# Disparities in Home Loans: Evidence from India

Nirupama Kulkarni  Prashant Bharadwaj  Abhiman Das  Niranjan Kumar

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**Abstract**

Analyzing the universe of home loans (2015-2020) from a large Indian state-owned bank, we find that minorities receive appraisal ratios 31% lower than those of the majority. This gap lessens but persists after controlling for detailed borrower, property, and zipcode characteristics. We argue that statistical discrimination contributes to this gap. First, although defaults are rare, minorities exhibit higher default rates conditional on observables. This suggests underlying unobserved risk differences might be driving the results. Second, we use several interventions to assess whether banks respond to more information about borrower quality. Consistent with models of statistical discrimination, we find that interventions that improve the bank's information environment significantly reduce the appraisal gap.

**JEL Codes: D14, R21, R23, R31**

**Keywords: Statistical discrimination, collateral, segregation, mortgages, India**

Kulkarni: CAFRAL, nirupama.kulkarni@cafral.org.in. Bharadwaj: UC San Diego, prbharadwaj@ucsd.edu. Das: IIM Ahmedabad, abhiman@iima.ac.in. Kumar: CAFRAL, niranjan@wustl.edu. Arvind Gururaj provided excellent research assistance. Thanks to Kate Antonovics, David Arnold, Satyajit Chatterjee, Rahul Deb, Maher Said, Adrian de la Garza, Alesandro Bonatti, and Matt Mitchell for fruitful discussions.

# 1 Introduction

Housing disparities in India are stark. Religious and caste minorities are concentrated in highly segregated neighborhoods that often have worse access to public services and infrastructure. Measured at fine geographic levels, segregation in India is comparable to that observed in the United States (Adukia et al., 2025). A large body of work, notably by Chetty et al. (2025); Chetty and Hendren (2018a,b); Chetty et al. (2016), has established the causal importance of neighborhoods in shaping long-term economic outcomes and intergenerational mobility. Segregated neighborhoods can therefore function as micro-centers of poverty traps. For most households, escaping such neighborhoods requires residential mobility, and residential mobility in turn requires access to formal housing finance. Whether this channel can mitigate spatial inequality depends crucially on how fairly the housing finance system treats different groups. This paper asks two questions: (i) do systematic disparities exist in the Indian home loan market between minority and majority borrowers, and (ii) to what extent can canonical models of taste-based versus statistical discrimination explain these disparities?

We study these questions using the universe of home-purchase mortgages originated between 2015 and 2020 by a large Indian state-owned bank. State-owned banks account for 70% of the home loan market, and our bank holds 40%, making it a central player in the provision of housing finance. We observe detailed loan contract terms, property characteristics, borrower characteristics (including directly reported religion and caste), and the appraised value of the collateral.

Our main outcome is the appraisal ratio, defined as the log of the appraised value of the property divided by the final sale price. This is a margin where lenders possess substantial discretion: given a regulatory ceiling on loan-to-value (LTV) ratios, a lower appraisal value for a given sale price directly tightens the collateral constraint, forcing the borrower to make a larger down payment or seek alternative finance. A persistent gap in appraisal ratios therefore has first-order implications for who can become a homeowner and on what terms.

We document three basic facts.

First, minority borrowers receive substantially lower appraisal ratios than majority borrowers. We define

minorities as borrowers who are Muslim or belong to Scheduled Castes (SC), Scheduled Tribes (ST), or Other Backward Classes (OBC); the comparison group are Hindu borrowers in the "General" category. Unconditionally, the appraisal ratio is about 0.37 log points lower for minority borrowers, implying that for homes purchased at the same price, the appraised value for minority borrowers is roughly 31 percent lower. Conditioning on borrower characteristics (including credit scores), property characteristics, and very fine geography (pincode fixed effects) reduces the gap to around 0.13 log points—about 13 percent—but does not eliminate it. The bulk of the raw gap reflects residential segregation, yet sizeable within-pincode differences remain.

Second, other loan terms differ much less across groups. Minorities have slightly lower LTV ratios (by about 0.003), somewhat shorter maturities (by roughly 0.06 years), and slightly different interest rates (around 0.01 percentage points), but these differences are economically negligible relative to the appraisal gap. In India, these margins are more tightly regulated by the Reserve Bank of India (RBI), which sets caps on LTVs and benchmarks for interest rates, leaving banks comparatively less discretion than on the appraisal margin. Our results suggest that group-level disparities in this bank's home lending are concentrated on the collateral valuation side rather than in the easily observed terms of the loan contract.

Third, the appraisal gap is large in economic terms. Given average property values and LTVs in our data, the baseline estimates imply that minority borrowers obtain loans that are on the order of several hundred thousand rupees smaller than those of observably similar majority borrowers purchasing similarly priced homes. This translates into substantially higher required down payments for minorities, and thus potentially delays or prevents homeownership.

A limitation of the data is that we observe only loans that were originated and accepted—we do not see applications, rejections, or offers that borrowers turn down. The disparities we document are therefore equilibrium objects. While this selection complicates the interpretation of levels, our main focus is on how appraisal gaps move across information environments and policies, comparisons that are less sensitive to unobserved application-stage selection. In light of this limitation and to make progress on understanding the source of these disparities, we interpret these patterns through the lens of canonical models of discrimination.

Taste-based discrimination à la Becker (1957) posits that some market participants hold a "taste" or animus against a particular group, which acts like a tax on transactions with that group. In the simplest formulations, this tax is independent of the information environment: even when the lender has precise information about a borrower or their collateral, animus depresses the terms offered to minority borrowers.

By contrast, statistical discrimination (Phelps, 1972; Arrow, 1973) arises when lenders use group identity as an additional signal about loan quality in the presence of noisy information. In our context, lenders may believe that (i) the average loan quality (a combination of borrower creditworthiness and collateral value) is lower for minorities than for majority borrowers, and/or (ii) signals about minority loans are noisier—for instance because documentation is less complete or properties are harder to evaluate. In either case, lenders might rationally assign lower appraisal values to minority loans even when formal observables are the same.

We present several pieces of evidence that are consistent with a statistical-discrimination interpretation.

First, although defaults are rare overall, minorities exhibit higher default rates. In our data, about 47 out of every 10,000 loans enter 90-day delinquency. The corresponding rates are roughly 32 per 10,000 for majority borrowers and 141 per 10,000 for minority borrowers. These differences persist after conditioning on detailed borrower, property, and geographic controls, with regression estimates indicating that default rates for minorities are about 20 basis points higher than for otherwise similar majority borrowers. This pattern is consistent with lenders holding priors that average loan quality is lower for minorities, one of the key ingredients required for statistical discrimination. We emphasize that these default differences may themselves reflect broader structural disadvantages and discrimination in other markets; we use them as descriptive evidence that statistical discrimination is a plausible channel, not as a normative justification.

Second, appraisal gaps are larger in information-poor environments. We show that minority appraisal ratios are relatively lower in rural pincodes, in "thin" markets with fewer housing transactions, and among borrowers with no prior formal credit history (and thus no credit score). Conversely, gaps are smaller in urban areas and high-transaction pincodes, where the bank can plausibly draw on richer information about both borrowers and local property markets. Under pure taste-based discrimination, one would not expect

the appraisal gap to systematically shrink in information-rich settings; under statistical discrimination, this is exactly what one would predict as signals become more precise.

Third, following Bharadwaj, Deb, and Renou (2025), we implement a distributional test for generalized statistical discrimination. Their model provides conditions under which the observed distribution of loan terms for two groups can be generated by a broad class of statistical-discrimination environments. In our setting, we construct the counterfactual distribution of appraisal ratios minorities would face if treated as majority borrowers, holding constant the joint distribution of covariates (using the decomposition framework of Chernozhukov, Fernández-Val, and Melly (2013)). The estimated quantile differences between the observed and counterfactual distributions change sign across the distribution, implying that neither distribution first-order stochastically dominates the other. This pattern is consistent with the generalized statistical discrimination model and inconsistent with some simple alternatives in which minorities are uniformly advantaged or disadvantaged at all points in the distribution.

To probe mechanisms further, we study two settings in which the bank's information environment changes or the composition of minority borrowers likely improves. Statistical discrimination predicts that in such settings, outcome gaps should shrink, as better information and higher quality reduce the value of group-level priors. Under a standard Beckerian taste-based model, by contrast, prejudice would depress minority outcomes even when information is rich or borrower quality improves.

Our first setting involves integrated developers—builders who work closely with the bank and buyers to streamline home purchase and financing. These projects are vetted by the bank, and the developer's sales team often coordinates documentation and appraisals. This institutional structure plausibly provides the bank with richer information about both the underlying collateral and borrowers, and may also attract relatively higher-quality borrowers among both minorities and majorities. In this environment, we find that appraisal gaps for minorities shrink dramatically and, in our most stringent specifications, essentially disappear. Within integrated-developer projects, minority borrowers no longer exhibit higher default rates than majority borrowers. These patterns are consistent with the idea that when the bank receives better signals—or screens borrowers more intensively—it appraises minority loans more favorably, and that the initial gap reflects a combination of informational frictions and group-level priors rather than fixed animus.

Our second setting exploits Priority Sector Lending (PSL) regulations. Under India's PSL policy, banks are required to allocate a fixed share of their loan portfolio to "weaker sections," a category that includes religious minorities. Following the Prime Minister's 15-Point Programme for the Welfare of Minority Communities, the RBI designated certain "minority concentration districts" (MCDs), based on whether the share of minorities exceeded a population threshold in the 2001 Census (RBI (2007)). In these districts, banks face stricter monitoring of credit allocation to minorities. Building on the regression discontinuity design in Khan and Ritadhi (2025), we compare districts just above and just below the minority-share cutoff. We find that in districts where the PSL rules effectively force the bank to expand lending to minorities, minority appraisal ratios increase significantly relative to districts just below the threshold, while minority default rates fall modestly. These patterns are consistent with banks responding to PSL mandates by screening more intensively and/or updating their priors about minority borrowers, thereby narrowing appraisal disparities.

Taken together, these results show that the appraisal gap between minority and majority borrowers is highly responsive to the information environment and lending incentives. The gap is largest where information is scarce, shrinks in settings where the bank is better informed or directly involved with developers, and responds to policy-induced changes in lending to minorities. These features are hard to reconcile with a benchmark model in which discrimination is purely taste-based and invariant to information, and are instead consistent with a significant role for statistical discrimination operating through informational frictions and group priors.

Our paper contributes to several literatures. First, we connect the canonical theoretical distinction between taste-based and statistical discrimination (Becker, 1957; Phelps, 1972; Arrow, 1973) to the context of housing finance in a large developing country, and we apply a recent general model and test of statistical discrimination due to Bharadwaj et al. (2025). Second, we add to the growing empirical literature on discrimination in mortgage markets, which has documented racial disparities in mortgage pricing (Bartlett et al., 2022) and in home appraisal values in the United States (Lang and Nakamura, 1993; Calem et al., 2020; Rothwell et al., 2018; Rothwell and Perry, 2022). We show that appraisal disparities also arise in India, but in an institutional environment where information frictions are particularly severe and where collateral

valuation plays an even more central role in lending.

Third, our paper contributes to the growing literature on the Indian real estate and mortgage markets (Anagol et al., 2025a,b; Agarwal et al., 2025b,a). For instance, Anagol et al. (2025a) develop a structural model to determine optimal tax policy in the presence of pervasive under-reporting in the Indian real estate sector, while their companion work examines how demonetization affected this reporting behavior (Anagol et al., 2025b). Similarly, Agarwal et al. (2025b) investigate how the Real Estate Regulation and Development Act of 2016—a policy aimed at improving developer accountability—transformed homeownership patterns. Complementing this institutional focus, Agarwal et al. (2025a) explore how targeted mortgage schemes for women influence intra-household financial decision-making.

Finally, we complement work on lending bias and cultural proximity in developing economies that exploits randomized or quasi-random assignment of loan officers to borrowers (Fisman et al., 2017, 2020). Whereas that work emphasizes taste-based or relational discrimination by individual officers, we show that disparities in lending terms also respond systematically to market-wide information structures such as integrated developer partnerships and PSL mandates.

Ultimately, models of taste-based and statistical discrimination are not mutually exclusive. In a complex setting like India—shaped by centuries of ethnic and caste-based stratification—observed disparities in credit markets are likely the product of a mix of direct, statistical, and systemic discrimination. Our aim is not to provide a complete accounting of all such channels. Rather, we show that a substantial component of the appraisal disparity is consistent with a model of statistical discrimination operating through informational frictions, and that this component responds to changes in the information environment and regulatory incentives.

The remainder of the paper is organized as follows. Section 2 describes the institutional context, including the appraisal process and the PSL regime. Section 3 presents the data and sample construction. Section 4 documents baseline disparities in appraisal ratios and other loan terms. Section 5 lays out the framework of statistical discrimination and our empirical test. Section 6 presents evidence on statistical discrimination in appraisal gaps, and Section 7 studies how appraisal gaps respond to changes in the information

environment through integrated developers and PSL. Section 8 concludes.

