Residential Segregation and Unequal Access to Local Public Services in India: Evidence from 1.5m Neighborhoods*

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Abstract

Rapid urbanization in lower-income countries has the potential to cause substantial improvements in well-being, but the residential segregation of marginalized groups could reinforce inequality and limit access to new opportunities. We study residential segregation, access to public services, and economic outcomes across 1.5 million urban and rural neighborhoods for two of India's marginalized communities: Scheduled Castes (SCs) and Muslims. Levels of urban segregation in India are comparable to Black/White segregation in the United States. Within cities, public facilities and public infrastructure are systematically allocated away from neighborhoods where many Muslims and Schedules Castes live. Nearly all of the regressive allocation is across neighborhoods within cities—at the most informal and least studied form of government. These inequalities are also not visible in the more aggregated data typically used to study unequal service allocation. Children and young adults growing up in marginalized group neighborhoods have less schooling, even after controlling for parent education and household consumption. Unequal access to public services in India's highly segregated neighborhoods may be a significant contributor to disadvantages faced by marginalized groups.

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1 Introduction

The concentration of marginalized social groups into poor neighborhoods is a key driver of persistent cross-group inequality in many contexts (Ananat and Washington, 2009; Alesina et al., 2011; Boustan, 2013; Cutler et al., 2008). Residential segregation can have a range of negative consequences: members of segregated groups may face worse discrimination in terms of provision of public services, they may have worse access to employment and employment networks, and stereotypes in the wider population may be more difficult to break, among others (**??**). Because residential settlement patterns tend to be highly persistent, these isadvantages may be particularly difficult to address.

Most of the empirical literature on residential segregation and neighborhood effects comes from developed countries, in large part due to the paucity of cross-neighborhood data in developing countries. But the role of neighborhoods is particularly important to study in poorer countries. Cleavages across social groups are just as important in developing countries as they are in developed countries, if not more so. However, developing countries are rapidly urbanizing, and thus the scope for policy to affect urban settlement patterns (which may stay in place for decades) is much greater than in richer countries. Whether cross-group disparities will be entrenched by urban settlement patterns remains to some extent a policy choice in cities which are still rapidly growing.

Studying outcomes and service delivery at the neighborhood level is also important because it is the geographic level which determines service accessibility, even if it is not the level at which service allocation is most closely studied. In India, the focus of this paper, federal and state policies largely prescribe the allocation of funding for public services at aggregate levels (state, district, or subdistrict), while the cross-neighborhood distribution of those services is determined through less formal local processes. But cross-neighborhood disparities can differ markedly from cross-region disparities. This creates a potential blind spot for policy makers. Policy makers who can only observe the world at an aggregate scale may fail to allocate public services fairly across neighborhoods, and may not even observe when misallocation takes place.

For example, the Indian government has frequently targeted extra public services to districts with many Scheduled Castes. Our *district-level* analysis below shows that disadvantages in access to services for Scheduled Castes have closed or even reversed. But within districts, if those services are delivered entirely to high status neighborhoods, marginalized groups' access to services could be very different from what the district analysis suggests.

In this paper, we mobilize new data describing settlement and segregation patterns of marginalized groups across Indian cities and villages, and we document the relationship between these settlement patterns and access to public services. Our data covers 1.5 million urban and rural neighborhoods spanning all of India and focuses on outcomes for Muslims and members of Scheduled Castes. India is an important context in which to study these questions for several reasons. First, it is huge: the marginalized groups that we study number over 300 million individuals. Second, disparities across these groups are rooted in historical inequalities that have persisted for generations, but the extent to which those inequalities are being changed by market liberalization and urbanization remains an open question. Third, the policy and planning process in India remains focused on disparities at aggregate levels like the district; a recognition of how these aggregate plans translate to neighborhood-level outcomes is essential to understanding whether these policies are achieving their objectives.

We have three primary aims. First, we document the extent of residential segregation in rural and urban areas. Second, we describe how a range of public services—including schools, medical clinics, water/sewerage, and electricity—are distributed across marginalized group (MG) and non-marginalized-group (non-MG) neighborhoods. Third, we study the educational outcomes of young men and women who live in MG neighborhoods, providing suggestive evidence on the impacts of residential segregation.

To do this, we create a dataset describing over 1.5 million neighborhoods covering over 75% of India's population, the first such dataset to link neighborhood demographics with access to public services. The challenge in constructing these data is that there is no systematic survey documenting public service availability across India. However, information about

service availability can be inferred from India's firm and poverty censuses, which use the same small neighborhood coding scheme across the country. The Socioeconomic and Caste Census (SECC 2012) describes a short list of assets at the household level for *every household in India*, along with a household roster that records the education, occupation, and SC status for every household member. The asset list records whether urban households have piped water, electricity, and drainage; while household access may be privately purchased, neighborhood infrastructure is a precondition for these services. Crucially, public listings of the SECC were released with respondent names; the distinctive naming patterns of Muslims allow us to predict the religious identity of household members (as Muslim or non-Muslim) with high accuracy.[1]

We get information on public facilities from the Indian Economic Census, which records data on India's 65 million non-farm economic establishments. This census is conventionally used to study firms, but it also records data on public schools, health centers, and hospitals, making it the only large-sample data source (to our knowledge) that can identify these services at the neighborhood level. Combining these datasets, we can document individual demographics, socioeconomic outcomes, and neighborhood-level public services in about 400,000 urban neighborhoods (in 3500 cities and towns) and 1.1 million rural neighborhoods (in about 400,000 villages).[2]

SCs and Muslims make up similar population shares in the country (17% and 14% respectively in 2011), but have distinct group histories. Scheduled Castes have been historically consigned to the lowest occupational rungs of society for over a thousand years, but have been targeted by decades of affirmative action policies since independence; empirical studies suggest some of these programs have had positive effects (Asher et al., 2021a; Gulzar et al., 2020).

Different Muslim groups have historically occupied heterogeneous positions in Indian society over the generations; some Muslims are descendants of India's 15th to 18th century ruling classes, while others descend from lower-caste groups who converted to Islam to escape their

[1]We classify names as Muslim or non-Muslim using a long-short-term-memory (LSTM) neural network based on a training set of two million takers of the Indian Railways Exam. The out-of-sample accuracy against a set of manually classified names is 97% (Ash et al., 2022).

[2]Due to incomplete data in the SECC, this represents about 80% of rural subdistricts and 45% of cities and towns. The excluded subdistricts and towns are broadly similar on a wide range of variables to those in the study.

status at the bottom of the social pyramid. Groups from both of these heritages increasingly find themselves politically marginalized and threatened. A large literature has discussed the relative outcomes of Scheduled Castes, and there is a more moderate literature on Muslims.[3] While disparities in access to public services have been documented for both of these groups, there is little systematic empirical work on disparities at the neighborhood level—the level at which these services are typically accessed.[4]

We present three key findings. First, Muslims and SCs have highly segregated residence patterns, comparable in magnitude to the urban segregation of Black people in the United States. Whether Muslims or SCs are more segregated depends on the measure of segregation used; SCs are more likely to experience moderate levels of segregation, while the distribution of Muslim shares across neighborhoods is notably bimodal, such that a greater share of Muslims live in neighborhoods that are almost entirely Muslim.[5]

Urban segregation is slightly lower than rural, and urban and rural segregation are highly correlated across regions, for both Muslims and SCs. In short, Indian cities are replicating the social group settlement patterns that have been in place for hundreds of years in villages.[6] Compared with SCs, Muslims are relatively more segregated in cities than in rural areas. People living in highly segregated cities are on average poorer than those in less segregated cities; this pattern holds for all social groups, a notable difference from the U.S. context where segregated cities are primarily associated with worse outcomes for Black Americans, but not for other groups. Younger cities are considerably less segregated than older cities; change over time is substantial, but without time series data, it is difficult to determine whether this implies a secular change in settlement patterns, or whether cities become more segregated as they get older and larger.

