail.

AIDIS also has information on the asset holding of the households. We use the data on agricultural equipment and ownership of livestock to understand a part of the agricultural labour market channel, which we shall explain in detail while discussing the results. In table 2, we furnish the summary statistics of the variables we use from AIDIS.

4.4 Economic Census

The economic census of India provides detailed information on all the entrepreneurial units (agricultural and non-agricultural) operating within the geographical boundary of India. It is carried out by the Ministry of Statistics and Program Implementation (MoSPI), Government of India, and covers all the districts in all states of India. So far, six economic censuses have been conducted in 1977,1980,1990, 1998, 2005 and 2013.

The economic census has a set of variables, including the nature of the entrepreneurial unit, its main source of finance, information about the caste of the owner, the location of the unit (rural/urban) etc. We use the data from the sixth economic census (EC 2013) and merge it with the RBI MOF data to analyze how the source of finance changes for entrepreneurial units owned by different caste categories after the policy. The information on the nature of the unit (agricultural/non-agricultural) further allows us to study the pattern of the change in the source of finance for these two types of enterprises. Then, we merge the fifth economic census (EC 2003) to check the pre-policy smoothness of the main results. In table 3, we present the summary statistics of the variables we use from the economic census.

5 Empirical Strategy

5.1 Regression Discontinuity Framework

In 2005, RBI introduced a bank branch authorization policy that incentivizes commercial banks (excluding Regional Rural Banks) to open branches in 'underbanked' districts in order to increase their chance of obtaining branch-opening licenses for favoured locations. The root of the RD framework lies in the definition of 'underbanked' districts used by RBI. A district is tagged as 'underbanked' when the ratio of population to the number of bank branches in the district exceeds the national ratio. Therefore, the district-level population-to-bank branch ratio acts as the running variable and the national-level ratio (computed to be 14,780) acts as the cutoff in our regression discontinuity framework. Panel (a) of figure 3 depicts the histogram for the running variable. As presented in equation 1, a district d is defined as underbanked or treated (T_d) if the district-level ratio is higher than the cutoff, and if the ratio is below the cutoff, the district falls into the set of 'banked' or 'control' districts.

$$Treated_d \ (T_d) = \mathbf{1}\left(\frac{Population\ of\ district\ d}{No\ of\ bank\ branches\ in\ district\ d} > \frac{National\ population}{Total\ no\ of\ bank\ branches}\right) \tag{1}$$

In 2006, RBI published a list of underbanked districts, but that list does not include the district-level population-to-branch ratios. So we reconstruct the ratio for each district using district population data from census 2001 and number of bank branches data (during quarter 1 of 2006) from RBI. However, there are 12 districts for which the predicted underbanked status from our reconstructed ratio is different from their 'underbanked' status as per the RBI list. As noted in Cramer [2021] and Gupta and Sedai [2023], RBI could have used its own discretion in determining the underbanked status of these 12 districts, which makes the treatment assignment rule probabilistic and not deterministic [Hahn et al., 2001]. However, this does not pose a threat to our identification as we adopt the fuzzy RD design instead of the sharp design [Lee and Lemieux, 2010; Dong and Lewbel, 2015]. Panel (b) of figure 3, which indicates a jump in the probability of being listed as underbanked by RBI at the cutoff, provides a graphical justification for our fuzzy design.

Insert figure 3 about here.

Following the fuzzy RD framework, we use the specification in equations 2 and 3 to estimate the impact of the bank authorization policy on different caste groups.

$$U_d = \beta_0 + \beta_1 T_d + \beta_2 R_d + \beta_3 T_d R_d + \alpha_1 X_d + e_d \tag{2}$$

$$Y_{h,d} = \delta_0 + \delta_1 U_d + \delta_2 R_d + \delta_3 R_d T_d + \alpha_2 X_d + v_d \tag{3}$$

Here, U_d is a dummy variable that takes the value one if district d is listed as underbanked by RBI, T_d is another dummy variable that takes the value one if the district-level ratio is higher than the cutoff and R_d is the running variable (the district-level population-to-branches ratio). $Y_{h,d}$ is the outcome variable of household h in district d and X_d is a vector of controls. Following Abadie et al. [2023], we cluster the standard errors at the district level as our treatment is homogeneous across districts. Under the identifying assumption, the coefficient δ_1 in equation 3 can be interpreted as the local average treatment effect (LATE) of belonging to a district that has received the 'underbanked' status.

5.2 Validity of identifying assumption

The main identifying assumption that makes the above RD framework empirically valid is that the districts above and below the cutoff are similar in all aspects except the status of banked/underbanked, which can be achieved if the local governments have no power to manipulate the value of the running variable. One implication of this assumption is the smoothness of the running variable around the cutoff. Intuitively, given that the district population data comes from 2001 census, four years before the policy, and the data for the number of branches comes straight from RBI, manipulation of both these components of the running variable by district administrations seems logically impossible [Cramer, 2021]. The histogram of the running variable around the cutoff in figure 3 tells the same story. Further, to test this 'smoothness around the cutoff' assumption formally, we employ the McCrary test, as proposed by McCrary [2008]. The result of the test is depicted in figure A1, which formally establishes the validity of our assumption. Additionally, to add another layer of robustness to the McCrary test results, we carry out the binomial test proposed by Cattaneo et al. [2017] in table A2, which further strengthens the validity of the RD design[9].

Another implication of the identifying assumption is that prior to the implementation of the pol-

[9] The binomial test verifies if the number of observations in the control and treatment groups around the cutoff is significantly different from the expected number in a random sample of Bernoulli trials with a specific probability. Unlike the McCrary test, this test does not depend on asymptotic approximations [Cattaneo and Titiunik, 2022].

icy, the outcome variables of interest should not be significantly different for the treated and control districts. We examine this empirically from pre-policy smoothness checks, using IHDS 2004-05, Economic Census 2005 and AIDIS 2003, as discussed in section 4. Results of pre-policy smoothness checks are furnished in tables A3, A4, A5 ,A6 and A7. As expected, the fuzzy RD coefficient, δ_1, is insignificant for all these results, implying that pre-policy smoothness holds for our outcome variables of interest. In figure 4, we show the pre-policy smoothness for the main welfare outcomes for SCs.

Another potential threat to identification is the existence of analogous policies during our study period. Here we refer to the previous study by Cramer [2021] that extensively furnishes evidence of the absence of similar contemporaneous policies, which provides strength to our identification.

Insert figure 4 about here.

6 Results

6.1 Banks and financial inclusion across caste groups

We start our analysis by examining the causal impact of the banking expansion policy on the financial inclusion of three caste categories in India: SC, OBC and General. We aim to compare the outcomes of socially marginalized castes with non-marginalized castes and thereafter examine if the marginalized castes catch up with their non-marginalized counterparts in terms of financial inclusion. We exclude Scheduled Tribes (STs) from our analysis for two reasons. First, the ST population is concentrated in a few states in India, especially in north-eastern states [Kijima, 2006] like Arunachal Pradesh (88.15% of the population are STs), Nagaland (80.59%), Mizoram (99.35%), Meghalaya (82.09%)[10] etc. In those areas, they are the majority group and

[10] Calculated from IHDS

are not likely to face social discrimination and marginalization. And second, they historically do not fall into *the so-called* 'Dalit' caste who face most discrimination [Kumar, 2013]. Muslims are also excluded from our analysis because of data constraints. In IHDS, data for castewise categorization is available only for Hindus, not for any other religions.

According to a 2008 report of a government committee, financial inclusion entails extending access to several financial services offered by the formal banking sector to underprivileged groups [Rangarajan et al., 2008]. These financial services include access to credit at an affordable rate, access to bank savings, insurance, remittance facilities and financial consulting/advisory services. In our analysis, we focus on five dimensions of financial inclusion: having a savings/current account in the bank, taking loan from the bank, having long-term savings (fixed deposit) in a bank, buying securities and buying insurance. We use RD estimates to demonstrate that overall financial inclusion increases across all caste categories. The results are furnished in table 4 and the discontinuities induced by the RD framework are graphically represented in figure 5. In treatment districts, the likelihood of having a bank account increases by 71% for SCs, 27% for OBCs and 37% for generals. This enormous improvement in bank account opening can be explained by examining clause 3.b of the relevant RBI policy circular, where it is stated that banks should prioritize basic/no-frills bank accounts. Another important indicator of financial inclusion, bank loan, increases for SCs and Generals by 40% and 21%, respectively[11]. Long-term fixed deposits with banks increase only for OBCs and Generals. The literature has established that marginalized castes are mostly economically backward compared to other castes [Kijima, 2006; Deshpande, 2011; Mosse, 2018]. They don't have enough savings for a long-term investment. Hence, we don't observe any statistically significant increase in long-term deposits for SCs. Another instrument for long-term investment is purchasing securities, including mutual funds, shares, bonds etc. The likelihood of investing in these financial instruments increases only for the general category

[11]The number of observations in the bank loan variable is smaller compared to the other financial inclusion indicators. This is because we restrict our sample to all the households who took any loan in last five years and our objective is to understand if the loan-taking households in treatment districts opt more for formal bank loans compared to control districts.

by 55% in treatment districts.

When a bank branch is established in an area, it strengthens not only the financial markets but also the entire financial system. In terms of risk mitigation, insurance companies are a significant element of the financial system. As the financial system strengthens, insurance companies begin to offer a variety of new insurance products, particularly tailored to those who previously could not afford coverage. On the other hand, sometimes banks also offer insurance and sometimes insurance products come as an add-on with the regular bank account. This affordability option helps marginalized caste groups to purchase life/health insurance products, which is reflected in a 42.2% increase in the likelihood of being insured for SCs in the treatment districts compared to SCs in control districts.

To sum up, we observe that after the implementation of the policy, SC households are more likely to open a bank account, obtain bank loans and purchase insurance. General category households are also more likely to take bank loans, but unlike SCs, they are likely to make long-term investments like fixed deposits or buying securities. For OBCs, all the impacts are in a positive direction but not statistically significant except for fixed deposits. Overall we can say that financial inclusion increases across all caste categories, albeit not necessarily along the same dimensions.

Insert Table 4 about here

Insert Figure 5 about here

6.2 Banks and household welfare across caste groups

In subsection 6.1, we find that financial inclusion, in a broad sense, increases for all caste categories. To answer the question 'to which caste category do the majority of benefits accrue?', we delve deeper and examine how various household well-being measures are affected across caste categories following the implementation of the policy. As mentioned before, we look at the causal impact of the banking expansion policy on five indicators of household welfare: consumption, food consumption, poverty, multidimensional poverty and social inclusion. The results are furnished in table 5. The graphical representations of the post-policy discontinuities are shown in figure 6.

From panel (a) of table 5, We find that only SC consumption increases by 16% in treatment districts. Consumption is an important indicator of welfare for SCs because, on average, they consume less than other caste categories due to lower levels of income and limited access to resources and opportunities [Deshpande, 2000; Kijima, 2006; Deshpande, 2011]. Consequently, the increase in consumption for SCs, not for other castes, has a broader implication in terms of convergence of consumption across castes.

Consumption can be subdivided into several categories like food consumption, clothing, household appliance expenditure etc. The most crucial among these is food consumption, which is linked to an individual's overall health/nutritional status and consequentially, to his/her income-earning potential. As presented in panel (b), food consumption increases by 19% for SCs and 18% for OBCs in treatment districts compared to SCs and OBCs in the control districts.[12]

Poverty is another indicator of household well-being, especially for SCs. As per the IHDS 2004-05 data, 27.3% SC households live below the poverty line, whereas the same numbers for OBCs and generals are comparatively lower, 21% and 9%, respectively. For SC households living under the poverty line, an additional component of poverty-based social exclusion is added to the existing caste-based social exclusion. Panel (c) of table 5 shows a 59.7% reduction in the likelihood of falling below the poverty line for SC households, compared to a control mean of 0.174. Poverty reduction for OBCs and generals is, however, not statistically significant. Since

[12] We estimate the impacts on other types of consumption as well, including household appliances, clothing and utensils. All of these significantly increase only for the SCs.

Tendulkar poverty cutoff is based primarily on consumption, this result is consistent with the result in panel (a).