## 2 Institutional Details

The basic features of the appraisal process in India are similar to practices globally. The lender commissions the appraiser. These are certified agents, independent of the lender and the borrower. Appraisers estimate the value of the property based on inputs such as the location of the property, size, condition, any additional amenities provided, and the recent sales of comparable properties nearby. The appraisal process helps the lender assess the collateral value, which it then uses to determine the loan amount that the lender is willing to extend. Too high a value may increase credit risk, and too low a value may result in the transaction not going through. Property appraisals are necessary to comply with regulatory requirements in India.[1]

Mortgage appraisal empanelments (that determine institutions included as official appraisers) are conducted regionally. For instance, the entire state of Maharashtra may hold a single empanelment, which is then approved centrally by the bank's head office (e.g., in Mumbai). Empanelments are usually held every three to four years, depending on the bank, and applications are typically available online. The valuers, especially those working in the large banks, must obtain a certification from the Insolvency and Bankruptcy Board of India (IBBI). After passing the required examination, valuers (which stand at approximately 2,700 certified individuals nationally) must apply to the bank with a wealth tax certificate. Once approved centrally, each one of them is assigned a zone and can conduct valuations across the state.

Valuers interact extensively with local branches. When an application for a mortgage comes to the bank, the branch redirects the customer to an approved valuer. In smaller cities, the bank manager often advises customers to directly contact a valuer to obtain a valuation report. In larger cities, such as when purchasing apartments in a residential complex, the builder's team usually handles the process. Branch managers collect documents, work with a designated valuer for the entire property, and streamline the reporting process. Customers in smaller cities typically approach valuers directly, submitting their documents and reports for site verification. While bank managers are generally not involved, there are exceptions where they might oversee the process. Once the valuation report is prepared, customers often pay the valuers directly in cash. In some rare cases, the bank pays the valuer instead.

[1] See https://www.godrejproperties.com/blog/the-role-of-property-appraisals-in-mortgage-lending-in-india.

During the appraisal process, the appraiser records four different values: the market value, the realizable value (appraisal value), the distressed sale value, and the government value or the registrar value. Both appraisal values and market values are important for our analysis. The market value reflects the price the property was purchased at if the purchase was within the last three years. Otherwise, the appraiser uses a sales comparison approach, an income approach, or a cost approach to determine the market values of the property.

The distressed sale value reflects liquidation discounts and is typically lower than the market value and the appraised value. The government value or the registrar value is a lower bound of the property price based on the location-specific valuation assigned by the tax authority, typically on a per-square-foot basis (Anagol et al., 2025a).

The Reserve Bank of India (RBI) typically sets the maximum loan-to-values (LTVs) by property value. For example, in November 2024, LTV limits based on the cost of the home up to ₹3 million was 90%, between ₹3-7.5 million was 80% and above ₹7.5 million was 75%. The LTV and the appraisal value (the value in the denominator of LTV) together determine the down payment that a borrower needs to pay. The appraisal value eventually determines the loan amount the bank is willing to extend to a borrower.

### 2.1 Priority Sector Lending

Priority Sector Lending (PSL) has a long history in India. The Prime Minister's 15 Point Programme for the Welfare of Minority Communities was a joint set of policies aimed at improving various socio-economic aspects of India's religious minorities. The program was launched in 2006 and later was revised and expanded in 2009. While the program's scope spanned multiple realms, one important goal was improving access to credit for minority communities, including ensuring "smooth flow of bank credit to minority communities" (RBI, 2007).

The Reserve Bank of India (RBI) was given the responsibility of framing the regulations governing credit allocation to minorities, as well as for overall monitoring. The RBI subsequently issued guidelines in July 2007 instructing commercial banks to monitor credit flow to minorities in 103 "minority concentration" districts (MCDs), classified based on whether their share of minorities exceeded 25% of their population as

per the 2001 population Census (RBI, 2007).

From the perspective of a bank, the primary incentive to comply with the directed credit guidelines towards minorities was that it would allow them to meet a key regulatory target. At present, banks are mandated to allocate 12% of their total loan portfolio towards "weaker sections", which include small farmers, village and cottage industries, and borrowers from historically marginalised communities. Following the directed lending guidelines, the RBI expanded the definition of "weaker sections" to include religious minorities. Therefore, lending to borrowers from religious minorities would contribute towards meeting the 12% quota.

Finally, in order to monitor adequate compliance of banks to these guidelines in MCDs, the RBI issued a set of instructions to banks (RBI, 2007). These measures included, but were not limited to, setting up a special division in each bank with a senior officer to provide oversight in relation to the policy, generating local awareness among religious minorities regarding the policy, and engaging with self-help groups. More concretely, banks were mandated to file half-yearly reports with both the RBI and the federal Ministry of Minority Affairs, detailing the disbursement of credit to minority borrowers (RBI, 2007).

## 3 Data

Our main dataset is mortgage-level data from one of the largest public sector bank with details on the loan. The bank in our sample holds close to 40% of home loans (by value) in the country and operates over 22,500 branches across all states and caters to nearly 93% of districts.[2] Our data contains details on contract terms (loan size, interest rates, maturity), loan performance, property details (sq. feet, property value, appraisal property value), and borrower characteristics (CIBIL score, caste/religion) are provided. Starting in 2015, information on vertically integrated developers is available. Hence, we use data for 2015 to 2020, which also covers periods where significant regulatory changes occurred. We have data on 1.12 million loans from 2015-2020. We retain loans with no missing appraisal values, property values, interest rates, loan-to-values, religion, and caste variables. We also retain only those records where pincode and district values are not missing. We drop observations with interest rates lower than 2% and if the borrower's age is above

[2]In aggregate, state-owned banks account for 70% of all bank credit and are subject to dual regulation wherein India's central bank (RBI) regulates all Scheduled Commercial Banks, and the Ministry of Finance (Department of Financial Services) regulates state-owned banks in India.

80 years. Table IA1 details the sample construction.

In our analysis, we focus on minority borrowers along both the religious and caste dimensions. Minority borrowers in our setting refer to Muslim borrowers and those belonging to Scheduled Castes (SC) and Scheduled Tribes (ST), and Other Backward Classes (OBC). The comparison group, the non-minority group, is Hindu borrowers from the "General" caste category. Unlike previous papers in the U.S. that rely on imputed race, our data uses the actual minority status of borrowers collected by the lender as part of its requirements to fulfill government mandates.

**Appraisal Ratio** Our analysis focuses on the appraisal value which is the valuation of the collateral by the lender. For a given loan-to-value, the appraisal value determines the loan amount a borrower receives. In our analysis, we compare "appraisal value" to "property value", defined as:

$$\text{Appraisal Ratio} = \text{Log}\left(\frac{\text{Appraisal Value}}{\text{Property Value}}\right) \tag{1}$$

We refer to the ratio of appraisal value to property value as the appraisal ratio.

### 3.1 Descriptive statistics

Table 1, Panel A presents the variable of interest, the appraisal gap. On average, appraisal ratios are negative indicating that appraisal values are lower than the sale price. This is in contrast to the U.S, where Calem et al. (2020) document that appraisal values are rarely lower than the sales price. However, consistent with the US data, median appraisal ratio is 0. Figure 1 also documents heavy bunching around 0, indicating that appraisers are most likely to estimate the appraisal values exactly at the sale price. Calem et al. (2020) conjecture that appraisers are more inclined to appraise property at the sale price as valuing too low might result in the transaction not going through, and valuing too high may increase credit risk. Within minority categories, Muslim borrowers have relatively higher appraisal ratios compared to OBC/SC/ST borrowers (Table IA2). Figure 2 shows the spatial variation of appraisal ratios and indicates wide variation across regions in India.

Panel B in Table 1 shows loan-level characteristics. Average loan amount is ₹2,691,099. The split by non-minority and minority categories reveals that non-minority borrowers have higher loan values on average

of ₹2,811,007, with minority borrowers at ₹1,957,673. Within the minority categories, Muslim borrowers have a higher loan amount of ₹2,162,197, whereas OBC and SC/ST borrowers have lower loan amounts of ₹1,952,708 and ₹1,841,352, respectively.

Loan-to-values (LTV) values are strikingly similar across the board at 63%. Default rates are low on average at 0.47% (47 loans default for every 10,000 loans), indicating that defaults in our sample are rare. Non-minority defaults are even less common (0.32%), but 4.4x larger for minority borrowers at 1.4%. On average, interest rates are 7.33%, 7.32% for non-minority borrowers and a higher 7.35% for minority borrowers. Within minority borrowers, Muslims had a higher interest rate of 7.36%, whereas OBC and SC/ST borrowers had comparatively lower interest rates of 7.35% and 7.33% respectively. Panel C shows statistics for borrower characteristics. Borrowers are more likely to be male (72%) with an average age of 41 years. 25% do not have a credit score, and conditional on having a credit score borrowers score is 747 overall, 748 for non-minority, and 736 for minority borrowers. The average credit score across categories corresponds to prime borrowers[3]

Property characteristics in Panel D indicate that built-up area is 1,282 sq. ft. with 2,265 plot area. Property characteristics are similar for minority and non-minority borrowers with 1,272 (2,382) sq.ft and 1,284 (2,246) sq.ft built-up (plot) area.

## 4 Disparities in Lending

We begin by documenting the disparities in lending to minority borrowers. To assess the relationship between various loan terms and how it differs for minority borrowers, we use the specification:

$$Y_i = \phi_p + \delta_t + \beta \text{Minority}_i + \gamma \mathbf{X}_i + \epsilon_i, \tag{2}$$

for loan $i$ in district $d(i)$ in pincode $p(i)$ originated in month-year $t$. Where $Y_i$ is the loan-level outcome of interest: log of appraisal ratio, LTV, maturity, and interest rate. The most stringent specification includes pincode fixed effects ($\phi_p$), allowing us to compare borrowers within very narrow geographies. In alternative specifications, we include only district fixed effects to control for regional variation at a more aggregate level. $\delta_t$ includes year fixed effects to control for aggregate bank-level variation and a month

[3]The credit score is the CIBIL score from TransUnion CIBIL, which classifies the continuous score ranging from 300-900 into: subprime = 300-680, near prime = 681-730, prime = 731-770, prime plus = 771-790, and super prime = 791-900.

fixed effect to control for seasonality. Given the wide and heterogeneous nature of Indian households, we focus on specific minority groups along the caste dimension and the religion dimension. Along caste, minority groups include scheduled castes, scheduled tribes, and OBC, and along religion, the minority group includes Muslims. The comparison group, the non-minority group, includes Hindu borrowers from the "General" category. While the baseline clubs all minority groups together in the interest of brevity in presenting our results, in additional analysis, we also analyze the groups individually as robustness. $\mathbf{X}_i$ are controls for borrower and property characteristics. Borrower characteristics include gender, age of borrower and borrower occupation. We also include indicators for credit score bands (super prime, above prime, prime, below prime, subprime, and new-to-credit) interacted with year to control for ex-ante borrower creditworthiness. Property controls include plot area and built-up area. Standard errors are clustered at the pincode level. The coefficient of interest, $\beta$, captures how various loan level terms differ for minority borrowers relative to non-minority borrowers.

**Appraisal Gaps.** We first examine appraisal ratios using the specification in Equation 2. In column 1 of table 2, we regress the log of the appraisal ratio directly on a categorical variable for minority status. Appraisal ratios are 0.369 log points, or 30.9% lower for minority borrowers relative to the comparison group of non-minority borrowers. On adding district fixed effects, appraisal ratios are 0.184 log points, or 16.8% lower. On adding pincode fixed effects (column 3), we see that the appraisal gap — defined as the difference in appraisal ratio between minority and non-minority borrowers — narrows to 0.144 log points, or 13.4%. Comparing column 1 to column 3 estimates indicates that geography/neighborhood accounts for a significant proportion (57% =1-13.4%/30.9%) of the variation in appraisal ratios, with the remaining variation coming from within-neighborhood differences. Adding time controls only minimally changes the gap estimates to 0.142 log points, or 13.2% (column 4). Similarly, on adding borrower controls appraisal ratios are 0.132 log points, or 12.3% lower for minority borrowers (column 5). Property controls do not change estimates. Overall, geography drives most of the variation in appraisal gaps with only marginal effects of borrower- and property-level characteristics.

What do these differences in appraisal values imply for minority borrowers' access to credit? Given average property values of ₹4,534,912 (from Table 1) and an average loan-to-value of 63%, the estimates in column 1

translate to nearly ₹882,811 ($10,593[4]) lower loan amounts for minority borrowers relative to non-minority borrowers.