[3] On Muslims, see, for example, Basant and Shariff (2010) and Jaffrelot and Gayer (2012).

[4] Because the Population Census records Scheduled Caste shares and the presence of a set of public services at the village level, the relationship between the village-level rural SC share and public services has been studied (Banerjee and Somanathan, 2007). However, village or neighborhood-level access to public services has not been studied on a national scale for Muslims, nor urban access to local services for either group.

[5] For example, 26% of Muslims live in neighborhoods that are $>80\%$ Muslim, while 17% of SCs live in neighborhoods that are $>80\%$ SC.

[6] While the data do not record when these settlement patterns emerged, the historical record suggests that rural Indians have been highly endogamous, such that village settlement patterns observed today have been static for decades, if not centuries.

Second, we show that, within cities, public services are systematically allocated away from neighborhoods where marginalized groups live. This holds for both Muslims and SCs, for almost every local service that we could measure, including primary and secondary schools, medical clinics, piped water, electricity, and closed drainage. Private providers are *not* making up for the reduced service access of marginalized groups; in fact, private services also systematically locate away from MG neighborhoods, in part because these neighborhoods are poorer.[7]

The magnitude of the disparities is large. For example, compared with a 0% Muslim neighborhood, a 100% Muslim neighborhood in the same city is 10% less likely to have piped water infrastructure and only half as likely to have a secondary school. For schools and clinics, facilities provided entirely by government, the disadvantage in Muslim neighborhoods is double that the disadvantage in SC neighborhoods, echoing a consistent finding across the qualitative literature that Muslims report difficulty in getting public facilities from their representatives (Jaffrelot and Gayer, 2012). For electricity, water, and drainage, goods which have both a private (hook-up) and public (infrastructure) component, SCs (who are somewhat poorer on average), face worse neighborhood-level disadvantages.

Disparities look different at higher levels of aggregation. Districts and subdistricts with many SCs have more public facilities on average, consistent with findings by Banerjee and Somanathan (2007). However, the cross-neighborhood allocation of these services eliminates nearly all of these advantages at the neighborhood level. Muslim neighborhoods, in contrast, have no advantage or disadvantage at higher levels of aggregation; the neighborhood disparity (which is large) is the aggregate disparity.

In short, marginalized groups are most systematically and substantively disadvantaged at the most local and informal levels of government — within towns and village clusters. These are the levels of government which operate with the least scrutiny, and at the greatest distance from the district and subdistrict levels at which affirmative action policies are codified.

[7]The fact that marginalized groups live in poor neighborhoods does not explain away the public facility results, since government service provision aims to be universal. The results also cannot be explained by poor service provision in slums, as they hold just as strongly in the set of non-slum neighborhoods.

Finally, we examine the relationship between residential settlement patterns and outcomes for the next generation. We find that young people growing up in marginalized group neighborhoods have systematically worse educational outcomes. The disadvantages are substantially worse in Muslim neighborhoods than in SC neighborhoods and are economically large even after controlling for parent education, and household consumption.[8] These disadvantages are experienced by members of all social groups living in marginalized group neighborhoods.

These results are descriptive. Further research is needed to understand whether the outcome disparities described here are causal effects of neighborhoods or driven by selection of marginalized groups into under-serviced neighborhoods. Equally, we do not prove that services are allocated away from marginalized group neighborhoods *because* of the people who live there, or because of some other characteristic of those neighborhoods. Our work serves as a necessary starting point for asking these questions, because these cross-neighborhood disparities have not previously been documented; even the extent of residential segregation has barely been measured, not only in India but in most developing countries. In Sections 5 and 6, we discuss in detail the external evidence for and against causal interpretation of these results. But decisively disentangling the causal direction of these disparities is an important subject for future work.

Systematic analysis of access to public services at the neighborhood level in developing countries has been elusive because of an absence of neighborhood-level census data. While several of India's major sample surveys contain neighborhood identifiers, they are not powered to measure neighborhood characteristics like social group shares, nor do they have enough sample to measure urban segregation. Prior work on segregation in India includes a number of ward-level studies that use spatial units with population sizes of up to 30,000–200,000 people, 30 times the size of neighborhoods in our analysis.[9] A series of recent studies has used enumeration block data

[8] Rural SC neighborhoods are an exception; they have worse access to facilities but no worse educational outcomes.

[9] Vithayathil and Singh (2012) use ward data from 2001 to show that residential segregation by caste is more prominent than by socioeconomic status in seven major cities. Singh et al. (2019) examine changes in caste-based segregation from 2001 and 2011, again at the ward level, finding that residential segregation by caste has persisted or worsened in 60% of the cities in their sample. Neither of these studies examine religion, which is rarely available in Indian Census microdata.

similar to ours to document average patterns of segregation in a subset of Indian cities,[10] but we are aware of no prior work studying public service provision or individual outcomes at the neighborhood level in India, or any other major developing country. Even at the village level in India, economic work on Muslim villages is rare, because data on village Muslim shares were unavailable. Finally, we are aware of no prior work systematically studying access disparities *within* villages.

Importantly, these neighborhood-level disparities are in many cases not apparent in aggregate data. Consequently, a policy maker observing school allocation only at the district level could arrive at at incorrect conclusions regarding access disparities and the efficacy of equalization policies. This paper underscores the value of leveraging high-resolution administrative data — which is available but under-used in many developing countries — to better understand and evaluate the performance of public programs.

2 Context and Background

2.1 Scheduled Castes and Muslims in India

India's Scheduled Castes (SCs) are historically endogamous groups who occupy the lowest tiers of the caste system. They have experienced occupational and social segregation for thousands of years; social norms have effectively compelled them to take on low status occupations — like scavenging, emptying of toilets, or handling animal carcasses — with virtually no prospect of upward mobility. The practice of untouchability, now banned but still practiced in some form by many households, can take the form of segregation in schools, temples and markets, restrictions against entering the homes or even wearing sandals in the presence of higher caste groups, among others. These restrictions have been enforced with various social sanctions, including violence and murder (Girard, 2021). Since independence, the government of India has worked to mitigate the socioeconomic disadvantages of SCs through a range of programs and policies. SC status is often used as a marker of poverty for means-tested welfare programs, and there are reserved positions for SCs in higher education, politics, and in government. SCs still

[10] Bharathi et al. (2018) report enumeration block-level segregation based on SC status for five major cities. Bharathi et al. (2021) use similar scale data on caste and religion to characterize segregation in urban Karnataka. Susewind (2017) measures Muslim segregation using microgeographic polling booth data in eleven cities.

experience substantial socioeconomic disadvantages, but by many measures the gap between SCs and forward castes has shrunk somewhat over recent decades (Hnatkovska et al., 2012; Emran and Shilpi, 2015; Cassan, 2019; Asher et al., 2021a).

Muslims occupy a similar share of the population to Scheduled Castes (14% for Muslims vs. 17% for SCs). Like SCs, they on average have lower socioeconomic status than non-Muslim non-SCs. However, they experience fewer legal protections and have not been targeted by affirmative action policies, a few exceptions notwithstanding. While SCs have been gaining ground on forward castes in socioeconomic terms, Muslims have if anything been losing ground, particularly in educational attainment, and have experienced significant losses in upward mobility in recent decades (Asher et al., 2021a). Post-independence India has been characterized by waves of anti-Muslim activism, sometimes resulting in riots, property destruction, and violence. Various social movements and political parties have mobilized around the idea of Hinduism as a key pillar of Indian identity, to the exclusion of Muslims (Jaffrelot, 2021). Our analysis uses data from 2011–13, and thus predates the rise of the current Modi regime (which has roots in these social movements), though the BJP (Modi's party) held power nationally in the early 2000s, and held power in many states before and during our sample period. Muslims have a higher share of members living in urban areas than any other major social group.