Apart from the conventional definition of poverty based on poverty cutoff, we also use a more comprehensive poverty indicator, multidimensional poverty. As discussed in section 4, it encompasses three dimensions of household welfare: education, health and living standards. From panel (d), we observe that multidimensional poverty declines across all caste categories in the treatment districts.

Our last household welfare indicator, social inclusion, is paramount for our study. Social inclusion signifies lesser discrimination against marginalized castes. Not only does it have direct implications for household welfare [Petrikova, 2020], but it also helps in understanding the underlying mechanisms of our findings. We define social inclusion as having a membership in more than one socioeconomic groups in the area. In panel (e) we show that the likelihood of social inclusion increases only for the SCs in treatment districts, and it almost doubles (increases by 123%).

In a nutshell, after the policy implementation, SC households in treatment districts experience the greatest improvements in household welfare, in terms of increased consumption, reduced poverty, and increased social inclusion. However, multidimensional poverty increases for all caste categories, indicating that the benefits accrue to other castes as well, albeit to a lesser extent than SCs. The convergence of fundamental welfare states across castes is implied by increased consumption and reduced consumption-based poverty only among SCs in treatment districts.

Insert Table 5 about here

Insert Figure 6 about here

7 Mechanisms

In the literature, it has widely been accepted that financial inclusion improves household welfare. In section 6, we demonstrate that financial inclusion increases across all caste categories, whereas household welfare increases predominantly for the SC category. Therefore, there should be some additional channels alongside the financial inclusion channel that reinforce welfare impacts of the policy for the SC category. This section attempts to investigate these additional indirect channels. We are particularly concerned with the indirect effects of the informal credit market and labour market. Additionally, to examine the labour market channel closely, we also try to comprehend the business finance channel.

7.1 Informal finance channel

In an underbanked area, the credit market is predominated by informal lenders, such as professional moneylenders, landlords, merchants etc. These informal lenders discriminate extensively against the marginalized castes [Dreze et al., 1997; Kumar, 2013; Kumar and Venkatachalam, 2019]. In most cases, the mode of discrimination is the excessive and unrealistic rate of interest demanded from the SCs, which almost always leads to them falling into a debt trap [Kumar, 2013]. According to AIDIS data, the average interest rate in 2003 for SCs was 28%, whereas the same for OBCs and generals was 22% and 16%.

When a bank branch is established in the area, informal lenders face competition because of lower interest rates offered by the formal banking sector and their non-discriminatory approach [Kumar, 2013]. To counter this competition, informal lenders are compelled to reduce the interest rate[13]. There is another reason why informal lenders opt for less discrimination after banks come in. As noted in Sagrario Floro and Ray [1997]; Ghate [1992]; Conning and Udry [2007], infor-

[13]Reduced interest rate for SCs implicates lower discrimination against them in the credit market, which ripples through other spheres of the society. The evidence of an increase in social inclusion for SCs supports this hypothesis.

mal lenders often acquire formal credits to cater to borrowers' needs. Therefore, the volume of available funds in informal credit market rises following the expansion of the formal sector. Due to the higher availability of funds to lend out, informal lenders consider lowering discrimination and expanding their customer base from the SC population.

The phenomenon of reduction in discrimination in the form of reduced interest rate is exactly what is reflected in panel (a) of table 6. The reduction in the annual informal interest rate is statistically significant for SCs and OBCs. The magnitude and percentage of reduction both are highest for the SCs. Therefore, the relative informal interest rate faced by SCs compared to other castes declines after the policy in treatment districts, which results in an increased informal borrowing for SCs as presented in panel (c). The AIDIS data allows us to examine what SCs further do with this informal loan. From AIDIS 2013, we find that more than 90% loans taken by SCs from the informal sector are used for non-productive purposes like household expenditure, medical expenditure, housing, repayment of debt etc. Consequently, we see an increase in consumption for SCs in panel (a) of table 5.

On the other hand, OBCs and generals do not encounter as much discrimination in the informal credit market as SCs do[14]. The interest rate charged from them has always been lower compared to SCs. As a result, their demand for informal loans does not increase significantly after banks enter the market.

There are multiple theories and concepts that try to study the interaction and coexistence of informal and formal credit sectors. One such concept is the 'cream-skimming' theory [Demont et al., 2010; Mookherjee and Motta, 2016], which argues in favor of an increase in informal interest rate after formal sector comes in, because of the possibility of low-risk borrowers moving to the formal sector, leaving high-risk borrowers in the informal credit market. At first glance, our result of reduced informal interest rate does not go hand-in-hand with this theory, but if we look

[14] In some parts of India, OBCs face discrimination to some extent, but not as prominent as SCs

closely, we can argue that the informal lenders incorporate this higher risk of default indirectly by taking more mortgages against the loan, not by directly increasing the interest rate. To back this argument up empirically, in panel (b) of table 6 we show that the informal lenders increase the likelihood of giving mortgaged loans[15] to the SC group, alongside reducing the interest rate[16]. Thus, we can infer that our findings do not contradict the cream-skimming theory.

Summing up, SCs benefit exclusively from the reduced interest rate in the informal credit market, which enables them to take up more informal loans, mainly for consumption purposes, and this gets reflected in higher consumption and reduced poverty for them as shown in table 5.

Insert Table 6 about here

7.2 Business finance channel

To comprehend the labour market mechanism, we first need to examine how banks finance enterprises owned by various castes. We use the 2013 economic census to study this business finance channel and present, in table 7, how the number of businesses with formal finance as their primary source of credit has changed as a result of the policy. The economic census data contains information on the caste of the business owner, which allows us to examine how credit availability has changed across different caste categories after the policy. The economic census also categorizes enterprises into two main groups: agricultural and non-agricultural. This enables us to further analyze which caste group is taking more agricultural loans and which one is taking more non-agricultural loans.

We can deduce three key findings from table 7. First, overall business loans increase for all

[15] Mortgage is a dummy variable; takes the value 1 if mortgage is taken with the loan and 0 if the loan is mortgage-free.

[16] This does not impact the borrowers much because, with lower interest rate, they are now more able to pay back the loan. But increased mortgaged loans help the informal lenders to minimize their risk of lending.

caste categories; second, agricultural loans increase for the SC and OBC owners; and third, non-agricultural business loans increase for the OBC and general categories.

In panel (a) of table 7, we report a significant increase in the number of enterprises with formal finance as the main source of credit in the treatment districts; 43.69%, 66.27% and 31.37% increase for SC, OBC and general owned businesses, respectively. This indicates that caste does not play a significant barrier in accessing formal sector loans.

In panel (b) of table 7, we observe that agricultural loan shows a significant sign of increase for SC and OBC categories in treatment districts, but not for generals. We argue that this is because the agricultural loans were collateral-free even before the introduction of the 2005 RBI policy. In 1998, RBI issued a circular saying agricultural loans up to INR 10,000 should be collateral-free[17]. In 2004, just one year before the 2005 branch authorization policy, this limit was further increased to INR 50,000[18] and five years after the policy, in 2010, it was again increased to INR 1,00,000[19]. The collateral-free nature of agricultural loan had already made it attractive for owners from marginalized castes. The RBI policy just removed the barrier to the access of agricultural loans for them[20].

On the other hand, non-agricultural business loans also show improvement for all caste categories in treatment districts, but the increase is statistically significant only for OBCs and generals. The number of OBC-owned and general-owned non-agricultural enterprises increases by 70.5% and 52.36%, respectively, in treatment districts. Why do OBCs and generals take more non-agricultural loans? We argue that, before the policy, these two caste groups were more likely to own a non-agricultural business compared to SCs. The pre-policy economic census (2005) data

[17]Circular number: RPCD. No. PLFS. BC. 123/05.05.18/1997-98 dated May 20, 1998

[18]Circular number: RPCD. Plan. BC. No. 87 /04.09.01/2003-04 dated May 18, 2004

[19]Circular number: RPCD.PLFS. BC. No. 85/05.04.02/2009-10 dated June 18, 2010

[20]One might argue that loans for micro, small and medium enterprises (MSME) are also collateral-free in India. However, MSME loans up to INR 5 lakhs are made collateral-free in 2009, four years after the policy. Naturally, awareness for this policy is expected to be less compared to the 1998 collateral-free agricultural loan policy. Also, MSME loans are generally larger than agricultural loans, which makes them non-feasible for most of the marginalized caste business owners.

reveals that 37.67% and 39.02% non-agricultural businesses were owned by OBCs and generals respectively. In contrast, the same number for SCs was 8.58%. This disparity exists because setting up a non-agricultural business requires a handsome amount of investment in fixed costs as well as a wide network in society. SC owners lack both of these most of the time. Predictably, it is easier for OBCs and generals to obtain a loan to expand their existing businesses than for the SCs to obtain a larger loan to start a business from scratch. This is precisely why OBCs and generals opt for more non-agricultural business loans when the availability of formal credit increases as a result of the policy.

Insert Table 7 about here

7.3 Labour market channel

Following our findings that SCs take more agricultural loans and generals take more non-agricultural business loans, the next question we ask is, what do SCs and generals do with these loans? The answer will provide insight into the labour market's response to the policy.

Beginning with the agricultural sector, we present our findings in table 8. From AIDIS 2013 data, we analyze the impact on the value of agricultural machinery, specifically the value of power-operated agricultural machinery and the number of livestock (columns 1, 2 and 3). In treatment districts, the value of agricultural machinery owned by SCs is 1946.32 rupees (INR) higher than in control districts; if only power-operated machinery is considered, the difference is INR 15047. The number of livestock owned increases by 23.2% for SCs and 13.8% for OBCs on average, compared to control means of 2.62 and 3.22, respectively. Combining these results, we can infer that as a result of the policy, SCs mainly use agricultural loans for mechanising their agricultural production and OBCs use them for expanding their animal stock. Overall, for generals, we do not observe any discernible impact in the agriculture sector, which is consistent with our findings in panel (b) of table 7.

To further support these findings, we use IHDS data (columns 4 and 5) to show that agricultural labour hours decrease by approximately 7 hours per week (29.25% increase compared to a control mean of 24 hours) and that agricultural crop income increases by INR 3625.58 (around 87% increase) in SC households in the treatment districts compared to SC households in the control districts. This indicates an increase in agricultural productivity, arguably caused by the mechanisation of agricultural production by SCs. As anticipated, no change in productivity is noticed for generals.

Insert Table 8 about here

Then, we turn to the non-agricultural sector, for which the results are furnished in table 9. The data used in this table is from IHDS 2011-12. From panel (a), we observe that earnings from non-agricultural businesses increase for OBCs and generals, by 9.2% and 4.5%, respectively. This aligns with our previous finding that non-agricultural business loan increases for OBCs and generals, with the rate of increase for OBCs being higher than that of generals. From this, we can deduce that OBCs and generals expand their businesses with loans from the formal sector.

The existence of discrimination against marginalized castes in the form of wage differential is an established phenomenon in the literature [Madheswaran and Attewell, 2007; Thorat and Attewell, 2007; Ito, 2009]. The extent of discrimination was the highest for SCs, whereas OBC's position was somewhere in between SCs and generals. Our data reflect the same story. In IHDS 2004-05 data, the average hourly wages for the SC and OBC categories were INR 17.44 and INR 19.62, while the same for the general category was INR 34.94. The business expansion resulting from increased access to formal credit creates an additional labour demand in the market. Therefore, the business owners find it more rational to meet that excess demand by raising the wages of cheaper SC labours. We furnish evidence for this in panel (b) of table 9 by showing an increase in SC wages by 11.9% in treatment districts. In a broader sense, this implicates a reduction in labour market discrimination against marginalized castes which contributes to the reduction in caste-based welfare disparity.

On the other hand, from the labour supply side, we see a 14.2% increase in the number of wage or salary jobs in SC households. We argue that the disguised agricultural labours in those households move to wage or salary jobs after the increase in agricultural productivity, as seen in columns (4) and (5) of table 8. This is another additional welfare-improving channel for the SCs.

