Describing Appraisal Gaps in India: Disparity in Collateral and Mortgage Access

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ABSTRACT

Marginalized households have limited access to mortgages in developing countries. This paper documents appraisal gaps in India wherein lenders value the housing collateral of minority borrowers lower than that of non-minority borrowers. Appraisals are 17% lower for minority borrowers, with 31% attributable to regional variation. However, gaps disappear once we condition on similar collateral. Sorting of minority borrowers to worse collateral and neighborhoods lowers appraisal values. Black money, borrower creditworthiness, and animus do not explain gaps. The staggered state-wise adoption of a real estate regulation that improved developer accountability increased lending to minority borrowers but continued sorting of minority households to worse collateral limits gap reductions.

JEL Codes: D14, R21, R23, R31

Keywords: Collateral, segregation, property rights, mortgages, discrimination, India

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1 Introduction

Households in developing countries, particularly marginalized households, have limited access to mortgage credit, which hampers their ability to build wealth through homeownership. A case in point is India. Though India's digital revolution has transformed the consumer lending space, it has largely bypassed the mortgage segment. Opaque markets and lender information asymmetries undermine mortgage access. Further, insecure property rights prevent collateral from being used to obtain credit (Besley and Ghatak, 2010), resulting in "dead capital" (De Soto, 2003). When these inefficiencies affect marginalized communities more, large sections of the population remain excluded. This paper examines a distinct channel influencing households' access to mortgage credit: lenders' appraisal of the collateral underlying mortgage loans.

Mortgage lenders obtain appraisals on properties they lend against as collateral, a process often mandated by regulation as part of the residential mortgage underwriting process. This paper examines the appraisal gap —– defined as the log of the appraisal value to the property sales price — of minority borrowers relative to non-minority borrowers.[1] Three reasons motivate our focus on appraisal gaps. First, appraisal gaps are not the direct target of policy in India.[2] Other loan terms, such as interest rates and loan-to-values, are standardized across loan rate sheets, making it a more difficult margin for lenders to adjust on. Second, appraisal ratios are defined relative to property prices and hence control for the myriad ways property prices differ for minority-owned houses. Lastly, appraisal gaps have been less documented in developing countries. The causes, consequences, and implications for minority borrowers (as we will see) can be very different in developing economies, underscoring the need for policy tailored to these unique needs.

Using the universe of mortgage data from the largest bank in India, we ask the question: do appraisal values differ for minority borrowers? 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

[1] Specifically, appraisal ratio is defined as the log of the appraisal value to the property sales price. Appraisal gap refers to the disparity in appraisal ratios between minority and non-minority borrowers.

[2] This is unlike the US where the US Department of Housing and Urban Development (HUD) launched an interagency Property Appraisal Valuation Equity (PAVE) taskforce in June 2021 to track misvaluation and undervaluation of minority-owned homes (Calem et al., 2020)

(OBC). The comparison group, the non-minority group, is Hindu borrowers from the “General" caste category. Importantly, we have information on the appraisal values of the underlying property used as collateral to obtain the mortgage and the identifier for borrower caste and religion.

We present five main findings. First, we document 17% lower appraisal ratios for minority borrowers relative to non-minority borrowers. Between-neighborhood effects account for nearly 32% of the variation, with the remaining attributable to within-neighborhood variation. Second, gaps disappear once we condition on similar collateral for minority and non-minority borrowers. Third, minority borrowers match to worse collateral and sort to more segregated districts, districts with worse property rights, poorer neighborhoods, neighborhoods with higher minority concentration, and collateral with greater lender information asymmetries. Fourth, differences in the “black money" component of property prices, borrower creditworthiness, or lender discrimination do not drive gaps. Finally, we analyze the staggered adoption of the 2016 Real Estate Regulatory Act (RERA) that improved developer transparency. Though credit to minority borrowers increases, gaps widen due to greater lender information asymmetries of minority collateral.

We start by analyzing baseline differences in property appraisal values relative to their market value for minority borrowers. Our primary specification regresses the appraisal ratio — defined as the log of the appraisal value to the property value — directly on a categorical variable for minority status and compares neighborhoods (pincodes) within districts across time. Our baseline estimate shows that appraisal ratios are 16.9% lower for minority borrowers relative to the comparison group of non-minority borrowers. These effects are economically meaningful and translate to nearly ₹468,076 ($5,617) lower loan amounts for minority borrowers relative to non-minority borrowers. On adding pincode-time fixed effect the appraisal ratio narrows to 11.5% lower appraisal ratios for minority borrowers. Across-neighborhood variation accounts for nearly 31% of the variation, with within-neighborhood differences accounting for the remaining 69%. Lenders do not adjust loan-to-values higher and hence the appraisal gaps translate to meaningful differences in loan amounts for minority borrowers.

The lower appraisal ratios for minority borrowers are reflected across different sub-samples and are not driven by individual states or districts. There is significant heterogeneity within mi-

nority groups. Appraisal ratios are 21.8% lower for SC/ST borrowers, corresponding to ₹603,790 ($7,245) lower credit access. OBC borrowers fare relatively better with 15.8% lower appraisal ratios, translating to ₹437,610 ($5,251) lower loan amounts. Muslim borrowers have the narrowest gap with 12.1% lower appraisal ratios, corresponding to ₹335,131 ($4,022) lower credit. These intermediate effects for Muslims are consistent with previous literature that documents better socioeconomic outcomes for Muslims than lower caste groups but worse outcomes than upper caste groups (Sacchar et al., 2006; Ash et al., 2022).

We next examine whether collateral differences explain appraisal gaps. Using information on the building developer for the collateral securing a loan, we control for collateral quality. Once we condition on similar collateral using developer-time and pincode-time fixed effects, appraisal gaps disappear.

Having established that collateral differences drive gaps, we examine whether matching of minority borrowers to worse collateral explains appraisal gaps. Defining worse developers as those with worse appraisal ratios, we show that indeed, minority borrowers are more likely to borrow against collateral of worse developers. Sorting of minority borrowers to worse neighborhoods or collateral could also explain gaps. We examine district-level, pincode-level, and collateral-level characteristics. Minority borrowers are more likely to be in segregated districts, districts with high property crime, and in poorer pincodes and high minority concentration pincodes. We also find that minority borrowers are associated with collateral with greater information asymmetries. Relying on the insight from Stroebel (2016) that lenders know more about the collateral of developers they are vertically integrated, we show that minority borrowers are associated with collateral from non-integrated developers. Appraisal ratios are higher for properties of integrated developers and outperform remaining mortgages, consistent with superior lender information. These differences in regional and collateral characteristics — namely segregation, poor property rights, poor neighborhoods, high minority fraction, and whether the underlying collateral is not associated with an integrated developer — widen appraisal gaps, highlighting that sorting of minority households determines appraisal gaps.

We hypothesize that the numerator of the appraisal ratio, that is, depressed appraisal values

arising from collateral quality drive gaps and rule out alternate mechanisms operating through other property attributes or borrower characteristics. In principle, appraisal values can be lower for minority borrowers either because the minority borrower is perceived to be riskier or, alternatively, the property or collateral of minority borrowers has more credit risk associated with it and hence requires greater down payment. Borrower creditworthiness cannot explain the appraisal gaps. Ex-ante measures of borrower riskiness (such as credit scores), and ex-post measures (default) have minuscule effects on the appraisal gap.

Gaps can also come from higher property prices (denominator of the appraisal ratio). Potentially, broader dynamics and discriminatory housing practices can force minority households to stay in poorer neighborhoods where they also need to pay a premium on property prices as has been documented for Black homeowners in the US (Avenancio-León and Howard, 2022). Contrary to the US findings, we find that property prices are similar in segregated districts. Further, appraisal gaps are lower for higher property prices contrary to the conjecture that price premiums drive property appraisal gaps. One could also argue official property prices do not reflect true values and real estate transactions often involve off-the-books sources of money or "black money" to avoid taxes (Gandhi et al., 2022). We exploit data on the borrowers' occupation on whether they are salaried or non-salaried to address this concern. Non-salaried borrowers plausibly have lower access to "white" money and, hence, are likely to finance a larger proportion of their real estate purchases with black money. Consistent with this hypothesis, salaried borrowers have lower appraisal ratios. The disparity between minority and non-minority borrowers does not vary by salaried households, highlighting the limited role of Black money in driving appraisal gaps.

We also examine alternate channels operating through depressed appraisal values arising from inter-ethnic animus. We explore two sources of bias: lender/appraiser bias, or alternatively differences in judge-bias in enforcement of property rights. While these channels are difficult to pin down using our data, we make some headway by examining differences across districts that historically faced religious conflicts. In an alternate specification, we use contemporaneous time variation in riots, when inter-ethnic animus is heightened. Neither shows wider appraisal gaps. Using case-level data from Ash et al. (2022) to examine judge bias, we show that out-group judge

bias and differences in enforcement of property rights also cannot explain gaps.

Finally we examine policies improving inefficiencies in the real estate markets and its impact on appraisal gaps. For decades, the real estate industry in India was highly unregulated with a high degree of developer uncertainty. Developers provided limited project details, stalled projects, and diverted funds through tunneling with limited legal recourse for home buyers and lenders. All this changed with the enactment of the 2016 RERA Act, which increased developer transparency and accountability. RERA affected appraisal gaps on two margins. First, by improving developer transparency, appraisal gaps narrowed for post-RERA for properties at integrated developers. Second, overall credit increased post-RERA and properties not associated with vertically integrated borrowers were more likely to get credit. However, appraisal gaps *widened* for remaining properties. A subsequent 2018 amendment to the pre-existing bankruptcy code (the Insolvency and Bankruptcy Code) that enabled home buyers to push errant developers into bankruptcy proceedings is in line with these findings.

Finally, using Delhi as a case study, we show that transfer of property rights can also narrow gaps. We collect data on disputed properties in Delhi and show that neighborhoods (pincodes) with more disputed properties face worse appraisal gaps for minorities. Importantly, a subset of neighborhoods also saw the withdrawal of Section 81, which legalized unauthorized colonies on agricultural land. The Delhi government passed a Bill formalizing Delhi Slum Colonies, essentially transferring property rights to home-dwellers. Appraisal gaps improved for minority borrowers, specifically, for scheduled caste and scheduled tribes, who were more affected by the withdrawal of Section 81.

Related literature Our paper is primarily related to the literature on segregation of minority households and its impact on household outcomes. Segregation can result in inequality in access to homeownership, public infrastructure, employment opportunities (Ananat, 2011; Cutler and Glaeser, 1997; Kulkarni and Malmendier, 2022; Massey and Denton, 1993; Shertzer et al., 2018, 2021; Wilson, 2012) and even perpetuate inequality into future generations (Derenoncourt, 2022). While much of this work focuses on developed countries such as the US, Adukia et al. (2023) study India and document that urban segregation in India is comparable to the Black-white seg-

regation in the US. This paper relates to similar segregation and sorting working through the mortgage markets in India. A large literature, mostly on the US, documents redlining, the historical practice of denying credit to areas with historically disadvantaged groups (Aaronson et al., 2021). This can also show up in appraisal values as poor precision due to limited transactions in minority-concentrated neighborhoods (Lang and Nakamura, 1993) can lead lenders to perceive minority borrowers as riskier and depress appraisal values (Blackburn and Vermilyea, 2007; Ling and Wachter, 1998; Avery et al., 1999). While policy in India (Sacchar et al., 2006) highlights such geographic disparity in access to credit, academic work is lacking. We document significant spatial variation in appraisal gaps — that determine how much credit minority borrowers get — in poorer, high minority and segregated neighborhoods, plausibly shedding light on one consequence of the persistent segregation documented in Adukia et al. (2023). While they find lower access to public facilities and infrastructure in minority-concentrated neighborhoods, these differences don't directly drive appraisal gaps, which already accounts for differences priced into property values. Thus, our paper documents a distinct channel affecting minority credit access through appraisal gaps and highlights an important consequence of segregation.

Our paper also relates to the literature on discrimination in mortgage markets. Bartlett et al. (2022) and Ambrose et al. (2021) on the US document racial disparities in mortgage and approval rates, while others (Bhutta and Hizmo, 2021; Bhutta et al., 2021) find no such disparity. In contrast to this long-standing literature on the US, there is limited work on discrimination in the mortgage markets in developing countries such as India. Notable exceptions include Fisman et al. (2020) and D'Acunto et al. (2022), which find evidence of in-group bias in lending in India.[3] A large literature studies the determinants of appraisal values (Lang and Nakamura, 1993; Calem et al., 2020), with recent renewed attention to appraisal gaps (Rothwell et al., 2018; Rothwell and Perry, 2022). Much of this work, too, focuses on the US.[4] In a significant departure, we document appraisal gaps in a large developing country like India.

[3] In the broader context of discrimination in developing economies, Ash et al. (2022) examine in-group bias in the Indian judiciary but find limited effects.

[4] Possibly due to limited information on race at the property level, papers documenting the racial bias in appraisal values have focused on neighborhood-level racial characteristics such as Black and Hispanic share of households. In a significant departure, we use loan-level data with precise indicators of minority status and document spatial and individual-specific differences in appraisal values in India.

The previous literature posits several hypotheses as to why appraisal values differ from sale prices. Disagreement between the borrower and the lender (Jiang and Zhang, 2022), greater lender information asymmetries (Martel and Woeppel, 2023; Stroebel, 2016), or alternatively, appraiser bias are possible mechanisms. Our paper highlights a distinct mechanism in developing countries: the role of property rights. In seminal work, De Soto (2003) highlights how insecure property rights hamper development, since assets in developing countries cannot be used as collateral to obtain credit. Besley and Ghatak (2010) similarly links property rights to economic development.[5] In our setting, weak property rights impede credit access in residential mortgage markets for minority borrowers through appraisal gaps in sharp contrast to developed country studies that highlight market failures and active discrimination as possible channels.

The remainder of the paper is organized as follows. Section 2 discusses institutional details. Section 3 details the data used in the analysis and the empirical strategy. Section 4 documents appraisal gaps and Section 5 collateral quality as a mechanism, and Section 6 rules out alternate mechanisms. Section 7 examines policies that target market inefficiencies that affect gaps. Section 8 concludes.

2 Institutional Details

We discuss details of the residential mortgage market in India and recent regulatory changes shaping the real estate industry in the past decade.

2.1 The Appraisal Process

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

[5]Property rights influence economic activity both by determining the level of investment as well as credit availability. Although evidence suggests that improving property rights increases investment (Field, 2007; Adamopoulos et al., 2022; Galiani and Schargrodsky, 2010; Gollin and Udry, 2021), evidence of improved property rights on credit access is mixed. On the one hand, improving property rights should encourage lenders to increase the supply of credit. On the other hand, financial frictions in developing markets impede substantial gains from improving property rights (Manysheva, 2022; Deininger and Chamorro, 2004; Galiani and Schargrodsky, 2010; Zegarra et al., 2008; Piza and de Moura, 2015).

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.[6]

Mortgage appraisal empanelments (that determines instutions 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 zones and can conduct valuations across the state.

Valuers interact extensively with local branches. After approval, valuers are recognized by local branch officers. 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. They 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.

There is some variation in the process across smaller and large cities. Ideally, the bank is expected to manage all communication with the customer, and valuers are not supposed to interact with customers directly. However, this protocol is often followed only in larger cities, while smaller cities see a more direct interaction between valuers and customers.

[6] 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 appraisal process for apartments is largely streamlined now in the case of new properties and is transparent for resale properties. For new properties, the developer takes care of loan applications, and the process is highly streamlined. A project team belonging to the developer handles all the steps for the end customer, starting from the application and valuation to legal, among other things. The developer team has a template of all these documents where they only change the customer's details, keeping the property details and values largely the same. For resale properties, both the branch manager and appraiser have discretion. Nearly 60% of all transactions in the top 8 cities are resale transactions. Properties within an apartment are again largely similar, and prices for apartments in top-10 cities are largely transparent with websites that cater to buyers, making this information easily available (for example, IndexTap, ZapKey, and NoBroker). As a result, the valuation is anchored on the rates set by developers for new properties or is based on data available for other flats in the same building. The process is more complicated for non-apartment loans, where appraisal prices are largely at the appraiser'sappraiser's discretion. Branch managers choose appraisers and hence also influence the appraisal process. For example, managers may be more familiar with local businessmen who have overdraft facilities at the branch or are known to them. Appraisers might also be inclined to comply as future engagements depend on their relationship with the branch manager.

The other two values, the distressed sale value, reflect liquidation discounts and are 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., 2023).

The Reserve Bank of India (RBI) typically sets the maximum loan-to-values 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 downpayment that a borrower needs to pay. The appraisal value eventually determines the loan amount the bank is willing to extend to a borrower.