While SCs and Muslims represent the largest disadvantaged groups in India, there are several other social groups not separately considered by our analysis. Other Backward Castes (OBCs) occupy an intermediate place in the caste system between Forward Castes and SCs, comprising 40% of the population; IHDS 2011 reports that about half of Muslims are OBCs, though this share varies substantially across years and surveys. OBCs are not coded as such in any of the datasets that we use and their names are less distinctive, making it difficult to identify them (or their prevalence in any neighborhood) in our data. We also exclude Scheduled Tribes (STs) from our analysis; they are among the poorest social groups in India, but are concentrated in rural areas and have very small population shares in the vast majority of cities.[11] Given the

[11] Only 4% of urban Indians report Scheduled Tribe status, compared with 15% who are SCs and 17% Muslims.

focus of this paper, we use the terms "marginalized groups" or "MGs" to describe SCs and Muslims, even though other groups in India could also reasonably be classified as such.

2.2 Marginalized Group Settlement Patterns in Rural and Urban India

Pre-independence cities in India were often characterized by neighborhoods with homogeneous occupational groups, often with mixed religion. In the absence of an effective municipal state, these neighborhoods were self-governing with respect to many public services, sometimes including even self-defense. Many neighborhoods had only a small number of entries, which made it possible to restrict access; this structure persists in many urban neighborhoods today, resulting in distinct boundaries between neighborhoods (Gist, 1957; Lynch, 1967; Gould, 1965; Doshi, 1991; Chakrabarti et al., 2002).[12] The ethnographic literature suggests a secular trend of increasing segregation by religion rather than by occupation, as Hindu-Muslim violence has reduced Muslim feelings of safety in mixed neighborhoods. These newly concentrated Muslim neighborhoods can house individuals from many classes, often with income segregation existing within the neighborhoods at a smaller scale. Jaffrelot and Gayer (2012) describe this pattern of Muslim segregation in a series of monographs spanning many parts of the country. In many of the case studies, Muslims report difficulty getting attention from politicians or access to public services in their segregated neighborhoods.

The literature on villages also suggests a high degree of spatial separation between different classes and religions; individuals from lower status social groups often live in hamlets that are separated by a moderate walking distance from the village's primary agglomeration, where schools and health centers typically are found (Beteille, 2012; Lanjouw et al., 2018).

While these patterns can be observed in many parts of the country, they are primarily documented in a qualitative literature (some of which is cited above), due to a general absence of large-scale data with neighborhood identifiers or of sufficient scale to characterize neighborhoods individually. There is a quantitative literature on unequal access to public services by caste

[12] These closed neighborhoods are described by different terms throughout the country: pols in Ahmedabad, mohallas in much of North India, paras in West Bengal, etc., often with names that reflect the occupational origins of the space. Muchipara, for instance, literally translates as "the neighborhood (para) of cobblers (muchi)."

across villages (Banerjee and Somanathan, 2007; Bailwal and Paul, 2021), in part because the decennial Population Census records the SC population share of every village, along with a series of public services. Nationwide data on village-level Muslim shares did not exist before this paper, nor was there data on either social group shares or public services at the neighborhood level *within* villages. To our knowledge, there has also been no large-sample study of public service variation *within* cities; a key innovation of this paper is assembling near-universal urban neighborhood-level data simultaneously describing both public services and marginalized group shares.

2.3 Levels of government in India

India has a federal system of government with major powers divided between center, state, and local governments. The administrative apparatus is also decentralized, such that officials at different hierarchical levels have substantial autonomy.

There are 36 states and union territories (35 at the time of our sample), which have substantial administrative and legislative power. Public services are financed and allocated by both central and state government programs. Program implementation often lies in the hands of District Collectors, who are the top administrative officers of districts; there were 640 districts in our sample, though an additional 100 have been subdivided since then.

Local governance bodies are called panchayats in villages and municipalities in towns and cities. These bodies have elected representatives who can substantially influence the selection and allocation of public services within their administrative areas, but have little control over their overall budgets, most of which derive from grants from higher levels of government.

The most high-profile policies intended to close disparities between marginalized and non-marginalized groups are conceived and designed at the state and federal level, and often prescribe allocations of public services across aggregated levels of government. For instance, the District Primary Education Programme (Khanna, 2022) targeted funds for building schools to districts with below-median female literacy. The specific neighborhood placement of new public facilities within districts, towns, and villages is rarely prescribed by these high-level policies; it is agreed upon through consultation with local elected leaders and bureaucrats. The

extent to which policies target certain groups can therefore be different at different levels of aggregation; the less formal decision-making process of local bodies could either enhance or undermine the progressivity of policies designed at higher levels of government (**?**).

3 Neighborhood-level Data on Social Groups and Public Services

3.1 Identifying Neighborhoods

Studying neighborhood-level disparities requires data with granularity (to be able to identify neighborhoods) but also with scale (to be able to accurately measure neighborhood-level MG shares in many neighborhoods and many cities). Few of India's major sample surveys achieve this; they typically cover a small fraction of neighborhoods in any city, and too small a number of households in each sampling unit to measure MG shares, MG segregation, or disparities in MG outcomes.

To bridge this gap, we combine a set of census data sources which use the internal survey block identifiers (enumeration blocks) that were created for the administration of India's 2011 Population Census. ǂThese "neighborhoods" consist of 100–125 households each (or about 700 people) and describe a compact cluster of residences meant to be efficient for an enumerator to visit in a single session of work. In cities, these are typically city blocks or single buildings, while in rural areas their boundaries are typically defined by grouped clusters of residences. When villages consist of fewer than 100–125 households—about half of villages—an enumeration block is a single village. Urban enumeration blocks are thus uniformly around 100–125 households, while rural blocks range from just a handful of households to the same upper limit around 125.[13] We exclude outlier neighborhoods which have fewer than 150 people (typically very small villages) or more than 1200 people.[14] Note that "enumeration blocks" are not the same

[13] Appendix Figure A.1 shows the distribution of block population in the sample. Results are very similar if we exclude rural villages that are too small to have a 100 household enumeration block, an analysis which results in similar distribution of urban and rural blocks.

[14] These make up less than 1% of the population and our results are unchanged if they are returned to the sample. Very large enumeration blocks are excluded because they are anomalous (suggesting potential data collection issues), and because segregation measures are scale-dependent (see below). However, there are so few of these neighborhoods, that the potential bias here would be small even if they were included.

units as "census blocks" (sometimes just called "blocks").[15]

While rural and urban enumeration blocks are similarly sized in terms of population, the geography of urban and rural access to public facilities are quite different. Urban areas are dense, such that individuals may travel across many enumeration blocks for work or access to public services. Rural areas are naturally more dispersed: neighboring enumeration blocks are separated by larger distances than neighboring blocks in cities. Indian villages often contain distinct hamlets, which can be separated by a few hundred meters or more from the main settlement. It is anecdotally common to have a hamlet inhabited by lower castes or Muslims, which tends to be located at some distance from the village center. Because enumeration block boundaries are defined for the convenience of enumerators, multi-block villages with multiple hamlets will typically have enumeration block boundaries that keep hamlets self-contained within blocks. Villages tend to be much further apart from each other, with separating distances that vary across the country. The geocodes describing locations and polygons of enumeration blocks were not available to us — they are sold as hand-drawn maps at high cost by the Indian Census.