Insert Table 9 about here

8 Robustness checks

8.1 Disentangling Class and Caste Effect

One inevitable question that arises from the results in table 5 is how do we ensure our results are attributable to caste effect and not class effect. Here, the RD framework comes to our rescue. The RD coefficients in our results compare the outcome difference between a particular caste group in the treatment districts with the same caste group in the control districts. This eliminates the class effect across different caste groups. To further eliminate the class effect within a particular caste group, we control for baseline permanent income and re-estimate the models in table 5, which is presented in table A9. We construct the permanent income using the adaptive LASSO model[21]. Our results remain intact even after controlling for permanent income, which ensures the origin of the impact to be caste discrimination.

[21] LASSO (Least Absolute Shrinkage and Selection Operator) is a regression-based method to select a set of variables for prediction from a large pool of variables. LASSO is also a regularization method that penalizes for over-fitting. Adaptive LASSO is an improvement over the LASSO in the sense that it has the oracle properties

8.2 Polynomial 2 results

All the results presented in sections 6 and 7 are linear RD estimates. According to Gelman and Imbens [2019], quadratic approximation is the highest order polynomial that researchers should use because using higher degree polynomials results in noisy estimates, sensitivity to the order of the polynomial, and inadequate coverage of confidence intervals resulting in poor inference.

We present the quadratic polynomial estimates in tables A10, A11, A12, A13, A14 and A15. These estimates are similar to our main results (linear estimates) in tables 4, 5, 6, 7, 8 and 9, respectively. We find that 88% of the main results and 83% of the mechanism results remain statistically significant for polynomial two estimates. Thus, we can safely assert that the results are robust to quadratic estimation as well.

8.3 Placebo cutoffs

Checking for the smoothness around placebo cutoffs is considered to be another robustness check in RD literature. Intuitively, since the likelihood of obtaining the treatment changes discontinuously only at the true cutoff value, the outcomes should also change discontinuously only at that cutoff value [Cattaneo and Titiunik, 2022]. The underlying assumption for this placebo cutoff test is the absence of any similar policy during the same period. Following Cramer [2021], we can say that this assumption is satisfied for our RBI branch authorization policy (2005).

To carry out the placebo cutoff test, we consider six placebo cutoffs, three on each side of the true cutoff (which is normalized to zero), $\pm$ 750, 1,500 and 2,250. Results of the placebo cutoff tests are shown in table A16 for the main results, and in tables A17 and A18 for the mechanism results[22]. We find that 96% of the results pass through the placebo cutoff test.

[22]For space constraint, we have shown the results only for the SC category, but similar results hold for OBC and generals as well

8.4 Bandwidth Selector

Next, we show that our results are robust to the choice of bandwidth selection method. In the main results, we use the common Mean-square-error (MSE)-optimal method following [Calonico et al., 2019], which selects equal bandwidth for both sides of the cutoff. As an alternative, we use a two-sided MSE optimal bandwidth selector that separately chooses optimal bandwidth for each side of the cutoff. We also use Coverage-error-rate (CER)-optimal bandwidth selector (both common and two-sided) following Calonico et al. [2020]. The main difference between MSE and CER methods is that the former aims to minimize the mean square error of the point estimator, whereas the latter aims to minimize the coverage error of the interval estimator [Calonico et al., 2020].

We present the results using different bandwidth selection methods in tables A19, A20 and A21. 72% of the main results and 75% of the mechanism results remain statistically significant, which suggests that our results are robust to different bandwidth selection methods.

8.5 Bandwidth Multipliers

Another method of checking whether the coefficients remain statistically significant for different bandwidth choices is to check for bandwidth multipliers. We consider multipliers in the range of 0.50 to 1.50, with gaps of 0.25. That is, if the MSE-optimal bandwidth in the main result is x, we additionally examine bandwidths of 0.50x, 0.75x, 1.24x, and 1.50x. The results are furnished in tables A22, A23 and A24. 80% of the main results and 72% of the mechanism results remain statistically significant. Hence, our results are robust to the selection of different bandwidth multipliers.

8.6 Donut Hole Test

The broad objective of the donut hole sensitivity test is to check if our results are drastically determined by the observations closest to the cutoff [Cattaneo et al., 2023]. To carry out this test, we create the so-called 'donut' [Dowd, 2021] by omitting the closest 1% observations from both sides of the cutoff and re-estimate the RD treatment effects. The results remain intact for the donut, as furnished in table A25, which signifies that our results pass through the donut-hole sensitivity test.

9 Conclusion

In a general equilibrium framework, our study examines the causal effect of a bank branch authorization policy on caste-based welfare disparities in India. Our findings demonstrate that this central bank policy enhances access to formal financial services across all caste categories, thereby promoting inclusivity, diversity and unbiasedness in the banking sector. Marginalized caste categories, who historically faced the highest degree of social exclusion and discrimination in Indian societies, benefit the most from this inclusive nature of the formal banking sector, in terms of increased consumption and reduced poverty. We carefully examine all direct and indirect channels that facilitate this welfare gain of marginalized castes, including informal finance channel, business finance channel and labour market channel. All of our results are based on a meticulously designed regression discontinuity framework and are, therefore, causal in nature. The results are also robust to standard RD literature checks, including bandwidth multiplier test, bandwidth selector test, placebo cutoff test, polynomial 2 and donut hole test. The causal and robust nature of our findings underlines the substantial importance of this study for policymakers, particularly in relation to policies formulated by the central bank. From a policy standpoint, this study is an attempt to highlight the importance of strengthening the formal banking sector and making it

Table 1: Summary statistics from IHDS data

	IHDS 1			IHDS 2		
	SC	OBC	Gen	SC	OBC	Gen
(a) Financial inclusion						
Bank account	-	-	-	0.51 (0.49)	0.55 (0.49)	0.68 (0.46)
Observations	-	-	-	8560	13573	8604
Bank loan	0.09 (0.28)	0.13 (0.34)	0.14 (0.34)	0.16 (0.36)	0.26 (0.44)	0.25 (0.43)
Observations	8533	13908	8428	8577	13614	8627
Fixed deposit	-	-	-	0.06 (0.25)	0.08 (0.27)	0.17 (0.38)
Observations	-	-	-	8562	13574	8599
Securities	-	-	-	0.01 (0.09)	0.01 (0.10)	0.03 (0.16)
Observations	-	-	-	8562	13575	8602
Insurance	0.15 (0.36)	0.21 (0.41)	0.35 (0.47)	0.30 (0.45)	0.38 (0.48)	0.47 (0.49)
Observations	8518	13891	8396	8569	13585	8617
(b) Household welfare						
Consumption	2.89 (1.39)	3.13 (1.39)	3.75 (1.28)	2.75 (1.34)	3.05 (1.38)	3.61 (1.30)
Observations	8526	13896	8413	8580	13610	8624
Food consumption	3.50 (1.25)	3.61 (1.24)	4.01 (1.09)	2.02 (1.08)	2.06 (1.09)	2.53 (1.20)
Observations	8526	13896	8413	7601	12081	7749
Poverty	0.27 (0.44)	0.21 (0.41)	0.09 (0.29)	0.22 (0.41)	0.15 (0.36)	0.07 (0.25)
Observations	8526	13896	8413	8580	13610	8624
Multidimensional poverty	0.90 (0.28)	0.86 (0.33)	0.73 (0.44)	0.86 (0.33)	0.82 (0.38)	0.67 (0.46)
Observations	30908	51599	31086	31276	50481	31990
Social inclusion	0.12 (0.33)	0.16 (0.37)	0.12 (0.32)	0.14 (0.34)	0.17 (0.38)	0.18 (0.38)
Observations	8487	13823	8380	8538	13530	8593
(c) Agricultural Sector						
Agriculture hours	24.17 (13.82)	20.75 (12.49)	22.83 (12.66)	20.08 (12.90)	17.50 (12.47)	20.01 (13.04)
Observations	4803	5708	1457	5196	5995	1343
Agriculture income	7723.22 (35896)	22991.65 (90388)	32591.49 (113804)	9635.52 (131654)	27986.5 (133602)	38560.28 (160651)
Observations	31462	52191	31579	31655	51113	32333
(d) Non-agri Sector						
Business Revenue	10.89 (1.35)	11.11 (1.32)	11.85 (1.26)	11.06 (1.27)	11.37 (1.31)	11.90 (1.31)
Observations	1106	2806	1916	1089	2808	1938
Hourly Wage	17.43 (17.61)	19.62 (23.24)	34.94 (42.38)	23.77 (23.13)	24.82 (28.28)	39.24 (43.71)
Observations	9412	11619	5449	12317	14093	6878
Number of jobs	1.11 (0.36)	1.10 (0.36)	1.02 (0.17)	1.33 (0.67)	1.27 (0.66)	1.29 (0.41)
Observations	4657	5696	2924	6081	7077	3468

Source: Authors' calculation. Standard deviations in parenthesis. Missing values indicate that there is no data for that particular variable at that particular time point.

more inclusive in order to reduce the sticky social norms like caste-based discrimination in India.

10 Tables Figures

Table 2: Summary Statistics of variables from AIDIS

	AIDIS 2003			AIDIS 2013		
	SC	OBC	Gen	SC	OBC	Gen
(a) Informal finance						
Rate of interest	23.79 (25.77)	22.10 (21.91)	16.36 (19.73)	20.41 (43.91)	17.10 (21.89)	13.25 (16.05)
Observations	17194	38714	27604	20268	51986	32033
Mortgage	0.87 (0.32)	0.84 (0.36)	0.80 (0.39)	0.77 (0.41)	0.69 (0.46)	0.67 (0.46)
Observations	17754	39269	28769	20391	52189	32159
Informal loan	0.55 (0.49)	0.56 (0.49)	0.46 (0.49)	0.31 (0.46)	0.29 (0.45)	0.21 (0.41)
Observations	17789	39319	28812	38436	95887	64034
(b) Agricultural Sector						
Value of agricultural machinery	1420.73 (11850)	3330.55 (21041)	5240.86 (27735)	2931.55 (11499)	6117.15 (21043)	8572.37 (64259)
Observations	26,632	63174	50881	17033	28850	18120
Value of agricultural machinery (power operated)	8430.45 (34180)	15738.65 (47996)	20015.51 (56202)	14831.85 (29938)	19694.27 (39383)	26779.65 (126547)
Observations	2980	10770	11003	1154	6721	4461
Number of livestocks	2.47 (1.70)	3.18 (2.51)	3.30 (2.40)	2.39 (1.55)	3.05 (2.38)	3.12 (2.45)
Observations	7532	17438	13459	4912	13481	8133

Source: Authors' calculation. Standard deviations in parenthesis.

Table 3: Summary statistics of variables from Economic Census

	EC 2005			EC 2013		
	SC	OBC	Gen	SC	OBC	Gen
All Enterprises	151.54 (265.66)	808.38 (1597.79)	1106.76 (2217.45)	147.01 (260.86)	672.21 (1310.49)	806.20 (1604.54)
Observations	581	581	581	581	581	581
Agricultural Enterprises	25.28 (99.52)	103.86 (394.35)	115.34 (764.75)	4.11 (25.63)	29.86 (193.70)	24.71 (119.95)
Observations	581	581	581	581	581	581
Non-agricultural Enterprises	126.25 (200.19)	704.51 (1286.61)	991.42 (1733.73)	142.91 (256.48)	642.35 (1285.99)	781.49 (1542.98)
Observations	581	581	581	581	581	581

Source: Authors' calculation. Standard deviations in parenthesis.