2.2 The 2016 RERA Act

The real estate markets in India have been opaque and plagued by massive inefficiencies. One reason is the lack of transparency and accountability for real estate developers. However, this changed due to the 2016 Real Estate Regulatory Authority (RERA) Act. Prior to RERA, developers often failed to provide clear information about project details, timelines, and costs to homebuyers. There were no standardized practices or regulations governing the sector, leading to unethical practices and consumer exploitation. Developers also frequently diverted funds collected from homebuyers for other purposes, leading to project delays. There was limited recourse provided to borrowers as there were no mechanisms to ensure proper utilization of funds for their intended projects. Homebuyers also faced significant delays in receiving possession of their properties, often without any recourse or compensation. Developers faced minimal consequences for such delays, and the lack of consumer protection compounded these problems. Homebuyers had limited legal remedies in case of disputes or grievances against developers. The existing Consumer Protection Act was often found to be inadequate in addressing real estate-related issues.

There has been a significant policy push for regulatory reforms in the past decade. Chief among them is the 2016 RERA Act, which protects homebuyers interests and regulates developers.[7] Importantly, it increased developer transparency and accountability. The RERA Act required mandatory registration and disclosure of projects with the respective state RERA authorities. In addition, escrow accounts needed to be set up for project funds where at least 70% of the funds collected from homebuyers had to be deposited. This ensured funds were not diverted into other projects or worse tunneled to parent entities. Strict penalties were to be imposed for delays. Mechanisms were also put in place for grievance redressal.

[7] See https://mohua.gov.in/cms/real-estate-regulation-and-development-act-2016.php.

The 2016 RERA Act was passed by the Rajya Sabha on 10th March, 2016 and by the Lok Sabha on 15th March, 2016. The bill was finally passed by the Parliament and assented to by the President on 25th March, 2016. As part of the RERA Act, each state/union territory was to establish a real estate and regulatory authority. The timeline of setting up of the state RERAs and the implementation dates are shown in Table IA7. RERA has been credited with increasing transparency and accountability and in increasing in consumer confidence. The Act led to standardization of processes, which in turn has led to decreased costs and other resource overheads. However, RERA has had a few limitations. The level of implementation and enforcement has been different in different states. Delayed justice in case of non-compliance was also an issue. A report by BCG and Omidyar Networks states that RERA has addressed many of the erstwhile challenges in the real estate ecosystem in India but challenges remain due to varying levels of implementation across states.

The 2018 IBC Amendment In June 2018, the Insolvency and Bankruptcy Code (IBC) Amendment was promulgated and allowed homebuyers to initiate insolvency proceedings against developers.[8] The ordinance recognized home buyers as financial creditors, thus allowing them to initiate insolvency proceedings against errant developers under Section 7 of the IBC. To prevent misuse the ordinance established strict procedures for withdrawal of cases after admission. At least 90% of the creditors needed to vote in favor of the withdrawal. The Ordinance also reduced the voting threshold for major decisions, such as approving resolution plans and extending the resolution process, from 75% to 66%, promoting resolution over liquidation. In effect, the ordinance ensured that the home buyers had legal recourse when developers failed to comply with the timelines. It also strengthened the newly instituted RERA Act by allowing for action against non-complying developers.

2.3 Property Rights in India

Land ownership is presumptive in India. Legal documents such as property deeds, tax receipts or survey documents are not guaranteed government title to ownership and property transactions

[8] See https://ibbi.gov.in.

represent only property transfer records from a granter to the grantee within a deed type, and rights are limited to the deed. Since no existing document provides information about property ownership, land ownership is established through multiple documents, including sale deeds, historical ownership records, survey documents, the legacy of the Zamindari system and its ledger, and property tax receipts. Therefore, all title deeds (transactions) are subject to challenges in India.

Although contracts or deed types are documented at the sub-Registrar's office of the registry department, they cannot protect the property ownership rights. To address poor administrative property records, the central government implemented the Digital India Land Records Modernization Programme (DILRMP) in 2008 to fully computerize the property registration process, including tax collection and record maintenance. Modernization of land records using records of rights and spatial records methods have been completed in almost 96% of villages as of May 2024[9].

However, the slow disposal rate of property disputes in court threatens land and property rights. In India, property disputes range from civil title suits, mortgage defaults, unauthorized construction, unauthorized occupation, boundary disputes, and forgery for different purposes related to property. Based on the National Judicial Data Grid [10]; out of 10,911,090 civil cases in the trial courts, almost 38% of cases are pending for more than 3 years and about 6.40% pending for more than 10 years. Surprisingly, in the high courts, the disposal rate of civil cases is even lower than in trial courts. Based on the National Judicial Data Grid, about 16.98% of cases out of 4,433,317 civil cases have been pending for more than 10 years in high courts. The huge backlog of property-related matters and delayed disposal also hinder property rights. Kato and Sato (2013) documents the deleterious effects on Indian manufacturing sector due to threats against private property rights using data on crime against private ownership properties. Crime against property is an additional risk to property rights.

According to Badarinza et al. (2017) the average household holds 77% of its total assets in real estate (i.e., buildings used for residential, farm and non-farm activities, constructions, rural and

[9] https://dilrmp.gov.in/

[10] https://njdg.ecourts.gov.in/njdgnew/?p=main/pend_dashboard

urban land). Delhi High Court is one of the five High Courts in India with original Jurisdiction [11]. This gives it the power to hear appeals for fresh cases with property value over ₹20 million[12]. As per Damle and Gulati (2022), land and property disputes constitute 17% of total litigation at Delhi High Court where a high fraction of cases are among private parties. Given the nature of original and geographical jurisdiction of Delhi High Court, these cases capture a significant variety of of disputes included from both original and appeal cases. The case website, DORIS, is maintained by Sub-Registrar offices in India where Delhi SROs documents all the properties with a court stay order. In most cases, a property is considered litigated if there is a dispute or a crime related to the dispute has occurred between parties. A property is considered disputed only after a court stay which prohibits any transaction on that property. One of the interpretations of a court stay is that based on current evidence ownership is ambiguous in nature. This is why we use Delhi as a case study for our empirical study. Another reason behind using Delhi as our laboratory for case study on ambiguous property rights mechanism is due to availability of Section 81 or slum dwellers dispute dataset.

Given the wide heterogeneity in the way property titles work across jurisdictions, we focus on property disputes in Delhi for our analysis. We use all litigated immovable properties confined to Delhi. The Delhi Land Reforms Act of 1954 was enacted to modify the Zamindari System and install a uniform proprietor body for peasants with no intermediaries. Under Section 81 of the Delhi Land Reforms Act, land used for anything other than agriculture activities would be considered a violation of law and hence subject to penalty. Unauthorized construction on such lands under Section 81 is considered a Section 81 dispute. Bhuwania (2017) in his book *Courting the People* documents that *"In the first decade of the twenty-first century, the Delhi High Court presided over the most comprehensive and ruthless campaign to remove informal 'slum' settlements that the city had seen in a generation. According to the official statistics, in 1998, Delhi had about 3 million people living in 1,100 Jhuggi- Jhompri clusters. When the next survey was conducted in March 2011, the official figure had fallen to 685 jhuggi-jhompri clusters housing around 2 million people."* Other than political negotiations to gain property rights, Delhi's appellate judiciary acted in public interest litigation as a vehicle

[11] The other High courts with original jurisdiction are Bombay, Madras, Shimla and Kolkata.
[12] Delhi High Court Act 1966, 26 of 1966

to relocate slum villages from their establishments. In 2019, India passed a bill to formalize the Delhi Slum Colonies by withdrawing the property disputes under Section 81 and extending the property rights for slum dwellers under the PM-UDAY scheme. Talks were underway since 2015 to extend rights to slum dwellers.

3 Data and Empirical Strategy

3.1 Data

Our main dataset is mortgage-level data from the largest public sector bank with details on the loan. State-owned banks account for the largest market share in housing loans by value and volume (45%) and as of December 2020, the top five state-owned banks held nearly 30% of home loans by value (CRIF High Mark Credit Bureau). 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 80 years.

In our analysis, we focus on Hindu and Muslim borrowers. We classify a minority borrower if they belong to Hindu OBC/SC/ST or if they are Muslims. The non-minority borrowers are those with religion Hindu and "General" category caste.

We supplement our analysis with several different datasets.

First, we use case-level data on property crimes provided by Development Data Lab for 2010–2014. Since these cases only capture criminal cases under the Indian Penal Code Act, we collect data on disputed properties. Ambiguity in property rights of an immovable property refers to when a court stays a notice of sale, transfer or any legal transaction on a property. Sub-Registrar offices maintain a database of disputed properties under their jurisdiction and list them on the

website.We retrieve the data for Delhi from the Delhi Online Registration Information System (DORIS)[13], an online application that allows us to retrieve information on property registrations, property taxes and litigated properties. We restrict to prohibited properties and extract data on disputed properties and Section 81 disputes. We focus on the 24,931 residential properties. The prohibited properties service lists two types of complaints - court cases and disputes. The also data contains a wealth of information, including the complaint type, SRO Name, Corporation Name (Municipality), Locality, Property Address, Date of Dispute, and Remarks. The remarks section displays information regarding complaint type, viz. in disputed complaint type, legal notice, forgery, complaint for cheating, mortgage default in tribunal court, etc. Similarly, for court complaint type, the case number and party names are listed on the service platform. Section 81 disputes relate to unauthorized construction or usage of private agricultural land in Delhi.

To examine animus as a channel we use two sets of data on religious conflicts. First, we measure historical conflict in a given district using Varshney and Wilkinson (2006) dataset for religious conflicts for 1950-2000. The dataset is collected from news articles in the Times of India and tracks occurrences of religious violence. We use information on the district, town/city, and village and manually map it to our primary dataset. Out of 310 districts, we are able to map 249 districts in our dataset. Second, we also measure contemporaneous religious conflict from ACCLED for 2016-2020.[14] Data is at the latitude and longitude level, which we map to our 2014 mortgage pincodes in our database. The dataset tracks all events of political violence, and we retain events marked as riots, which are the closest proxy for religious conflicts.

To test the enforcement of property titles and bias in the judicial system we rely on data from Ash et al. (2022). We retain only cases pertaining to crime against property. Appendix Table IA5 lists the Indian Penal Code sections and describes the related offense.[15]

[13] https://doris.delhigovt.nic.in/

[14] See https://acleddata.com/.

[15] We remove IPC Sections 183, 217, and 218 due to ambiguity in whether they relate to property. Results are not sensitive to these restrictions.

3.2 Empirical Strategy

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:

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

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

Our main analyses assess the relationship between the appraisal gap and how it differs for minority borrowers. Our baseline model estimates

$$\text{Ln(Appraisal Ratio)}_{it} = \phi_{pt} + \theta_{\text{Rate sheet-grid}\times t} + \beta \times \text{Minority}_i + \epsilon_{it}, \tag{2}$$

for loan i in district $d(i)$ in pincode $p(i)$ originated in month-year t. $\text{Ln(Appraisal Gap)}_{it}$ is log of the appraisal gap defined above. $\theta_{\text{Rate sheet-grid}\times t}$ is the fixed effect for the Rate sheet-grid $\times$ month-year. This controls for aggregate demand factors across credit scores. Further, these grids represent the rate-sheets that the lender offers to potential borrowers and hence ensures we are comparing similar sets of borrowers. ϕ_{pt} is district-time fixed effect. Minority_i is as defined before. Standard errors are clustered at the pincode level. The coefficient of interest, β captures how appraisal ratios differ for minority borrowers relative to non-minority borrowers.

We also conduct several heterogeneity tests. These specifications allow us to examine various heterogeneity and to pin down the mechanisms. A common model follows the specification

$$\begin{aligned}\text{Ln(Appraisal Ratio)}_{it} = \phi_{pt} + \theta_{\text{Rate sheet-grid}\times t} + \theta \times \text{X}_i + \beta \times \text{Minority}_i \\ + \gamma \times \text{Minority}_i \times \text{X}_i + \epsilon_{it},\end{aligned} \tag{3}$$

where X_i is a heterogeneity variable that we are interested in. While in the above specification, heterogeneity varies across individual borrowers, i, in some specifications the heterogeneity variable varies across districts or pincode. In these specifications, the coefficient θ will drop out since it includes pincode-time fixed effects (ϕ_{pt}). γ is the coefficient of interest and will differ based on the context. We relegate the interpretation to subsequent sections.

3.3 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 U.S, the 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. While the descriptive statistics for the non-minority borrowers follow similar trends with bunching around 0, the statistics for minority borrowers are strikingly different. Even the median values indicate that appraisal values are 26% lower than the sales price. Within minority categories, Muslim borrowers have relatively higher appraisal ratios compared to OBC/SC/ST borrowers consistent with the patterns we saw in loan amounts. Figure 2 shows the spatial variation of appraisal ratios and indicates wide variation across regions in India.

Panel B in Table 1 shows the aggregate summary statistics. Panel A shows the loan-level characteristics. Average loan amount is ₹1.87 million. The split by non-minority and minority categories reveals that non-minority borrowers have higher loan values on average of ₹1.96 million, with minority borrowers at ₹1.33 million. Within the minority categories, Muslim borrowers have a higher loan amount of ₹1.43 million, whereas OBC/SC/ST borrowers have a lower loan amount of ₹1.29 million.

Loan-to-values (LTV) values are strikingly similar across the board at 59%. Default rates are low on average at 1% and similar for non-minority borrowers. For minority borrowers, default rates are higher at 3%. Interest rates were 7.51%, on average; 7.5% for non-minority borrowers and a higher 7.54$ for minority borrowers. Within the minority borrowers, Muslims had a higher interest rate of 7.6%, whereas OBC/SC/ST borrowers had comparatively lower interest rates of 7.52%.

4 The Appraisal Gap

This section documents the baseline differences in property appraisal values relative to their market value for minority borrowers and highlight distinct spatial variation.

4.1 Baseline Estimates

Our primary specification follows Equation 2. The appraisal ratios are regressed directly on a categorical variable for minority status. Our most stringent specification includes pincode-year fixed effects to absorb variation arising from differences in the local economy or regional differences. 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 mechanisms driving differences may differ across minority groups.

Panel A in Table 2 presents our baseline findings. Column 1 shows that the appraisal ratio is 16.9% lower for minority borrowers relative to the comparison group of non-minority borrowers (column 1). On adding controls, specifically controlling for borrower creditworthiness and time-varying changes within different credit groups, results remain quantitatively similar with a 16.6% lower appraisal ratio for minority borrowers (column 3). On adding pincode-time fixed effects (column 3), we see that the appraisal ratio narrows to 11.5% lower appraisal ratios for minority borrowers. Adding controls in column 4 yields similar estimates. Comparing column 1 to column 3 estimates indicates that adding pincode-time fixed effects narrows the appraisal gap by 31% (=1-11.5%/16.9%). Differences are similar on comparing column 2 and column 4, suggesting that across-neighborhood variation accounts for nearly 31% of the variation and within-neighborhood differences account for the remaining 69%.

What do these differences in appraisal values imply for minority borrowers' access to credit? Given average property values of ₹4,694,374 (from Table 1) and an average loan-to-value of 59%,

the estimates in column 1 translate to nearly ₹468,076 ($5617[16]) lower loan amounts for minority borrowers relative to non-minority borrowers.

However, 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. Panel B shows the differences in LTV, where "value" in the denominator in LTV is the appraised value. LTV is *lower* by 0.003-0.001. A lower LTV of -0.003 translates to only ₹4694 ($56) lower loan assuming the average proper average property values of ₹4,694,374 (Table 1). LTV does not adjust upward to compensate for lower appraisal values. If anything, the LTVs are slightly lower, although with minuscule magnitudes compared to the appraisal gaps documented in Panel A possibly because LTVs are more closely scrutinized by regulators and market participants.

In Panel C, we examine the differences in loan amounts for minority versus non-minority borrowers. Loan amounts are 12.7% lower for minority borrowers (column 1) and effects are similar after controlling for borrower creditworthiness (column 2). On adding pincode-time fixed effects, loan amounts are 10.5% lower minority borrowers (column 3) with similar effects on further controlling for borrower creditworthiness (column 4). The absolute value of the estimates in columns 1–2 are higher than those in columns 3–4, again highlighting the significant spatial component in borrowers' access to credit.

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 state of Nagaland 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 613 districts, this condition is satisfied for 452 districts. Point estimates are negative and significant at 5% in 162 districts, negative and insignificant in 391 districts, positive and significant in 54 districts, and positive and insignificant at 5% in 6 districts.

[16] Assuming a conversion rate of 0.012

Heterogeneity within minority groups. In our baseline estimates, we 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, appraisal ratios are 21.8% lower for SC/ST borrowers, which translates to ₹603,790 ($7245) lower credit access. OBC borrowers fare relatively better with 15.8% lower appraisal ratios, which corresponds to ₹437,610 ($5251) lower loan amount. Muslim borrowers have the narrowest gap with 12.1% lower appraisal ratios, corresponding to ₹335,131 ($4022) lower credit.

While the point estimates are similar controlling for borrower creditworthiness (column 2), pincode-time fixed effects narrow the appraisal gap. On comparing estimates in column 2 to column 4, we see that across-neighborhood variation accounts for 31% of the appraisal for SC/ST borrowers, a lower 28% for OBC borrowers, and a strikingly higher 42% for Muslim borrowers. The findings 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., 2022).