The baseline estimates club together distinct minority groups, namely, SC/ST, OBC, and Muslim borrowers. While this choice is made in the interest of brevity, these groups are economically and socially very different. Table 3 includes a categorical variable for each group. As in the baseline estimation, the comparison group is borrowers classified as Hindu and belonging to the "General" caste category. Column 1 shows that compared to the non-minority group, Muslim borrowers have the narrowest gap with 0.093 log points, or 8.9% lower appraisal ratios, which corresponds to ₹254,272 ($3051) lower credit. OBC borrowers fare better with 0.128 log points, or 12% lower appraisal ratios, which translates to ₹342,839 ($4114) lower loan amount and SC/ST borrowers fare the worst with appraisal ratios 0.174 log points, or 16% lower compared to majority borrowers (₹457,119 ($5,485) lower loan amount). The worse outcomes for SC/ST households compared to Muslim borrowers align with prior research that shows Muslims tend to have better socioeconomic outcomes compared to lower caste groups but worse outcomes relative to upper caste groups (Sacchar et al., 2006; Ash et al., 2025).

We also examine two results characterizing the distribution of appraisal gaps, which also act as robustness tests of our baseline estimates and ensure that outliers are not driving differences. Panel A in Figure 3 shows the appraisal gap for minority borrowers by state. The point estimates for the baseline specification in Equation 2 for the sub-sample of mortgages in each state are shown. The dashed lines represent the 95% confidence interval. The figure indicates that barring the states of Manipur, Daman & Diu, and Goa, the appraisal gap is negative across all states in India. Panel B in Figure 3 shows the appraisal gap for minority borrowers by districts. We run the baseline estimate for districts with at least 500 observations. Of the 529 districts, this condition is satisfied for 345 districts. Point estimates are negative and significant at 5% in 173 districts, negative and insignificant in 138 districts, positive and significant in 1 district, and positive and insignificant at 5% in 33 districts.[5]

[4] Assuming a conversion rate of 0.012

[5] In robustness tests, we build grids of 100 m x 100 m that control for properties located within extremely narrow geographies. Results are robust to including grid fixed effects (Table IA4).

**Other loan terms.** Even with lower appraisals, lenders could potentially adjust LTVs higher muting adverse effects and lower appraisal ratios may not be economically meaningful if not reflected in loan values. Table 4 shows the differences in LTV, where "value" in the denominator in LTV is the appraised value. LTV is *lower* by 0.003. A lower LTV of -0.003 translates to only ₹12,153 ($146) lower loan assuming the average appraisal value of ₹4,050,938 (Table 1). Thus, LTVs do not adjust substantially upward to compensate for lower appraisal values. If anything, the LTVs are slightly lower, although not economically meaningful compared to the appraisal gaps documented in Table 2 plausibly because LTVs are more closely scrutinized by regulators and industry compared to appraisal values. Similarly minority borrowers have shorter maturities by around (column 2, Table 4). However, the effect of 0.06 years is economically negligible when compared to the average maturity of 20.3 years for the mortgages in our sample.

Finally, we examine the disparity in interest rates. Column 3 in Table 4 shows the results from specification (2) while also adding LTV and loan amount as controls. Interest rates are 0.01 pp lower for minority borrowers. Again, while this effect is statistically significant, it is economically insignificant in relation to the average interest rate of around 7.31% on mortgages in our sample. Taking the average value of mortgage, maturity, and interest rate from Table 1 of ₹2.7 million, 20 year maturity, and 7.31% interest rate, average monthly payment for a fixed rate mortgage would be ₹21,302 ($255.6). A 0.01% lower interest rate translates to a ₹21 ($0.25) lower monthly payment, which is negligible.

A key limitation of our analysis is that our dataset captures only the equilibrium loans in which the borrower accepted the lender's offer. We do not observe loan applications, rejections, or borrowers who walk away due to unattractive loan terms (e.g., a low appraisal value). This sample selection creates an identification challenge for the baseline appraisal gap, as it could lead to either an underestimation (if the lowest-quality minority borrowers drop out) or an overestimation (if the highest-quality minority borrowers sort to other lenders) of the true population disparity. However, the core of our analysis is not the absolute magnitude of the baseline gap, but rather how it changes when we alter the information environment. We argue in the next section that the direction of these changes aligns with models of statistical discrimination.

# 5 Framework: Statistical Discrimination

What drives appraisal gaps? To understand the mechanisms, we rely on a model of statistical discrimination in the classic style of Phelps (1972). This framework highlights how information frictions can lead to systematic differences in appraisals across groups. This framework formalizes how a profit-maximizing lender forms valuations under uncertainty and how group-level differences in information quality can generate systematic disparities in appraisals.

Consider a population of borrowers belonging to two groups, $G \in \{M, m\}$, where $M$ denotes the majority group and $m$ denotes the minority group. Each borrower $i$ has a true, unobserved quality $\theta_i$, which represents their creditworthiness or the true value of their collateral. We assume that $\theta_i$ is normally distributed within each group with a group-specific mean $\bar{\theta}_G$ and a common variance[6] $\sigma^2_\theta$:

$$\theta_i \sim N(\bar{\theta}_G, \sigma^2_\theta) \tag{3}$$

The lender does not observe $\theta_i$ directly. Instead, the lender observes a noisy signal $s_i$ (e.g., income documents, credit history, property details). The signal is an imperfect measure of true quality:

$$s_i = \theta_i + \epsilon_i \tag{4}$$

where $\epsilon_i$ is a random noise term, distributed normally with mean zero and a group-specific variance $\sigma^2_{\epsilon,G}$:

$$\epsilon_i \sim N(0, \sigma^2_{\epsilon,G}) \tag{5}$$

The variance of the error term, $\sigma^2_{\epsilon,G}$, represents the "noisiness" or precision of the signal for group $G$.

## 5.1 The Lender's Problem

The lender's objective is to form an accurate estimate of the borrower's true quality $\theta_i$ given the observed signal $s_i$ and the group identity $G$. The lender's optimal estimate is the posterior expectation of $\theta_i$, denoted as $\hat{\theta}_i$:

$$\hat{\theta}_i = E[\theta_i | s_i, G] \tag{6}$$

[6] We assume a common underlying variance $\sigma^2_\theta$ to isolate information frictions as the driver of differential treatment, consistent with the canonical literature. Allowing for group-specific underlying variances would complicate the identification of signal noise effects without altering the qualitative predictions regarding information shocks.

Using Bayesian updating, this posterior expectation is a weighted average of the individual signal $s_i$ and the group prior mean $\bar{\theta}_G$:

$$\hat{\theta}_i = (1 - \gamma_G)\bar{\theta}_G + \gamma_G s_i \tag{7}$$

where the weight $\gamma_G$ is the *reliability* or signal-to-noise ratio for group $G$:

$$\gamma_G = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_{\epsilon,G}^2} \tag{8}$$

The parameter $\gamma_G \in [0, 1]$ determines how much weight the lender places on the individual's signal versus the group average. When the signal is precise ($\sigma_{\epsilon,G}^2 \to 0$), $\gamma_G \to 1$, and the lender relies almost entirely on the individual signal. When the signal is noisy ($\sigma_{\epsilon,G}^2 \to \infty$), $\gamma_G \to 0$, and the lender shrinks their estimate toward the group mean.

### 5.2 Appraisals and Discrimination

We assume the bank's appraisal value, $A_i$, is a monotonic function of the estimated quality: $A_i = f(\hat{\theta}_i)$. For simplicity, let $A_i = \hat{\theta}_i$. The *appraisal gap* between a majority and minority borrower with the same observed signal $s$ is given by:

$$E[A_M|s] - E[A_m|s] = \underbrace{[(1 - \gamma_M)\bar{\theta}_M - (1 - \gamma_m)\bar{\theta}_m]}_{\text{Difference in Priors}} + \underbrace{(\gamma_M - \gamma_m)s}_{\text{Difference in Slopes}} \tag{9}$$

This decomposition highlights two distinct channels through which statistical discrimination can arise:

**1. Differences in Means: Quality Differences.** If the lender believes that the average quality of the minority group is lower ($\bar{\theta}_m < \bar{\theta}_M$), they will rationally appraise minority borrowers lower, even if the signals are equally precise. If, for example, minority borrowers exhibit higher default rates conditional on observables, then banks might give them lower appraisal values based on $\bar{\theta}_m < \bar{\theta}_M$.

**2. Differences in Variances: Signal Precision.** Even if the groups have identical means ($\bar{\theta}_m = \bar{\theta}_M$), discrimination can arise if the signal precision differs. If minority signals are noisier ($\sigma_{\epsilon,m}^2 > \sigma_{\epsilon,M}^2$), then $\gamma_m < \gamma_M$. The lender will place less weight on the minority applicant's signal and shrink their valuation more aggressively toward the mean. In cases where $A_i$ is a non-linear function of $\hat{\theta}_i$, we would see appraisal gaps arise on average.

This framework suggests that, under statistical discrimination, either a change in average quality or in signal precision, or a combination of both, should result in changes in appraisal gaps (as long as these changes are not in opposite directions and offset each other, which would require complicated stories). In our context, it is not possible to cleanly distinguish which channel is operative; it well might be that lenders are updating on both margins simultaneously. We wish to emphasize that regardless of the precise mix of signal improvement versus quality change, our results are not consistent with taste-based discrimination (or at least *direct* taste based discrimination in the language of Bohren, Hull, and Imas (2025). In a standard Beckerian model, taste-based animus acts as a tax on minority transactions that persists *regardless* of the broader information environment.

## 6 Statistical Discrimination in Appraisal Gaps

We begin by viewing the disparities in appraisal gaps through the lens of the canonical discrimination models of taste-based versus statistical discrimination.

**Heterogeneity in appraisal gaps** Several heterogeneity tests support the interpretation that our results are likely driven by statistical discrimination.

First, we examine appraisal ratios in urban versus rural pincodes. Table 5 presents the results using the specification in Equation 2 with an interaction term for whether a pincode is urban.[7] The interaction terms indicates that urban pincodes have higher appraisal ratios for minority borrowers compared to minority borrowers in rural pincodes. This is consistent with the idea that from a bank's perspective, urban areas are relatively more information rich (better income verification, more frequent sale transactions, etc.).

Second, we examine how appraisal ratios vary for minority borrowers with no prior formal credit history and hence do not have a credit score (unscored). Minority borrowers with no credit score have 2.8% lower appraisal ratios compared to unscored majority borrowers (column 2). Pure taste-based discrimination would depend entirely on whether the borrower is minority. Since lenders have less information on unscored borrowers, statistical discrimination would imply that minority unscored borrowers have worse appraisals.

[7] Classification of urban and rural pincodes is from TransUnion CIBIL.

Unscored loans represent borrowers with thin files. We take an alternate approach and define "thin" markets as pincodes with below median transactions in the sample period. Appraisal ratios are lower for minority borrowers in thin markets, again consistent with the idea that statistical discrimination drives appraisal gaps.

**Defaults.** To further examine whether statistical discrimination drives appraisal gaps, we examine defaults. On average, defaults are rare and only 47 out of 10,000 loans enter 90-day delinquency overall (Table 1). However default are much higher for minority borrowers (approximately 147 out of 10,000 loans) compared to majority borrowers (32 out of 10,000 loans). Consistent with classic model of statistical discrimination (Phelps, 1972) disparities in appraisal gaps will arise if the lender believes that the average quality of minority borrowers is lower than average quality of non-minority borrowers as the average default rates show. Alternatively, holding quality fixed, the signals from minority are noisier than those from majority. Table 6 presents the results from the specification in Equation 2 with default as the dependent variable. Even in the most stringent specification with geography, borrower, and properly controls, we find that default rates are 20 bps higher for minority borrowers compared to majority borrowers.

**A general test for statistical discrimination.** Most recently, Bharadwaj, Deb, and Renou (2025) propose a generalized model of statistical discrimination and show that a simple non-parametric test maps to a distributional decomposition à la DiNardo, Fortin, and Lemieux (1996) or Chernozhukov, Fernández-Val, and Melly (2013). Using this test, we find evidence that appraisal gaps in our data can arise through a general form of statistical discrimination.

Bharadwaj, Deb, and Renou (2025) ask and answer a simple question: when can the distribution of wages from two groups be consistent with a model of general statistical discrimination? Applied to our setting, the main theoretical result of Bharadwaj, Deb, and Renou (2025) implies that in order to be consistent with a generalized model of statistical discrimination, if $\bar{\theta}_m = \bar{\theta}_M$, it must be the case that neither group's distribution of loan terms (in this case appraisal values) displays first order stochastic dominance over the other. This forms a testable implication, which we exploit by constructing the counterfactual decomposition of appraisal ratios for minority borrowers if they had been treated as non-minorities by appraisers/banks.

Formally, this is implemented by using the methodology of Chernozhukov, Fernández-Val, and Melly (2013) to obtain the counterfactual distribution of appraisal ratios for minorities based on the observed distribution of controls. For controls, we employ pincodes, property and borrower characteristics, and the year and month of the mortgage. For estimation, we use the default settings of the CDECO command in STATA, which performs estimation via linear quantile regressions. Hundred bootstrap replications are performed for inference, and both pointwise and uniform confidence intervals at 95% are constructed.