3.2 Public Facilities

The Population Census town and village directories report a wide range of public services, but these are only identified at the town/village level and map on to neighborhoods only for very small villages. To identify public facilities at the neighborhood level, we instead use the 2013 Economic Census (EC13). EC13 is a complete enumeration of non-farm establishments in the country, which includes schools, clinics, and hospitals, which are separately coded as private or public. EC13 records enumeration block identifiers, making it possible to identify public health centers, primary schools, and secondary schools at the neighborhood level.[16] Health centers include hospitals, inpatient and outpatient clinics, and traditional care providers. EC13 also records whether a firm owner is Muslim or SC. The employment share in SC or Muslim firms is highly correlated

[15] Census blocks have population of about 200,000 each, and are unrelated to any units used in this paper.

[16] The earlier rounds of the Economic Census (1990, 1998, 2005) record similar data, but with neighborhood identifiers (urban frame survey units) that do not match any census. It is thus not possible to study changes in neighborhood-level services over time.

with the group share in each neighborhood. We measure public service availability with binary measures that indicate whether an enumeration block contains a given type of public facility.

3.3 Demographic Data

Data on individuals comes from the Socioeconomic and Caste Census (SECC), a national asset census which recorded information on every household and individual in India (mostly in 2012) to determine eligibility for social programs. The SECC describes age, gender, education, occupation, and caste for every household member, as well as a short list of assets used to rapidly assess socioeconomic status. The SECC was made publicly available online in a combination of formats; we scraped and processed the data, with the approach described in detail in Asher and Novosad (2020). The urban data were not posted in their entirety; our sample covers 160 million urban residents, compared with the census urban population of 370 million.[17]

Consumption is not directly measured in the SECC, but we generate small area estimates of household per capita consumption on the basis of all of the household assets on the SECC schedule, using the IHDS-II (2011–12) survey as our data source for consumption (Elbers et al., 2003). This process generates similar rural and urban consumption distributions to direct survey measures; see Asher and Novosad (2020) and Asher et al. (2021b) for more details.

The SECC surveyed individual caste and religion, but religion was not posted with the public data.[18] We therefore classify individuals as Muslims or non-Muslims using their first and last names, which were posted in the public data. Because of the distinctive naming patterns of Muslims, we can identify Muslim names with an out-of-sample accuracy of 97%. We do this with an LSTM neural network, which classifies names on the basis of repeated letter sequences, using a religion-labeled dataset of 2 million applicants to the Indian Railways as a training sample. This approach has much higher accuracy than a fuzzy merge; the latter creates classification

[17] To the best of our knowledge, missing data was a function of the actions of IT administrators and was unrelated to the data contents. Town and neighborhood data were to be posted in 30-day rolling periods; at some times, the SECC site was completely inaccessible, and some locations were posted for shorter periods or not posted at all. We discuss the representativeness of these data in Section 5.

[18] Subcaste, or jati, was also recorded but not posted. The only caste identifier are broad indicators for Scheduled Caste or Scheduled Tribe status.

errors when small letter substitutions change a name identity, such as *Khan* (a stereotypical Muslim name) vs. *Khanna* (a Hindu name). The neural network implementation is described in detail in (Ash et al., 2022); a similar approach is taken by (Chaturvedi and Chaturvedi, 2020). We verified the classification accuracy on a withheld subset of the names in the railway data, as well as on a set of manually classified names in the SECC. Our classification also closely predicts the subdistrict-level population share of Muslims (Appendix Figure A.2). We pool Hindus with the 6% of Indians who are Jain, Christian, Sikh, or some other non-Hindu religion; we describe this group as "non-Muslims."[19]

For comparison with the United States, we use data from the Diversities and Disparities project, which is based on the 2010 U.S. Census, and from the 2020 U.S. Census.

4 Methods

4.1 Measuring and Comparing Residential Segregation

Our first objective is to document the extent of residential segregation of Muslims and SCs; we estimate the canonical dissimilarity and isolation indices.

The dissimilarity index ranges from zero to one and answers the question: what share of the marginalized group would need to change neighborhoods for it to be evenly distributed within a city? We calculate this index for marginalized group MG and majority group MAJ across the set of blocks B in city c as:

$$DISSIMILARITY_c = \frac{1}{2}\sum_{b \in B}\left|\frac{N_{\text{MG,b}}}{N_{\text{MG,c}}} - \frac{N_{\text{MAJ,b}}}{N_{\text{MAJ,c}}}\right|, \tag{1}$$

where $N_{\text{g,b}}$ is the number of members of group g in block b, and $N_{\text{g,c}}$ is the population of that group in the city.

The isolation index measures the extent to which a population group is exposed only to members of its own group. It can be summarized as the marginalized group share in the average neighborhood of a member of the marginalized group:

[19] The non-Hindu, non-Muslim groups are small and we do not yet have an algorithm that can accurately classify them on the basis of names.

$$ISOLATION_c = \sum_{b \in B} \left| \frac{N_{\text{MG,b}}}{N_{\text{MG,c}}} \cdot \frac{N_{\text{MG,b}}}{N_{\text{total,b}}} \right|, \tag{2}$$

where $N_{\text{total,b}}$ is the population of all groups in the given block.

When measuring Muslim segregation, we treat SCs as majority group members, and vice versa when measuring SC segregation. We take this approach because Muslim and SC segregation may have very different dynamics, causes, and consequences, suggesting that they should be considered separately. Tripartite segregation measures exist, but they do not describe the dynamics that we aim to explore here, as we are specifically interested in differences between SC and Muslim segregation. We conduct this pooling only when calculating segregation; when looking at access to public service and social group outcomes below, we always separate Muslims, SCs, and non-Muslim non-SCs.

For urban areas, we calculate dissimilarity and isolation for each city/town, defining enumeration blocks as neighborhoods. In rural areas, we calculate the indices for each subdistrict, again with enumeration blocks as neighborhoods.[20] Following convention in the U.S. segregation, we weight the indices across cities by each group's city or subdistrict population, providing an aggregate measure which reflects the experience of members of the marginalized group in question.

Measures of segregation can change depending on the level of aggregation used to define neighborhoods. To take an extreme example, if we defined a "neighborhood" as a single household, we would calculate a dissimilarity index close to 1, given the very high rates of caste and religious endogamy. Our analysis defines neighborhoods at the enumeration block level (i.e. units of about 125 households or 700 people), as these are the most accurate contiguous residential units that we can identify. This scale also fits our intuitive understanding of the set of households with which individuals will most often interact.

The scale-variance of the segregation indices means that a comparison with the United States — where census tracts have populations ranging from 1000 to 8000 and average around 4000

[20] A subdistrict consists of about 110 villages; there are about 5500 subdistricts in India. The rural measure thus captures a combination of segregation across villages and within villages.

— would be biased toward finding greater segregation in India. Therefore, when we benchmark our segregation measures against the United States (and at no other place in the paper), we aggregate enumeration blocks based on their numeric identifiers to form neighborhoods of at least 4000 people.[21] While the level of the segregation index changes, except where noted, our comparative results are robust to aggregating neighborhoods to higher sizes.

4.2 Marginalized Group Shares and Neighborhood Public Services

Our second objective is to describe differences in access to public services between marginalized group and non-marginalized-group neighborhoods. We present the methods for the case of urban areas; the methods for rural areas are analogous.