5 Does Collateral Quality Explain Appraisal Gaps?

We examine whether differences in collateral quality drive appraisal gaps. Our data provides information on the developer of each loan for 104,739 mortgages. These developers are vertically integrated with the lender in our sample and allow us to more finely control for collateral quality. Using this data, we look at the within-builder differences in appraisal gaps in Table 4. Column 1 also controls for within district-time and shows that appraisal gaps are 3.4% for minority borrowers. On comparing this to the baseline estimates in column 1 in Table 2, we see that appraisal gaps reduce by 80%(=1-3.4%/16.9%) indicating that collateral quality as proxied by the developer indeed explains appraisal gaps. Controlling for credit score banks yields a similar 3.2% lower appraisal gap. However, once we control more finely for the exact collateral using pincode-time

fixed effects, appraisal gaps disappear. Including pincode-time fixed effect ensures that we are comparing two borrowers with collateral in the same society/complex.[17] Two interesting facts emerge. First, the appraisal gap disappears once we condition on (plausibly) similar properties. Second, spatial differences — in this case across different developer properties — account for any remaining differences in collateral. Hence collateral quality does play a role in determining appraisal gaps. Thus, collateral quality and neighbourhood differences drive appraisal gaps.

The observed appraisal gaps in Table 4 suggest that minority borrowers may be disproportionately associated with worse quality developers. Using appraisal ratios as a proxy for poor collateral quality, we rank the integrated developers. We regress the appraisal ratios on developer fixed effects to get the average developer-level appraisal ratios and then rank the extracted developer fixed effects into four quartiles from highest appraisal ratio (developer rank =1) to lowest appraisal ratio (developer rank=4). We examine whether the appraisal gap — defined by the minority coefficient estimates using the model in Equation 2 —- varies by developer rank. Note, there is no ex-ante reason to expect the appraisal gap (the minority versus non-minority difference) to vary by builder since the sorting into different ranks was not explicitly based on whether appraisal ratios *differed* between minority and non-minority borrowers for a particular developer rank. Figure 4 shows the results of this estimation. The vertical lines represent the 95% confidence interval. The worse the developer rank, higher the appraisal gap (coefficient on minority).

Are minority borrowers matched to worse quality developers? To examine this we use the following specification:

$$\text{Developer Rank}_{it} = \phi_{pt} + \theta_{\text{Rate sheet-grid}\times t} + \theta \times \text{X}_i + \beta \times \text{Minority}_i + \epsilon_{it}, \tag{4}$$

for mortgage in i originated in time t. As defined above, developer rank is obtained by regressing the log of the appraisal value to the market value on developer fixed effects. The coefficients in the developer fixed effects are split into 4 quartiles. Developers are ranked from 1 (best) to 4 (worst) corresponding to the highest appraisal ratio to the worst appraisal ratio. Table 5 indicates that

[17] For example, the Lodha Group is a pan-India real estate developer. Consider Lodha Group properties in the city of Mumbai, which can have distinct properties in Chembur and Thane, but within the same district of Mumbai. As one starts conditioning on the pincode-time fixed effects, we are essentially conditioning on properties belonging to the same project, that is, within a housing society or housing complex.

indeed, minority borrowers are matched to worse developers (defined by higher developer rank) compared to non-minority borrowers.

5.1 Sorting across neighborhoods

A large proportion of the appraisal gap comes from across-neighborhood variation (Section 4). We examine whether minority borrowers disproportionately match to worse neighborhoods and whether specific features of different neighborhoods explain gaps. To examine sorting of borrowers, we use the specification:

$$\text{Minority}_{it} = \phi_{pt} + \theta_{\text{Rate sheet-grid}\times t} + \theta \times \text{X}_i + \beta \times \text{Characteristic}_i + \epsilon_{it}, \tag{5}$$

for loan i in district $d(i)$ in pincode $p(i)$ originated in month-year t. The LHS variable is an indicator for whether the loan is to a minority borrower. Minority_i is as defined before. $\theta_{\text{Rate sheet-grid}\times t}$ is the fixed effect for the Rate sheet-grid $\times$ month-year. This controls for aggregate demand factors across credit scores. Characteristic_i are the different deposit-level, pincode-level, and collateral-level characteristics we examine. ϕ_{pt} denotes the pincode-time fixed effect, though we vary the fixed effect depending on whether the characteristic varies at the district level, pincode level, or the collateral level. Standard errors are clustered at the pincode level. The coefficient of interest, β captures whether minority borrowers are more strongly associated with the characteristic being measured.

Segregation. To examine how the appraisal gap varies with segregation, we first define the segregation measure using the commonly used dissimilarity index defined as:

$$\text{Segregation Index}_d = \frac{1}{2} \sum_{p \in P} \frac{N_{\text{Minority},p}}{N_{\text{Minority},d}} - \frac{N_{\text{Non-minority},p}}{N_{\text{Non-minority},d}},$$

where $N_{\text{Minority},p}$ is the number of minority households in pincode p. Similarly, $N_{\text{Minority},d}$ is the number of minority households in district d. The summation is over all pincodes p belonging to district d denoted by the set P. The dissimilarity index takes values from 0 to 1 with higher values indicating higher segregation. Intuitively, it measures what share of minority households would need to be moved across pincodes to be evenly distributed within a district.

Panel A in Table 6 reports the estimates using Equation 5. Minority borrowers are 1% more

likely to be in segregated neighborhoods. Can segregation explain gaps? Panel A in Figure 5 variation across different deciles of the segregation measure. There is a steady decline in the appraisal gap as segregation increases. We test this more formally using the heterogeneity specification in model (3) with segregation as the heterogeneity measure. Estimates are presented in column 1 of Table 6. A 1 SD higher segregation in a district explains nearly 72%[=17.6/(17.6+6.8)] of the appraisal gap.

The differences in appraisal gaps by segregation highlight a distinct channel: even for the same level of minority fraction, the concentration of minority borrowers in certain neighborhoods has an adverse effect on appraisal gaps. This is not the mere aggregation of effects at the individual level but an effect over and above the level of minority borrowers.

Property Crimes Can differences in property rights account for the variation in gaps? Since property rights can vary across states, we use district-level property crimes per capita as a proxy. Data is from the e-Courts database for criminal offenses pertaining to property crimes. Panel A in Table 6 shows that more likely to be in districts with high property crime. Replacing district-level property crimes per capita (above median) as the interaction term in Equation 3, we see 25% (=0.025/0.102) higher appraisal gaps in districts with worse property rights (column 2, panel B Table 6).

Minority Fraction. Moving to more granular neighborhood-level characteristics, we examine pincode-level minority fraction. Panel A shows that indeed, minority borrowers are secluded to neighborhoods with high minority fraction. Combining with the estimates in column 1, this suggests that minority borrowers are secluded to more segregated districts and within districts to neighborhoods with higher minority concentration. There is a long history of spatial variation in credit access in developed countries, also referred to as redlining. Panel B Figure 5 presents the point estimates using our baseline model in Equation 2 for different deciles of the pincode-level minority fraction. The disparity in appraisal ratios is steadily increasing in minority fraction.

We confirm these findings using the heterogeneity model in (3). Panel B Table 6 (column 3) presents the results. Minority borrowers in neighborhoods with high minority households have

lower appraisal ratios. Minority borrowers have 18.5% lower appraisal ratios for a 1% higher neighborhood-level minority fraction.

5.2 Sorting across collateral

Now, we examine whether minority borrowers sort to collateral with greater information asymmetry between borrower and lender. We rely on the insight from Stroebel (2016) that there is lower lender information asymmetry about the collateral value of the developers it is integrated with. The lender in our setting collaborates with vertically integrated developers to offer financing options to new homebuyers (integrated developer). Column 5 in Panel A, Table 6 shows that minority borrowers match to collateral with greater information asymmetry. Panel B examines the appraisal gap for properties of vertically integrated borrowers relative to remaining properties using the heterogeneity specification in Equation 3. Appraisal ratios are higher for properties of integrated developers, consistent with the baseline hypothesis that lenders know more about the collateral quality of vertically integrated developers. The coefficient on minority indicates an appraisal gap of 11.9%. However, almost all of the appraisal gap is undone when the collateral belongs to integrated developers with only small appraisal ratio difference of 1.8% (=11.9%-10.1%). If our hypothesis is indeed true that the lender has superior information about the collateral quality of integrated developers, then we should see these mortgages outperform remaining mortgages. Table IA2 shows higher default rates for mortgages not associated with integrated developers. In contrast, default rates are similar for minority and non-minority borrowers when the collateral belongs to integrated developers, confirming our hypothesis.

The real estate industry in India has been highly unregulated for decades. A chief concern for home buyers has been the uncertainty associated with real estate developers. 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. Lenders and home buyers had limited legal remedies in the case of disputes or grievances with the developer. Though recent policies have attempted address these issues (see Section 7), these inefficiencies are a persistent feature of the real estate sector in India.

6 What Does Not Explain Appraisal Gaps?

In principle, the lender's expected return from making a mortgage is based on two factors: (i) borrower characteristics and (ii) Property characteristics. Along the property dimension, there are two potential sources of disparity for appraisal gaps. The appraisal ratio of minority borrowers is low because the numerator (appraisal value) is low or because the denominator (sale deed value) is high. We rule out these alternate mechanisms one by one and establish that collateral quality is driving differences in appraisal gaps.

6.1 Borrower creditworthiness

Larger the loan amount, greater is the default risk (Calem et al., 2020) and lenders might adjust appraisal values lower to account for this credit risk. We control for borrower creditworthiness — as captured by the borrowers' credit score — in both the baseline and heterogeneity specifications in Equations (2) and (3). Controlling for borrower creditworthiness barely changes the point estimates (c.f column 1 to column 2 in Table 2), plausibly indicating limited impact of borrower creditworthiness on appraisal gaps.

Figure 6, Panel A shows the raw appraisal gap across CIBIL scores, where higher values correspond to more creditworthy borrowers. Across the borrower risk profile, the appraisal gaps for minority borrowers are persistently lower. Panel B shows the point estimates from column 3 in Table 2 for each subsample of CIBIL score: greater than 750, between 700 and 749, between 650 and 699, between 550 and 549, and unscored. Across the board, appraisal gaps are persistently negative for minority borrowers indicating that even conditional on ex-ante borrower creditworthiness, appraisal gap persist.

These results help assuage another concern. Martel and Woeppel (2023) argue that the lender's value from a loan can be decomposed into two parts. First, is the principal and interest payments conditional on the borrower remaining solvent. Second, is the realized value from foreclosing on the collateral if the borrower defaults. The value of the collateral matters more for more risky borrowers. One could argue that the lower appraisal gaps for minority borrowers is an artifact of greater lender reliance on collateral values if most minority loans go into foreclosure. At face

value, the average CIBIL scores of minority borrowers is similar to non-minority borrowers (Panel B, Table 1) indicating this channel may not play a role. Panel A in Figure 6 underscores this point as appraisal gaps persist across the borrower risk profile.

One could still argue that credit scores do not fully control for borrower creditworthiness (Blattner and Nelson, 2021) and one could still attribute the appraisal gap to residual default risk not captured by credit scores. Additionally, credit scores may be particularly poor measures of default risk of minority borrowers. To gauge the impact of the borrowers' creditworthiness channel, we use the ex-post default status of each loan. Of course, lenders do not have this information at the time of loan origination[18]. Instead, we ask the question: assuming lenders can perfectly estimate borrower riskiness, do appraisal gaps reflect these differences? We use the baseline specification in Equation 2 and then add the ex-post default as a control. Results are presented in Table A.1. Reassuringly, the coefficient on the categorical variable, minority status in columns 1–4 indicates a 17%, 16.6%, 11.5%, and 11.4% lower appraisal ratios for minority borrowers from the less stringent to the most stringent specifications. This is strikingly similar to the baseline estimates in Panel A in Table 2: 16.9%, 16.6%, 11.5%, 11.4%, respectively. We noted previously in Table 2 that the relative stability of the specifications with and without controlling for credit scores indicates that ex-ante borrower default risk accounts for very little of the appraisal gap. The coefficients on the minority variable in Table A.1 assure us that even ex-post default cannot account for the appraisal gap. The coefficient on the default variable is negative, which is to be expected and in line with our starting conjecture that appraisal ratios also reflect borrower creditworthiness.

6.2 Disparity in Property Prices

Premium on property prices If High purchase values by minority borrowers can potentially explain low appraisal ratios results. Why would a minority borrower be willing to pay more? It could be that segregation forces people into neighborhoods where they pay more beyond the actual value of the property. However, high purchase prices may not translate into high collateral and borrowers are essentially sitting on "dead" capital that cannot be used to access credit

[18]See d'Avernas et al. (2023) that uses a similar strategy to argue that differences in mortgage interest rates for minority borrowers are not driven by default rates.

(De Soto, 2003).

It has been documented that minority borrowers in the U.S., i.e., Black homeowners pay more relative to white homeowners Bayer et al. (2017). To examine this channel, we plot the point estimates from column 4 of Table 2 for the subsample of mortgages across different deciles of property value in Figure 7. For higher property values, the appraisal gap is *lower* counter to the price premium narrative. Unless we believe that price premiums should be lower for minority borrowers for *high*-valued properties, Figure 7 indicates that the price premium channel is unlikely to be a primary driver of the appraisal disparity.

We reiterate this finding using an alternate strategy[19] by examining the hedonic model determining the appraisal values and property prices separately. This allows us to examine how responsive market values and appraisal values are neighborhood and property-level attributes. The specification is:

$$ln(y_{ipdt}) = \phi_{dt} + \beta^{y}_{att} X_{ipdt} + \delta^{y}_{att} W_{pdt} + \epsilon_{ipdt} \tag{6}$$

where $y \in$ {Appraisal value, Property Value} for each mortgage i, originated in pincode p(i) in a district d(i) in month-year t. X_{ipdt} is the vector of property characteristics including carpet area, builtup area and plot area. W_{pdt} is the vector of neighborhood characteristics including minority fraction, subprime fraction and poverty index.

We estimate two separate hedonic price models for appraisal values and property prices to examine sensitivity to neighborhood-level attributes and home-level attributes using 6. The neighborhood-level characterics included are subprime fraction, minority fraction and poverty index and the property-level characteristics included are carpet area, builtup are and plot area. The dependent variables are market value and assessed value in log. Table IA1 presents the results for the hedonic model for property values (column 1) and for appraisal values (column 2). In both hedonic price models, we find the point estimates are statistically significant and economically meaningful for subprime fraction, minority fraction and poverty index with 99% confidence. The estimates are negligible for the property-level characteristics — carpet area, built-up area and

[19] See Avenancio-León and Howard (2022) who use a similar strategy to examine whether assessment gaps are driven by the numerator or the denominator.

plot area — across both specifications.

Figure 8 shows the difference of estimated gradients on all characteristics variables from both hedonic price models. A bar in the figure represents the difference in the gradients on both property and neighborhood variables and conveys the proportional shift in the appraisal ratio. Each bar in Figure 8 is interpreted as the estimate of a one standard deviation change in underlying variables shift appraisal ratios (in percentage terms). Strikingly, there is a mismatch between appraisal values and property values with neighborhood characteristics. Based on our hedonic estimations, a one SD change in the property characteristics has no impact on the appraisal ratio. In comparison, a one standard deviation change in the subprime fraction, minority fraction, and poverty index shifts the appraisal ratio by 0.57%, 0.45% and 0.15%, respectively.

The hedonic analysis helps address several concerns. First, as Avenancio-León and Howard (2022) note, minority borrowers might pay a premium on their property as they are secluded to certain neighborhoods possibly due to discriminatory housing practices. The hedonic model suggests that, if anything, property prices respond more to neighborhood characteristics like minority fraction and neighborhood poverty. Thus. the price premiums are not driving the results. Similarly, Adukia et al. (2023) note that more segregated neighborhoods also have worse public infrastructure and facilities. If these differences are already priced in, prices will be lower not higher and hence do not drive appraisal gaps. The hedonic analysis, indeed, suggests that prices will respond more harshly to deterioration in neighborhood characteristics, and hence does not explain gaps.

Black money component of property prices Real estate transactions in India usually involve partial payment with off-the-books sources of money or "black money", typically to avoid taxes (Gandhi et al., 2022). Real estate thus acts as a vehicle to conceal undeclared income from tax authorities. In our setup, if non-minority borrowers are more likely to partially finance their real estate transactions through black money, then property values may reflect only the white component and not the black component of the transaction. Hence, differences in the black money component may account for the appraisal gaps.

Consider a simple example. The latent "true" value of property A and property B is ₹5,000,000.