Let $G_m(.)$ denote the observed distribution of appraisal ratios for minorities and $\widehat{G}_m(.)$ denote the counterfactual distribution, with $G_m^{-1}$ and $\widehat{G}_m^{-1}$ being the corresponding quantile functions. First order stochastic dominance between them is equivalent to either $G_m^{-1}(q) \geq \widehat{G}_m^{-1}(q)$ for all $q \in [0,1]$ or $\widehat{G}_m^{-1}(q) \geq G_m^{-1}(q)$ for all $q \in [0,1]$. That is, the appraisal ratios of one of the distributions must be higher than the other for *all* quantiles. If this were not true for even some quantiles, we would not have first order stochastic dominance between $G_m$ and $\widehat{G}_m$.

Figure 4 displays the coefficients plot of the decomposition, which is the difference $G_m^{-1} - \widehat{G}_m^{-1}$ at each quintile. We see that the plot starts above 0, slopes downward and crosses zero, and finally turns negative. By the logic outlined previously, this clearly implies lack of first order stochastic dominance since we have some quantiles where $G_m^{-1} \geq \widehat{G}_m^{-1}$ and some quantiles where $\widehat{G}_m^{-1} \geq G_m^{-1}$. Therefore, we find evidence that appraisal gaps in our data is consistent with a generalized model of statistical discrimination as outlined in Bharadwaj, Deb, and Renou (2025).

# 7 Do Banks Respond to Changes in the Information Environment?

We examine how appraisal gaps respond under two interventions that alter the information environment.

## 7.1 Developer-affiliated loans

The lender in our setting collaborates with vertically integrated developers to offer financing options to new home buyers (integrated developer). We rely on the insight from Stroebel (2016) that there is lower lender information asymmetry because (a) lender can better gauge quality of the underlying collateral, and/or (b) lender can better assess borrower creditworthiness. Information frictions are especially salient in the Indian context where the real estate industry has been unregulated for decades. Developers often

do not provide clear information about project details, delivery timelines, approvals or estimated and incurred costs. Developers are also known to divert funds either to fund other companies or by tunneling to parent companies, often delaying, stalling, or even abandoning projects altogether. When developers are integrated with the lender, the lender has access to information on aspects of construction quality that are hard for non-integrated lenders to observe. In addition, the lender can glean more information while guiding a home buyer through the home purchase process with integrated developers, and obtain information on borrower propensity to pay and maintain the property.

The framework in Section 5 would predict that with statistical discrimination, appraisal gaps should reduce. If appraisal gaps are driven by statistical discrimination, appraisal gaps are lower for integrated developer properties either because the lender can better gauge collateral quality, or alternatively, because integrated developers attract better quality minority borrowers, potentially because the lender can offer better terms to minority borrowers. In contrast, under classic taste-based discrimination Becker (1957), lender prejudice would imply that appraisal gaps persist irrespective of the information environment.

We use the following specification to examine heterogeneity in appraisal gaps:

$$\begin{aligned} Y_{it} = \phi_p &+ \delta_t + \beta_1 \text{Minority}_i + \beta_2 \text{Integrated Developer}_i \\ &+ \beta_3 \text{Minority}_i \times \text{Integrated Developer}_i + \gamma \mathbf{X}_i + \epsilon_i, \end{aligned} \tag{10}$$

for loan $i$ in district $d(i)$ in pincode $p(i)$ originated in month-year $t$. $Y_{it}$ is the loan-level outcome of interest (appraisal ratio, LTV, maturity, interest rate, and default). Integrated Developer$_i$ indicates whether the mortgage is associated with an integrated developer's property. $\phi_p$ indicate pincode fixed effects. $\delta_t$ indicates year and month fixed effect. $\mathbf{X}_i$ includes borrower controls (gender, age, occupation, and CIBIL band x year dummies), and property controls (plot area and built-up area). Standard errors are clustered at the pincode level. The coefficient of interest, $\beta_3$, captures how the appraisal ratios for minority borrowers differs from non-minority for integrated developer properties relative to remaining properties.

There are 10,199 builders across 105,147 apartment complexes (buildings) in our sample period. 7.7% of Bank loans are through integrated developers and spread across the country. Karnataka, Maharashtra, and Gujarat account for the largest share of mortgages associated with integrated developers at 13.83%, 12.94%,

and 12.16% of loans, respectively. Developers in our sample are typically associated with more than one building complex, though they are geographically concentrated: 5,339 builders operate in only one state, whereas 303 integrated developers operate across more than 10 states. Figure 5 shows the percentage of loans made to minority borrowers across buildings in Panel A. The bulk of the mass in concentrated at the extremes indicating that borrowers segregated into buildings with only minority or only majority borrowers, consistent with similar segregation across broader geographies documented in Adukia et al. (2025). Panel B shows similar segregation across developers, though to a lesser extent compared to building segregation and some integrated developers cater to both minority and majority borrowers. Overall, building complexes and developers tend to serve one group.

How do appraisal gaps vary for integrated developer properties? Table 7, Panel A presents the estimates for the specification in Equation 10 with log appraisal ratio as the dependent variable. Columns 1–3 suggest that appraisal gaps shrink for minorities in integrated developer-related projects. The most stringent specification in column 3 shows that the minority gap disappears for properties in integrated developer projects. The other loan-terms similarly adjust with higher LTVs, higher maturities and lower interest rates, though as before economic magnitudes are small. Overall, the disparity in lending — seen in Section 4 which was most stark in appraisal gaps — disappears for integrated developer properties. We conjecture that the lender can better gauge collateral value and borrower creditworthiness of integrated-developer properties. Consistent with this hypothesis, default rates of minority borrowers relative to majority borrowers narrows suggesting that banks rationally update their lending behavior based on the new information environment.

In 2016, India enacted the Real Estate Regulatory Authority (RERA) Act, which increased developer transparency and accountability. In Table IA6, we show that our results are robust to controlling for RERA. In column 1, we add state-time fixed effects to account for the staggered state-wise REA implementation across states. Thus, these estimates compare mortgages in a state within the same RERA regime. Columns 2 and 3 restrict to pre- and post-RERA periods. Across all three specifications, appraisal gaps disappear for integrated developer properties.

Often, official property prices do not reflect true values and real estate transactions involve off-the-books

sources of money or "black money" to avoid taxes (Gandhi et al., 2022). This is less of a concern in our setting as Anagol et al. (2025a) show that misreporting of property prices is lower in purchases through mortgages as in our case. Nonetheless, as robustness, we show robustness to adding fixed effects for 100 m X 100 m grids that presumably allow us to compare properties with similar circle rates (Table IA5). Our results are also robust to accounting for the demonetization event, which reduced 86% of currency in circulation. Table IA7 shows the effects on appraisal gaps for integrated developers across three periods, before demonetization (column 1), intermediate period following demonetization where cash in circulation was still low (column 2); appraisal gaps for integrated developers disappear for all three sub-samples.

Overall, the narrowing of appraisal gaps for integrated developers is consistent with statistical discrimination under the framework discussed in Section 5. While we emphasize the improvement in lender information regarding collateral quality/borrower creditworthiness, the results are also consistent with a change in average quality of minority borrowers. Indeed, Table IA3 shows that minority borrowers associated with integrated developer properties have higher average quality as indicated by their credit scores. While we cannot distinguish whether it is the information channel or the improvement in average quality (or both) that drive reduction in appraisal gaps, our tests rule out taste-based discrimination. Taste-based discrimination as in a standard Beckerian model would persist irrespective of the improvement in information quality. Since the appraisal gaps disappear for integrated developers, the appraisal disparity is likely not attributable to lender (or loan officers') animus, but due to combination of statistical priors and information frictions that respond to market structure.

### 7.2 Priority Sector Lending

We next examine appraisal gaps in the context of priority sector lending (PSL) in India. Under the PSL, following the Prime Minister's 15-Point Programme for the Welfare of Minority Communities, the RBI designated certain "minority concentration districts" (MCDs), based on whether the share of minorities exceeded a population threshold of 25%. Under this policy, banks are required to allocate a fixed share of their loan portfolio to weaker sections.

We build on the regression discontinuity design in Khan and Ritadhi (2025) and compare districts just above and just below the minority-share cutoff. We exploit the district-level threshold of 25%, in a regression

discontinuity (RD) design. The running variable is:

$$\text{RV}_{ds} = (\text{MinorityShare}_{ds} - 0.25), \tag{11}$$

where $\text{MinorityShare}_{ds}$ is the fraction of minorities in district $d$ of state $s$ as per the Census of 2011.

We then estimate the following RD specification:

$$\text{Y}_{idst} = \alpha_{st} + \beta \times \text{Treat}_{ds} + \gamma f(\text{RV}_{ds}) + \epsilon_{idst} \tag{12}$$

where $Y_{idst}$ is the outcome of interest for mortgage $i$ in district $d$ of state $s$ originated in month-year $t$ and $Treat_{ds} = \mathbb{1}\{RV > 0\}$ is the treatment dummy. We include state-year fixed effects $\alpha_{st}$ and a linear polynomial $f(.)$ in the running variable and its interaction with the treatment dummy. We use a triangular kernel to weight observations near the cutoff, and employ the MSERD optimal bandwidth. Standard errors are clustered at the district level.

Before proceeding to the formal regressions, Figure 6 graphically shows the regression discontinuity. In all three panels, the horizontal axis displays the running variable, whereas the vertical axis shows log of the appraisal ratio after residualizing state-year fixed effects. The solid dots show the residualized means of the outcome in each bin. The lines show the linear fit from a local-linear regression. The dotted lines show the 95% confidence intervals. The MSERD optimal bandwidth is used, and estimates are weighted using a triangular kernel. We see that there is discontinuous jump at the RD threshold. This is true across all panels depicting the aggregate (panel A), minority (panel B), and non-minority (panel C).

Table 8 shows the estimates from the local linear regression RD specification in Equation 12. The specifications control for state-time fixed effects. The RD design identifies a 55% higher appraisal ratio in the high minority concentration districts (Panel A, column 1). By design, our RD setup captures districts that were targeted by the PSL policy. Table 2 and the related discussion in Section 4 highlights that nearly 40% of the variation in appraisal gap comes from geographic variation. We hypothesize that this particular policy under PSL forced banks to increase lending in high minority concentration districts, improving the information environment. This enabled the increase in appraisal ratios for mortgages in targeted districts. Both minority and non-minority borrowers see an increase in appraisal ratios of 67.7% and 40.5%, respectively. Consistent with the improved information environment, we show that default rates do not increase

in targeted districts (Figure 7 and corresponding Panel B in Table 8).

# 8 Conclusion

This paper provides systematic evidence of disparities in the Indian home loan market. By analyzing the universe of loans from a major state-owned bank, we document a large and persistent appraisal gap for minority borrowers. Our findings highlight that in a regulatory environment with rigid rules on interest rates and loan-to-value ratios, discrimination is channeled into the one remaining margin of discretion: the property appraisal.

We argue that this disparity is driven by statistical discrimination and we offer several pieces of evidence consistent with this: 1) while default is incredibly rare, minorities in our sample display slightly higher rates of default, 2) appraisal gaps are lessened in cases where building developers work with banks, and 3) appraisal gaps are lower for minorities in areas with priority lending for minorities.

Our analysis is subject to specific limitations that point toward fruitful avenues for future research. First, our data represents equilibrium outcomes; we do not observe loan applications, rejections, or the borrowers who sort away from our bank. While we account for this selection in our interpretation of the mechanism, future work utilizing loan application data or experimental audits could more precisely isolate the demand-side behavior of minority borrowers. Second, while we identify the information channel, we cannot fully disentangle whether the "developer effect" is driven by improved signal quality for the average borrower or by a change in the composition of borrowers who buy into these projects.

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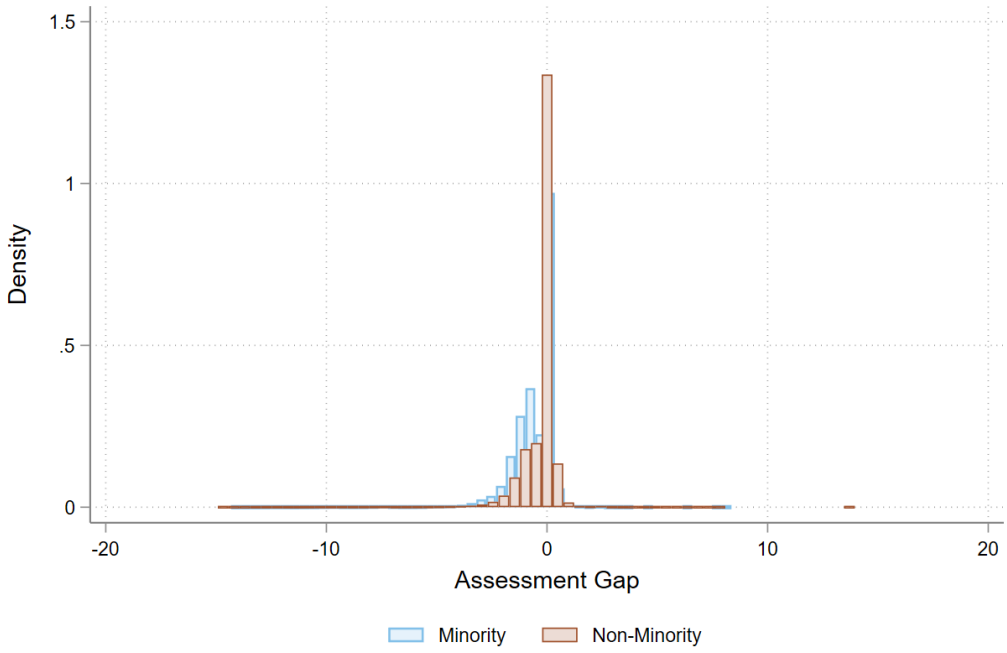
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**Figure 1**
**Variation in appraisal ratios across minority status**

The figure shows the histogram of the appraisal ratios for minority and non-minority borrowers in Panel A. Minority borrowers belong to scheduled caste/scheduled tries (SC/ST), other backward classes (OBC), or are Muslims. Non-minority borrowers belong to Hindu religion and are classified under the "General" category. Panel B shows the histograms for appraisal values for each of the groups separately. Appraisal ratio is the log of the appraisal value to the market value of the collateral underlying the mortgage loan. Mortgage-level data is for the period 2015 to 2020.