Table 4: Banks and financial inclusion of SC, OBC and General caste

	(1)	(2)	(3)
	SC	OBC	Gen
(a) Bank account			
Treatment	0.400***	0.149**	0.263***
	(0.157)	(0.084)	(0.087)
Control mean	0.56	0.55	0.72
Robust p value	0.008	0.035	0.004
Bandwidth	3600	5060	5342
Effective obs	3920	8510	4673
Observations	8,451	13,291	8,425
(b) Bank loan			
Treatment	0.143*	0.095	0.120*
	(0.074)	(0.077)	(0.072)
Control mean	0.35	0.50	0.58
Robust p value	0.066	0.242	0.095
Bandwidth	5664	4107	6605
Effective obs	2991	4297	2767
Observations	4,813	8,088	3,997
(c) Fixed deposit			
Treatment	0.036	0.115***	0.082**
	(0.024)	(0.041)	(0.043)
Control mean	0.09	0.11	0.22
Robust p value	0.113	0.007	0.035
Bandwidth	5666	3490	7255
Effective obs	5107	6362	6649
Observations	8,453	13,292	8,420
(d) Securities			
Treatment	-0.002	0.009	0.022*
	(0.002)	(0.007)	(0.010)
Control mean	0.01	0.02	0.04
Robust p value	0.309	0.330	0.085
Bandwidth	2253	3834	6749
Effective obs	2664	6862	5949
Observations	8,453	13,293	8,423
(e) Insurance			
Treatment	0.135**	0.045	-0.004
	(0.054)	(0.066)	(0.048)
Control mean	0.32	0.43	0.53
Robust p value	0.024	0.613	0.745
Bandwidth	4418	5940	6639
Effective obs	4467	6989	5894
Observations	8,452	13,293	8,437

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Data used: IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table 5: Banks and household welfare of SC, OBC and General caste

	(1)	(2)	(3)
	SC	OBC	Gen
(a) Consumption quintiles			
Treatment	0.488**	0.121	-0.005
	(0.300)	(0.246)	(0.223)
Control mean	3.08	3.37	3.83
Robust p value	0.050	0.550	0.864
Bandwidth	3176	3851	5931
Effective obs	3652	7053	5285
Observations	8,580	13,610	8,624
(b) Food consumption quintiles			
Treatment	0.416**	0.398**	0.110
	(0.179)	(0.202)	(0.215)
Control mean	2.19	2.23	2.68
Robust p value	0.014	0.040	0.457
Bandwidth	3792	3997	6103
Effective obs	3610	6375	4973
Observations	7,601	12,081	7,749
(c) Poverty			
Treatment	-0.104***	-0.033	-0.011
	(0.049)	(0.049)	(0.024)
Control mean	0.174	0.098	0.047
Robust p value	0.009	0.393	0.260
Bandwidth	4635	4997	5160
Effective obs	4718	8605	4751
Observations	8,580	13,610	8,624
(d) Multidimensional poverty			
Treatment	-0.061**	-0.090*	-0.127**
	(0.033)	(0.062)	(0.067)
Control mean	0.802	0.727	0.609
Robust p value	0.041	0.068	0.034
Bandwidth	5483	3561	7071
Effective obs	18363	23980	24424
Observations	31,090	50,181	31,333
(e) Social inclusion			
Treatment	0.172*	-0.018	0.083
	(0.084)	(0.096)	(0.078)
Control mean	0.14	0.24	0.21
Robust p value	0.058	0.628	0.290
Bandwidth	5843	3676	6938
Effective obs	5198	6747	6420
Observations	8,538	13,530	8,593

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12 household file for panels (a), (b), (c), (e) and individual file for panel (d). District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table 6: Banks and informal finance channel

	(1)	(2)	(3)
	SC	OBC	Gen
(a) Annual informal interest rate on loan			
Treatment	-8.113**	-5.025*	-3.377
	(3.329)	(2.574)	(2.586)
Control mean	34.72	32.51	30.25
Robust p value	0.016	0.092	0.189
Bandwidth	3016	4312	4670
Effective obs	3613	9958	3604
Observations	7,401	16,856	6,426
(b) No mortgage informal loan			
Treatment	-0.152*	-0.131**	0.004
	(0.097)	(0.080)	(0.021)
Control mean	0.88	0.89	0.93
Robust p value	0.075	0.050	0.949
Bandwidth	3521	3819	5234
Effective obs	5554	13374	7827
Observations	12,127	27,828	14,037
(c) Informal loan			
Treatment	0.090**	-0.022	-0.006
	(0.040)	(0.029)	(0.035)
Control mean	0.32	0.29	0.22
Robust p value	0.015	0.587	0.814
Bandwidth	4395	5307	5732
Effective obs	19693	60570	37941
Observations	38,436	95,887	64,034

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Data used: AIDIS 2013. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table 7: Banks and the number of enterprises with formal finance as main source of credit

	(1) SC	(2) OBC	(3) Gen
(a) All enterprises			
Treatment	80.80*	647.41**	376.27**
	(50.85)	(298.73)	(237.17)
Control mean	184.92	976.91	1199.38
Robust p value	0.081	0.031	0.048
Bandwidth	4481	4486	4805
Effective obs	284	284	296
Observations	581	581	581
(b) Agricultural enterprises			
Treatment	7.64*	31.31*	7.24
	(5.39)	(21.33)	(22.03)
Control mean	5.64	39.98	35.93
Robust p value	0.083	0.093	0.305
Bandwidth	4160	4361	4237
Effective obs	260	277	268
Observations	581	581	581
(c) Non-agricultural enterprises			
Treatment	83.51	661.1**	609.28*
	(65.86)	(291.9)	(375.38)
Control mean	179.28	936.94	1163.45
Robust p value	0.159	0.024	0.073
Bandwidth	4608	4405	4960
Effective obs	280	280	307
Observations	581	581	581

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: Economic Census 2013. District population, number of bank branches in 1996 and pre-policy values of the outcome variables are controlled for. Source: Authors' calculation.

Table 8: Banks and agricultural sector

	(1) Value of agricultural machinery	(2) Value of agricultural machinery: power-operated	(3) Number of livestock	(4) Labour hours: agriculture	(5) Income: agriculture
(a) SC					
Treatment	1,946.328**	15047***	0.608*	-7.109**	3,625.582**
	(838.012)	(7,288.128)	(0.352)	(3.241)	(1,969.989)
Control mean	2118.502	8778.52	2.62	24.30	4166.69
Robust p value	0.024	0.004	0.060	0.042	0.047
Bandwidth	3926	3394	2709	4336	3666
Effective obs	3767	401	1232	3160	4033
Observations	9,632	1,154	4,912	5,196	8,583
(b) OBC					
Treatment	-729.233	2,760.711	0.446**	-4.671	-1,281.121
	(1,315.220)	(2,190.110)	(0.248)	(3.398)	(4,680.583)
Control mean	3882.38	12336.34	3.22	22.87	9225.86
Robust p value	0.668	0.123	0.044	0.401	0.804
Bandwidth	4791	4621	8414	3712	3997
Effective obs	14929	3305	10703	3157	7275
Observations	28,850	6,721	13,481	5,995	13,619
(c) Gen					
Treatment	2,104.938	693.683	0.230	-4.973	-4,361.575
	(1,488.745)	(2,151.968)	(0.417)	(4.246)	(6,035.694)
Control mean	5330.11	14374.01	3.45	22.59	13092.28
Robust p value	0.102	0.597	0.513	0.549	0.556
Bandwidth	4408	7004	4289	4110	5739
Effective obs	7936	3231	3572	761	5136
Observations	18,120	4,461	8,133	1,343	8,630

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12 and AIDIS 2013. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table 9: Banks and Non-agricultural business sector

	(1) SC	(2) OBC	(3) Gen
(a) Log nonfarm business revenue			
Treatment	0.481	1.06***	0.551**
	(0.332)	(0.327)	(0.306)
Control mean	11.20	11.48	12.04
Robust p value	0.103	0.001	0.039
Bandwidth	4879	3486	5070
Effective obs	581	1301	1026
Observations	1089	2808	1938
(b) Hourly wage/salary (Rs)			
Treatment	2.84*	2.58	2.59
	(1.72)	(2.24)	(2.28)
Control mean	23.75	24.53	27.61
Robust p value	0.079	0.363	0.270
Bandwidth	5567	3700	5067
Effective obs	7285	6839	3083
Observations	11,464	13,076	5,591
(c) Number of wage/salary jobs in the household			
Treatment	0.172*	0.139	0.035
	(0.105)	(0.120)	(0.074)
Control mean	1.21	1.12	1.08
Robust p value	0.081	0.191	0.566
Bandwidth	4488	4791	5946
Effective obs	3348	4419	2157
Observations	6,081	7,077	3,468

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12, household file [for panels (a) and (c)] and individual file [for panel (b)]. District population and number of bank branches in 1996 are controlled for. For hourly wage, we winsorize the outcome at 5th and 95th percentile to remove outliers and additionally control for pre-policy values of the outcome, education, union membership and region dummies to separate out the wage increment induced by reduced labour market discrimination. Source: Authors' calculation.

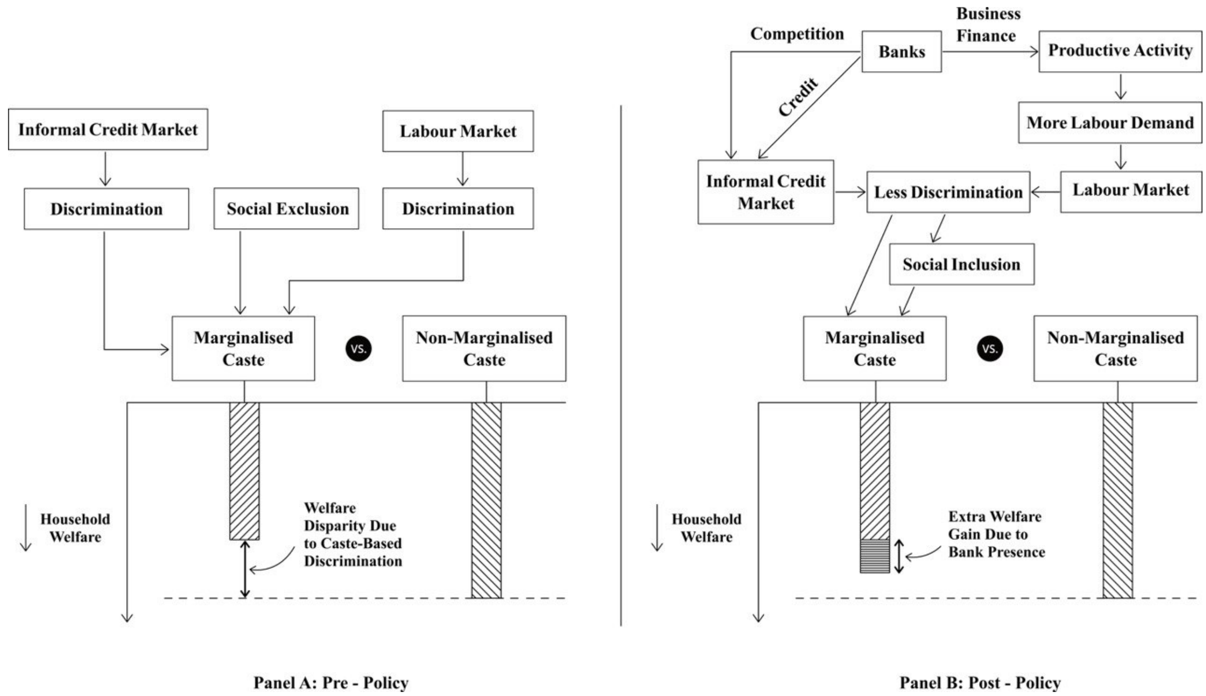


Figure 1: Role of Bank Presence in Improving Household Welfare of marginalized Castes