Suppose property A has no black money component, whereas property B is financed with ₹1,000,000 of black money. Thus, the sales deed would report ₹5,000,000 for property A and ₹4,000,000 for property B. Suppose the lender and appraiser can gauge the true value of the property. The appraisal ratio for property A is 1, but 1.25 for property B. If non-minority borrower transactions include a higher black component[20], then our estimated appraisal gap could simply reflect these differences in the way real estate is purchased by minority and non-minority borrowers. One could argue that after accounting for the true property prices used in the appraisal gap, minority and non-minority borrowers have similar appraisal gaps.

Anagol et al. (2023) show that misreporting of property prices is lower in purchases through mortgages, further supporting evidence that the black componenet is not driving gaps. However, they also document greater under-reporting for purchases facilitated by public sector bank mortgages. Since our data is from a state-owned bank, we conduct further tests to rule out the black money channel.

To test the black money hypothesis, we exploit data on the occupation of the borrower, which can be classified into salaried borrowers and non-salaried borrowers (for example, businessmen). We assume that non-salaried borrowers have lower access to "white" money and, hence, are likely to finance a larger proportion of their real estate purchases with black money.

We use the specification in Equation 3 with whether a borrower is salaried as the heterogeneity variable. Table A.2 presents the results. The coefficient on salaried is negative and significant in all specifications. The most stringent specification in column 4 indicates that the appraisal ratios for salaried borrowers is lower, consistent with our hypothesis that salaried borrowers have lower black component in their real estate transactions. The minority coefficients in columns 1–4 range from 15.8% to 11.5% and are similar in magnitude to the effects documented in Table 2, indicating that the difference in the black component of properties cannot completely account for the appraisal gap. In the model in Equation 3 we allow for differential effects for salaried borrowers for minority and non-minority borrowers. While there is an effect when we compare within districts (columns 1–2), the differential effect disappears once we include pincode-time

[20]Indeed, higher valued properties are likely to be financed with a higher black component.

fixed effects (columns 3–4) confirming that black money does not drive appraisal gaps.

Another related concern may be that demonetization affected appraisal values due to changes in the black money component of property prices. **?**, however, find limited impact of demonetization on tax evasion. Table IA2 shows that the appraisal gap is a consistent feature through all years in our analysis.

6.3 Disparity in appraisals: Animus and bias

While the focus up until now was on structural drivers of the appraisal gap disparity, intentional discriminatory or biased practices of lenders, appraisers, or judges enforcing property rights can also explain these patterns.

The appraisal process often involves extensive interaction of the lender/appraiser and borrower. In addition, the branch manager has discretion in who he assigns as an appraiser and may also indirectly influence appraisal values.

Even though the appraiser cannot directly see the caste/religion of the borrower, given how segregated Indian cities are and from the distinct names, it is entirely likely that the appraiser is able to fully able to guess the caste or religion of the borrower. We do not have information on the caste and religious identity of appraisers to assess out-group bias.

To directly examine animus as a mechanism, we use historical and contemporaneous religious conflicts and show that there are no differences in appraisal gaps shown in Internet Appendix Table IA6.

Animus can also manifest through out-group bias of judges during enforcement of property rights. We use case-level data for property crimes from Ash et al. (2022).[21] Table IA3 shows no own-group bias on the likelihood of acquittal rate or decision within six months of filing. Point estimates for both the outcome variables on non-Muslim and Muslim defendants are zero and insignificant. To test the caste dimension, we use shared-identity based on same last names. Though Table IA4 shows some bias, a stronger test based on uncommon names among the shared caste-identity indicates no judicial bias consistent with Ash et al. (2022) who also include non-property

[21] We use the same specification in Ash et al. (2022) to measure out-group bias:

related crimes in their analysis. [22]

7 Policy Solution: The 2016 Real Estate Regulatory Act

The 2016 RERA Act and its implementation across states provide an ideal setting to examine if policy can address the asymmetric information arising from lenders' uncertainty about a particular developer's collateral values. Since RERA increased developer transparency and accountability (see Section 2 for further details), and since minority borrowers are matched to worse developers, there is reason to expect minority borrowers may benefit the most from the RERA Act.

We use a staggered difference-in-difference specification to examine the impact of RERA on the appraisal ratios of minority borrowers:

$$\text{Ln(Appraisal Ratio)}_{id(i)b(i)s(i)t} = \delta_{dt} + \gamma \times \text{Minority}_i + \beta \times \text{RERA}_{s(i)} \times \text{Minority}_i + \epsilon_{it}, \quad (7)$$

for mortgage i originated in state $s(i)$ and district $d(i)$ at time t with developer $b(i)$. We restrict the sample to mortgages of vertically integrated developers. $\text{RERA}_{s(i)}$ is a state-level indicator for whether a state has adopted RERA (see Table IA7). District-level fixed effects are included.
We examine the developer-level effects using a similar difference-in-difference specification:

$$\begin{aligned}\text{Ln(Appraisal Ratio)}_{id(i)b(i)s(i)t} = \delta_{dt} &+ \omega \times \text{Integrated Developer}_{b(i)} \\ &+ \phi \times \text{RERA}_{s(i)} \times \text{Integrated Developer}_{b(i)} + \epsilon_{it},\end{aligned} \quad (8)$$

where $\text{Integrated Developer}_{b(i)}$ is an indicator for whether vertically integrated developers.

To examine the heterogeneity in RERA impact with minority *and* developer, we use the following difference-in-difference-in-difference specification:

$$\begin{aligned}\text{Ln(Appraisal Ratio)}_{id(i)b(i)s(i)t} = \delta_{dt} &+ \gamma \times \text{Minority}_i + \beta \times \text{RERA}_{s(i)} \times \text{Minority}_i \\ &+ \omega \times \text{Integrated Developer}_{b(i)} + \phi \times \text{RERA}_{s(i)} \times \text{Integrated Developer}_{b(i)} \\ &+ \psi \times \text{RERA}_{s(i)} \times \text{Integrated Developer}_{b(i)} \times \text{Minority}_i + + \epsilon_{it},\end{aligned} \quad (9)$$

where ψ is the coefficient of interest and shows the differential impact of RERA on minority borrowers by integrated developer.

We do not include controls for credit scores because we are interested in sorting by borrow-

[22] As Ash et al. (2022) note, the shared caste-identity based on same last name is imperfect.

ers types, and hence including these fixed effects may remove some of the very variation we are interested in. Similarly, we do not include pincode-time fixed effects since in column 4 Table 4 we argued that by including pincode-time fixed effects we essentially compare minority and non-minority borrowers in the same housing complex, and the appraisal gap disappears. Since we are interested in the impact across developers and not on appraisal gaps within the same housing complex (which we know to be zero), we do not include pincode-fixed effects.[23] Before proceeding to the main analysis, we show that there was no systematic differences between early and late adopter states (Internet Appendix Table IA8) or in the time to adoption (Internet Appendix Table IA9).

Table 7 presents the effects of RERA on appraisal gaps. Surprisingly, the appraisal gap widens post RERA (column 1). Figure 9 shows the temporal dynamics using an event study plot. Consistent with the baseline finding, there is a decline in appraisal gap. Importantly, the pre-period trend suggests that the parallel trend assumption in the canonical staggered difference-in-differences assumption is met.

Can sorting explain these differences? Table IA10 shows that post-RERA, minority borrowers match to worse collateral in terms of collateral not belong to integrated developers. Other neighborhood characteristics cannot explain the decline in gaps after RERA adoption.

Table 7 shows that the increase in appraisal gaps is not driven by projects at integrated developers (column 2), but for the remaining properties (column 3). To explain this counterintuitive result, we dig further into the impact of RERA on the extensive margin in Panels B and C. The specification examines the total amount of loans (Panel B) and total number of loans (Panel C). We see that total amount and number of loans to minority borrowers increases (column 2) despite muted effect on non-minority borrowers (column 1). The increase is entirely driven by loans to minority borrowers in projects not related to integrated developers. Finally in Panel D, we examine the heterogeneity in impact on appraisal gaps across minority borrowers and see that all of the reduction in appraisal gap is driven by developer-level effects for the integrated developers with no differential impact on minority borrowers.

[23] In unreported results, effects are similar on including pincode-time fixed effects but not developer-time fixed effects, consistent with our interpretation.

2018 Insolvency and Bankruptcy Code (IBC) Amendment In June 2018, the Insolvency and Bankruptcy Code (Amendment) Ordinance was promulgated. This amendment treated homebuyers on par with financial creditors, allowing them to invoke Section 7 of the 2016 Insolvency and Bankruptcy Code (IBC) against errant developers. The 2018 IBC Amendment strengthened RERA and provided homebuyers recourse to start recovery proceedings against developers. Table IA11 presents the estimates for IBC. Results are strikingly similar to effect of RERA.

Case Study: Transfer of Property Rights in Delhi One concern is that district-level property crimes data miss variation in property crimes registered as civil cases. To shed light on this, we collect data on disputed properties. Table 8 presents the results using the specification in Equation 3 with the interaction variable as the pincode-level number of disputed properties per capita. Appraisal gaps are larger in more litigated neighborhoods. Though coefficients are negative but statistically insignificant for overall and Muslim borrowers, appraisal gaps are significantly 34% lower for OBC borrowers. The effects are surprisingly positive (insignificant) for SC/ST borrowers. Panel B sheds light on this. A significant proportion of slum areas were built on agricultural land and not intended for non-agricultural purposes. Section 81 disputes capture these disputes. However, starting 2016, the government initiated the process of transferring ownership to slum dwellers. Panel B shows that neighborhoods with more pincode-level Section 81 disputed properties (per capita) have narrower appraisal gaps for SC/ST borrowers who were the most affected.

8 Conclusion

This paper investigates the appraisal gap, where lenders value housing collateral of minority borrowers lower than that of non-minority borrowers. Using data from mortgages in India, the study finds that mortgage collateral for minority borrowers is appraised 17% lower. The gap can be attributed to two main factors. First, neighborhood effects accounting for nearly 32% of the variation, with the remaining attributable to within-neighborhood variation. Lower appraisals of collateral values arise from ambiguous property titles. In Delhi, minority borrowers in the neighborhoods with more disputed properties face lower appraisal values. However, the transfer of property rights from landowners to home-dwellers improved appraisal gaps for minority borrowers,

specifically scheduled caste and scheduled tribe borrowers.

Our results are descriptive and are similar in spirit to Adukia et al. (2023), who also provide largely descriptive evidence of segregation in India. As their paper highlights, data paucity in developing countries results in a lack of even basic evidence of sorting and segregation. Documenting disparities in India is important so that policy can respond accordingly. Indeed, our paper exploits the enactment of RERA to provide causal estimates of the impact of the policy on appraisal gaps, but shows that minority sorting patterns limit reductions in appraisal gaps. Our paper highlights how preexisting segregation and sorting patterns can perpetuate inequality. Although policies that directly target market inefficiencies have the potential to address inequities that land along caste and religious lines, persistent patterns of spatial disparity can reinforce inequities.

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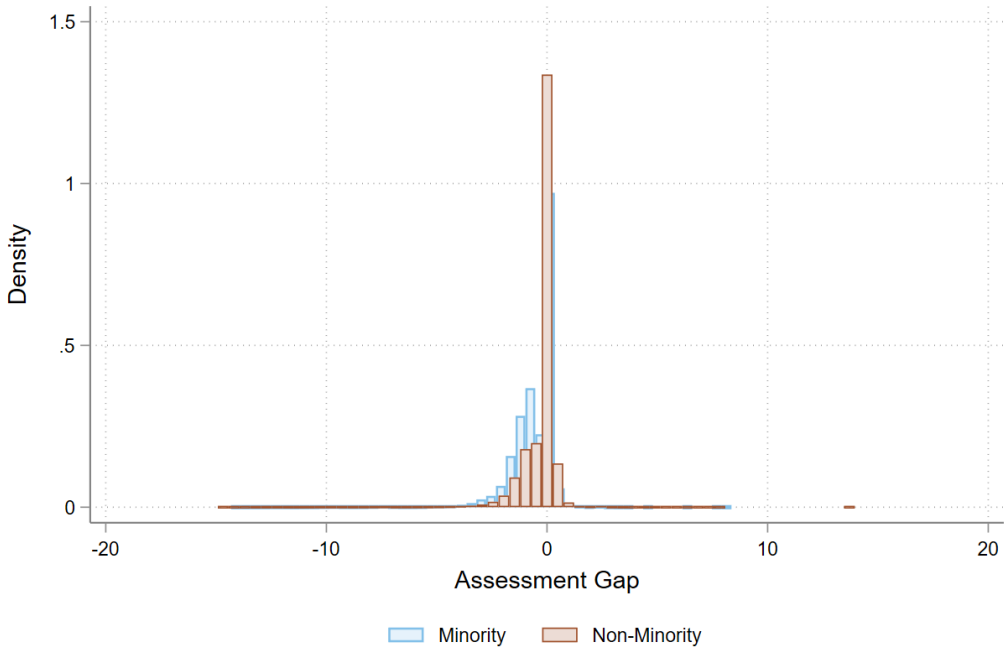
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Figure 1
Variation in appraisal ratios aross minority status

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

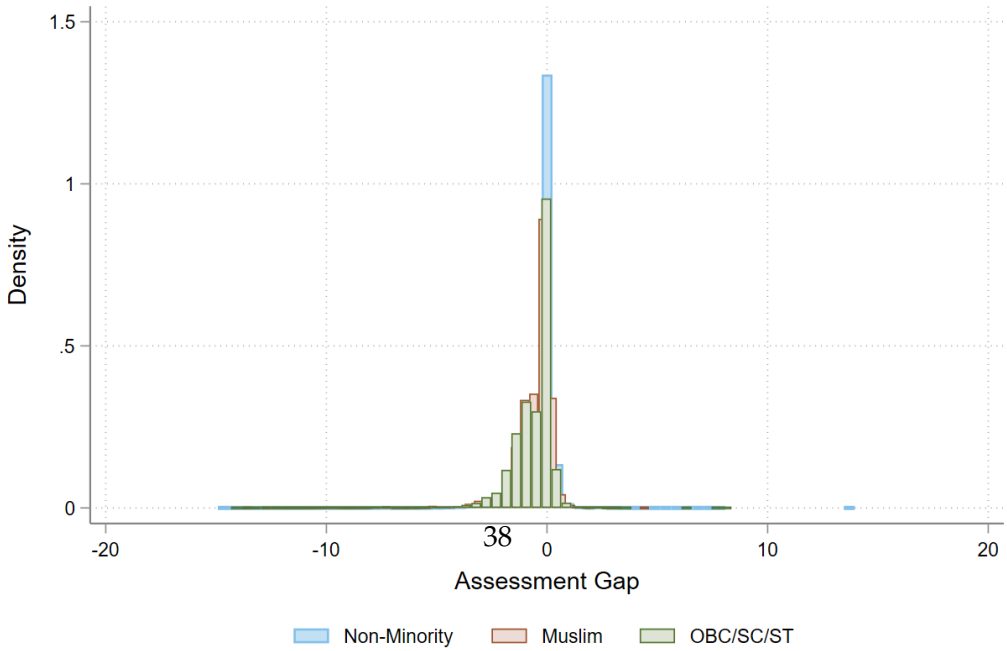


Figure 2
Variation in appraisal ratios across neighborhoods

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.