**Panel A: Minority vs Non-Minority**




**Panel B: Across Heterogeneity Minority Groups**

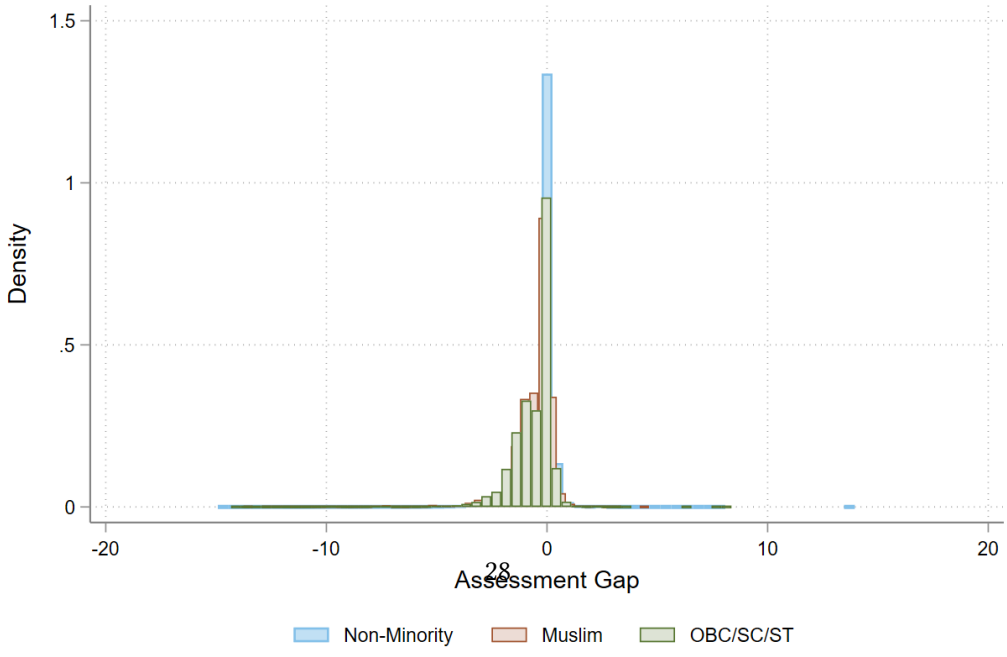


**Figure 2**
**Variation in appraisal ratios across neighborhoods**

The figure shows the pincode-level map of appraisal ratios across India. Appraisal gap is the log of the appraisal value to the market value of the collateral underlying the mortgage loan. Mortgage-level data is for the period 2015 to 2020.

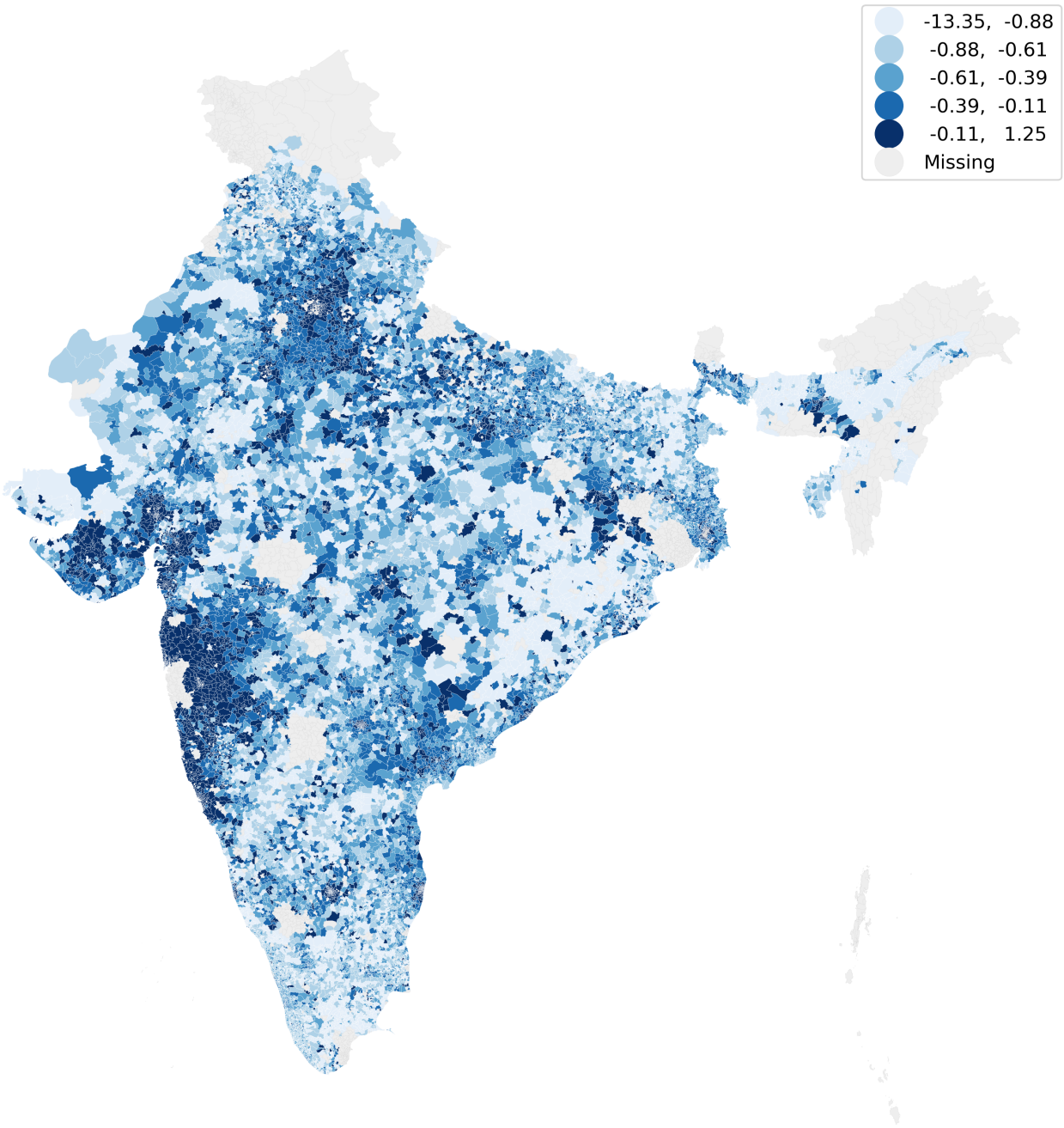
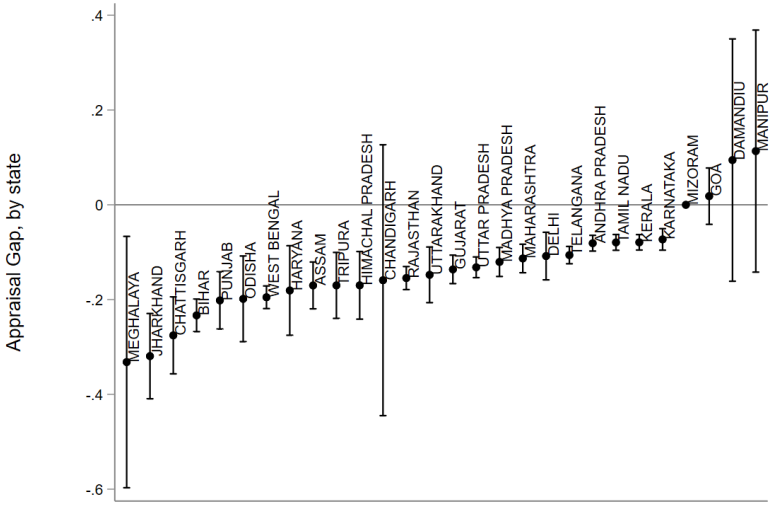


**Figure 3**
**State-level and District-level Estimates of the Appraisal Gap**

This figure shows the point estimates for the appraisal gap for each state (Panel A) and district (Panel B). Each point represents the point estimates from column 6 in Table 2 for the subsample of mortgages in each state and district. The vertical lines represent the 95% confidence interval. In the baseline empirical specification, we regress the appraisal ratios — defined as the log of appraisal value to the market value — on an indicator for minority. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Control variables included are credit score band and time indicators. District, pincode, year and month fixed effects are included. Standard errors are clustered at the pincode level. Mortgage-level data is for the period 2015 to 2020. In Panel B, only districts with at least 500 observations are retained in the analysis.

**Panel A: State level**




**Panel B: District level**

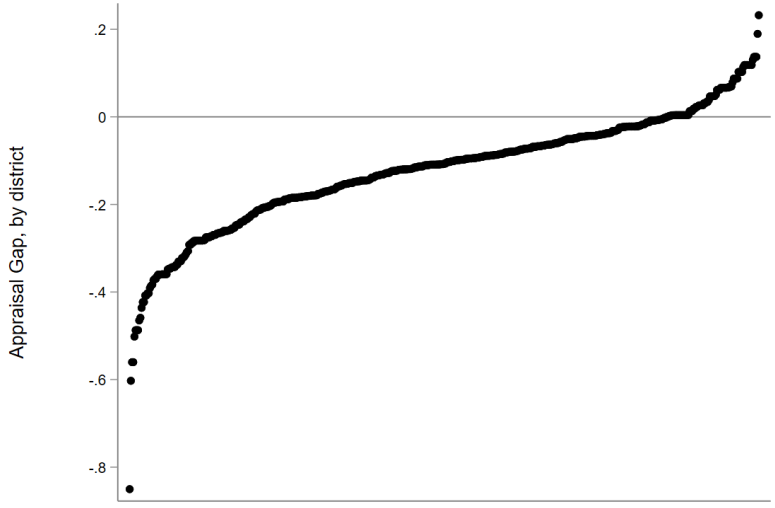


**Figure 4**
**Test for Statistical Discrimination**

This figure shows the 'Coefficients' plot from the distributional decomposition based on Chernozhukov, Fernandez-Val, and Melly (2013). The counterfactual distribution is constructed using pincodes, property controls , borrower controls, year and month. The bands report 95% bootstrapped confidence intervals.