Our main interest is in understanding how a fixed supply of public services is allocated across MG and non-MG neighborhoods within cities. We measure the allocation disparity with the following neighborhood-level regression:

$$SERVICE_{n,c} = \beta_c MG\_Share_{n,c} + \Omega_c + \boldsymbol{\nu} POPULATION_{n,c} + \epsilon_{n,c}, \tag{3}$$

where $SERVICE_{n,c}$ is a measure of the supply or availability of public services in neighborhood n and city c, e.g. an indicator for the presence of a secondary school, and $MG\_Share_{n,c}$ is the marginalized group share. We include a control for neighborhood population, since it could be mechanically related to the supply of public services (though most neighborhoods are similarly populated). We include a city fixed effect Ω_c, which controls for differences in the availability of public services in cities with more or fewer members of marginalized groups.[22]

The coefficient β_c describes how service availability changes as the marginalized group share

[21] In the handful of cities where we have enumeration block maps or neighborhood names, we confirm that adjoining enumeration blocks are almost always adjoining in geography. Aggregating to 4000-person units based on block number inevitably adds a small amount of noise to the neighborhood definition, which is why we use the disaggregated neighborhoods for everything except the U.S. comparison. Note that the U.S. Census defines neighborhoods according to existing informal boundaries, which are more likely to divide racial groups, overstating segregation relative to an approach studying random geographic units. Replicating this approach in India is not possible given the data available. As a result, the U.S. segregation measures may be biased upward relative to those in India.

[22] Standard errors are clustered at the city level in the urban analysis and at the subdistrict level in the rural analysis, to account for correlated outcomes within regions.

increases. A negative estimate indicates that neighborhoods with more members of marginalized groups receive fewer services. We use the subscript c, because this measure describes a characteristic of the political economy equilibrium in each *city*. For each service, we first show the non-parametric relationship between availability and the MG share, and then summarize it with the linear estimate from Equation 3.

We then turn to estimating disparities at higher levels of aggregation. If we estimate Equation 3, but replace the city fixed effect with a *district* fixed effect (Ω_d), the coefficient on $MG\_SHARE_{n,c}$ will describe the allocation of services as a function of the neighborhood MG share, controlling for the availability of services in the *district*; we call this β_d. This measure describes a combination of (1) the allocation of services across towns within districts; and (2) the allocation of services across neighborhoods within towns. It is therefore useful to define $\alpha_d = \beta_d - \beta_c$, which specifically identifies the component of service access which comes from variation *within* districts and across towns.[23] We call this α_d because it describes the political economy equilibrium of the district — the outcome of the process by which public services are allocated within the district.

We repeat this process at progressively higher scales. Equation 3 with state fixed effects gives us $\alpha_s = \beta_s - \beta_d$, and the same equation with no fixed effects gives us $\alpha_f = \beta_o - \beta_s$.[24] With no fixed effects, Equation 3 describes the disparity in service access actually experienced by people living in marginalized group neighborhoods. This outcome arises from an additive combination of political economy processes at different scales of geography and government, such that $\beta_o = \alpha_f + \alpha_s + \alpha_d + \alpha_c$.

All of the α terms are independently interesting, as they describe the allocation process at different scales of geography and government, where different forces apply. For example, if a state explicitly allocates services to districts with higher Scheduled Caste shares, this would

[23] One could estimate a similar parameter directly in a town-level regression with district fixed effects. The advantage of our approach is that our estimates are additive across geographic levels. The approach is similar to the Blinder-Oaxaca decomposition, but with a disparity measured as a regression coefficient, and where the covariates are hierarchical locations.

[24] We use subscript "f" because α_f describes the federal (i.e. cross-state) political economy equilibrium, and we use the subscript "o" to denote the estimate from Equation 3 with no fixed effects.

suggest a positive value of α_s.

The decomposition also has implications for progressive policy. For example, suppose that α_c is highly negative (i.e. marginalized group neighborhoods have worse services, conditional on city fixed effects). In this case, the disparity can be reduced through policies that increase α^S (e.g. through affirmative action programs operating across districts), but these district-level transfers will be less efficient at reducing disparities than neighborhood-level transfers (which would reduce α_c directly).

Identifying the geographic scale of disparity is particularly relevant given the very different nature of the institutions governing the allocation of public services at different levels of aggregation, as described in Section 2. In particular, most policy research in India operates at the district level, as do many programs which determine the allocation of public services. High level policy-makers and researchers may not have access to systematic data describing the political economy processes at the local level, causing them to misunderstand the nature of inequality. Our decomposition clarifies what information is lost by studying differences at aggregate levels. If we studied only the relationship between marginalized group share and public service outcomes at the district level, we would be measuring $\alpha_f + \alpha_s$, which may be a biased measure of β_o if local disparities are large.

The estimations described here do not isolate a causal effect of marginal group share on outcomes. For example, if marginalized groups are poor, and municipal governments undersupply public facilities to poor neighborhoods, then we would find $\beta_c < 0$ even if service provision was orthogonal to MG status, conditional on neighborhood income. In this case, MGs would still have worse access to public services—the outcome that we aim to measure.[25] Our null hypothesis is that the government allocates public facilities across neighborhoods equally, irrespective of neighborhood economic or social group status, in which case we would find $\beta_c = 0$.

We can think of the α terms as allocation rules; they describe the de facto outcomes of the allocation process at different geographic levels. For example, α_d can be thought of as the

[25] We do not necessarily get closer to causal identification by adding control variables for neighborhood average education or consumption, because these outcomes are plausibly caused by a shortage of public services.

district allocation rule, which describes how a district's resources are allocated across towns in that district. These "rules" are outcomes of a complex and obscure political economy process that is a function of decisions by politicians, bureaucrats, firms, and citizens. These "rules" are outcomes not only of the public service allocation process, but also of the decision choices of individuals. They are statistics that describe the entire political economy equilibrium. A negative α could reflect government discrimination, or it could reflect historical inequalities that make marginalized groups poorer and more likely to select into neighborhoods with worse public services. It describes the equilibrium inequality in public service allocation at one level of governance, but does not attribute it to a specific policy or actor.

4.3 Marginalized Group Shares and Living Standards

Disparities in access to public services in marginalized group neighborhoods are most concerning if they result in unequal outcomes for people living in those neighborhoods, as they can entrench inequality across groups. But if people in under-serviced neighborhoods can compensate by traveling to other neighborhoods for services or by consuming private services, then unequal allocation may be less harmful. The final part of our analysis therefore examines whether individuals experience worse outcomes in MG neighborhoods.

We use the following equation to examine the relationship between neighborhood MG share and the young generation's educational outcomes:

$$ED_{i,n,c} = \beta_1 MG\_Share_{n,c} + \beta_2 MG_i + \Omega_c + \boldsymbol{\nu} \boldsymbol{X}_{i,n,c} + \epsilon_{i,n,c}. \tag{4}$$

The outcome is the number of years of education of individual i in neighborhood n and city c. As above, $MG\_share_{n,c}$ is the marginalized group share of the neighborhood, and MG_i is an indicator for whether individual i is in the marginalized group. We estimate the regression with both marginalized group indicators and neighborhood measures (SC and Muslim) included simultaneously. The sample consists of men and women aged 17–18. We show unadjusted estimates, as well as estimates controlling for parent education and household consumption.

The analysis is descriptive, and is only suggestive of the causal relationship between neighborhood and child outcomes for several reasons. First, we do not know individuals' place of birth. We focus on young people, and test robustness by looking at younger respondents (who are very likely to still live with parents), but we do not have the data to exclude recent migrants from the sample. More importantly, there may be unobserved characteristics of households which cause them to have worse outcomes and also choose to live in neighborhoods with other minorities.

Nevertheless, these results tell us the extent to which children growing up in MG neighborhoods are getting the human capital investments necessary for them to have opportunities for future socioeconomic success. We discuss the appropriate interpretation of the controlled and uncontrolled estimates of β_1 with the results in Section 5.4.