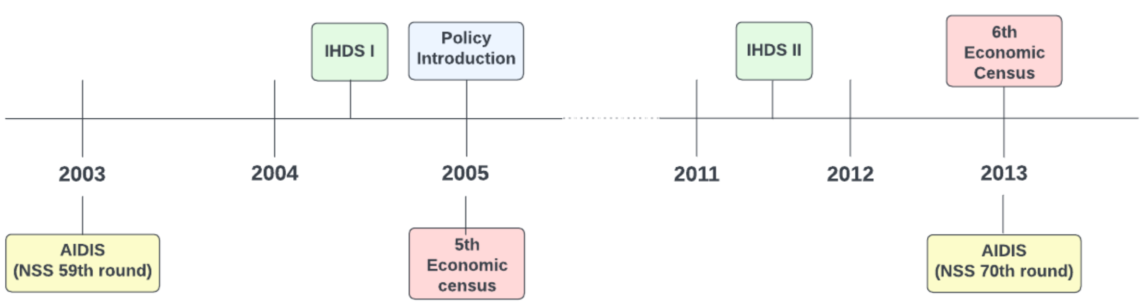
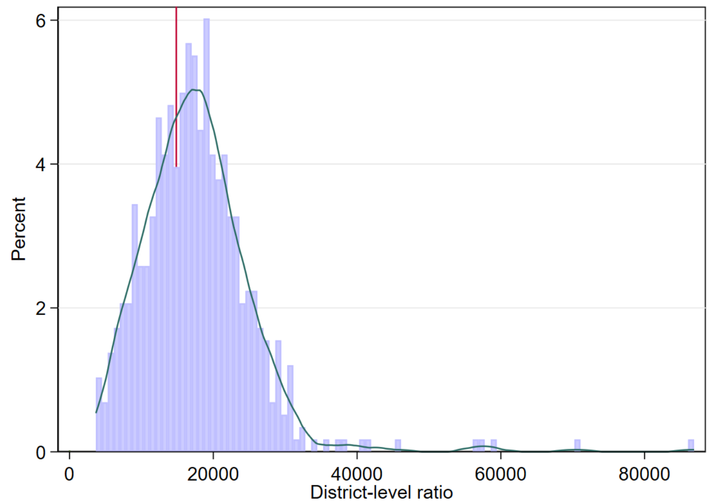
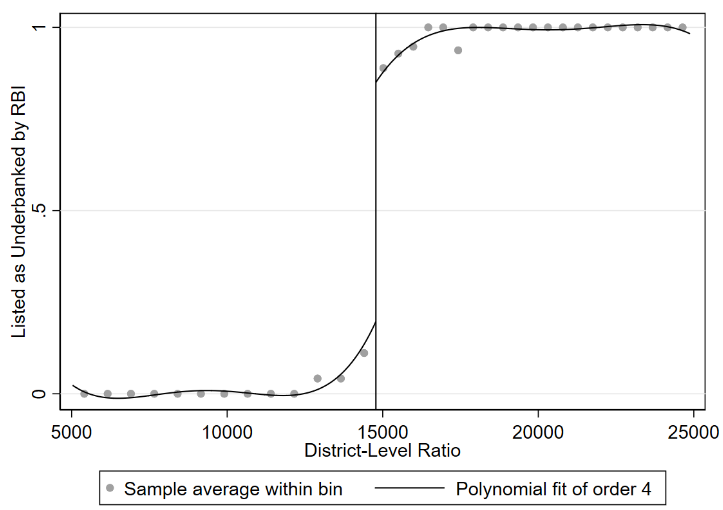


Figure 2: Timeline of the datasets used

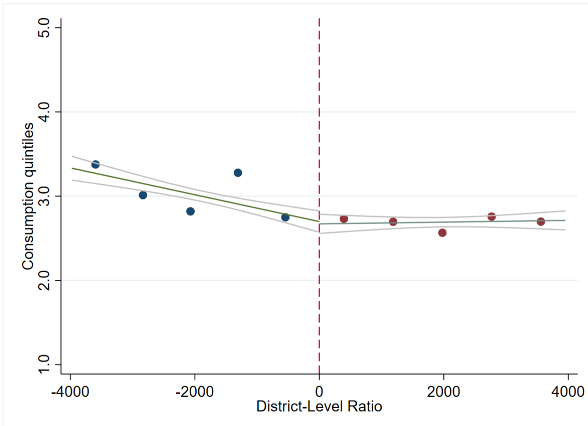


(a) Histogram

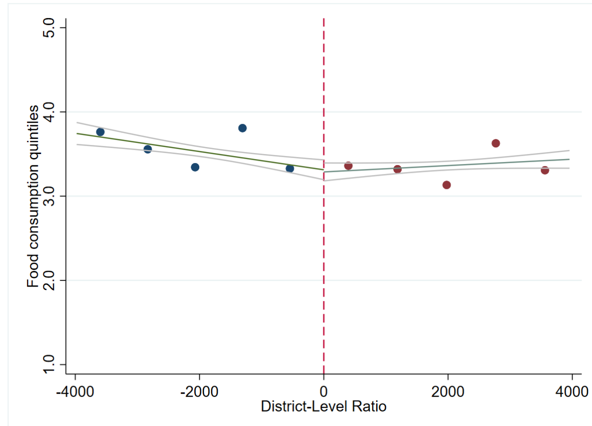


(b) First Stage RD plot

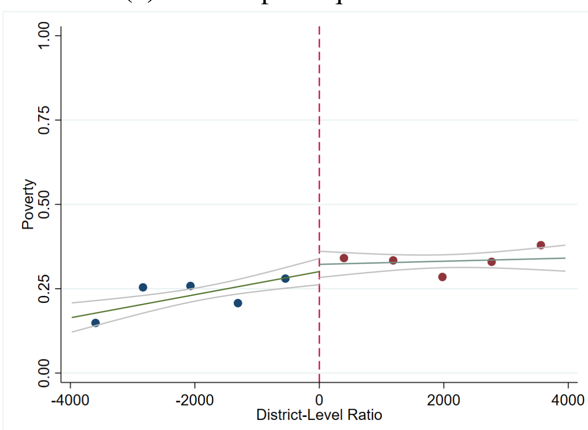
Figure 3: Histogram and First stage RD plot



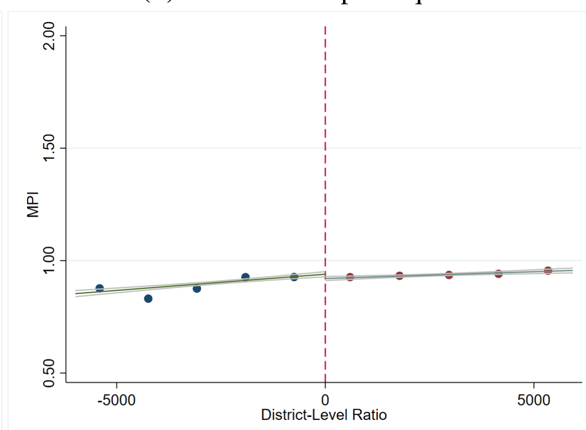
(a) Consumption quintiles



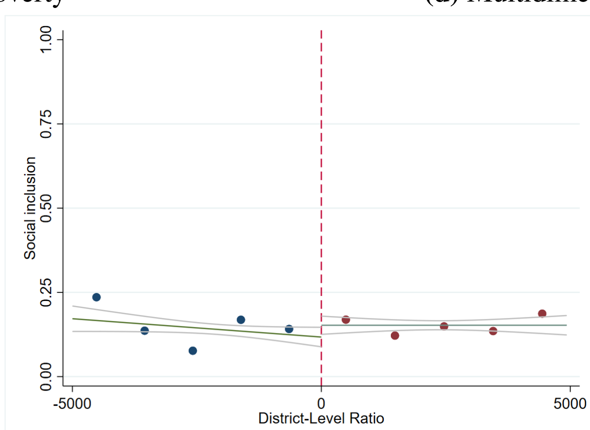
(b) Food consumption quintiles



(c) Poverty

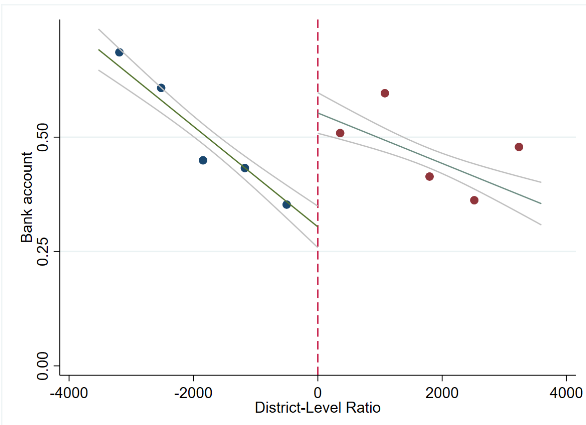


(d) Multidimensional Poverty

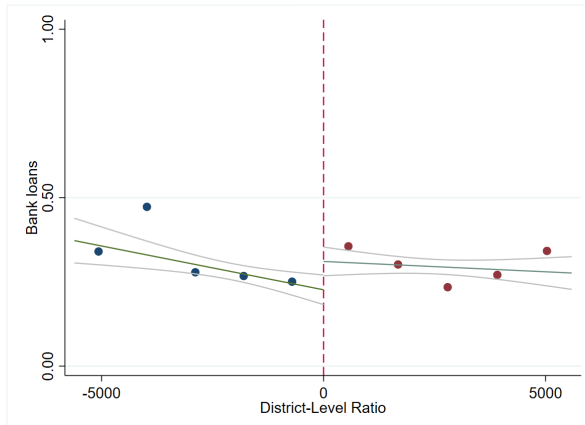


(e) Social Inclusion

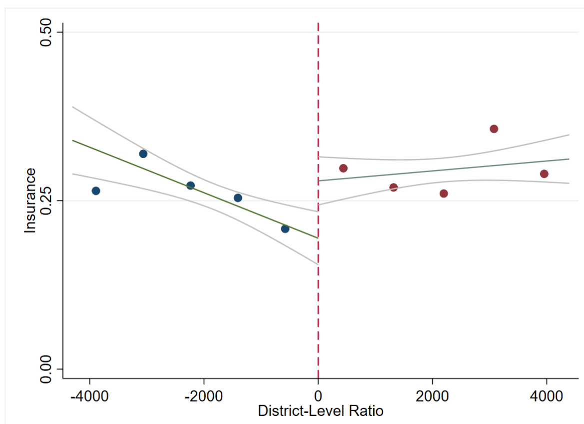
Figure 4: Pre-policy smoothness of household well-being outcomes for SCs