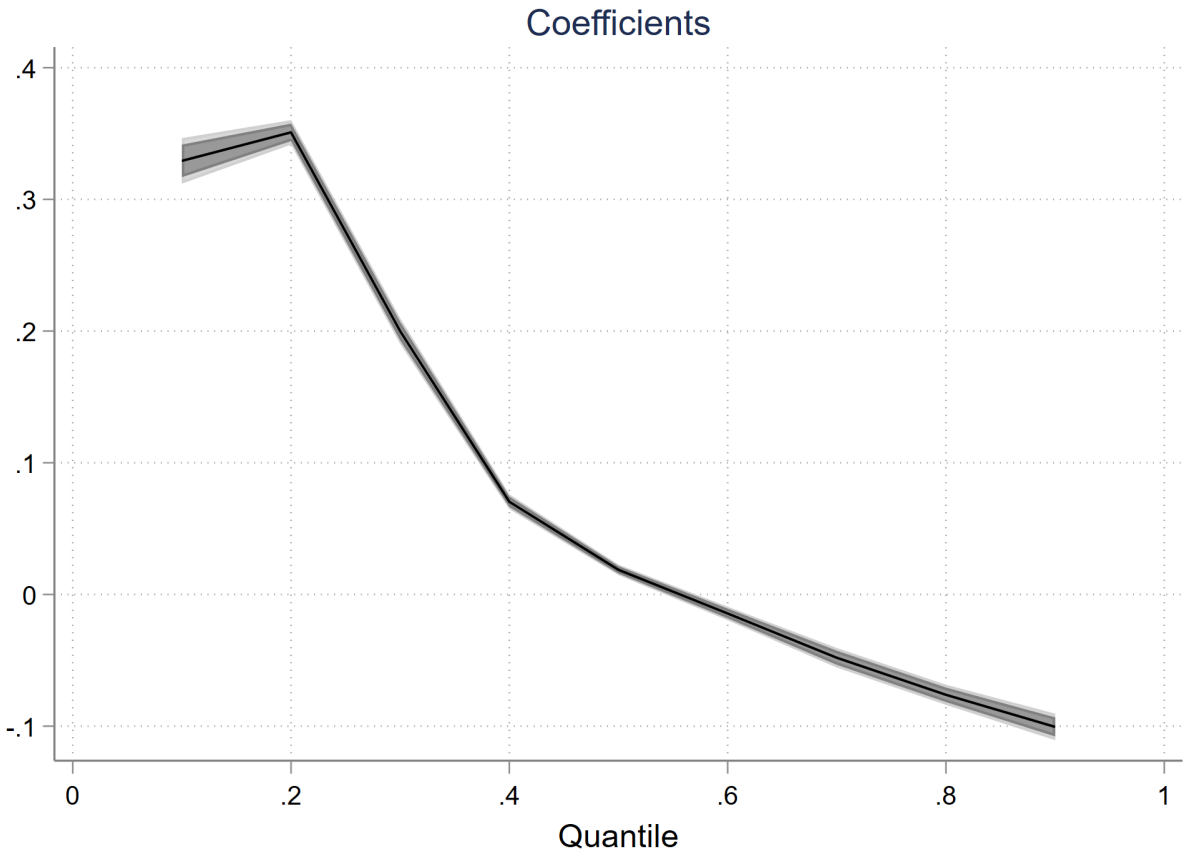
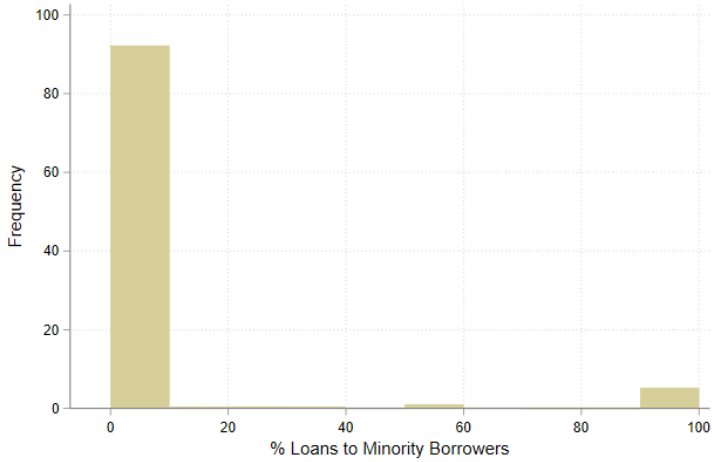


**Figure 5**
**Integrated Developers: Segregation**

These figures show the distributions of the percentage of loans made to minority borrowers across buildings and developers. Panel A shows the histogram of the percentage of loans to minority borrowers across buildings, where a building is defined as an integrated developer operating in a given pincode. Panel B shows the histogram of the percentage of loans to minority borrowers across developers.

**Panel A: Segregation in Buildings**




**Panel B: Segregation in Clientele**

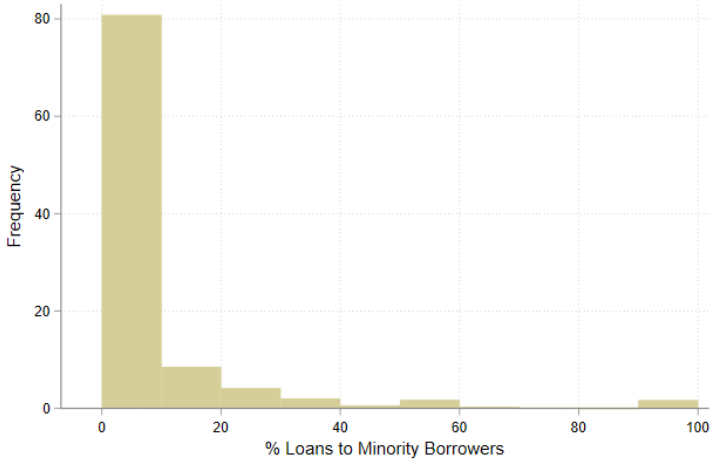


**Figure 6**
**Priority Sector Lending: Appraisal Ratio**

This figure shows RD plots corresponding to the log of the appraisal ratio as the outcome variable. Panel A shows the treatment effect for the entire sample, whereas panel B and panel C show the heterogeneity in treatment effect for the minority and non-minority subsamples. The horizontal axis displays the running variable, whereas the vertical axis shows the log of the appraisal ratio after residualizing on state-year fixed effects. The solid dots show the residualized means of the outcome in each bin. The lines show the linear fit from a local-linear regression. The dotted lines show the 95% confidence intervals. The MSERD optimal bandwidth is used, and estimates are weighted using a triangular kernel.

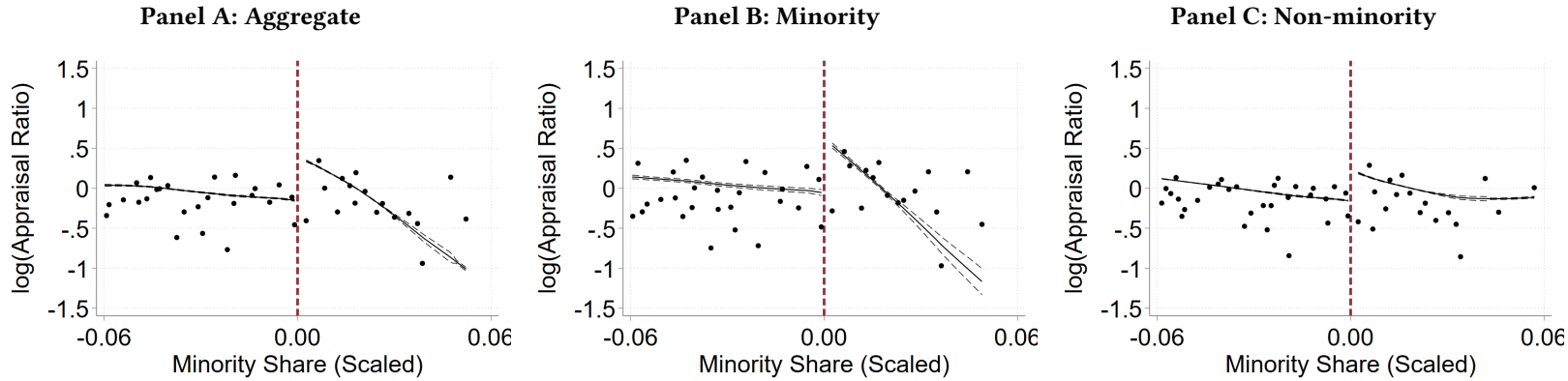


**Figure 7**
**Priority Sector Lending: Default**

This figure shows RD plots corresponding to default as the outcome variable. Panel A shows the treatment effect for the entire sample, whereas panel B and panel C show the heterogeneity in treatment effect for the minority and non-minority subsamples. The horizontal axis displays the running variable, whereas the vertical axis shows NPA after residualizing on state-year fixed effects. The solid dots show the residualized means of the outcome in each bin. The lines show the linear fit from a local-linear regression. The dotted lines show the 95% confidence intervals. The MSERD optimal bandwidth is used, and estimates are weighted using a triangular kernel.

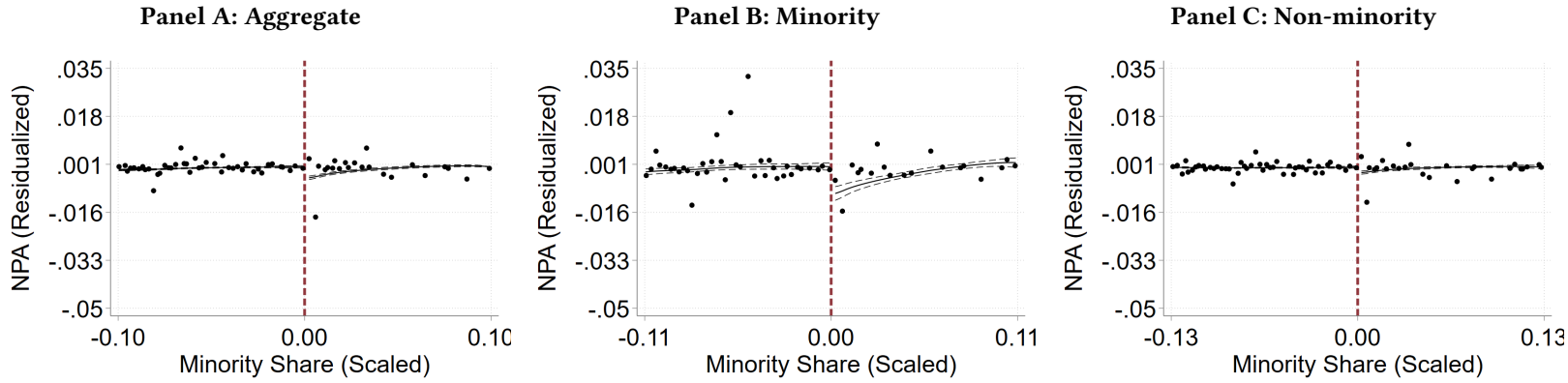


**Table 1**
**Summary Statistics**

This table shows the summary statistics for variables in our analysis by minority status. Variables shown are appraisal gaps (Panel A), borrower characteristics, including gender, age, credit score (if it exists) and an indicator for whether a credit exists (Panel B), property characteristics including plot area and built-up area (Panel C), loan-level characteristics including loan amount, the loan-to-value, interest rate, maturity, and whether defaulted (Panel D). Data is for 2015–2020.

| | N | Mean | SD |
|---|---|---|---|
| | | Panel A: Appraisal Gap | |
| **Overall** | | | |
| Assessment Gap | 983,184 | -0.31 | 0.85 |
| Appraisal value (in ₹) | 983,184 | 4,050,938 | 3,565,904 |
| Property value (in ₹) | 983,184 | 4,534,912 | 3,383,131 |
| **Non-minority** | | | |
| Assessment Gap | 845,030 | -0.26 | 0.80 |
| Appraisal Value (in ₹) | 845,030 | 4,287,503 | 3,636,181 |
| Property Value (in ₹) | 845,030 | 4,697,907 | 3,451,527 |
| **Minority** | | | |
| Appraisal Gap | 138,154 | -0.63 | 1.07 |
| Appraisal value (in ₹) | 138,154 | 2,603,968 | 2,680,269 |
| Property value (in ₹) | 138,154 | 3,537,943 | 2,725,791 |
| | | Panel B: Loan Characteristics | |
| **Overall** | | | |
| Loan-to-Value | 983,184 | 0.63 | 0.19 |
| Interest Rate | 983,184 | 7.33 | 0.55 |
| Loan Amount (in ₹) | 983,184 | 2,691,099 | 3,056,699 |
| Maturity (in years) | 916,355 | 20.32 | 6.39 |
| Default (in bps) | 983,184 | 47.02 | 684.10 |
| **Non-minority** | | | |
| Loan-to-Value | 845,030 | 0.63 | 0.19 |
| Interest Rate | 845,030 | 7.32 | 0.55 |
| Loan Amount (in ₹) | 845,030 | 2,811,007 | 3,210,868 |
| Maturity (in years) | 781,489 | 20.40 | 6.41 |
| Default (in bps) | 845,030 | 31.68 | 561.95 |
| **Minority** | | | |
| Loan-to-Value | 138,154 | 0.63 | 0.19 |
| Interest Rate | 138,154 | 7.35 | 0.59 |
| Loan Amount (in ₹) | 138,154 | 1,957,673 | 1,675,122 |
| Maturity (in years) | 134,866 | 19.90 | 6.31 |
| Default (in bps) | 138,154 | 140.86 | 1,178.45 |

| | N | Mean | SD |
|---|---|---|---|
| | Panel C: Borrower Characteristics | | |
| **Overall** | | | |
| Male | 983,184 | 0.72 | 0.45 |
| Age | 983,184 | 41 | 9 |
| Credit Score | 742,535 | 747 | 55 |
| Unscored | 983,184 | 0.25 | 0.43 |
| **Non-minority** | | | |
| Male | 845,030 | 0.72 | 0.45 |
| Age | 845,030 | 41 | 9 |
| Credit Score | 642,061 | 748 | 55 |
| Unscored | 845,030 | 0.24 | 0.43 |
| **Minority** | | | |
| Male | 138,154 | 0.73 | 0.45 |
| Age | 138,154 | 41 | 9 |
| Credit Score | 100,474 | 736 | 56 |
| Unscored | 138,154 | 0.27 | 0.45 |
| | Panel D: Property Characteristics | | |
| **Overall** | | | |
| Plot Area (in sq. feet) | 983,184 | 2,265 | 16,431 |
| Built-up Area (in sq. feet) | 983,184 | 1,282 | 3,640 |
| **Non-minority** | | | |
| Plot Area (in sq. feet) | 845,030 | 2,246 | 16,808 |
| Built-up Area (in sq. feet) | 845,030 | 1,284 | 3,839 |
| **Minority** | | | |
| Plot Area (in sq. feet) | 138,154 | 2,382 | 13,906 |
| Built-up Area (in sq. feet) | 138,154 | 1,272 | 2,031 |