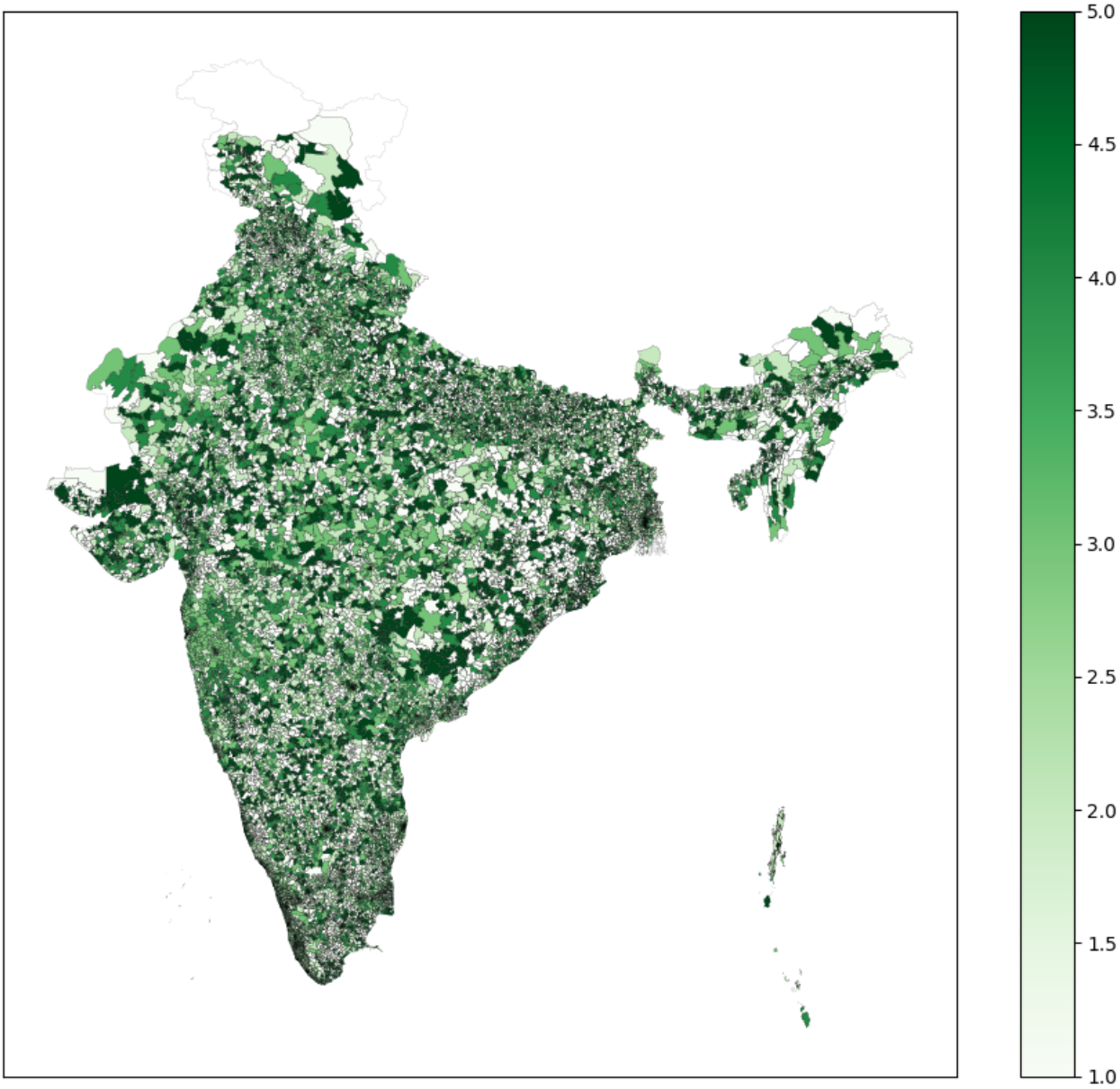
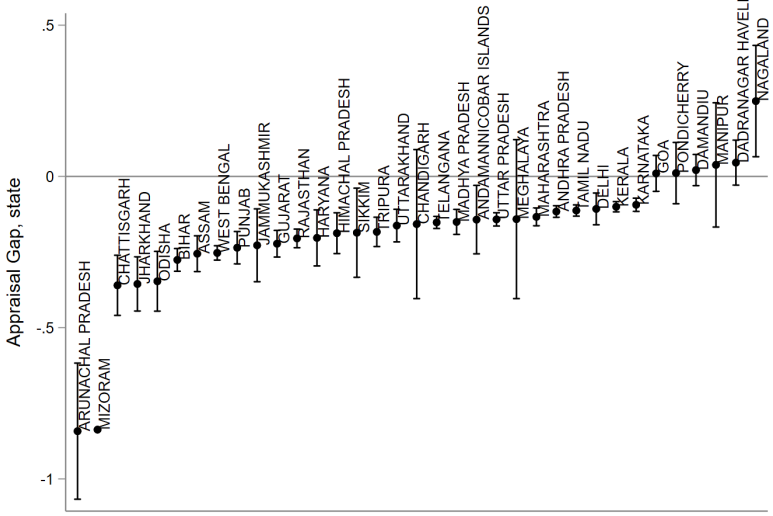


Figure 3
State-level and District-level Estimates of the Appraisal Gap

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 4 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-time and pincode-time 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

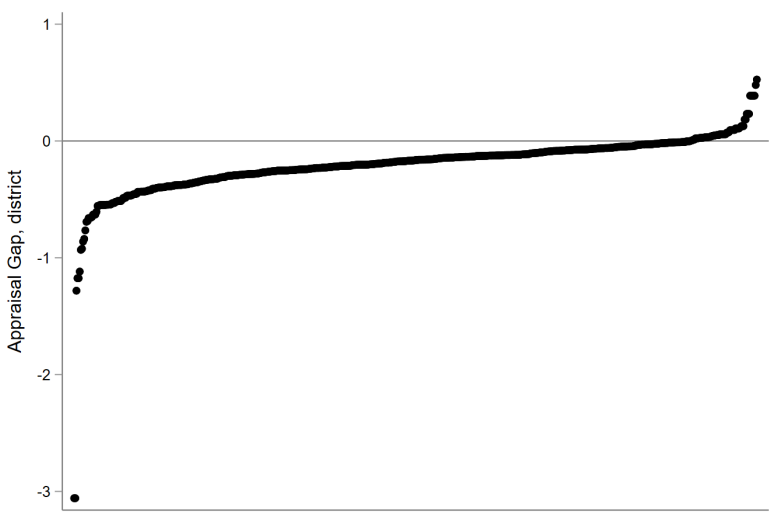


Figure 4
Appraisal Gap by Developer Rank

This figure shows the point estimates for the appraisal gap by developer rank (1=Good, 4= Worst). Each point represents the point estimates from column 4 in Table 2 for the subsample of mortgages by developer rank defined as below. The vertical lines represent the 95% confidence interval. Developer rank is obtained by regressing the log of the appraisal value to the market value on developer fixed effects. The coefficients in the developer fixed effects is then split into 4 quartiles. Developers are ranked from 1 (best) to 4 (worst) corresponding to the highest appraisal ratio to the worst appraisal ratio. In the baseline empirical specification, the appraisal ratios — defined as the log of appraisal value to the market value — is regressed 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-time and pincode-time fixed effects are included. Standard errors are clustered at the pincode level. Mortgage-level data is for the period 2015 to 2020.

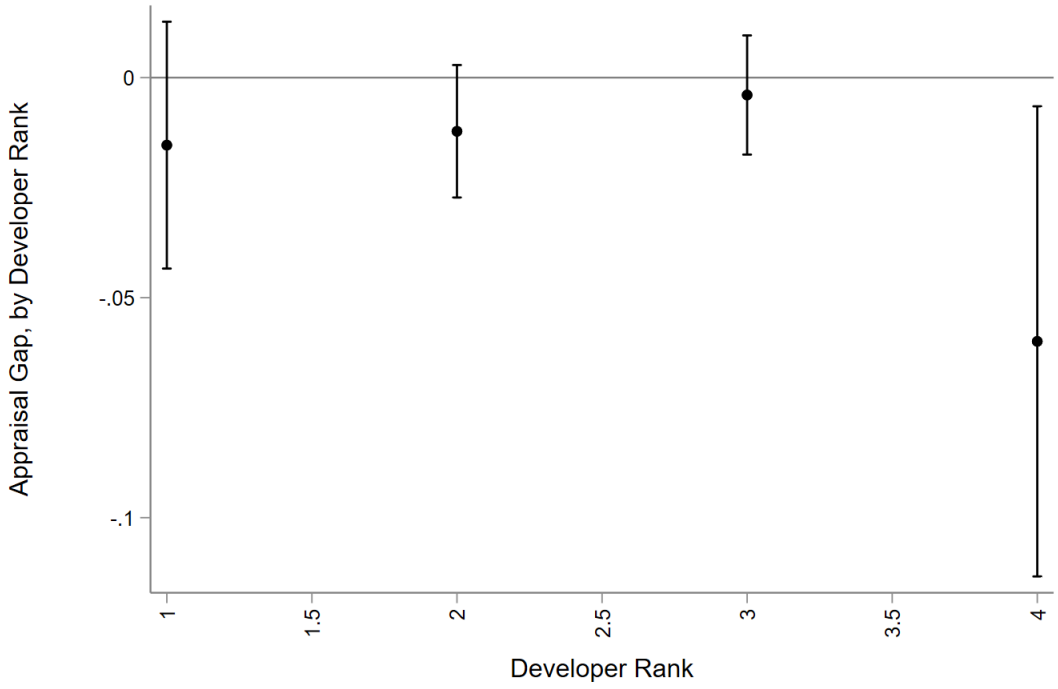
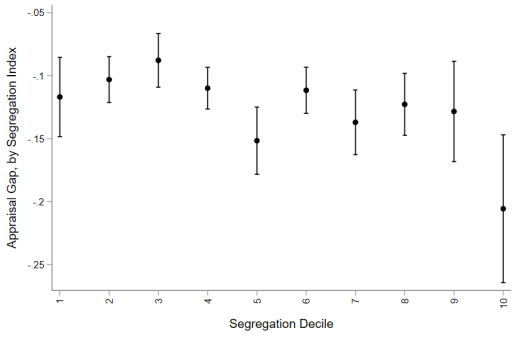


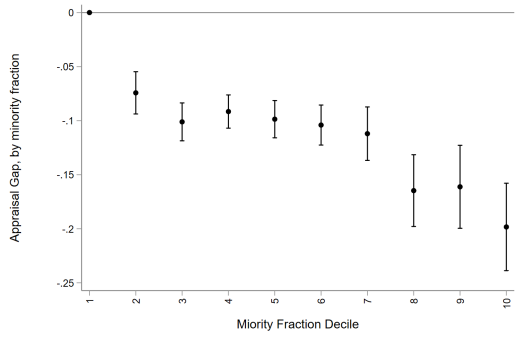
Figure 5
Appraisal Gap by Minority Fraction, Segregation and Relative Wealth Decile

This figure shows the point estimates for the appraisal gap for each year. Each point represents the point estimates from column 4 in Table 2 for the subsample of mortgages across different deciles as described below. In Panel A, each subsample is for the decile of district-level segregation measured using the dissimilarity index and measures how segregated minority borrowers are from non-minority borrowers. In panel B each subsample is for the decile of minority fraction defined at the pincode-level. In panel C each subsample is for the decile of Wealth Index defined at the pincode-level. Wealth Index data is from Facebook. are at the pincode-level. 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-time and pincode-time fixed effects are included. Standard errors are clustered at the pincode level. Mortgage-level data is for the period 2015 to 2020.

Panel A: Relative Segregation Decile



Panel B: Minority Fraction Decile



Panel C: Relative Wealth Decile

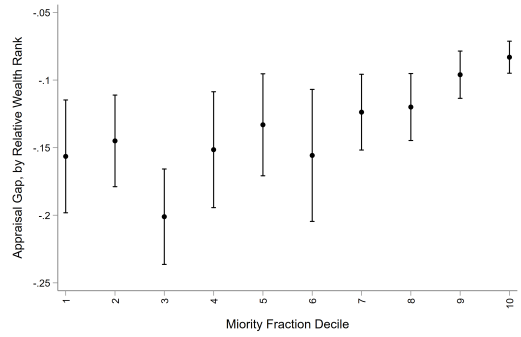


Figure 6
Appraisal Gap by CIBIL Score

Panel A shows the binscatter of the appraisal gap by CIBIL credit score for minority and non-minority borrowers. Panel A excluded unscored borrowers. Panel B shows the point estimates for the appraisal gap by CIBIL Score. Each point represents the point estimates from column 3 in Table 2 for the subsample of mortgages in each CIBIL score band: greater than 750, between 700 and 749, between 650 and 699, between 550 and 549, and unscored. 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-time and pincode-time fixed effects are included. Standard errors are clustered at the pincode level. Mortgage-level data is for the period 2015 to 2020.

Panel A: Raw CIBIL Score



Panel B: Heterogeneity by CIBIL Score bands

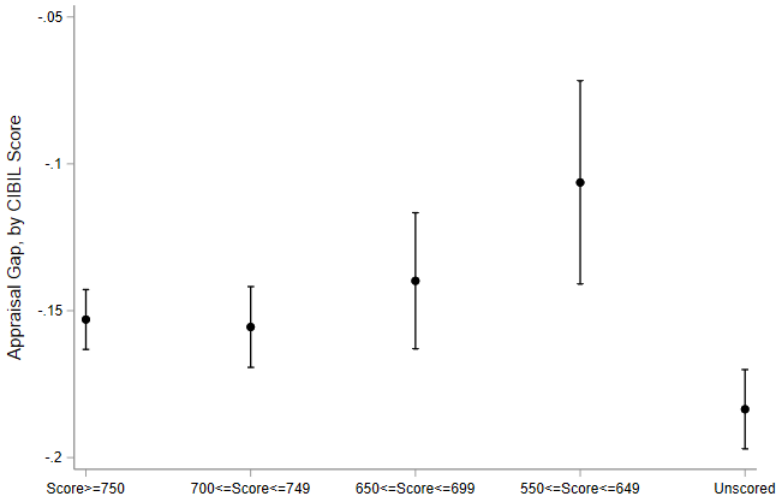


Figure 7
Appraisal Gap by Property Rights

This figure shows the point estimates for the appraisal gap for crime against property. Each point represents the point estimates from column 2, Panel B in Table 6 for the subsample of mortgages across different deciles of property crime at district level. The vertical lines represent the 95% confidence interval. In this 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. State-time, District-time and Pincode-time fixed effects are included. Standard errors are clustered at the pincode level. Mortgage-level data is for the period 2015 to 2020.

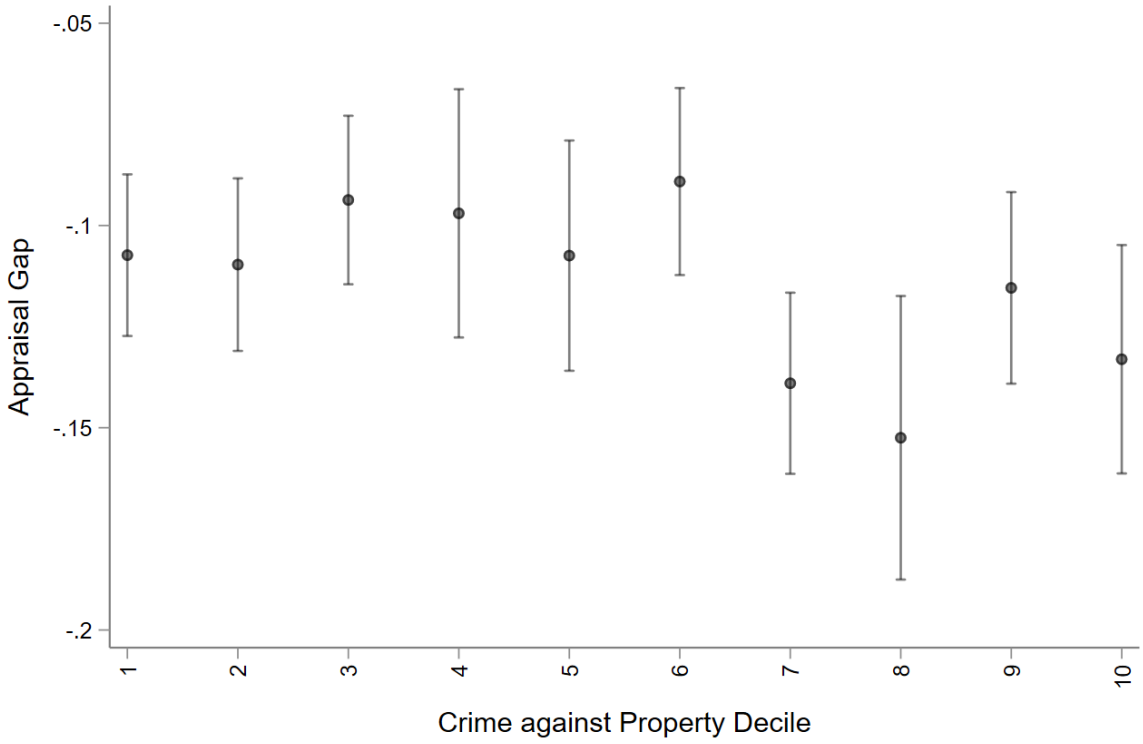


Figure 8
Hedonic Models: Mismatch

The figure presents the difference between two estimation of hedonic price models on home characteristics and neighborhood characteristics. Both the hedonic price models are estimated with the market values and assessment values as the dependent variables. In the figure, each bar represents the difference between these two estimation on the underlying variables on x-axis. There are six underlying variables used in both estimation and first three represents the spatial characteristics and last three variables are property characteristics. Effectively the bars for property characteristics are at zero means there is no disconnect between market-hedonic price and assessment hedonic price. Both the outcome variables are logged in the models thus the difference between the two estimated hedonic prices represents a proportional shift in the assessment ratio to 1 SD shift in underlying locality and property characteristics. Bars in red are quite large for the spatial level attributes which signify the level of mismatch between the market value and assessment value.