(a) Bank Account

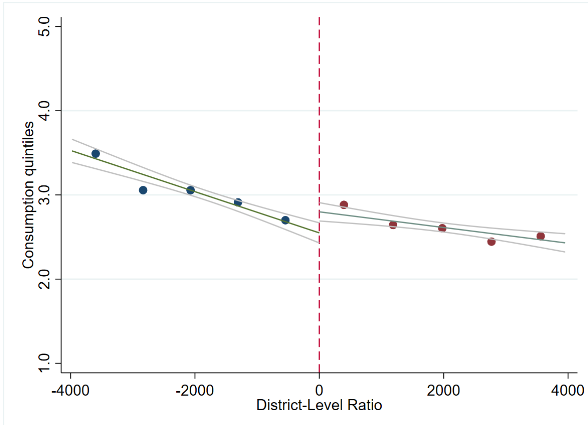


(b) Bank Loan

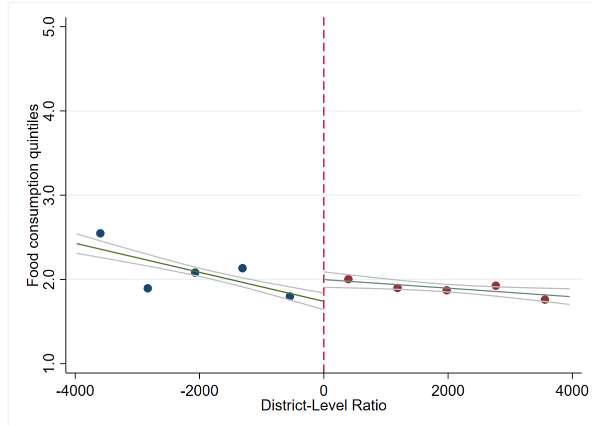


(c) Insurance

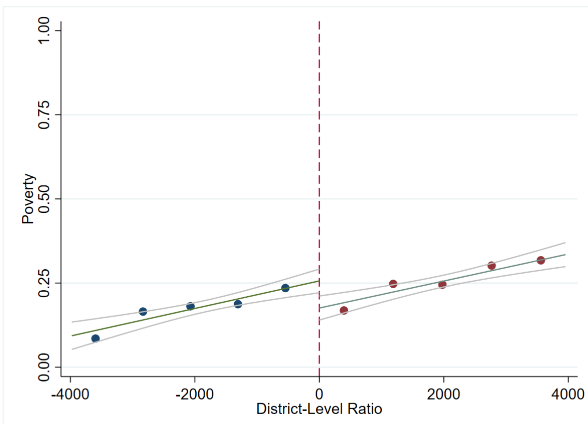
Figure 5: Financial inclusion for SCs



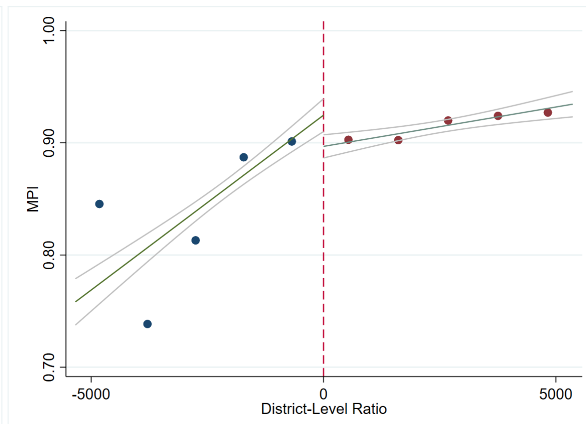
(a) Consumption quintiles



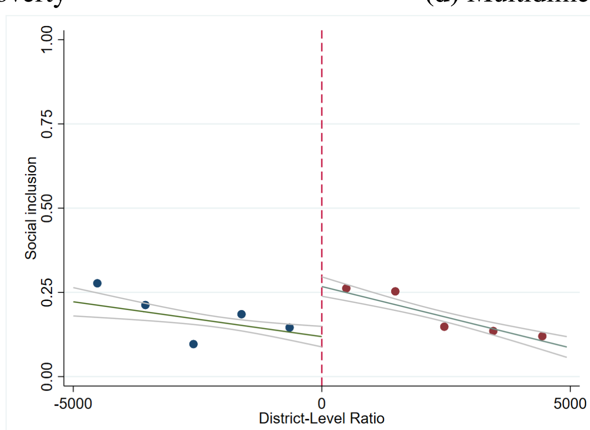
(b) Food consumption quintiles



(c) Poverty



(d) Multidimensional Poverty



(e) Social Inclusion

Figure 6: Household Well-being outcomes for SCs

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Appendix

Table A1: Comparison of IHDS with other nationally representative datasets

		Caste			
Survey	Survey year	Other backward classes	Scheduled Castes	Scheduled Tribes	Other
IHDS	2004-2005	41.79	21.14	7.06	30.01
NFHS -III	2005-2006	39.6	19.2	8.4	31.9
NSS	2004-2005	40.96	19.59	8.64	30.81
CENSUS	2001	NA	16.2	8.2	NA

Source: Indian Human Development Survey: Technical Paper No. 1 (Table 2)
Accessible from https://www.icpsr.umich.edu/web/pages/DSDR/idhs-II-data-guide.html

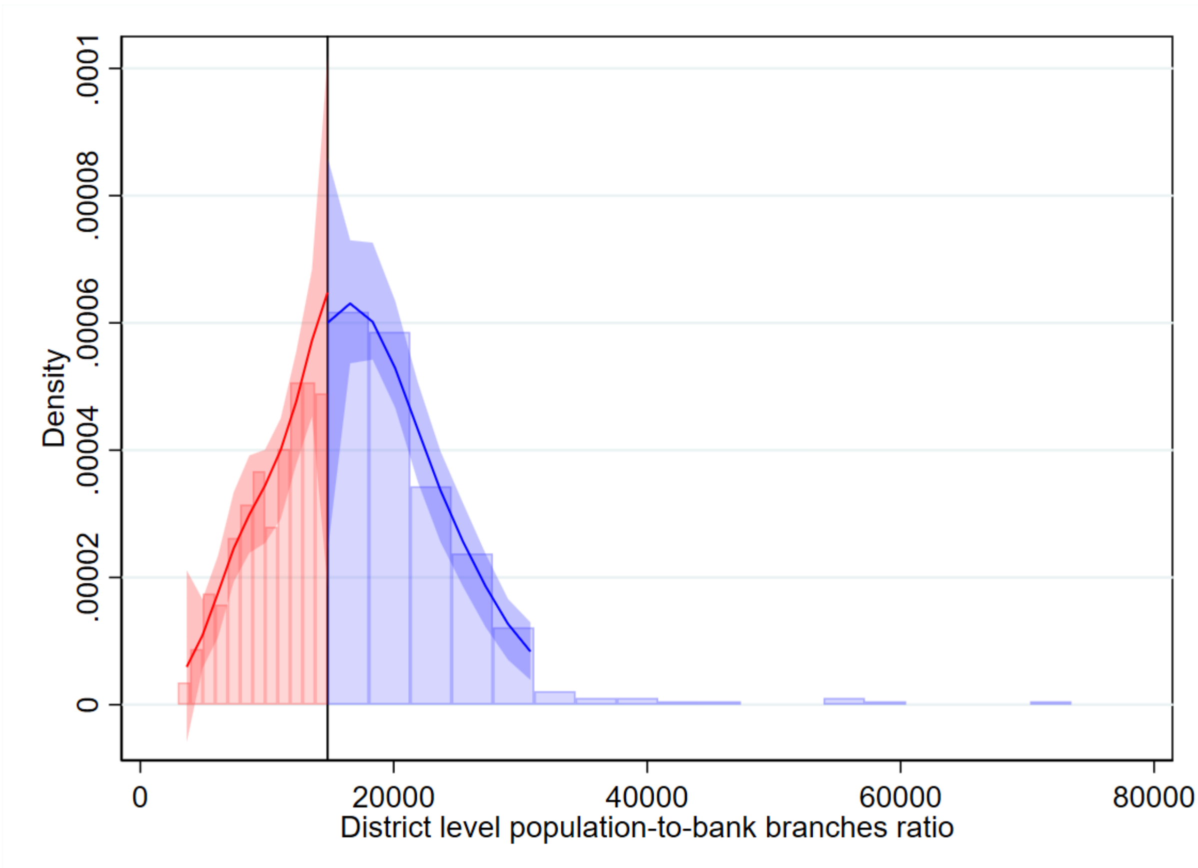

Figure A1: McCrary Test

Note: The null hypothesis of this test [McCrary, 2008] is that the running variable's density function is continuous around the cutoff. The McCrary estimate is -0.1996, and the associated p-value is 0.8418. Hence, we fail to reject the null hypothesis and conclude that there is no evidence of manipulation around the cutoff. Data used: RBI master office file data. Source: Authors' calculation.

Table A2: Binomial test

Window length/2 (h)	Observations below cutoff	Observations above cutoff	p-value
600.000	11	20	0.1496
1200.000	35	42	0.4944
1800.000	54	62	0.5159
2400.000	71	90	0.1558
3000.000	88	111	0.1186

Note: Cutoff (c) is normalized to 0. Window (W)= [c-h, c+h]. The p-values associated with this binomial test are calculated using an exact binomial distribution with probability=0.5

Table A3: Pre-policy smoothness of household welfare outcomes

	(1) SC	(2) OBC	(3) Gen
(a) Consumption quintiles			
Treatment	0.037	0.163	-0.389
	(0.328)	(0.297)	(0.238)
Observations	8,526	13,896	8,413
(b) Food consumption quintiles			
Treatment	-0.071	0.068	-0.189
	(0.314)	(0.300)	(0.161)
Observations	8,526	13,896	8,413
(c) Poverty			
Treatment	0.080	0.075	0.046
	(0.073)	(0.064)	(0.034)
Observations	8,526	13,896	8,413
(d) Multidimensional poverty			
Treatment	-0.043	-0.058	-0.060
	(0.028)	(0.037)	(0.059)
Observations	30,639	51,329	30,534
(e) Social inclusion			
Treatment	0.039	0.044	-0.097
	(0.086)	(0.099)	(0.073)
Observations	8,487	13,823	8,380

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2004-05. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A4: Pre-policy smoothness: Informal finance channel

	(1) SC	(2) OBC	(3) Gen
(a) Informal interest rate			
Treatment	4.913	3.918	1.766
	(5.402)	(4.653)	(3.329)
Observations	6,302	14,287	6,189
(b) No mortgage loan			
Treatment	-0.009	-0.009	0.000
	(0.011)	(0.013)	(0.014)
Observations	9,927	22,018	13,368
(c) Informal loan			
Treatment	0.081	0.041	-0.035
	(0.056)	(0.073)	(0.053)
Observations	17,789	39,319	28,812

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2003. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A5: Pre-policy smoothness: Business finance channel

	(1) SC	(2) OBC	(3) Gen
(a) All enterprises			
Treatment	-1.099	-218.088	660.540
	(115.199)	(474.035)	(1,162.673)
Observations	581	581	581
(b) Agricultural enterprises			
Treatment	28.878	33.292	418.807
	(61.384)	(139.516)	(477.259)
Observations	581	581	581
(c) Non-agricultural enterprises			
Treatment	-44.227	-248.278	137.121
	(64.704)	(386.039)	(670.851)
Observations	581	581	581

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Data used: Economic Census 2005. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A6: Pre-policy smoothness: Agricultural sector

	(1) Value of agricultural machinery	(2) Value of agricultural machinery: power-operated	(3) Number of livestock	(4) Labour hours: agriculture	(5) Income: agriculture
(a) SC					
Treatment	60.997	1,087.810	0.282	0.128	1,012.208
	(150.143)	(920.832)	(0.194)	(3.571)	(2,232.781)
Observations	26,632	2,980	7,532	4,803	8,533
(b) OBC					
Treatment	106.004	149.144	0.120	0.002	-6,480.221
	(314.894)	(1,077.033)	(0.428)	(3.767)	(4,716.493)
Observations	63,174	10,770	17,438	5,708	13,908
(c) Gen					
Treatment	426.281	305.365	0.221	-0.897	-5,039.682
	(445.848)	(1,170.995)	(0.289)	(4.780)	(5,061.666)
Observations	50,881	11,003	13,459	1,457	8,428

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Data used: AIDIS 2003. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A7: Pre-policy smoothness: Non-agricultural business sector

	(1) SC	(2) OBC	(3) Gen
(a) Log nonfarm business revenue			
Treatment	0.558	0.298	0.036
	(0.545)	(0.292)	(0.312)
Observations	565	1,484	1,046
(b) Hourly wage/salary (Rs)			
Treatment	1.428	4.019	3.653
	(2.479)	(2.922)	(4.087)
Observations	8,451	10,267	4,517
(c) Number of wage/salary jobs in the household			
Treatment	0.034	-0.130	-0.024
	(0.064)	(0.094)	(0.023)
Observations	4,657	5,696	2,924

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Data used: IHDS 2004-05. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A8: Validity of RD Design For Survey Subsamples

	(1) Full Sample	(2) SC Subsample	(3) OBC Subsample	(4) General Subsample
Treatment	-0.0002	-0.0414	0.0279	0.0854
	(0.1483)	(0.1646)	(0.1507)	(0.1579)
Robust p-value	0.965	0.827	0.826	0.572
Bandwidth	4398	4065	4364	4337
Effective Observations	280	254	277	276
Observations	581	581	581	581

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India branch authorization policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Since all the coefficients are insignificant here, we can conclude that in IHDS, full sample along with SC, OBC and General subsamples separately satisfy the randomization prerequisite for carrying out RD analysis. Source: Authors' calculation.

Table A9: Disentangling Class and Caste

	(1) SC	(2) OBC	(3) General
(a) Consumption Quintiles			
Treatment	0.369*	0.118	-0.135
	(0.230)	(0.215)	(0.146)
Observations	7965	12448	7428
(b) Food Consumption Quintiles			
Treatment	0.303**	0.366**	-0.033
	(0.158)	(0.183)	(0.200)
Observations	7066	11078	6732
(c) Poverty			
Treatment	-0.065*	-0.027	-0.016
	(0.050)	(0.039)	(0.028)
Observations	7965	12448	7428
(d) Multidimensional Poverty			
Treatment	-0.058**	-0.079**	-0.102*
	(0.026)	(0.044)	(0.063)
Observations	23898	38045	22278
(e) Social Inclusion			
Treatment	0.164*	-0.042	0.033
	(0.087)	(0.100)	(0.073)
Observations	7926	12374	7401

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India branch authorization policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12. In addition to district population and number of bank branches in 1996, permanent income of the household, predicted using the adaptive LASSO model, is controlled for. This helps us to disentangle caste effect from class effect. Source: Authors' calculation.