**Table 2**
**Appraisal Gap**

This table shows the mortgage level analysis of appraisal gaps based on minority status. The dependent variable in all the regressions is the natural log of the ratio of the appraisal value to the market value of the property. District, pincode, year and month fixed effects are included as indicated. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | ln(Appraisal Ratio) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Minority | -0.369*** | -0.184*** | -0.144*** | -0.142*** | -0.132*** | -0.132*** |
| | (0.008) | (0.005) | (0.004) | (0.004) | (0.004) | (0.004) |
| $R^2$ | 0.0227 | 0.167 | 0.231 | 0.231 | 0.237 | 0.237 |
| Mean dep. var | -0.310 | -0.310 | -0.310 | -0.310 | -0.310 | -0.310 |
| District FE | N | Y | - | - | - | - |
| Pincode FE | N | N | Y | Y | Y | Y |
| Year and Month FE | N | N | N | Y | Y | Y |
| Borrower Controls | N | N | N | N | Y | Y |
| Property Contols | N | N | N | N | N | Y |
| No. of obs. | 983184 | 983184 | 983184 | 983184 | 983184 | 983184 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 3**
**Appraisal Gap by minority type**

This table shows the mortgage level analysis of appraisal gaps based on minority status for different minority groups. The dependent variable in all the regressions is the natural log of the ratio of the appraisal value to the market value of the property. Pincode, year and month fixed effects are included as indicated. The three groups of minorities considered are Muslims, Scheduled castes/Scheduled Tribes and Other backward castes. The comparison group in each case is Hindu general caste borrowers. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | ln(Appraisal Ratio) | | |
|---|---|---|---|
| Minority type: | Muslim | OBC | SC/ST |
| | (1) | (2) | (3) |
| Minority | -0.093*** | -0.128*** | -0.174*** |
| | (0.007) | (0.005) | (0.007) |
| $R^2$ | 0.230 | 0.229 | 0.229 |
| Mean dep. var | -0.268 | -0.284 | -0.278 |
| Pincode FE | Y | Y | Y |
| Year and Month FE | Y | Y | Y |
| Borrower Controls | Y | Y | Y |
| Property Contols | Y | Y | Y |
| No. of obs. | 870204 | 910829 | 887631 |

**Table 4**
**Disparity in Other Loan Terms**

This table shows the mortgage level analysis of different loan terms based on minority status. The dependent variable in each of the regressions is the loan-to-value ratio, maturity of the loan (in years), and the interest rate respectively. Pincode, year and month fixed effects are included as indicated. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Controls for LTV, Maturity, and loan amount are included in the interest rate regression. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| | LTV | Maturity | Int. Rate |
|---|---|---|---|
| | (1) | (2) | (3) |
| Minority | -0.003*** | -0.063*** | -0.009*** |
| | (0.001) | (0.020) | (0.002) |
| $R^2$ | 0.123 | 0.246 | 0.480 |
| Mean dep. var | 0.634 | 20.33 | 7.310 |
| Pincode FE | Y | Y | Y |
| Year and Month FE | Y | Y | Y |
| Borrower Controls | Y | Y | Y |
| Property Contols | Y | Y | Y |
| Other loan terms | N | N | Y |
| No. of obs. | 983184 | 916355 | 916355 |

**Table 5**
**Heterogeneity in Appraisal Gaps**

This table shows the heterogeneity in appraisal gaps based on different characteristics. In the first column, urban refers to pincodes classified as urban based on the status of the pincode's post office type. In the second column, unscored is an indicator that takes value 1 if the borrower does not have a CIBIL score. In the third column, thin market is an indicator for whether a pincode has fewer than the median number of mortgages over the entire sample period. District, pincode, year and month fixed effects are included as indicated. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | ln(Appraisal Ratio) | | |
|---|---|---|---|
| Characteristic (X) | Urban | Unscored | Thin Market * |
| | (1) | (2) | (3) |
| Minority | -0.196*** | -0.135*** | -0.095*** |
| | (0.007) | (0.004) | (0.009) |
| X | 0.104*** | -0.029*** | -0.102*** |
| | (0.005) | (0.002) | (0.005) |
| Minority × X | 0.099*** | -0.028*** | -0.103*** |
| | (0.010) | (0.006) | (0.011) |
| $R^2$ | 0.180 | 0.232 | 0.180 |
| Mean dep. var | -0.311 | -0.310 | -0.310 |
| District FE | Y | - | Y |
| Pincode FE | N | Y | N |
| Year and Month FE | Y | Y | Y |
| Borrower Controls | Y | N | Y |
| Property Contols | Y | Y | Y |
| No. of obs. | 979205 | 982384 | 982568 |

**Table 6**
**Default Rates**

This table shows how default rates vary based on minority status. The dependent variable in all the regressions is an indicator for whether the mortgage becomes 90-day delinquent. District, pincode, year and month fixed effects are included as indicated. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Controls for other loan terms include LTV, Maturity, and loan amount. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | Default (in bps) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Minority | 109.178*** | 52.490*** | 27.163*** | 24.910*** | 21.823*** | 21.806*** | 20.324*** |
| | (10.908) | (6.383) | (4.325) | (4.206) | (3.733) | (3.733) | (3.746) |
| $R^2$ | 0.00308 | 0.0659 | 0.142 | 0.146 | 0.214 | 0.214 | 0.224 |
| Mean dep. var | 47.02 | 47.02 | 47.05 | 47.05 | 47.04 | 47.04 | 49.90 |
| District FE | N | Y | - | - | - | - | - |
| Pincode FE | N | N | Y | Y | Y | Y | Y |
| Year and Month FE | N | N | N | Y | Y | Y | Y |
| Borrower Controls | N | N | N | N | Y | Y | Y |
| Property Contols | N | N | N | N | N | Y | Y |
| Other loan terms | N | N | N | N | N | N | Y |
| No. of obs. | 983184 | 983184 | 983184 | 983184 | 983184 | 983184 | 916355 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 7**
**Intervention I: Integrated Developers**

This table shows how differences in outcomes varies with whether the mortgage for a property is with a vertically integrated developer. The dependent variable in the columns 1-3 is the log of the appraisal ratio, and for columns 4-6 is the loan-to-value ratio, maturity in years of the loan, and the interest rate respectively. District, pincode, year and month fixed effects are included as indicated. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Integrated developer is an indicator for whether the collateral securing the mortgage is from a vertically integrated developer. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Controls for other loan terms include LTV, Maturity, and loan amount. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

Panel A: Appraisal Ratios

| Dependent variable: | ln(Appraisal Ratio) | | | LTV | Maturity | Int. Rate |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Minority | -0.354*** | -0.183*** | -0.135*** | -0.002** | -0.066*** | -0.008*** |
| | (0.008) | (0.005) | (0.004) | (0.001) | (0.020) | (0.002) |
| Integrated Developer | 0.339*** | 0.227*** | 0.181*** | 0.051*** | 0.325*** | 0.001 |
| | (0.007) | (0.006) | (0.006) | (0.001) | (0.025) | (0.002) |
| Minority × Integrated Developer | 0.275*** | 0.167*** | 0.138*** | 0.012*** | 0.236*** | -0.026*** |
| | (0.012) | (0.010) | (0.009) | (0.002) | (0.076) | (0.006) |
| $\beta_1 + \beta_3$ | -0.079*** | -0.015* | 0.003 | 0.011*** | 0.169** | -0.034*** |
| | (0.010) | (0.009) | (0.008) | (0.002) | (0.074) | (0.005) |
| $R^2$ | 0.0442 | 0.176 | 0.242 | 0.131 | 0.247 | 0.480 |
| Mean dep. var | -0.310 | -0.310 | -0.310 | 0.634 | 20.33 | 7.310 |
| District FE | N | Y | - | - | - | - |
| Pincode FE | N | N | - | - | - | - |
| Year and Month FE | N | N | Y | Y | Y | Y |
| Borrower Controls | N | N | Y | Y | Y | Y |
| Property Contols | N | N | Y | Y | Y | Y |
| Other loan terms | N | N | N | N | N | Y |
| No. of obs. | 983184 | 983184 | 983184 | 983184 | 916355 | 916355 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel B: Defaults

| Dependent variable: | Default (in bps) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Minority | 112.737*** | 54.696*** | 28.151*** | 26.536*** | 23.270*** | 23.255*** | 21.416*** |
| | (11.369) | (6.753) | (4.591) | (4.482) | (3.977) | (3.976) | (3.973) |
| Integrated Developer | -22.958*** | -16.023*** | -12.876*** | -2.274 | -4.892*** | -4.879*** | -5.431*** |
| | (2.305) | (1.776) | (1.664) | (1.615) | (1.543) | (1.544) | (1.722) |
| Minority × Integrated Developer | -94.670*** | -46.859*** | -23.000*** | -25.012*** | -23.584*** | -23.598*** | -19.506*** |
| | (15.634) | (10.728) | (8.580) | (8.448) | (7.272) | (7.273) | (7.475) |
| $\beta_1 + \beta_3$ | 18.066 | 7.837 | 5.151 | 1.524 | -0.314 | -0.343 | 1.910 |
| | (12.732) | (8.915) | (7.497) | (7.371) | (6.244) | (6.244) | (6.535) |
| $R^2$ | 0.00343 | 0.0660 | 0.142 | 0.146 | 0.214 | 0.214 | 0.224 |
| Mean dep. var | 47.02 | 47.02 | 47.05 | 47.05 | 47.04 | 47.04 | 49.90 |
| District FE | N | Y | - | - | - | - | - |
| Pincode FE | N | N | Y | Y | Y | Y | Y |
| Year and Month FE | N | N | N | Y | Y | Y | Y |
| Borrower Controls | N | N | N | N | Y | Y | Y |
| Property Contols | N | N | N | N | N | Y | Y |
| Other Loan Terms | N | N | N | N | N | N | Y |
| No. of obs. | 983184 | 983184 | 983184 | 983184 | 983184 | 983184 | 916355 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 8**
**Intervention II: Priority Sector Lending**

This table reports the RD treatment effect estimates of Priority Sector Lending on two main outcomes. Panel A reports the effect on the log of the appraisal ratio, and Panel B reports the effect on default rate. Column 1 reports the estimate from using the whole sample, whereas columns 2 and 3 report the estimates for the minority and non-minority subsamples separately. All specifications include state-year fixed effects and a linear polynomial in the running variable and its interaction with the treatment indicator. The sample is restricted to the outcome-specific MSERD optimal bandwidth, and a triangular kernel is used to weight observations. Standard errors are clustered by district.

| | (1) | (2) | (3) |
|---|---|---|---|
| Sample: | Aggregate | Minority | Non-minority |
| Dependent variable: | | Panel A: ln(Appraisal Ratio) | |
| Treatment | 0.552** | 0.677*** | 0.405** |
| | (0.192) | (0.237) | (0.161) |
| Minority - Non-minority | | 0.272 | |
| | | (0.287) | |
| State × Year FE | Y | Y | Y |
| No. of obs. | 124,202 | 17,332 | 171,982 |
| Dependent variable: | | Panel B: Default | |
| Treatment | -0.004 | -0.010 | -0.002 |
| | (0.004) | (0.007) | (0.003) |
| Minority - Non-minority | | -0.008 | |
| | | (0.008) | |
| State × Year FE | Y | Y | Y |
| No. of obs. | 351,380 | 42,931 | 425,786 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

# Disparities in Home Loans: Evidence from India

## Appendix

**Table IA1**
**Sample Construction Summary**

This table provides a summary of our sample construction including how many observations remain after each stage. We drop missing appraisal, property, interest rate, LTV, religion, or caste values. We exclude if pincode/district missing, interest rate $< 2\%$, or age $> 80$. Covariates include borrower controls (CIBIL score, age, gender, and occupation) and property controls (Plot area and Built-up area). Finally, geo-located mortgages is the sample of mortgages for which addresses are present and we are able to extract the latitude and longitude.

| | **Obs. remaining** |
|---|---|
| Entire dataset | 2,071,602 |
| Drop obs. with missing loan terms | 1,065,831 |
| Drop obs. with missing covariates | 983,184 |
| Mortgages geo-located | 56,942 |

**Table IA2**
**Summary Statistics within minorities**

This table shows the summary statistics for variables in our analysis within minorities by substatus. Variables shown are appraisal gaps (Panel A), borrower characteristics, including gender, age, credit score (if it exists) and an indicator for whether a credit exists (Panel B), property characteristics including plot area and built-up area (Panel C), loan-level characteristics including loan amount, the loan-to-value, interest rate, maturity, and whether defaulted (Panel D). Data is for 2015–2020.