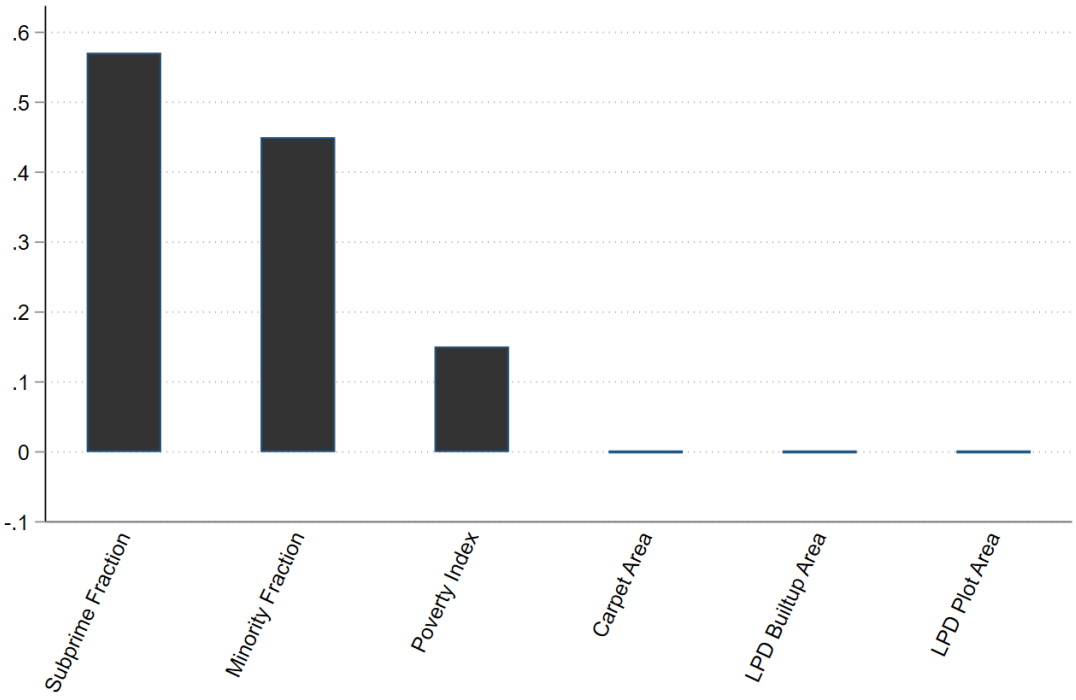
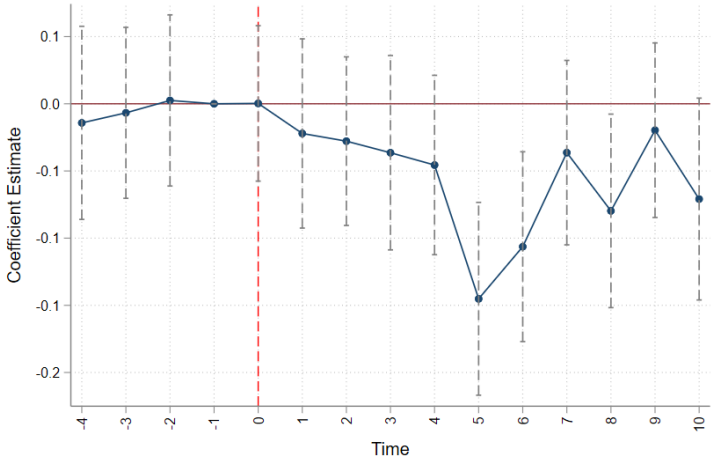


Figure 9
RERA: Event-study plot

This figure shows shows the event study plot for RERA implementation. In Panel B, the coefficient for each period from time of implementation of RERA is plotted. In panel B, each point represents the point estimates from column 4 in Table 2 for the subsample of mortgages by state. The vertical lines represent the 95% confidence interval. The dependent variable in both panels is the appraisal ratios — defined as the log of appraisal value to the market value — is regressed 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-time and pincode-time fixed effects are included. Standard errors are clustered at the pincode level. Mortgage-level data is for the period 2015 to 2020.

Panel A: Event Study



Panel B: State-wise effects

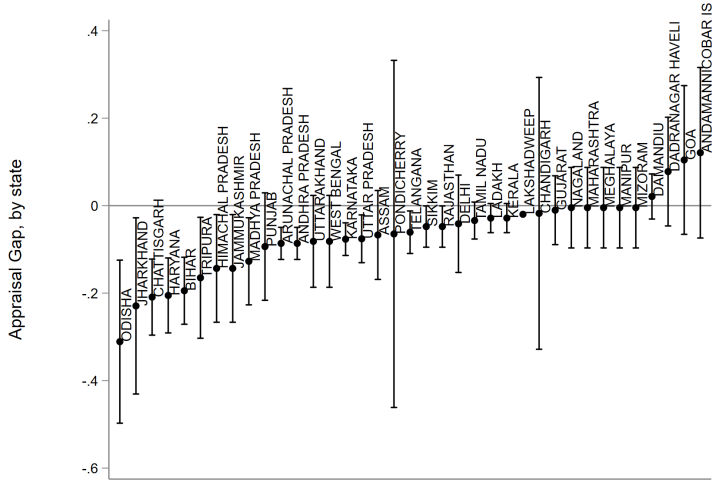


Table 1
Summary Statistics

This table shows the summary statistics for mortgage-level and the pincode-level data used in our analysis in Panel A. Mortgage-level data included are the loan amount in ₹million, loan-to-value, whether a loan was classified as 90-day delinquent, and the interest rates. Pincode level data are the number of loans per capita, number of loans per capita, loan amount and the average default rate. Panel B presents the summary statistics for the appraisal gap defined as the log of appraisal value to the market value of the property. Mortgage data is from a large bank in India for 2015–2020. Population data in per capita calculations comes from Facebook.

Panel A: Appraisal Gap

	N	Mean	SD	p25	Median	p75
Overall	1123125	-0.30	0.84	-0.52	0.00	0.02
Non- minority	967024	-0.25	0.79	-0.35	0.00	0.03
Minority	156101	-0.62	1.06	-1.04	-0.26	0.00
Muslim	31168	-0.60	1.10	-0.99	-0.21	0.00
OBC	75072	-0.60	1.02	-1.03	-0.25	0.00
SC/ST	49861	-0.66	1.10	-1.10	-0.29	0.00

Panel B: Loan-level characteristics

	N	Mean	SD	p25	Median	p75
Overall						
Log (loan amount)	2,886,531	13.75	1.44	13.22	14.14	14.73
Loan amount (in INR million)	2,886,531	1.87	12.44	0.55	1.38	2.50
Loan-to-value (in %)	2,886,531	59.21	21.57	44.44	63.38	76.27
Non-performing assets	2,886,531	0.01	0.10	0.00	0.00	0.00
Interest rate	2,886,531	7.51	0.74	7.20	7.45	7.80
CIBIL Score	1,172,891	735.76	101.48	716.00	752.00	780.00
Non-minority						
Log (loan amount)	2,465,289	13.81	1.44	13.30	14.20	14.75
Loan amount (in INR million)	2,465,289	1.96	13.44	0.60	1.47	2.55
Loan-to-value (in %)	2,465,289	59.30	21.58	44.54	63.59	76.39
Non-performing assets	2,465,289	0.01	0.09	0.00	0.00	0.00
Interest rate	2,465,289	7.50	0.73	7.20	7.45	7.80
CIBIL Score	1,010,542	737.52	100.82	718.00	754.00	781.00
Minority						
Log (loan amount)	421,242	13.40	1.45	12.61	13.82	14.43
Loan amount (in INR million)	421,242	1.33	1.51	0.30	1.00	1.85
Loan-to-value (in %)	421,242	58.69	21.52	44.11	62.38	75.42
Non-performing assets	421,242	0.03	0.17	0.00	0.00	0.00
Interest rate	421,242	7.54	0.75	7.20	7.45	7.85
CIBIL Score	162,349	724.87	104.82	707.00	743.00	773.00
Muslim						
Log (loan amount)	83,594	13.56	1.41	13.12	13.89	14.51
Loan amount (in INR million)	83,594	1.48	1.81	0.50	1.08	2.00
Loan-to-value (in %)	83,594	56.58	22.31	40.23	59.78	74.68
Non-performing assets	83,594	0.01	0.12	0.00	0.00	0.00
Interest rate	83,594	7.60	0.79	7.25	7.45	8.00
CIBIL Score	33,123	725.31	108.50	709.00	744.00	773.00
OBC						
Log (loan amount)	202,323	13.35	1.48	12.21	13.82	14.45
Loan amount (in INR million)	202,323	1.31	1.49	0.20	1.00	1.89
Loan-to-value (in %)	202,323	58.55	21.26	44.29	62.03	75.00
Non-performing assets	202,323	0.03	0.18	0.00	0.00	0.00
Interest rate	202,323	7.55	0.71	7.20	7.50	7.80
CIBIL Score	77,874	724.64	104.42	706.00	743.00	773.00
SC/ST						
Log (loan amount)	135,330	13.36	1.42	12.61	13.82	14.39
Loan amount (in INR million)	135,330	1.26	1.31	0.30	1.00	1.78
Loan-to-value (in %)	135,330	60.20	21.30	46.67	64.33	76.92
Non-performing assets	135,330	0.03	0.18	0.00	0.00	0.00
Interest rate	135,330	7.48	0.79	7.20	7.45	7.80
CIBIL Score	51,352	724.93	102.99	707.00	744.00	772.00

Table 2
Appraisal Gap

This table shows mortgage level analysis of appraisal gaps. The dependent variable in panel A is the log of appraisal value to the market value of the property. The dependent variables in panels B and C are loan-to-value and log of the loan amount, respectively. District-time and pincode fixed effects are included, as shown. 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. The dependent variables are winsorized at the 1% level. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

Panel A: Appraisal Gap

Dependent variable:	Log (Appraisal Ratio)			
	(1)	(2)	(3)	(4)
Minority	-0.169***	-0.166***	-0.115***	-0.114***
	(0.004)	(0.004)	(0.004)	(0.004)
R^2	0.235	0.238	0.448	0.449
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1120674	1104569	936102	920952

Panel B: Loan-to-Value

Dependent variable:	Loan-to-Value			
	(1)	(2)	(3)	(4)
Minority	-0.002***	-0.003***	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.080	0.089	0.248	0.258
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	2176122	2157224	1965384	1946837

Panel C: Loan Amount

Dependent variable:	Log (Loan amount)			
	(1)	(2)	(3)	(4)
Minority	-0.127***	-0.115***	-0.105***	-0.096***
	(0.004)	(0.003)	(0.004)	(0.004)
R^2	0.184	0.312	0.314	0.435
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	2176122	2157224	1965384	1946837

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3
Heterogeneity Across Minority Groups

This table shows mortgage-level analysis of appraisal gaps for different minority groups. The dependent variable in panel is the log of appraisal value to the market value of the property. District-time and pincode fixed effects are included, as shown. SC/ST is an indicator for whether a borrower belongs to scheduled cases/scheduled tribes. OBC and Muslim are indicators for whether a borrower belongs to other backward classes or Muslims, respectively. Control variables included are credit score band and time indicators. The dependent variables are winsorized at the 1% level. Standard errors are clustered at the pincode level. Data is for the period 2015 to 2020.

Dependent variable:	Log (Appraisal Ratio)			
	(1)	(2)	(3)	(4)
SC/ST	-0.218***	-0.215***	-0.151***	-0.149***
	(0.008)	(0.008)	(0.007)	(0.007)
OBC	-0.158***	-0.154***	-0.112***	-0.111***
	(0.005)	(0.005)	(0.006)	(0.006)
Muslim	-0.121***	-0.118***	-0.070***	-0.069***
	(0.007)	(0.007)	(0.007)	(0.007)
R^2	0.235	0.238	0.448	0.450
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1120674	1104569	936102	920952

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4
Within-Collateral Appraisal Gaps

This table examines within-developer variation in appraisal gap and the matching between minority borrower and developer. Only mortgages with collateral belonging to vertically integrated developers are retained in the analysis. The dependent variable in panel A is the log of appraisal value to the market value of the property. The dependent variable in panel B is the developer rank which ranges from 1 (best) to 4 (worst) based on the average appraisal ratio. Developer rank is obtained by regressing the log of the appraisal value to the market value on developer fixed effects. The coefficients in the developer fixed effects is then split into 4 quartiles. Developers are ranked from 1 (best) to 4 (worst) corresponding to the highest appraisal ratio to the worst appraisal ratio. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. District-time and pincode-time fixed effects are included, as shown for each column. Control variables included are credit score band and time indicators. The dependent variables are winsorized at the 1% level. Standard errors are clustered at the pincode level. Data is at the mortgage-level for the period 2015 to 2020.

Dependent variable:	Log (Appraisal Ratio)			
	(1)	(2)	(3)	(4)
Minority	-0.034***	-0.032***	-0.010	-0.008
	(0.009)	(0.009)	(0.013)	(0.012)
R^2	0.591	0.595	0.730	0.734
Int. Developer × Time FE	Y	Y	Y	Y
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	104733	102886	57735	56479

Table 5
Matching of Minority Borrowers by Collateral Quality

This table examines within-developer variation in appraisal gap and the matching between minority borrower and developer. Only mortgages with collateral belonging to vertically integrated developers are retained in the analysis. The dependent variable in panel A is the log of appraisal value to the market value of the property. The dependent variable in panel B is the developer rank which ranges from 1 (best) to 4 (worst) based on the average appraisal ratio. Developer rank is obtained by regressing the log of the appraisal value to the market value on developer fixed effects. The coefficients in the developer fixed effects is then split into 4 quartiles. Developers are ranked from 1 (best) to 4 (worst) corresponding to the highest appraisal ratio to the worst appraisal ratio. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. District-time and pincode-time fixed effects are included, as shown for each column. Control variables included are credit score band and time indicators. The dependent variables are winsorized at the 1% level. Standard errors are clustered at the pincode level. Data is at the mortgage-level for the period 2015 to 2020.

Dependent variable:	(Worse) Developer Rank			
	(1)	(2)	(3)	(4)
Minority	0.061***	0.062***	0.039**	0.043**
	(0.012)	(0.012)	(0.017)	(0.018)
R^2	0.354	0.355	0.527	0.529
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	157534	155334	108068	106365

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Borrower Sorting

This table shows sorting of borrowers at the district, neighborhood (pincode), and collateral level. The dependent variable in panel A is an indicator for minority and the log of appraisal value to the market value of the property in Panel B. Fixed effects are included, as shown. Minority is an indicator for whether a borrower belongs to SC, ST, OBC, or is Muslim. In Panels A and B, characteristics (RHS variable) are district-level segregation (column 1) and property crime (column 2), pincode-level measure of wealth (rich, column 3), and fraction of minority households (column 4), and whether a whether the mortgage is for a property with a vertically integrated developer. Segregation measure is a dissimilarity index measuring how segregated minority borrowers are from non-minority borrowers. District-level property crimes per capita is based on e-Courts data pertaining to "crime" against property from Ash et al. (2022) and is 1 for above median values of property crimes per capita. Appraisal ratios are winsorized at 1% level. Standard errors are clustered at the pincode level. Mortgage-level data is for 2015–2020.

	District-level		Pincode-level		Collateral-level
Characteristic	Segregation	Property crime	Wealthy	Minority fraction	Integrated Developers
Dependent variable:	Panel A: Minority				
Characteristic	0.096***	0.918***	-0.050***	0.842***	-0.034***
	(0.021)	(0.003)	(0.003)	(0.007)	(0.002)
R^2	0.054	0.536	0.152	0.186	0.369
State × Time FE	Y	Y	Y	Y	Y
District × Time FE	N	N	Y	Y	Y
Pincode × Time FE	N	N	N	N	Y
N	1006164	1006176	937414	1004308	836763
Dependent variable:	Panel B: Log (Appraisal Ratio)				
Minority	-0.068***	-0.105***	-0.145***	-0.080***	-0.119***
	(0.014)	(0.005)	(0.007)	(0.007)	(0.005)
Integrated Developer					0.157***
					(0.006)
Minority × Characteristic	-0.176***	-0.025***	0.054***	-0.185***	0.100***
	(0.045)	(0.009)	(0.008)	(0.033)	(0.011)
R^2	0.447	0.447	0.448	0.447	0.451
District × Time FE	Y	Y	Y	Y	Y
Pincode × Time FE	Y	Y	Y	Y	Y
N	836763	836763	777896	836763	836763

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7
Policy Solution:
The 2016 Real Estate Regulatory Authority Act

This table examines the impact on appraisal ratios from the staggered implementation of the 2016 Real Estate Regulatory Authority (RERA) Act across states. RERA is an indicator equal to 1 if the state adopts the RERA Act as shown in Table IA7. The dependent variable in Panels A and D is the Appraisal Gap. Appraisal Gap and minority is as defined in Table 2. The dependent variable in Panels B and C is the pincode-level log of loan amount and number of loans for non-minority borrowers (colimn 1), all minority borrowers (column 2), minority borrowers in integragted projects (column 3), and remaining minority borrowers (column 4). Fixed effects are included as indicated. Standard errors are clustered at the pincode level. Data is at the mortgage-level in Panels A and D and at the pincode-level in Panels B and C for the period 2015–2020.