5 Results

5.1 Segregation in Indian Villages and Cities

Table 1 presents summary statistics of the neighborhood-level sample, separately for urban and rural neighborhoods. Both rural and urban neighborhoods have about 500 people each; there are about 1.1 million rural neighborhoods and 400,000 urban neighborhoods in the sample. The difference in sample size reflects India's low urbanization rate (31% in 2011), slightly magnified by our worse sample coverage of urban places. Scheduled Castes are more likely to live in rural areas, while Muslims are more likely to live in towns and cities.

Table 2 similarly describes the data at a higher level of aggregation: the town or city for urban areas, and the subdistrict for rural. The table compares our sample characteristics with the full set of towns and villages in the Population Census. In rural areas, our sample is highly representative, and covers 81% of rural subdistricts and 84% of rural people. In urban areas, we have higher sample coverage of larger cities (which are also older); smaller and more recent cities were less likely to have data posted by the SECC, making information about their residential composition unavailable.[26] Towns excluded from our sample have slightly fewer public services,

[26]The table does not show the public infrastructure measured in the SECC, because we don't observe these out of sample or in rural areas.

but similar marginalized group shares. While not totally representative, our urban sample covers 48% of towns and 77% of India's urban population.

Differences in segregation across the two groups are not captured in a single dimension. Measured by the dissimilarity index (Panels A and B), Scheduled Castes are more segregated than Muslims in both rural and urban areas (Table 2). By the isolation index (Panels C and D), Muslims are more segregated in urban areas. Figure 1 shows the distribution of these measures across cities and rural subdistricts, which shows thpat Muslims are relatively more segregated in cities by both measures.

Appendix Figure A.3 helps to unpack these differences by showing the distribution of MG shares across neighborhoods. The Muslim distribution is notably bimodal, in both urban and rural areas. SCs are more integrated on average, but a greater share of Muslims live in the most segregated neighborhoods. 26% of urban Muslims live in neighborhoods that are >80% Muslim, while 17% of urban SCs live in neighorhoods that are >80% SC.[27]

It is useful to benchmark the segregation measures against those in MSAs in the United States, where segregation has been most studied. To match the definitions used by the U.S. Census, we aggregate neighborhoods to populations of at least 4000 people (as described in Section 4), and we limit our sample to cities with more than 100,000 people. Appendix Figure A.4 shows the density functions of dissimilarity and isolation across cities. Using the 700 people per neighborhood definition in India, Muslims are systematically more segregated than U.S. Blacks, while for SCs it depends on the measure of segregation. Using the 4000 people per neighborhood definition, the distribution of U.S. Black segregation looks very close to that of Muslims. The first measure biases Indian segregation upward relative to U.S. segregation (because of the smaller neighborhood size), while the second biases Indian segregation downward (because of measurement error in neighborhood pooling). By both measures, we can conclude that segregation in India, particularly of Muslims, is comparable in magnitude to that of modern U.S. Blacks.[28]

[27] In cities, the median Muslim lives in a neighborhood that is 47% Muslim. In rural areas, this is 37%. For SCs, these numbers are 38% and 46%, almost exactly the reverse.

[28] Note, however, that this is a considerably lower level of segregation than peak U.S. segregation in the 1960s and 1970s, when the weighted dissimilarity index across U.S. MSAs was close to 80, compared with

Figure 2 shows maps of SC and Muslim segregation across the country. While there are pockets of high and low segregation, they do not follow obvious geographic patterns; the north, which is poorer and where people are less disposed toward cross-caste marriage,[29] is no less segregated than the south.

We next examine whether rural segregation patterns are being replicated in cities. Given India's rapid urbanization in the second half of the twentieth century, settlement patterns in cities reflect more recent decisions and norms around integration and separation of social groups. Panel A of Figure 3 plots the average urban Muslim dissimilarity index in each district, as a function of the rural Muslim dissimilarity index in the same district. The urban and rural dissimilarity indices are very highly correlated ($\rho = 0.56$), suggesting that the regional dynamics that lead to the separation of social groups in rural areas are also important in cities and towns. Panel B of the same figure shows that segregation patterns of Scheduled Castes are also highly correlated across urban and rural spaces, but less so than for Muslims ($\rho = 0.43$).

We can shed light on how national segregation patterns change over time by comparing recently urbanized places with more established settlements. Table 3 shows results from town-level regressions of Muslim and SC dissimilarity on the decade that a town or city first appeared as a town in the Population Census.[30] To account for the fact that our sample underrepresents the smallest and youngest towns, we also present results with controls for population and group shares.

SC and Muslim dissimilarity are systematically and substantially lower in younger towns. A town that is 100 years older has a dissimilarity index which is 0.09 points lower for Muslims and 0.07 points lower for SCs. This change represents about a 0.5 standard deviation change in the cross-town distribution of dissimilarity indices, or a change from the median to the 25th least segregated Indian city. The city age effect is robust to the inclusion of additional town-level covariates. Appendix Figure A.5 shows that the dissimilarity difference between young and old towns is largely stable across settlements with different population size; it is not a mechanical

60 in the 2020 U.S. Census (**?**).

[29] See, for example, **?**.

[30] The Census classifies a settlement as a town once it has more than 5000 people, an agricultural labor share (among men) below 25%, and a population density of at least 400 person per square kilometer.

function of size.

This result can be interpreted in one of two ways. First, segregation could be falling over time, in the sense that newly settled cities develop less segregated neighborhood patterns than cities settled in the past. Second, cities themselves could become more segregated over time: as cities age, marginalized group neighborhoods could coalesce and absorb more group members. Without a time series, it is difficult to distinguish between these two stories, but the data are clear that the aggregate pattern of segregation has changed substantially over time.

5.2 Access to Public Services in Marginalized Group Neighborhoods

The previous section established that many members of marginalized groups live in concentrated neighborhoods, and that urban places are replicating the segregation of their hinterlands. In this section, we examine how the supply of public services varies across neighborhoods with and without concentrated marginalized groups. We focus on availability of public services at the most granular geographic level—the neighborhood—because it is the most relevant for individual access to services, and is also the least studied in prior work.

Figure 4 shows a binned scatterplot of the neighborhood-level relationship between the supply of secondary schools (an indicator for the presence of a neighborhood school) and the neighborhood marginalized group share, for each group, in both urban and rural areas. The urban series is residualized on city fixed effects and thus describes how schools are distributed across neighborhoods, conditional on the total supply of schools in a city. Secondary school availability falls monotonically with the neighborhood Muslim share (Panel A); raising the Muslim share of a neighborhood by 50 percentage points is associated with a 22% lower likelihood of the neighborhood having a public secondary school (approximately a 0.5 percentage point decline on a mean of 2.4%). Neighborhoods with a >50% Muslim share stand out for being particularly underprovisioned; there are not so many of these neighborhoods in India, but as shown in Appendix Figure A.3, a large share of Muslims live in them. Rural locations look broadly similar, with the most Muslim neighborhoods having substantially fewer schools (Panel C).

The relationship between Scheduled Caste share and secondary school access is non-monotonic

in both urban and rural areas; at low levels of SC shares, it is flat or rising in the SC share, but above a 20% SC share, secondary school presence falls precipitously, such that 50% SC neighborhoods have similar school availability to 50% Muslim neighborhoods (Panels B and D).[31]

We summarize this nonparametric relationship between neighborhood MG share and public facility presence with a linear regression of facility presence on the group shares and city fixed effects, for each type of facility that we can measure (Equation 3). SC and Muslim shares are included simultaneously to ensure that the allocation of facilities to one group's neighborhoods does not drive our estimate for the other group. Panel A of Table 4 shows that, in urban areas, SC and Muslim neighborhoods are systematically allocated fewer public services; with the exception of urban primary schools in SC neighborhoods, the point estimates are all negative, substantial, and highly significant. In rural areas (Panel B), the estimates are negative and significant for all facilities, for both groups. In short, the urban political economy equilibrium systematically results in marginalized groups living in neighborhoods that are less well-served by public facilities.[32]

Table 5 tests whether private schools and clinics substitute for the absence of public sector facilities. In fact, private facilities are also disproportionately allocated away from marginalized group neighborhoods, presumably because people in those neighborhoods have limited ability to pay for services. There are some exceptions: out of 12 group * urban/rural * facility estimates, 10 show statistically and economically significant allocation away from MG neighborhoods, but private primary schools and health facilities are more common in rural Muslim neighborhoods (but not urban).[33]

We find similar results for household infrastructure services (access to electricity, closed drainage, and clean water) (Table 6). These services are only measured in urban areas. All three services are systematically less available in both Muslim and Scheduled Caste neighborhoods.