Table A10: Polynomial 2: Banks and financial inclusion

	(1) SC	(2) OBC	(3) Gen
(a) Bank account			
Treatment	0.399***	0.105*	0.301***
	(0.159)	(0.081)	(0.102)
Observations	8,451	13,291	8,425
(b) Bank loan			
Treatment	0.172**	0.094	0.144
	(0.080)	(0.078)	(0.096)
Observations	4,813	8,088	3,997
(c) Fixed deposit			
Treatment	0.043*	0.088***	0.139***
	(0.027)	(0.032)	(0.058)
Observations	8,453	13,292	8,420
(d) Securities			
Treatment	-0.003	0.014	0.006**
	(0.004)	(0.006)	(0.015)
Observations	8,453	13,293	8,423
(e) Insurance			
Treatment	0.144**	0.058	-0.007
	(0.062)	(0.053)	(0.060)
Observations	8,452	13,293	8,437

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A11: Polynomial 2: Banks and household welfare outcomes

	(1) SC	(2) OBC	(3) Gen
(a) Consumption quintiles			
Treatment	0.607**	0.093	-0.092
	(0.325)	(0.255)	(0.269)
Observations	8,580	13,610	8,624
(b) Food consumption quintiles			
Treatment	0.434**	0.403**	0.194
	(0.202)	(0.210)	(0.263)
Observations	7,601	12,081	7,749
(c) Poverty			
Treatment	-0.118**	-0.012	-0.030
	(0.057)	(0.040)	(0.035)
Observations	8,580	13,610	8,624
(d) Multidimensional poverty			
Treatment	-0.023	-0.073	-0.150**
	(0.036)	(0.061)	(0.078)
Observations	31,090	50,181	31,333
(e) Social inclusion			
Treatment	0.140*	-0.020	0.125
	(0.088)	(0.085)	(0.110)
Observations	8,538	13,530	8,593

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A12: Polynomial 2: Informal finance channel

	(1) SC	(2) OBC	(3) Gen
(a) Informal interest rate			
Treatment	-8.113***	-5.025*	-3.377*
	(3.329)	(2.574)	(2.586)
Observations	7,401	16,856	6,426
(b) No mortgage loan			
Treatment	-0.152	-0.131*	0.004
	(0.097)	(0.080)	(0.021)
Observations	12,127	27,828	14,037
(c) Informal loan			
Treatment	0.090*	-0.022	-0.006
	(0.040)	(0.029)	(0.035)
Observations	38,436	95,887	64,034

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2013. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A13: Polynomial 2: Business finance channel

	(1) SC	(2) OBC	(3) Gen
(a) All enterprises			
Treatment	6.552	752.849*	422.479
	(42.749)	(388.800)	(274.271)
Observations	581	581	581
(b) Agricultural enterprises			
Treatment	10.917	39.953	19.697
	(8.389)	(61.826)	(28.549)
Observations	581	581	581
(c) Non-agricultural enterprises			
Treatment	89.499	739.586*	739.006
	(79.884)	(385.309)	(470.991)
Observations	581	581	581

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: Economic census 2013. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A14: Polynomial 2: Agricultural sector

	(1) Value of agricultural machinery	(2) Value of agricultural machinery: power-operated	(3) Number of livestocks	(4) Labour hours: Agriculture	(5) Income: Agriculture
(a) SC					
Treatment	2,013.037***	16,206.719**	0.239	-7.480**	3,093.469**
	(841.527)	(7,288.128)	(0.316)	(3.614)	(1,910.163)
Observations	9,632	1,154	4,912	5,196	8,583
(b) OBC					
Treatment	-979.696	2,494.162*	0.669**	-4.256	-2,542.783
	(1,244.245)	(1,986.704)	(0.334)	(3.356)	(4,176.103)
Observations	28,850	6,721	13,481	5,995	13,619
(c) Gen					
Treatment	2,900.308**	1,429.467	0.345	-3.060	-4,367.131
	(1,684.957)	(2,778.128)	(0.486)	(4.683)	(7,417.267)
Observations	18,120	4,461	8,133	1,343	8,630

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2013 and IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A15: Polynomial 2: Non-agricultural business sector

	(1) SC	(2) OBC	(3) Gen
(a) Log nonfarm business revenue			
Treatment	0.558	0.298	0.036
	(0.545)	(0.292)	(0.312)
Observations	565	1,484	1,046
(b) Hourly wage/salary (Rs)			
Treatment	3.518	2.068	4.035
	(2.276)	(2.159)	(2.684)
Observations	11,464	13,076	5,591
(c) Number of wage/salary jobs in the household			
Treatment	0.203**	0.176	0.070
	(0.124)	(0.127)	(0.090)
Observations	6,081	7,077	3,468

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A16: Placebo cutoff test: Financial inclusion and household welfare outcomes for SCs

	(1) c=-2250	(2) c=-1500	(3) c=-750	(4) c=0	(5) c=750	(6) c=1500	(7) c=2250
				Financial inclusion (SC)			
(a) Bank account							
Treatment	0.02	0.77	0.01	0.40***	-0.35	1.34*	1.47
	(1.18)	(0.44)	(0.35)	(0.16)	(0.45)	(0.45)	(0.88)
Observations	8,451	8,451	8,451	8,451	8,451	8,451	8,451
(b) Bank loan							
Treatment	0.26	0.72	0.07	0.14*	1.26	0.56	0.71
	(0.43)	(0.49)	(0.17)	(0.07)	(0.96)	(0.39)	(0.49)
Observations	4,813	4,813	4,813	4,813	4,813	4,813	4,813
(c) Insurance							
Treatment	0.96*	0.31	0.22	0.13**	0.21	0.36	-0.05
	(1.00)	(0.21)	(0.18)	(0.05)	(0.39)	(0.26)	(0.38)
Observations	8,452	8,452	8,452	8,452	8,452	8,452	8,452
				Welfare outcomes (SC)			
(d) Consumption quintiles							
Treatment	-3.66	0.15	0.12	0.49**	1.99	0.51	2.75
	(5.00)	(1.14)	(0.91)	(0.30)	(4.72)	(1.39)	(2.07)
Observations	8,580	8,580	8,580	8,580	8,580	8,580	8,580
(e) Food consumption quintiles							
Treatment	-4.20	-0.50	3.00	0.42**	1.04	0.80	2.21*
	(4.65)	(0.83)	(9.86)	(0.18)	(2.56)	(0.86)	(1.13)
Observations	7,601	7,601	7,601	7,601	7,601	7,601	7,601
(f) Poverty							
Treatment	0.14	0.25	-1.22	-0.11***	-0.24	-0.66	-0.84
	(0.41)	(0.26)	(27.36)	(0.05)	(0.50)	(0.39)	(0.43)
Observations	8,580	8,580	8,580	8,580	8,580	8,580	8,580
(g) Multidimensional poverty							
Treatment	-0.74	0.26	-0.17	-0.06**	-0.11	-0.30	-0.36
	(0.91)	(0.23)	(0.22)	(0.03)	(0.29)	(0.23)	(0.26)
Observations	31,090	31,090	31,090	31,090	31,090	31,090	31,090
(h) Social inclusion							
Treatment	0.26	-0.16	0.12	0.17*	-0.81	0.25	0.46
	(0.57)	(0.39)	(0.24)	(0.08)	(1.04)	(0.49)	(0.49)
Observations	8,538	8,538	8,538	8,538	8,538	8,538	8,538

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Data used: IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A17: Placebo cutoff test: Informal and business finance channel for SCs

	(1) c=-2250	(2) c=-1500	(3) c=-750	(4) c=0	(5) c=750	(6) c=1500	(7) c=2250
				Informal finance (SC)			
(a) Interest rate: SC							
Treatment	599.23	-123.54	6.10	-8.11**	90.61	8.15	-14.87
	(50,636.60)	(182.32)	(17.33)	(3.33)	(439.70)	(23.93)	(17.44)
Observations	7,401	7,401	7,401	7,401	7,401	7,401	7,401
(b) No mortgage: SC							
Treatment	0.43	0.51	-0.82	-0.15*	-0.05	-0.73	-0.11
	(0.57)	(0.64)	(0.84)	(0.10)	(0.13)	(0.40)	(0.27)
Observations	12,127	12,127	12,127	12,127	12,127	12,127	12,127
(c) Informal loan: SC							
Treatment	-0.18	-0.03	0.27	0.09**	-2.89	0.72	0.23
	(0.29)	(0.16)	(0.27)	(0.04)	(10.84)	(0.28)	(0.15)
Observations	38,436	38,436	38,436	38,436	38,436	38,436	38,436
				Business finance (SC)			
(d) All Enterprises: SC							
Treatment	-293.22	153.36	-10,585.61	80.80*	883.37	163.02	177.66
	(368.85)	(229.41)	(135,554.07)	(50.86)	(1,704.50)	(207.78)	(122.53)
Observations	581	581	581	581	581	581	581
(e) Agri Enterprises: SC							
Treatment	-58.48	12.23	5.82	7.65*	-25.34	28.91	1.49
	(64.25)	(47.51)	(16.05)	(5.39)	(25.55)	(39.03)	(6.10)
Observations	581	581	581	581	581	581	581

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2013 and EC 2013. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A18: Placebo cutoff test: Agricultural and non-agricultural business sector for SCs

VARIABLES	(1) c=-2250	(2) c=-1500	(3) c=-750	(4) c=0	(5) c=750	(6) c=1500	(7) c=2250
				Agricultural sector (SC)			
(a) Agri machinery value							
Treatment	14,590.50	-3,262.34	854.53	1,946.33**	1,273.64	-2,822.09	4,709.80
	(10,037.06)	(5,890.82)	(2,159.05)	(838.01)	(1,267.63)	(5,363.33)	(3,264.33)
Observations	9,632	9,632	9,632	9,632	9,632	9,632	9,632
(b) Agri (power) machinery value							
Treatment	-24,287.61	-147,386.87	-1,565.18	15,047.18***	-7,542.18	-38,122.90	12,303.80
	(379,336.97)	(727,351.34)	(17,366.47)	(5,332.61)	(21,367.12)	(33,533.90)	(17,515.23)
Observations	1,154	1,154	1,154	1,154	1,154	1,154	1,154
(c) Number of livestocks							
Treatment	1.03	2.98	1.51	0.61*	-3.90	1.96	-0.07
	(3.14)	(1.79)	(2.42)	(0.35)	(5.22)	(1.11)	(1.16)
Observations	4,912	4,912	4,912	4,912	4,912	4,912	4,912
(d) Agri labour hours							
Treatment	-18.16	-21.00	-1.21	-7.11**	-18.50	-36.61*	12.36
	(18.37)	(20.79)	(8.23)	(3.24)	(53.80)	(17.47)	(38.02)
Observations	5,196	5,196	5,196	5,196	5,196	5,196	5,196
(e) Agri income							
Treatment	-58,543.24	8,655.79	-67,158.16	3,625.58**	-4,958.76	-20,014.77	18,065.87
	(52,030.10)	(10,642.79)	(164,374.99)	(1,969.99)	(11,690.45)	(11,764.45)	(19,667.69)
Observations	8,583	8,583	8,583	8,583	8,583	8,583	8,583
				Non-agricultural business sector (SC)			
(f) Nonfarm wage							
Treatment	2.58	28.88	-5.44	2.84*	-1.58	6.35	32.27*
	(15.50)	(26.23)	(4.19)	(1.72)	(9.83)	(8.50)	(15.11)
Observations	11,464	11,464	11,464	11,464	11,464	11,464	11,464
(g) Number of jobs							
Treatment	0.32	0.58	1.87	0.17*	-0.50	-0.42	-0.38
	(1.14)	(0.47)	(3.61)	(0.11)	(1.00)	(0.72)	(1.10)
Observations	6,081	6,081	6,081	6,081	6,081	6,081	6,081

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2013 and IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A19: Bandwidth selector test: Financial inclusion and household welfare outcomes for SCs