| | N | Mean | SD |
|---|---|---|---|
| | | Panel A: Appraisal Gap | |
| **Muslim** | | | |
| Assessment Gap | 26,724 | -0.61 | 1.11 |
| Appraisal Value (in ₹) | 26,724 | 3,030,912 | 3,031,906 |
| Property value (in ₹) | 26,724 | 4,023,558 | 3,005,821 |
| **OBC** | | | |
| Assessment Gap | 67,315 | -0.61 | 1.02 |
| Appraisal value (in ₹) | 67,315 | 2,607,816 | 2,668,882 |
| Property value (in ₹) | 67,315 | 3,558,495 | 2,761,063 |
| **SC/ST** | | | |
| Assessment Gap | 44,115 | -0.66 | 1.11 |
| Appraisal Value (in ₹) | 44,115 | 2,339,462 | 2,424,858 |
| Property value (in ₹) | 44,115 | 3,212,407 | 2,431,708 |
| | | Panel B: Loan Characteristics | |
| **Muslim** | | | |
| Loan-to-Value | 26,724 | 0.62 | 0.20 |
| Interest Rate | 26,724 | 7.36 | 0.55 |
| Loan Amount (in ₹) | 26,724 | 2,162,197 | 2,038,856 |
| Maturity (in years) | 25,890 | 19.76 | 6.61 |
| Default (in bps) | 26,724 | 47.52 | 687.74 |
| **OBC** | | | |
| Loan-to-Value | 67,315 | 0.63 | 0.19 |
| Interest Rate | 67,315 | 7.35 | 0.57 |
| Loan Amount (in ₹) | 67,315 | 1,952,708 | 1,672,129 |
| Maturity (in years) | 65,604 | 19.98 | 6.19 |
| Default (in bps) | 67,315 | 143.36 | 1,188.71 |
| **SC/ST** | | | |
| Loan-to-Value | 44,115 | 0.65 | 0.18 |
| Interest Rate | 44,115 | 7.33 | 0.63 |
| Loan Amount (in ₹) | 44,115 | 1,841,352 | 1,401,498 |
| Maturity (in years) | 43,372 | 19.85 | 6.31 |
| Default (in bps) | 44,115 | 193.58 | 1,377.83 |

| | N | Mean | SD |
|---|---|---|---|
| | Panel C: Borrower Characteristics | | |
| **Muslim** | | | |
| Male | 26,724 | 0.77 | 0.42 |
| Age | 26,724 | 42 | 9 |
| Credit Score | 19,811 | 738 | 55 |
| Unscored | 26,724 | 0.26 | 0.44 |
| **OBC** | | | |
| Male | 67,315 | 0.72 | 0.45 |
| Age | 67,315 | 41 | 9 |
| Credit Score | 48,663 | 736 | 56 |
| Unscored | 67,315 | 0.28 | 0.45 |
| **SC/ST** | | | |
| Male | 44,115 | 0.71 | 0.45 |
| Age | 44,115 | 42 | 9 |
| Credit Score | 32,000 | 735 | 56 |
| Unscored | 44,115 | 0.27 | 0.45 |
| | Panel D: Property Characteristics | | |
| **Muslim** | | | |
| Plot Area (in sq. feet) | 26,724 | 3,269 | 22,260 |
| Built-up Area (in sq. feet) | 26,724 | 1,351 | 2,139 |
| **OBC** | | | |
| Plot Area (in sq. feet) | 67,315 | 2,165 | 10,855 |
| Built-up Area (in sq. feet) | 67,315 | 1,262 | 1,535 |
| **SC/ST** | | | |
| Plot Area (in sq. feet) | 44,115 | 2,176 | 11,183 |
| Built-up Area (in sq. feet) | 44,115 | 1,240 | 2,559 |

**Table IA3**
**Balance Table: Integrated and Non-Integrated developer samples**

This table tests for balance of borrower characteristics between the sample of mortgages associated with an integrated developer and the remaining mortgages. The pariwise tests of differences in means are reported.

| | (1) Integrated | | (2) Non-Integrated | | (1)-(2) Pairwise t-test | |
|---|---|---|---|---|---|---|
| Variable | N | Mean | N | Mean | N | Diff. |
| **Overall** | | | | | | |
| Male | 136,167 | 0.716 | 847,017 | 0.718 | 983,184 | -0.003* |
| | | (0.001) | | (0.000) | | |
| Age | 136,167 | 38.805 | 847,017 | 41.260 | 983,184 | -2.455*** |
| | | (0.025) | | (0.010) | | |
| Credit Score | 105,369 | 755.086 | 637,166 | 745.315 | 742,535 | 9.771*** |
| | | (0.168) | | (0.069) | | |
| Unscored | 136,167 | 0.227 | 847,017 | 0.248 | 983,184 | -0.022*** |
| | | (0.001) | | (0.000) | | |
| **Non-minority** | | | | | | |
| Male | 127,906 | 0.716 | 717,124 | 0.716 | 845,030 | 0.000 |
| | | (0.001) | | (0.001) | | |
| Age | 127,906 | 38.772 | 717,124 | 41.231 | 845,030 | -2.459*** |
| | | (0.026) | | (0.011) | | |
| Credit Score | 99,296 | 755.398 | 542,765 | 747.098 | 642,061 | 8.300*** |
| | | (0.174) | | (0.074) | | |
| Unscored | 127,906 | 0.224 | 717,124 | 0.243 | 845,030 | -0.019*** |
| | | (0.001) | | (0.001) | | |
| **Minority** | | | | | | |
| Male | 8,261 | 0.704 | 129,893 | 0.729 | 138,154 | -0.024*** |
| | | (0.005) | | (0.001) | | |
| Age | 8,261 | 39.314 | 129,893 | 41.417 | 138,154 | -2.104*** |
| | | (0.101) | | (0.025) | | |
| Credit Score | 6,073 | 749.988 | 94,401 | 735.062 | 100,474 | 14.926*** |
| | | (0.681) | | (0.181) | | |
| Unscored | 8,261 | 0.265 | 129,893 | 0.273 | 138,154 | -0.009* |
| | | (0.005) | | (0.001) | | |

**Table IA4**
**Appraisal Gap, geo-coded sample**

This table shows the mortgage level of appraisal gaps based on minority status for the subsample of mortgages for which we have the latitude and longitude. The dependent variable in all the regressions is the natural log of the ratio of the appraisal value to the market value of the property. District, pincode, grid, year and month fixed effects are included as indicated. To construct the grid fixed effects, mortgages have been assigned to geographical grids of size 100m x 100m. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | ln(Appraisal Ratio) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Minority | -0.400*** | -0.399*** | -0.402*** | -0.409*** | -0.406*** | -0.344*** | -0.339*** |
| | (0.013) | (0.013) | (0.013) | (0.016) | (0.016) | (0.016) | (0.016) |
| $R^2$ | 0.0264 | 0.0333 | 0.0619 | 0.182 | 0.185 | 0.217 | 0.223 |
| Mean dep. var | -0.273 | -0.273 | -0.272 | -0.270 | -0.270 | -0.270 | -0.270 |
| District FE | N | Y | - | - | - | - | - |
| Pincode FE | N | N | Y | - | - | - | - |
| Grid FE | N | N | N | Y | Y | Y | Y |
| Year and Month FE | N | N | N | N | Y | Y | Y |
| Borrower Controls | N | N | N | N | N | Y | Y |
| Property Contols | N | N | N | N | N | N | Y |
| No. of obs. | 56942 | 56942 | 56942 | 56942 | 56942 | 56942 | 56942 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table IA5**
**Integrated developers, geo-located sample**

This table shows how appraisal gaps vary with whether the mortgage for a property is with a vertically integrated developer for the subsample of mortgages for which we have the latitude and longitude. The dependent variable in all the regressions is the log of the appraisal ratio. District, pincode, grid, year and month fixed effects are included as indicated. To construct the grid fixed effects, mortgages have been assigned to geographical grids of size 100m x 100m. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Integrated developer is an indicator for whether the collateral securing the mortgage is from a vertically integrated developer. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | ln(Appraisal Ratio) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Minority | -0.388*** | -0.387*** | -0.392*** | -0.397*** | -0.394*** | -0.345*** | -0.340*** |
| | (0.013) | (0.013) | (0.014) | (0.017) | (0.017) | (0.017) | (0.017) |
| Integrated Developer | 0.314*** | 0.314*** | 0.312*** | 0.310*** | 0.310*** | 0.249*** | 0.241*** |
| | (0.005) | (0.006) | (0.006) | (0.008) | (0.008) | (0.008) | (0.008) |
| Minority × Integrated Developer | 0.334*** | 0.332*** | 0.342*** | 0.338*** | 0.337*** | 0.316*** | 0.305*** |
| | (0.037) | (0.038) | (0.038) | (0.049) | (0.048) | (0.049) | (0.049) |
| $\beta_1 + \beta_3$ | -0.054 | -0.055 | -0.050 | -0.059 | -0.057 | -0.028 | -0.034 |
| | (0.034) | (0.035) | (0.036) | (0.044) | (0.044) | (0.045) | (0.045) |
| $R^2$ | 0.0497 | 0.0564 | 0.0841 | 0.202 | 0.204 | 0.230 | 0.235 |
| Mean dep. var | -0.273 | -0.273 | -0.272 | -0.270 | -0.270 | -0.270 | -0.270 |
| District FE | N | Y | - | - | - | - | - |
| Pincode FE | N | N | Y | - | - | - | - |
| Grid FE | N | N | N | Y | Y | Y | Y |
| Year and Month FE | N | N | N | N | Y | Y | Y |
| Borrower Controls | N | N | N | N | N | Y | Y |
| Property Contols | N | N | N | N | N | N | Y |
| No. of obs. | 56942 | 56942 | 56942 | 56942 | 56942 | 56942 | 56942 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table IA6**
**Robustness to the 2016 RERA Act**

This table examines how the impact of integrated developers on appraisal gaps varies with RERA implementation. The dependent variable in all three regressions is the log of the appraisal ratio. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. RERA is an indicator for whether the mortgage has been made after a given state implemented RERA. Integrated developer is an indicator for whether the collateral securing the mortgage is from a vertically integrated developer. Column 1 estimates the specification over the whole sample, whereas columns 2 and 3 report the estimates for the subsamples of mortgages across all states before and after they implemented RERA respectively. District, pincode, year and month fixed effects are included as indicated. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | ln(Appraisal Ratio) | | |
|---|---|---|---|
| Sample | Aggregate | Pre-RERA | Post-RERA |
| | (1) | (2) | (3) |
| Minority | -0.132*** | -0.070*** | -0.144*** |
| | (0.004) | (0.009) | (0.004) |
| Integrated Developer | 0.180*** | 0.148*** | 0.184*** |
| | (0.005) | (0.008) | (0.006) |
| Minority × Integrated Developer | 0.135*** | 0.091*** | 0.140*** |
| | (0.009) | (0.025) | (0.010) |
| $\beta_1 + \beta_3$ | 0.003 | 0.021 | -0.004 |
| | (0.008) | (0.023) | (0.009) |
| $R^2$ | 0.247 | 0.349 | 0.250 |
| Mean dep. var | -0.310 | -0.348 | -0.303 |
| State x Year-month FE | Y | N | N |
| District FE | Y | Y | Y |
| Pincode FE | Y | Y | Y |
| Year and Month FE | Y | Y | Y |
| Borrower Controls | Y | Y | Y |
| Property Contols | Y | Y | Y |
| No. of obs. | 983184 | 174018 | 752969 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table IA7**
**Demonetization: Integrated Developers with Minority Interaction**

This table examines how the impact of integrated developers on appraisal gaps varies with different phases of demonetization. The dependent variable in all three regressions is the log of the appraisal ratio. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Integrated developer is an indicator for whether the collateral securing the mortgage is from a vertically integrated developer. Column 1 estimates the specification over the period before November 2016, column 2 estimates the specification over the period between November 2016 and September 2017, and column 3 reports the estimates over the period post November 2017. District, pincode, year and month fixed effects are included as indicated. Borrower controls include age, gender, occupation, and CIBIL band-year indicators. Property controls include the plot area and built-up area. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

| Dependent variable: | log(Appraisal Ratio) | | |
|---|---|---|---|
| Sample | Pre Nov 2016 | Nov 2016 to Sept 2017 | Post Nov 2017 |
| | (1) | (2) | (3) |
| Minority | -0.071*** | -0.080*** | -0.156*** |
| | (0.010) | (0.009) | (0.004) |
| Integrated Developer | 0.137*** | 0.154*** | 0.186*** |
| | (0.009) | (0.010) | (0.005) |
| Minority × Integrated Developer | 0.062* | 0.079*** | 0.161*** |
| | (0.036) | (0.020) | (0.010) |
| $\beta_1 + \beta_3$ | -0.009 | -0.001 | 0.005 |
| | (0.034) | (0.018) | (0.009) |
| $R^2$ | 0.376 | 0.342 | 0.255 |
| Mean dep. var | -0.341 | -0.323 | -0.298 |
| District FE | Y | Y | Y |
| Pincode FE | Y | Y | Y |
| Year and Month FE | Y | Y | Y |
| Borrower Controls | Y | Y | Y |
| Property Contols | Y | Y | Y |
| No. of obs. | 129770 | 129324 | 699001 |

Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$