Panel A: Mortgage-level impact by integrated and non-integrated developers

Dependent variable:	Log (Appraisal Ratio)		
	All	Integrated	Other
	(1)	(2)	(3)
Minority	-0.063***	-0.008	-0.059***
	(0.009)	(0.016)	(0.009)
Minority × RERA	-0.059***	-0.035	-0.050***
	(0.010)	(0.023)	(0.010)
R^2	0.449	0.518	0.460
District × Time FE	Y	Y	Y
Pincode × Time FE	Y	Y	Y
Controls	Y	Y	Y
N	851365	90042	717199

Panel B: Pincode-level impact on loan amount

Dependent variable:	Log(Loan Amount)			
	Non-Minority	Minority		
		All	Integrated	Other
	(1)	(2)	(3)	(4)
RERA	0.054	0.596***	0.008	0.588***
	(0.409)	(0.144)	(0.022)	(0.141)
R^2	0.778	0.351	0.093	0.346
District FE	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
N	477979	477979	477979	477979

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Pincode-level impact on number of loans

Dependent variable:	Log(No. of Loans)			
	Non-Minority	Minority		
		All	Integrated	Other
	(1)	(2)	(3)	(4)
RERA	0.008	0.018**	-0.019	0.018**
	(0.005)	(0.008)	(0.025)	(0.008)
R^2	0.703	0.361	0.273	0.360
District FE	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
N	427873	159907	6446	156054

Panel D: Mortgage-level heterogeneity by integrated developer

Dependent variable:	Log (Appraisal Ratio)	
	(1)	(2)
RERA × Int. developer	0.041***	0.038***
	(0.009)	(0.009)
Integrated Developer	0.124***	0.118***
	(0.009)	(0.009)
RERA × Integrated developer × Minority		0.025
		(0.025)
Int. developer × Minority		0.074***
		(0.022)
RERA × Minority		-0.059***
		(0.010)
Minority		-0.064***
		(0.009)
R^2	0.450	0.451
District × Time FE	Y	Y
Pincode × Time FE	Y	Y
Controls	Y	Y
N	865161	865161

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8
Case Study:
Transfer of Property Rights in Delhi

This table shows appraisal gaps by property disputes in Delhi. The dependent variable in both panels is the log of appraisal value to the market value of the property. Panel A and B restricts to mortgages in Delhi and examines heterogeneity by disputed properties. Disputed properties data and Section 81 disputed properties are collected from the DORIS website. Disputed properties and Section 81 properties are aggregated to the pincode level and normalized per capita. Minority is an indicator of whether a borrower belongs to a scheduled caste, scheduled tribe, other backward class, or is Muslim. District-time and pincode-time fixed effects are included, as shown for each column. Control variables included are credit score band and the interaction with time indicators. Standard errors are clustered at the pincode level. Data is at the mortgage-level for the period 2015 to 2020.

Panel A: Disputed properties

Dependent variable:	Log (Appraisal Ratio)			
Sample:	All	Muslim	OBC	SC/ST
	(1)	(2)	(3)	(4)
Minority	-0.080***	-0.104	-0.061**	-0.066
	(0.027)	(0.102)	(0.030)	(0.044)
Disputed properties × Minority	-13.151	-27.356	-34.370***	10.757
	(12.629)	(63.686)	(9.404)	(9.035)
R^2	0.183	0.185	0.189	0.188
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
N	20098	19598	19634	19633

Panel B: Section 81 disputes

Dependent variable:	Log (Appraisal Ratio)			
Sample:	All	Muslim	OBC	SC/ST
	(1)	(2)	(3)	(4)
Minority	-0.103***	-0.093*	-0.138***	-0.073**
	(0.022)	(0.051)	(0.033)	(0.034)
Section 81 disputes × Minority	-0.011	-0.402	0.102	0.177**
	(0.121)	(0.323)	(0.073)	(0.076)
R^2	0.183	0.187	0.189	0.188
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
N	20098	19598	19634	19633

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

Table A.1
Mechanism: Borrower Creditworthiness

This table shows the appraisal gaps controlling for borrower default. The dependent variable is the log of appraisal value to the market value of the property. District-time and pincode-time fixed effects are included, as shown for each column. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Default is an indicator for whether the loan has become 90-days delinquent. Control variables included are credit score band and time indicators. Standard errors are clustered at the pincode level. Data is at the mortgage-level for the period 2015–2020.

Dependent variable:	Log (Appraisal Gap)			
	(1)	(2)	(3)	(4)
Minority	-0.169***	-0.166***	-0.115***	-0.114***
	(0.004)	(0.004)	(0.004)	(0.004)
Default	-0.056***	-0.046***	-0.033***	-0.034**
	(0.015)	(0.016)	(0.012)	(0.013)
R^2	0.235	0.238	0.448	0.449
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1120655	1104550	936102	920952

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2
Mechanism: Black Money Component of Property Values

This table shows the heterogeneity in appraisal gaps with whether the borrower's is a salaried individual. The dependent variable is the log of appraisal value to the market value of the property. District-time and pincode-time fixed effects are included, as shown for each column. Minority is an indicator for whether a borrower belongs to scheduled caste, scheduled tribes, other backward class, or is Muslim. Salaried is an indicator for whether a borrower's occupation is classified as salaried. Control variables included are credit score band and time indicators. The dependent variables are winsorized at the 1% level. Standard errors are clustered at the pincode level. Data is at the mortgage-level for the period 2015 to 2020.

Dependent variable:	Log (Appraisal Ratio)			
	(1)	(2)	(3)	(4)
Minority	-0.158***	-0.154***	-0.118***	-0.115***
	(0.009)	(0.009)	(0.011)	(0.011)
Salaried	-0.021***	-0.030***	-0.019***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
Minority × Salaried	-0.029***	-0.031***	-0.006	-0.008
	(0.010)	(0.010)	(0.012)	(0.012)
R^2	0.262	0.264	0.467	0.468
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	682014	672651	531347	522985

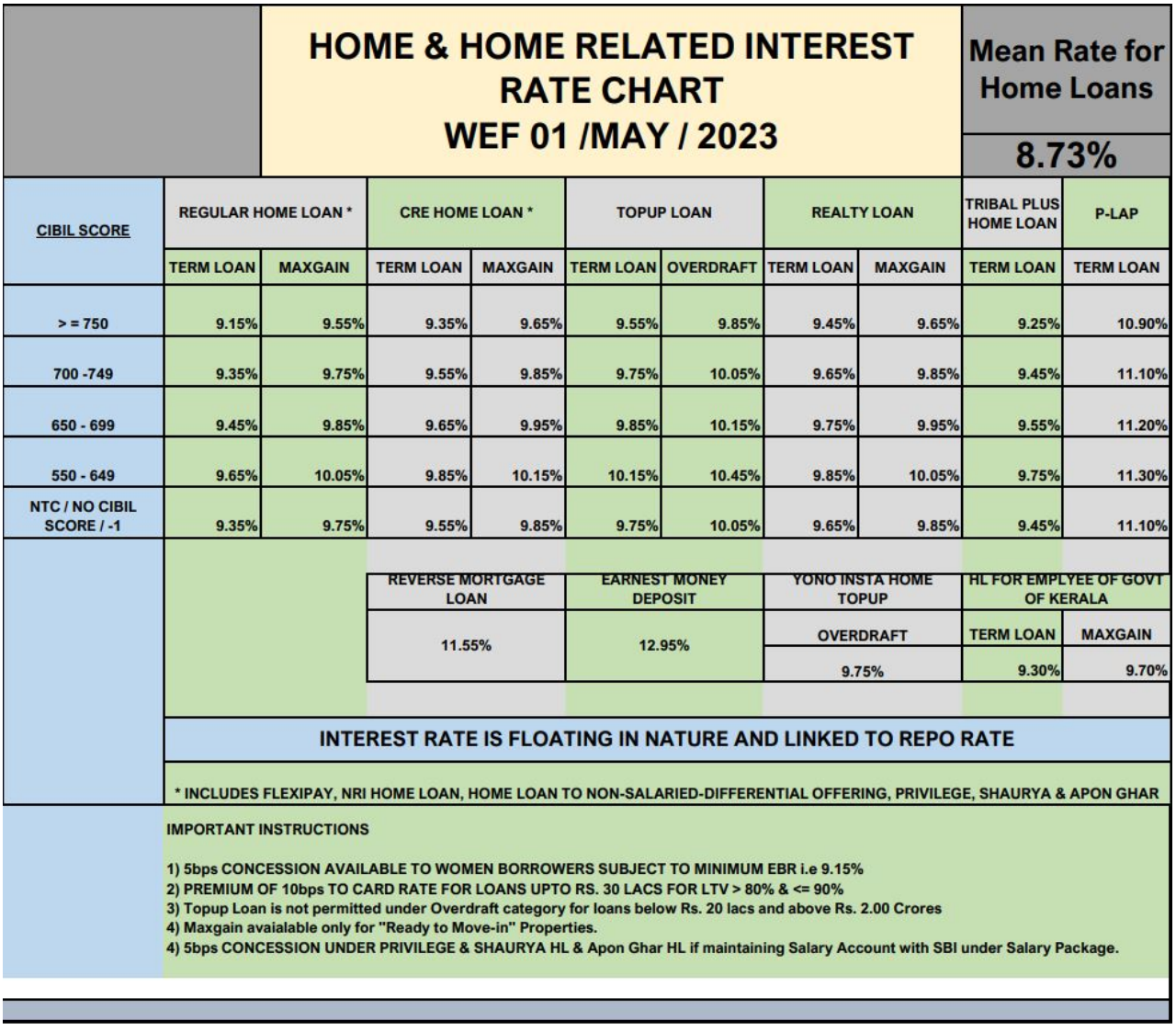
Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Describing Appraisal Gaps in India: Disparity in Collateral and Mortgage Access

Internet Appendix

Figure IA1
Rate Sheet

This figures shows a typical rate-sheet for mortgages from the lender in our sample.



HOME & HOME RELATED INTEREST RATE CHART
WEF 01 /MAY / 2023

Mean Rate for Home Loans
8.73%

CIBIL SCORE	REGULAR HOME LOAN *		CRE HOME LOAN *		TOPUP LOAN		REALTY LOAN		TRIBAL PLUS HOME LOAN	P-LAP
	TERM LOAN	MAXGAIN	TERM LOAN	MAXGAIN	TERM LOAN	OVERDRAFT	TERM LOAN	MAXGAIN	TERM LOAN	TERM LOAN
> = 750	9.15%	9.55%	9.35%	9.65%	9.55%	9.85%	9.45%	9.65%	9.25%	10.90%
700 -749	9.35%	9.75%	9.55%	9.85%	9.75%	10.05%	9.65%	9.85%	9.45%	11.10%
650 - 699	9.45%	9.85%	9.65%	9.95%	9.85%	10.15%	9.75%	9.95%	9.55%	11.20%
550 - 649	9.65%	10.05%	9.85%	10.15%	10.15%	10.45%	9.85%	10.05%	9.75%	11.30%
NTC / NO CIBIL SCORE / -1	9.35%	9.75%	9.55%	9.85%	9.75%	10.05%	9.65%	9.85%	9.45%	11.10%

REVERSE MORTGAGE LOAN	EARNEST MONEY DEPOSIT	YONO INSTA HOME TOPUP	HL FOR EMPLYEE OF GOVT OF KERALA	
		OVERDRAFT	TERM LOAN	MAXGAIN
11.55%	12.95%	9.75%	9.30%	9.70%

INTEREST RATE IS FLOATING IN NATURE AND LINKED TO REPO RATE

* INCLUDES FLEXIPAY, NRI HOME LOAN, HOME LOAN TO NON-SALARIED-DIFFERENTIAL OFFERING, PRIVILEGE, SHAURYA & APON GHAR

IMPORTANT INSTRUCTIONS

1) 5bps CONCESSION AVAILABLE TO WOMEN BORROWERS SUBJECT TO MINIMUM EBR i.e 9.15%
2) PREMIUM OF 10bps TO CARD RATE FOR LOANS UPTO RS. 30 LACS FOR LTV > 80% & <= 90%
3) Topup Loan is not permitted under Overdraft category for loans below Rs. 20 lacs and above Rs. 2.00 Crores
4) Maxgain avaialable only for "Ready to Move-in" Properties.
4) 5bps CONCESSION UNDER PRIVILEGE & SHAURYA HL & Apon Ghar HL if maintaining Salary Account with SBI under Salary Package.

Figure IA2
Year-wise Estimates of the Appraisal Gap

This figure shows the point estimates for the appraisal gap for each year. Each point represents the point estimates from column 3 in Table 2 for the subsample of mortgages in each year between 2015 and 2020. 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-time and pincode-time fixed effects are included. Standard errors are clustered at the pincode level. Mortgage-level data is for the period 2015 to 2020.

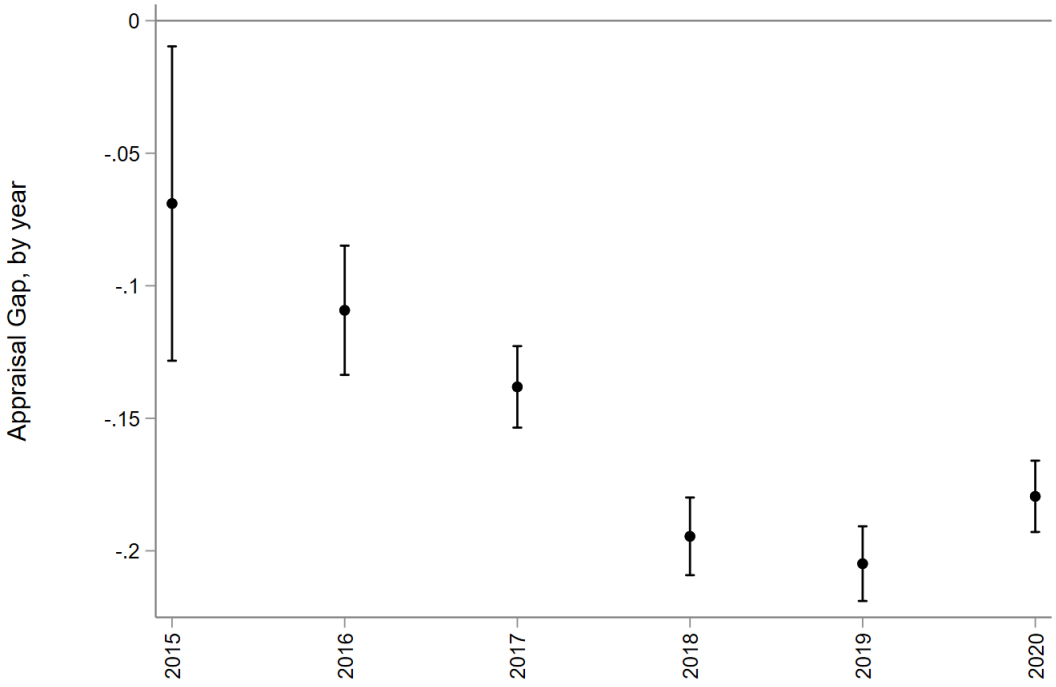


Table IA1
Hedonic Models

This table presents the hedonic price regressions for two dependent variables: Property Value (column 1) and Appraised Value (column 2) on two types of independent variables. One is home characteristics which includes Carpet Area, LPD Builtup Area, LPD Plot Area and second is neighborhood characteristics which includes Minority Share, Subprime share and Poverty Index. Neighborhood characteristics and home characteristics are continuous variables. District-time fixed effects are included in both hedonic models. Standard errors are clustered at pincode level. Property-characteristics variables: Carpet Area, LPD Built-up Area and LPD Plot Area are divided by 10000. Thus, the gradients for both hedonic price models on home attribute variables must interpreted after dividing the estimated results by 10,000.

Dependent variable:	Log (Appraised Value)	Log (Property Value)
	(1)	(2)
Carpet area	0.930***	1.237***
	(0.0510)	(0.0624)
LPD Builtup area	0.0794***	0.102***
	(0.0197)	(0.0239)
LPD Plot area	0.00381	0.00502*
	(0.00530)	(0.00273)
Minority Fraction	-0.682***	-0.232***
	(0.0384)	(0.0172)
Subprime fraction	-0.880***	-0.310***
	(0.150)	(0.0522)
Poverty Index	-0.292***	-0.142***
	(0.00957)	(0.00583)
R^2	0.310	0.298
District $\times$ Time FE	Y	Y
N	655783	655783

Table IA2
Default Rates of Nonintegrated Versus Integrated Developers

This table shows the heterogeneity in default rate with whether the mortgage is for a property with a vertically integrated developer. The dependent variable is the whether a mortgage becomes 90-day delinquent. District-time and pincode-time fixed effects are included, as shown for each column. 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 mortgages is from a vertically integrated developer. Control variables included are credit score band and time indicators. The dependent variables are winsorized at the 1% level. Standard errors are clustered at the pincode level. Data is at the mortgage-level for the period 2015 to 2020.