	MSE optimal		CER optimal	
	(1)	(2)	(3)	(4)
	Common	Two-sided	Common	Two-sided
	Financial inclusion (SC)			
(a) Bank account				
Treatment	0.40***	0.43*	0.41**	0.49
	(0.16)	(0.24)	(0.19)	(0.46)
Observations	8,451	8,451	8,451	8,451
(b) Bank loan				
Treatment	0.14*	0.21**	0.18**	0.22
	(0.07)	(0.10)	(0.09)	(0.14)
Observations	4,813	4,813	4,813	4,813
(c) Insurance				
Treatment	0.13**	0.21**	0.16**	0.24
	(0.05)	(0.10)	(0.07)	(0.19)
Observations	8,452	8,452	8,452	8,452
	Welfare outcomes (SC)			
(d) Consumption quintiles				
Treatment	0.49**	0.47	0.55*	0.96
	(0.30)	(0.36)	(0.36)	(0.74)
Observations	8,580	8,580	8,580	8,580
(e) Food consumption quintiles				
Treatment	0.42**	0.52**	0.47**	0.75**
	(0.18)	(0.20)	(0.20)	(0.30)
Observations	7,601	7,601	7,601	7,601
(f) Poverty				
Treatment	-0.11***	-0.12**	-0.13**	-0.18**
	(0.05)	(0.06)	(0.06)	(0.08)
Observations	8,580	8,580	8,580	8,580
(g) Multidimensional poverty				
Treatment	-0.06**	-0.08	-0.07*	-0.09
	(0.03)	(0.04)	(0.04)	(0.06)
Observations	31,090	31,090	31,090	31,090
(h) Social inclusion				
Treatment	0.17*	0.21	0.18*	0.32
	(0.08)	(0.12)	(0.10)	(0.22)
Observations	8,538	8,538	8,538	8,538

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A20: Bandwidth selector test: Informal and business finance channel for SCs

	MSE optimal		CER optimal	
	(1) Common	(2) Two-sided	(3) Common	(4) Two-sided
	Informal finance (SC)			
(a) Interest rate: SC				
Treatment	-8.11**	-7.28	-6.74*	-9.69*
	(3.33)	(4.71)	(4.16)	(4.69)
Observations	7,401	7,401	7,401	7,401
(b) No mortgage: SC				
Treatment	-0.15*	-0.12*	-0.19**	-0.20**
	(0.10)	(0.07)	(0.10)	(0.10)
Observations	12,127	12,127	12,127	12,127
(c) Informal loan: SC				
Treatment	0.09**	0.05**	0.10**	0.09**
	(0.04)	(0.04)	(0.04)	(0.04)
Observations	38,436	38,436	38,436	38,436
	Business finance (SC)			
(d) All Enterprises: SC				
Treatment	80.80*	29.09	92.65	85.23*
	(50.86)	(47.83)	(61.27)	(54.19)
Observations	581	581	581	581
(e) Agri Enterprises: SC				
Treatment	7.65*	5.91	11.77*	6.27*
	(5.39)	(3.65)	(7.20)	(3.69)
Observations	581	581	581	581

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). Standard errors clustered at district level. Data used: AIDIS 2013 and EC 2013. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A21: Bandwidth selector test: Agricultural and non-agricultural business sector for SCs

	MSE optimal		CER optimal	
	(1) Common	(2) Two-sided	(3) Common	(4) Two-sided
	Agricultural Sector (SC)			
(a) Agri machinery value				
Treatment	1,946.33**	1,819.46***	2,047.61**	1,793.12***
	(838.01)	(558.82)	(1,039.91)	(592.51)
Observations	9,632	9,632	9,632	9,632
(b) Agri (power) machinery value				
Treatment	15,047.18***	10,020.05**	18,141.54***	9,935.63***
	(5,332.61)	(3,543.99)	(6,739.51)	(3,427.54)
Observations	1,154	1,154	1,154	1,154
(c) Number of livestocks				
Treatment	0.61*	0.61**	0.44	0.62*
	(0.35)	(0.30)	(0.38)	(0.37)
Observations	4,912	4,912	4,912	4,912
(d) Agri labour hours				
Treatment	-7.11**	-6.60	-7.95**	-7.84*
	(3.24)	(3.62)	(3.81)	(3.91)
Observations	5,196	5,196	5,196	5,196
(e) Agri income				
Treatment	3,625.58**	8,663.61	5,099.88**	41,356.79
	(1,969.99)	(9,732.22)	(2,288.57)	(347,737.36)
Observations	8,583	8,583	8,583	8,583
	Non agricultural business sector (SC)			
(f) Nonfarm wage				
Treatment	2.84*	2.94	3.76*	2.62
	(1.72)	(1.94)	(2.12)	(3.00)
Observations	11,464	11,464	11,464	11,464
(g) Number of jobs				
Treatment	0.17*	0.50	0.23*	0.72
	(0.11)	(0.38)	(0.12)	(0.86)
Observations	6,081	6,081	6,081	6,081

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2013 and IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A22: Bandwidth multiplier test: Financial inclusion and household welfare of SCs

	(1) 0.50x	(2) 0.75x	(3) 1.00x	(4) 1.25x	(5) 1.50x
			Financial inclusion (SC)		
(a) Bank account					
Treatment	0.37	0.41	0.40***	0.33**	0.26***
	(0.35)	(0.19)	(0.16)	(0.13)	(0.11)
Observations	8,451	8,451	8,451	8,451	8,451
(b) Bank loan					
Treatment	0.19	0.18*	0.14*	0.13**	0.12**
	(0.11)	(0.09)	(0.07)	(0.06)	(0.06)
Observations	4,813	4,813	4,813	4,813	4,813
(c) Insurance					
Treatment	0.21*	0.16***	0.13**	0.13***	0.13**
	(0.10)	(0.07)	(0.05)	(0.05)	(0.04)
Observations	8,452	8,452	8,452	8,452	8,452
			Welfare outcomes (SC)		
(d) Consumption quintiles					
Treatment	1.11***	0.55**	0.49**	0.47	0.37*
	(0.87)	(0.36)	(0.30)	(0.26)	(0.23)
Observations	8,580	8,580	8,580	8,580	8,580
(e) Food consumption quintiles					
Treatment	0.65**	0.47***	0.42**	0.38**	0.30***
	(0.28)	(0.20)	(0.18)	(0.16)	(0.15)
Observations	7,601	7,601	7,601	7,601	7,601
(f) Poverty					
Treatment	-0.15***	-0.13**	-0.11***	-0.07***	-0.03**
	(0.07)	(0.06)	(0.05)	(0.04)	(0.04)
Observations	8,580	8,580	8,580	8,580	8,580
(g) Multidimensional poverty					
Treatment	-0.05	-0.07	-0.06**	-0.03**	-0.02*
	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)
Observations	31,090	31,090	31,090	31,090	31,090
(h) Social inclusion					
Treatment	0.13	0.18	0.17*	0.14*	0.12*
	(0.12)	(0.10)	(0.08)	(0.07)	(0.06)
Observations	8,538	8,538	8,538	8,538	8,538

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A23: Bandwidth multiplier test: Informal and business finance channel for SCs

	(1) 0.50x	(2) 0.75x	(3) 1.00x	(4) 1.25x	(5) 1.50x
			Informal finance (SC)		
(a) Interest rate: SC					
Treatment	-6.47**	-6.87	-8.11**	-8.44	-7.72**
	(5.38)	(4.11)	(3.33)	(2.94)	(2.70)
Observations	7,401	7,401	7,401	7,401	7,401
(b) No mortgage: SC					
Treatment	-0.28	-0.19	-0.15*	-0.13**	-0.10**
	(0.16)	(0.10)	(0.10)	(0.10)	(0.09)
Observations	12,127	12,127	12,127	12,127	12,127
(c) Informal loan: SC					
Treatment	0.11	0.10	0.09**	0.07**	0.06**
	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)
Observations	38,436	38,436	38,436	38,436	38,436
			Business finance (SC)		
(d) All Enterprises: SC					
Treatment	147.35	91.44**	80.80*	54.99*	40.72*
	(76.73)	(60.62)	(50.86)	(43.61)	(38.91)
Observations	581	581	581	581	581
(d) Agri Enterprises: SC					
Treatment	16.15	11.40	7.65*	8.79	7.00
	(11.39)	(7.01)	(5.39)	(6.03)	(6.08)
Observations	581	581	581	581	581

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2013 and EC 2013. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A24: Bandwidth multiplier test: Agricultural and non-agricultural business sector for SCs

	(1) 0.50x	(2) 0.75x	(3) 1.00x	(4) 1.25x	(5) 1.50x
			Agricultural Sector (SC)		
(a) Agri machinery value					
Treatment	3,053.95*	2,053.58*	1,946.33**	1,942.25*	1,573.30**
	(1,745.13)	(1,029.76)	(838.01)	(700.04)	(603.11)
Observations	9,632	9,632	9,632	9,632	9,632
(b) Agri (power) machinery value					
Treatment	18,228.79	18,202.46**	15,047.18***	11,610.53***	9,521.20***
	(6,742.08)	(6,816.27)	(5,332.61)	(4,393.23)	(3,787.66)
Observations	1,154	1,154	1,154	1,154	1,154
(c) Number of livestocks					
Treatment	0.26	0.45	0.61*	0.45**	0.24**
	(0.42)	(0.38)	(0.35)	(0.31)	(0.27)
Observations	4,912	4,912	4,912	4,912	4,912
(d) Agri labour hours					
Treatment	-6.33	-7.96	-7.11**	-6.26*	-6.05*
	(4.46)	(3.83)	(3.24)	(2.80)	(2.56)
Observations	5,196	5,196	5,196	5,196	5,196
(e) Agri income					
Treatment	7,301.54*	5,087.81**	3,625.58**	2,979.76***	2,500.19**
	(3,844.46)	(2,290.45)	(1,969.99)	(1,781.08)	(1,642.89)
Observations	8,583	8,583	8,583	8,583	8,583
			Non agricultural business sector (SC)		
(f) Nonfarm wage					
Treatment	3.62	3.75	2.84*	2.11*	1.61*
	(2.57)	(2.12)	(1.72)	(1.45)	(1.28)
Observations	11,464	11,464	11,464	11,464	11,464
(g) No of jobs					
Treatment	0.25*	0.23**	0.17*	0.14**	0.09*
	(0.16)	(0.12)	(0.11)	(0.09)	(0.09)
Observations	6,081	6,081	6,081	6,081	6,081

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: AIDIS 2013 and IHDS 2011-12. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.

Table A25: Donut Hole Test

Financial Inclusion				Household Well-being			
	SC	OBC	Gen		SC	OBC	Gen
(a) Bank account				(f) Consumption			
Treatment	0.360***	0.177**	0.293***	Treatment	0.345*	0.088	0.056
	(0.110)	(0.096)	(0.086)		(0.244)	(0.234)	(0.220)
Observations	8,356	13,144	8,364	Observations	8,485	13,462	8,561
(b) Bank loan				(g) Food consumption			
Treatment	0.150*	0.093	0.126*	Treatment	0.457***	0.434**	0.293
	(0.073)	(0.076)	(0.066)		(0.172)	(0.208)	(0.232)
Observations	4,752	8,002	3,952	Observations	7,513	11,956	7,691
(c) Fixed Deposit				(h) Poverty			
Treatment	0.036	0.136***	0.168***	Treatment	-0.102**	-0.043	-0.036
	(0.027)	(0.042)	(0.058)		(0.050)	(0.046)	(0.028)
Observations	8,358	13,145	8,359	Observations	8,485	13,462	8,561
(d) Securities				(i) MPI			
Treatment	-0.002	0.011	0.029***	Treatment	-0.052*	-0.078	-0.169**
	(0.002)	(0.007)	(0.011)		(0.032)	(0.063)	(0.081)
Observations	8,358	13,146	8,362	Observations	30,713	49,648	31,074
(e) Insurance				(j) Social inclusion			
Treatment	0.143**	0.082	0.014	Treatment	0.162*	-0.016	0.124
	(0.054)	(0.065)	(0.047)		(0.094)	(0.103)	(0.085)
Observations	8,357	13,147	8,376	Observations	8,444	13,382	8,530

Note: Treatment is district-level expansion of bank branches following the Reserve Bank of India, Branch Authorization Policy in 2005. Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1). Standard errors clustered at district level. Data used: IHDS 2012. District population and number of bank branches in 1996 are controlled for. Source: Authors' calculation.