[31]Rural school shares are higher on average because rural areas are characterized by a greater number of smaller schools, reflecting the greater distance between neighborhoods. The relationship looks very similar with a continuous measure of school size (total employment in the school) as an outcome (Appendix Figure A.6).

[32]Results are similar when we use a measure of the scale of the facilities (log employment, shown in the even-numbered table columns). Results are virtually unchanged (i) by the inclusion of a control for whether a neighborhood is classified as a slum; and (ii) by restricting the sample to non-slum villages (Appendix Table A.1).

[33]Note that the public facility results are not adequately explained by marginalized groups being poorer — since the role of government is ostensibly to provide equal access to public services whether people are rich or poor.

For these infrastructure goods, the coefficients on the SC share are more negative than those on the Muslim share, suggesting that SC neighborhoods are the most poorly served by public infrastructure.[34]

For some of these services, chiefly schools and clinics in urban areas, people can walk to a facility in a nearby neighborhood, mitigating the cost of not having a facility in one's own neighborhood. However in rural areas, the nearest facility outside the "neighborhood" can be quite far away. For the infrastructure goods, substitutes in nearby neighborhoods (e.g. for clean water) clearly imply substantial welfare costs.[35]

5.3 Access Disparities at Different Geographic Levels of Aggregation

So far, we have found that public services are systematically allocated away from marginalized group neighborhoods at the most local level. However, this disparity does not summarize the total access disparity faced by marginalized groups, because there could be favorable or unfavorable differences in the supply of services at higher geographic levels of aggregation. For instance, districts with more Scheduled Castes might have more schools or better sanitation infrastructure; indeed, the Indian government has used the district or subdistrict Scheduled Caste share as a targeting mechanism for many programs (see Section 2).

We measure allocation at each geographic level of aggregation by varying the fixed effects in Equation 3. As described in Section 4, we can thus additively decompose the total urban access disparity into a disparity across neighborhoods, towns, districts, and states.

Panel A of Figure 5 summarizes the results for Muslim access to urban primary schools. We take some time to explain these figures as they describe a central result of this paper. The outcome variable is the number of primary schools per 100,000 people; the sample mean of

[34]Note that these infrastructure services are not strictly public. They typically require some kind of household investment in addition to a base level of public infrastructure, but none of them can be accessed if that public infrastructure is not in place. Our estimations are run at the neighborhood level, and thus do not identify off of within-neighborhood differences in whether members of different social groups choose whether or not to hook up to each infrastructure service. Indeed, the distributions of neighborhood availability of these services are highly bimodal, suggesting that the public component of the infrastructure is a key determinant of individual access.

[35]Because we only have GIS locations for neighborhoods in a handful of places, it is not possible to run a test with the textitdistance to the nearest neighborhood with a facility.

this variable is 15. The rightmost (dark gray) box (positioned at -1.9) tells us that a 100% Muslim neighborhood is estimated to have 1.9 fewer primary schools per 100,000 people than a 0% Muslim neighborhood.[36] This is simply the coefficient from a regression of the primary school indicator on the neighborhood Muslim share, with no fixed effects (β_o from Section 4.2). This coefficient reflects the access disparity in Muslim neighborhoods; it implies that a 100% Muslim neighborhood is expected to have 1.9 fewer primary schools per 100,000 people.

This gap can then be decomposed into the different levels of geographic aggregation at which it appears. The leftmost estimate $\alpha^f = -0.4$ tells us that states with more Muslims have fewer schools, and that 0.4 out of the 1.9 gap above can be accounted for by this variation across states. The second estimate from the left ($\alpha^S = +1.1$) implies that — conditional on the number of primary schools in a state — districts with more Muslims on average have *more* primary schools.[37] The next two bars respectively give us α^D, which tells us how schools are allocated across towns/cities within districts, and α^C, which tells us how schools are allocated across neighborhoods within towns — the latter being exactly the estimates from the previous subsection (5.2).

The sum of all the α coefficients gives us the final estimate of -1.9; the graph makes clear that the neighborhood disadvantage faced by Muslims is driven almost entirely by the allocation of primary schools across urban neighborhoods within towns. In fact the allocation combining all aggregates *higher* than the town level is marginally favorable to Muslims; but this small advantage is swamped by the unfavorable allocation across neighborhoods.

The remaining five panels of Figure 5 show how the other public facilities (secondary schools and health centers) are allocated across Muslim and non-Muslim neighborhoods, towns, districts, and states. We highlight several features of the combined results. First, the cross-neighborhood allocation (labeled "x-block") is systematically unfavorable for Muslims — again, these bars are just the graphical representations of the estimates in Table 4. Second, in urban areas, the magnitude of the cross-neighborhood inequality swamps the magnitude of the inequality

[36] The sample means for the other variables are in the figure note.

[37] We denote this α^S because it is informative about allocation choices at the *state government* level — it describes how schools are allocated across districts within states.

at every other level of aggregation. It is at the lowest and most informal level of governance where Muslim neighborhoods are the most left out. In rural areas, allocation is unfavorable at every level of aggregation for all three facility types, and the impact is more uniform across geographic scales. Third, without neighborhood level data, we would detect no disadvantage in access to public facilities for Muslims in cities, and we would substantially underestimate the disadvantage in rural areas. Since the Indian government does not release data on Muslim shares below the subdistrict level, about half of the rural inequality in service access is invisible in the data available prior to this paper, as is all of the urban inequality.

Figure 6 shows the same results for SC neighborhoods. The patterns are distinct from those observed for Muslims, even though both groups face substantial disadvantages at the most local level. A clear pattern emerges for secondary schools and health centers, in both rural and urban areas (Panels C–F). The allocation of these services is progressive across states, districts, towns, and villages; at all of these levels, areas with more SCs have more secondary schools and clinics. But *within* towns and villages, the distribution of schools and clinics is highly regressive across neighborhoods, undoing almost all of the progressivity at higher levels of government. Ignoring the cross-neighborhood allocation of secondary schools and clinics (which no prior data source has made visible) would make it appear that public services are strongly favorably targeted to places where SCs live, but in fact the allocation is approximately neutral.

The allocation of primary schools to SC neighborhoods does not follow this pattern. Urban primary schools have progressive allocations for SCs at all levels of aggregation, while the allocation of rural primary schools is unfavorable to SCs at all geographic levels, but with the neighborhood being relatively unimportant. This distinct result could arise from the government's efforts to make primary schools universal across India, though clearly Muslim neighborhoods have been left out. The neutral to positive neighborhood allocation of primary schools could possibly result from an interaction of that universal goal with a preference for segregating upper class children from SC children, but this is left as a topic for future work.

The previous section showed that the cross-neighborhood allocation of public facilities was

more unfavorable to Muslims than to SCs. This section shows that this is even more true across larger geographic units; the effects combine to make Muslim neighborhoods severely lacking in public facilities, while SC neighborhoods in the end have similar service levels to non-SC neighborhoods — the latter result arises from favorable allocation across large geographic units but unfavorable allocation across neighborhoods.