Dependent variable:	Default			
	(1)	(2)	(3)	(4)
Minority	0.003***	0.003***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Integrated Developer	-0.000**	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Minority × Integrated Developer	-0.004***	-0.003***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.182	0.216	0.359	0.384
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	2176105	2157207	1965384	1946837

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA3
Impact of assignment to a non-Muslim judge on defendant outcomes for crime against properties

This table shows the impact on acquittal rate (Panel A) and decision within six months of filing (Panel B) for a muslim and non-muslim defendant respectively, of a case being randomly assigned to a non-muslim judge. The point estimates of a non-muslim judge delivering acquittal and decsion within six months of filing on non-muslim and muslim defendants are nearly zero across all the specifications. In the third row of both the panels, the own-religion bias estimate is effectively zero and non-significant. The table results suggest that there is no evidence for in-group religion bias in the Indian judiciary for crime against property. Demographic controls are included in the second column of each set of three column results in both the panels. E-court data used for this analysis is from 2010-2018 and provided by Development Data Lab.

Dependent variable:	Acquittal rate					
	(1)	(2)	(3)	(4)	(5)	(6)
Non-Muslim judge on Muslim defendant	0.016	0.015	—	-0.004	-0.022	—
	(00.027)	(00.029)		(00.020)	(00.024)	
Non-Muslim judge on non-Muslim defendant	0.015	0.019	—	0.010	-0.001	—
	(00.026)	(00.028)		(00.018)	(00.022)	
Difference = Own religion bias	0.000	0.004	0.006	0.014	0.022	0.005
	(00.017)	(00.019)	(00.019)	(00.016)	(00.017)	(00.017)
Reference group mean	0.123	0.131	0.126	0.132	0.139	0.136
Observations	79701	73962	71965	89294	83277	80609
Dependent variable:	Decision within six months of filing					
Non-Muslim judge on Muslim defendant	-0.020	-0.043	—	-0.003	-0.031	—
	(00.040)	(00.040)		(00.033)	(00.037)	
Non-Muslim judge on non-Muslim defendant	-0.020	-0.043	—	-0.013	-0.040	—
	(00.036)	(00.036)		(00.030)	(00.032)	
Difference = Own religion bias	0.000	0.001	0.017	-0.011	-0.010	0.027
	(00.029)	(00.028)	(00.026)	(00.026)	(00.026)	(00.024)
Reference group mean	0.493	0.496	0.498	0.47	0.474	0.485
Observations	69529	64500	62676	77692	72433	70023
Demographic controls	No	Yes	Yes	No	Yes	Yes
Judge fixed effect	No	No	Yes	No	No	Yes
Fixed Effect	Court-month	Court-month	Court-month	Court-year	Court-year	Court-year

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA4
Effect of assignment to judge for crime against properties with same last name on defendant outcomes

This table examines in-group bias on the basis of shared caste identity. Shared caste identity is determined on the basis of same last name of defendant and judge. The reported results suggest that there is an in-group bias among individuals with same last names which is statistically significant, representing about 4.2 percentage points in the likelihood of the acquittal. There is no effect when we include rare names in the specification. The sample is restricted to individuals with last names that match at least one judge in their district at any time. The act/section fixed effects is included in the all the specifications to adjust for the possibility that judge assignment rules not driven by the seriousness of the crime. There is also last-name fixed effects rule out the possibility some social groups may be more or less likely to be acquitted than others or some judges from certain social groups have different average for acquittal rates. E-court data used for this analysis is from 2010-2018 provided by Development Data Lab.

Dependent variable:	Acquitted					
	(1)	(2)	(3)	(4)	(5)	(6)
Same last name	-0.020***	-0.014*	-0.013	-0.009	-0.022*	-0.041***
	(0.007)	(0.007)	(0.024)	(0.033)	(0.012)	(0.012)
Same name * Rare name					0.011	0.042
					(0.044)	(0.045)
Observations	59315	56995	56995	66949	69682	66949
Fixed Effect	Court-month	Court-month	Court-month	Court-year	Court-year	Court-year
Judge Fixed Effect	No	Yes	No	Yes	No	Yes
Inverse Group Weight	No	No	Yes	Yes	Yes	Yes
Last Name Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA5
Indian Penal Codes related to immovable property

IPC Section	Offense Description
169	Public servant unlawfully buying or bidding for a property
183	Resistance to the talking of property by the lawful authority of a public service
184	Obstructing sale of property offered for sale by authority of a public servant
185	Bidding, by a person under a legal incapacity to purchase it for property at a lawfully authored sale, or bidding without intending to perform the obligations incurred thereby
206	Fraudulent removal or concealment, etc., of property to prevent its seizure as a fine, or both forfeiture, or in satisfaction of a fine under sentence, or in execution of a decree.
207	Claiming property without right, or practising deception touching any right to it, to prevent its being taken as a forfeiture, or in satisfaction of a fine under sentence, or in execution of a decree
208	Fraudulently suffering decree for sum not due
217	Offering gift or restoration of property in consideration of screening offender if the offence be capital.
218	Public servant disobeying a direction of law with intent to fine, or both save person from punishment, or property from forfeiture.
380	Theft in a building, tent or vessel
381	Theft by clerk or servant of property in possession of master or employer.
382	Theft, after preparation having been made for causing death, or hurt, or restraint,fear of death, or of hurt or of restraint, in order to the committing of such theft, or to retiring after committing it, or to retaining property taken by it.
403	Dishonest misappropriation of property
404	Dishonest misappropriation of property, knowing that it was of the first in possession of a deceased person at his death, and that it has not since been in the possession of any person legally entitled to it.
409	Criminal breach of trust by public, servant. or by banker, merchant or agent
421	Fraudulent removal or Any concealment of property, etc., to prevent distribution among creditors
422	Fraudulently preventing from being made available for his creditors a debt or demand due to the offender.
423	Fraudulent execution of deed of transfer containing a false statement of consideration
424	Fraudulent removal or concealment of property, of himself or any other person or assisting in the doing thereof, or dishonestly releasing any demand or claim to which he is entitled.
443-446	Different versions of house-trespassing
461	Dishonestly breaking open receptacle containing property

Table IA6
Robustness to Animus as a Mechanism

This table examines the role of religious conflicts and political violence on minority group. In Panel A, we use Varshney-Wilkinson dataset and Panel B uses ACCLED dataset. Both the tables have distinct definitions of Riots. Conflicts in Panel A is based on actors associated with different religions but in Panel B actors are more than religious groups (Political Parties, militants etc.). Religious conflict variable is defined at district level which is a continuous variable. If a district has high number of religious conflict then it is historically highly conflicted. On the other hand, riots in Panel B is a dichotomous variable which is defined at pincode year month level. Riots take 1 when a pincode had a conflict in a month of a year. We find no significant other than zero on minority due to religious conflicts or riots. As indicated, we include district-time, pincode-time fixed effects. For historical religious conflict, our dataset is from 1950-2000. Panel B data on riots is from 2016-2020. In both the specification, standard errors are clustered at pincode level.

Panel A: Historical Religious Conflict

Dependent variable:	Log (Appraisal Ratio)			
	(1)	(2)	(3)	(4)
Minority	-0.171***	-0.167***	-0.124***	-0.122***
	(0.007)	(0.007)	(0.007)	(0.007)
Minority × Religious Conflict	0.003	0.003	0.015*	0.013
	(0.009)	(0.009)	(0.009)	(0.009)
R^2	0.235	0.238	0.448	0.449
District × Time FE	Y	Y	Y	Y
Pincode × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	1120655	1104550	936102	920952

Panel B: Contemporaneous Religious Conflict

Dependent variable:	Log (Appraisal Ratio)			
	(1)	(2)	(3)	(4)
Minority	-0.115***	-0.114***	-0.115***	-0.114***
	(0.004)	(0.004)	(0.004)	(0.004)
Minority × Riots	-0.003	-0.006	-0.003	-0.006
	(0.022)	(0.022)	(0.022)	(0.023)
R^2	0.448	0.449	0.448	0.449
Pincode × Time FE	Y	Y	Y	Y
District × Time FE	N	N	Y	Y
Controls	N	Y	N	Y
N	936102	920952	936102	920952

Table IA7
Dates for RERA Implementation across states

State/UT	RERA Notification Date	RERA Notified Month	Source	Notes
States				
Andhra Pradesh	27/03/2017	March 2017	Source	-
Arunachal Pradesh	-	-	Source	Appellate tribunal/website not established
Assam	06/05/2017	May 2017	Source	-
Bihar	28/04/2017	April 2017	Source	-
Chhattisgarh	29/04/2017	April 2017	Source	-
Goa	25/05/2017	May 2017	Source	-
Gujarat	29/10/2016	October 2016	Source	-
Haryana	28/07/2017; 25/11/2017	July 2017	Source	Two different dates for HARERA (Panchkula) and HARERA (Gurugram), earlier date used.
Himachal Pradesh	28/09/2017	September 2017	Source	-
Jharkhand	18/05/2017	May 2017	Source	-
Karnataka	10/07/2017	July 2017	Source	-
Kerala	18/06/2018	June 2018	Source	-
Madhya Pradesh	22/10/2016	October 2016	Source	-
Maharashtra	08/03/2017	March 2017	Source	-
Manipur	-	-	Source	Website not established
Meghalaya	-	-	Source	Authority/appellate tribunal/website not established
Mizoram	-	-	Source	Did not establish the appellate tribunal
Nagaland	-	-	Source	Ruled not notified
Odisha	25/02/2017	February 2017	Source	-
Punjab	08/06/2017	June 2017	Source	-
Rajasthan	01/05/2017	May 2017	Source	-
Sikkim	-	-	Source	Authority/appellate tribunal/website not established
Tamil Nadu	22/06/2017	June 2017	Source	-
Telangana	31/07/2017	July 2017	Source	-
Tripura	27/10/2017	October 2017	Source	-
Uttar pradesh	27/10/2016	October 2016	Source	-
Uttarakhand	28/04/2017	April 2017	Source	-
West Bengal	-	-	Source	Appellate tribunal not established as of July 2024 according to the MoHUA RERA status tracker. The WBREAT website claims to function from Feb 2022.
Union Territories				
Andaman & Nicobar Islands	31/10/2016	October 2016	Source	-
Chandigarh	31/10/2016	October 2016	Source	-
Dadra & Nagar Haveli and Daman & Diu	31/10/2016	October 2016	Source	-
Jammu & Kashmir	-	-	Source	Appellate tribunal not established
Ladakh	-	-	Source	Authority/appellate tribunal/website not established
Lakshadweep	31/10/2016	October 2016	Source	-
NCT of Delhi	21/11/2016	October 2016	Source	-
Puducherry	31/10/2016	October 2016	Source	-

Table IA8
Balance Table for RERA Implementation

This table compares ex-ante differences in logs and growth in economic activity across early-rera and late-rera implemented states. The variables included are GSDP year on year growth rate from CEIC database, natural logarithm of monthly household income and expenditure from CPHS database, unemployment rate from CPHS database, night light intensity mean from SHRUG database and night light intensity mean without Delhi and Chandigarh.

	(1)		(2)		(1)-(2)	
	Quick Implementation		Late Implementation		Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean difference
GSDP YoY growth rate	9	11.832	15	12.358	24	-0.527
		(1.215)		(0.593)		
Ln(Monthly Household Income)	9	9.499	15	9.496	24	0.003
		(0.163)		(0.125)		
Ln(Monthly Household Expenditure)	9	9.049	15	9.123	24	-0.074
		(0.123)		(0.110)		
Unemployment Rate	9	7.097	15	5.223	24	1.874
		(1.231)		(0.879)		
Night Light Intensity Mean	9	4.977	15	0.979	24	3.997*
		(2.763)		(0.104)		
Night Light Intensity Mean (Without Delhi and Chandigarh)	7	0.962	15	0.979	22	-0.018
		(0.415)		(0.104)		

Table IA9
Time to RERA Implementation

This table looks at the correlation between relative quarter with respect to RERA implementation and checks if any of the ex-ante economic activity variables influence RERA adoption. The variables included are GSDP year on year growth rate from CEIC database, natural logarithm of monthly household income and expenditure from CPHS database, unemployment rate from CPHS database, night light intensity mean from SHRUG database and night light intensity mean without Delhi and Chandigarh.

	Relative Quarter (w.r.t RERA Implementation)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GSDP YoY growth rate	-0.041						-0.056
	(0.111)						(0.133)
Ln(Monthly Household Income)		-0.150					0.158
		(0.658)					(2.174)
Ln(Monthly Household Expenditure)			0.145				0.859
			(0.786)				(2.469)
Unemployment Rate				-0.037			0.020
				(0.088)			(0.106)
Night Light Intensity Mean					-0.105*		
					(0.055)		
Night Light Intensity Mean (Without Delhi and Chandigarh)						-0.255	-0.488
						(0.472)	(0.671)
R^2	0.006	0.002	0.002	0.008	0.141	0.014	0.085
N	24	24	24	24	24	22	22

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table IA10
Policy Solution:
The 2016 Real Estate Regulatory Authority Act

This table examines the impact on appraisal ratios from the staggered implementation of the 2016 Real Estate Regulatory Authority (RERA) Act across states. RERA is an indicator equal to 1 if the state adopts the RERA Act as shown in Table IA7. The dependent variable is an indicator for minority borrower. Each characteristic (X) is interacted with the indicator for RERA. The district-level, pincode-level, and collateral-level characteristics are segregation, property crime, rich, high minority fraction, and whether a mortgage belongs to an integrated developer. Variables are as defined in Table 6. Data is at the mortgage-level for the period 2015–2020. Standard errors are clustered at the pincode level.

Dependent variable:	Minority				
	District-level		Pincode-level		Collateral-level
RHS variable (X)	Segregation	Property crime	Rich	Minority	Intergrated
X	0.066**	0.898***	-0.049***	0.934***	-0.019***
	(0.029)	(0.006)	(0.004)	(0.016)	(0.003)
RERA × X	0.027	0.024***	-0.000	-0.120***	-0.018***
	(0.023)	(0.005)	(0.004)	(0.018)	(0.003)
R^2	0.054	0.549	0.153	0.186	0.367
State × Time FE	Y	Y	Y	Y	Y
District × Time FE	N	N	Y	Y	Y
Pincode × Time FE	N	N	N	N	Y
N	940078	940078	878355	938514	784692

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IA11
Policy solution:
2018 Insolvency and Bankruptcy Code Amendment

This table examines the impact on appraisal ratios from the implementation of the 2018 Insolvency and Bankruptcy Code (IBC) Amendment pertaining to real estate developers. IBC is an indicator equal to 1 after June 2018. The dependent variable in Panels A and D is the Appraisal Gap. Appraisal Gap and minority is as defined in Table 2. The dependent variable in Panels B and C is the pincode-level log of loan amount and number of loans for non-minority borrowers (colimn 1), all minority borrowers (column 2), minority borrowers in integragted projects (column 3), and remaining minority borrowers (column 4). Fixed effects are included as indicated. Standard errors are clustered at the pincode level. Data is at the mortgage-level in Panels A and D and at the pincode-level in Panels B and C for the period 2015–2020.

Panel A: Mortgage-level impact by integrates and non-integrated developers

Dependent variable:	Log (Appraisal Ratio)		
	All	Integrated	Other
	(1)	(2)	(3)
Minority	-0.094***	-0.035***	-0.087***
	(0.006)	(0.009)	(0.006)
Minority × IBC	-0.039***	-0.007	-0.032***
	(0.008)	(0.016)	(0.008)
R^2	0.450	0.517	0.461
District × Time FE	Y	Y	Y
Pincode × Time FE	Y	Y	Y
Controls	Y	Y	Y
N	920952	98519	771543

Panel B: Pincode-level impact on loan amount

Dependent variable:	Log(Loan Amount)			
	Non-Minority	Minority		
		All	Integrated	Other
	(1)	(2)	(3)	(4)
IBC	3.689***	0.526***	0.107***	0.419***
	(0.592)	(0.139)	(0.023)	(0.135)
R^2	0.775	0.350	0.091	0.345
District FE	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
N	526392	526392	526392	526392

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel C: Pincode-level impact on number of loans

Dependent variable:	Log(No. of Loans)			
	Non-Minority	Minority		
		All	Integrated	Other
	(1)	(2)	(3)	(4)
IBC	-0.025***	0.022**	0.011	0.018*
	(0.007)	(0.009)	(0.016)	(0.010)
R^2	0.695	0.358	0.274	0.358
District FE	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y
Time FE	Y	Y	Y	Y
N	471453	171764	7033	167402

Panel D: Mortgage-level heterogeneity by integrated developer

Dependent variable:	Log (Appraisal Ratio)	
	(1)	(2)
IBC × Int. developer	0.032***	0.029***
	(0.006)	(0.006)
Integrated Developer	0.140***	0.132***
	(0.006)	(0.006)
IBC × Integrated developer × Minority		0.026
		(0.018)
Int. developer × Minority		0.090***
		(0.013)
IBC × Minority		-0.038***
		(0.008)
Minority		-0.097***
		(0.006)
R^2	0.451	0.452
District × Time FE	Y	Y
Pincode × Time FE	Y	Y
Controls	Y	Y
N	936102	936102

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$