Patterns like these could arise if affirmative action policies for Scheduled Castes (which have been prominent in India since independence) primarily affect the distribution of public services across higher units of aggregation, like states and districts. If these policies bind only at high levels of aggregation, and the less formal political processes of neighborhoods and municipal governments remain biased, then the cross-neighborhood allocation of services can undo some of the progressive allocation at higher levels of government. Muslims face the same or worse disadvantages as Scheduled Castes at the cross-neighborhood level, but with no systematic policy of affirmative action, there is no force to mitigate those disadvantages and they end up substantially less well-served.

Figure 7 shows the same analysis for the infrastructure services: electric lighting, piped water, and closed drainage. For SCs, the cross-neighborhood variation in access drives almost all of the substantial access disparity, and there is little association between the SC share and infrastructure availability at the state, district, or town level. For Muslims, at the state and district levels, we find that piped water access is more common in districts with many Muslims, while electric light and drainage are less common. As noted above, the allocation across neighborhoods is economically significant and adverse for all of these services, for both groups.

For the infrastructure services, there is thus less systematic evidence of affirmative action in favor of any marginalized group, but both groups systematically fare worse at the neighborhood level. Indeed, we are aware of no national programs to improve urban infrastructure services like these or to equalize access to them. It is also notable that the relative access of the two groups is reversed for the infrastructure services; at both the cross-neighborhood and the overall level, Scheduled Castes neighborhoods have disproportionately worse access to water, electricity, and

sewerage infrastructure than Muslims.[38]

5.4 Outcomes for Marginalized Groups in Segregated Neighborhoods

Marginalized group neighborhoods are underserved with public facilities and infrastructure. How does this affect the well-being of people who live in these neighborhoods? This section examines the relationship between the educational outcomes of young people and the marginalized group share in the neighborhoods where they live. We use Equation 4, which describes a regression of individual years of education on neighborhood marginalized group shares, for individuals aged 17–18 years.

The evidence here is descriptive: raw differences in outcomes across neighborhoods reflect some combination of discrimination and preferences of those who live there. Controlling for individual and neighborhood characteristics is useful descriptively, but it does not necessarily improve the identification of discrimination, because those control variables may themselves be the result of discrimination. The empirical challenge is analogous to that of measuring gender discrimination in wages, where it is useful to know both the unadjusted gender wage gap and the wage gap controlling for job characteristics, but neither of these measures is sufficient proof of discrimination.

Table 7 shows the results for urban places; the outcome variable is years of education. We control for town/city fixed effects; the results are strictly across neighborhoods within cities. We also control for whether the individual is a Muslim or member of a Scheduled Caste. The ideal sample would be a set of people who grew up in the neighborhood and had completed their education. The best we can do is to focus on individuals aged 17–18 years old, though clearly some of them fail to meet both of these criteria, as we discuss below.

Column 1 shows the results for men aged 17–18, with only the household SC and Muslim indicators and town fixed effects; this shows the average difference between SC, Muslim, and non-SC non-Muslim outcomes, conditioning on town of residence. SCs have 1.1 fewer years of education than non-SC non-Muslims, and Muslims have 1.3 years fewer. Column 2 adds the

[38] Appendix Figures A.7 and A.8 shows similar estimates to Figures 6 and 7 for private facilities. We spend less attention on these since there are no political forces driving their allocation at higher levels of aggregation.

neighborhood shares. Including the neighborbood share drives down the coefficient on the SC indicator by 45%, and on the Muslim indicator by 55% — about half of the disadvantage faced by marginalized groups is explained just by the marginalized group share of their neighborhood. We focus on the coefficient on the neighborhood marginalized group shares going forward.

Still looking at Column 2, controlling only for the town fixed effects and the household SC and Muslim indicators, we see that Muslim and SC neighborhoods have significantly worse educational outcomes. 17–18-year-olds living in a 100% Muslim neighborhoods have 2.1 fewer years of education than those in 0% Muslim neighborhoods; the coefficient for Scheduled Caste neighborhoods is −1.6.

In Column 3, we add controls for both parents' years of education and household consumption. Unsurprisingly, all these controls are positively correlated with individual outcomes in the expected direction, and the inclusion of these controls brings down the magnitude of the coefficients on both of the neighborhood marginalized group shares.[39] The coefficient on the SC share is driven close to zero in the specification with all controls, while the coefficient on the neighborhood Muslim share falls to less than half of its value in the unadjusted Column 2. The effect sizes have similar orders of magnitudes for members of marginalized and non-marginalized groups (Appendix Table A.2). Living in a marginalized group neighborhood is associated with much worse outcomes regardless of an individual's identity.

We interpret these results as follows. Young people in SC neighborhoods have systematically worse outcomes than those in non-SC neighborhoods — but the difference is mostly explained by the economic status of their families. This does not rule out a negative causal effect of growing up in an SC neighborhood on child outcomes, because those parent outcomes could themselves be caused by living in a bad neighborhood. For example, parents might invest less in their house (lowering the value of the consumption control) if they lack security of tenure.[40]

[39]The additional inclusion of the mean neighborhood income has little effect beyond the individual consumption measures.

[40]The result is analogous to finding that a gender wage gap goes to zero if occupation, job description and job rank are controlled for — a result that does not disprove discrimination, since discrimination could result in different occupations and job ranks and descriptions.

In Muslim neighborhoods, outcomes for young people are equally poor, but can be only partially explained by parent consumption and education. Children in these neighborhoods grow up in families with fewer resources, and yet have even worse outcomes (about 1 year lesser in a 100% Muslim neighborhood) than similarly poor children in non-Muslim neighborhoods. Again, this is a function of the neighborhood, not of the social group of the individual, as it holds for members of all social groups.

Table 8 shows the same results for rural areas, with results separated by social group in Appendix Table A.3; the results for Muslims are broadly similar. As in urban areas, young rural people in neighborhoods with high Muslim shares end up with substantially less education than those living in non-Muslim, non-SC neighborhoods. Rural SC neighborhoods do not show the same disadvantages; the coefficient on the SC share is close to zero, and even marginally positive for young women.[41]

A limitation of these findings is that we do not observe individuals' places of birth, so the results here in part could be driven by less-educated 17- and 18-year-olds moving into neighborhoods with high marginalized group shares. We can show, however, that these results hold for children at all ages, including those arguably too young to be responsible for their own migration choices (see Appendix Tables A.4 and A.5).

These results suggest that marginalized group neighborhoods and the disadvantages associated with living in them reduce access to opportunity for people who grow up there. Our data does not allow us to calculate neighborhood exposure effects, as in Chetty and Hendren (2018) and Alesina et al. (2021), which would be even more dispositive; this is an important area for future research.

6 Conclusion

This paper describes a national-scale analysis of socio-economic outcomes and access to public services in India's urban and rural neighborhoods. Analysis of this kind has previously been im-

[41] Young women in 100% SC neighborhoods have on average 0.07 additional years of education; the effect is statistically significant, but economically small. Though in comparison with the other results in this paper, even a non-negative estimate here is notable.

possible on a large scale due to the absence of sufficient neighborhood-level data to characterize MG and non-MG neighborhoods.

India's growing cities are highly segregated. They are only marginally less segregated than rural areas, where neighborhood structure is strongly conditioned by centuries of occupation- and status-based division via the caste system. The religious and caste identity of the people who live in a given urban neighborhood are strongly predictive of both access to public services and of socioeconomic status in those neighborhoods. Both Muslims and Scheduled Castes are highly segregated, but Muslims experience much worse access to public services as a function of that segregation. India's rapidly growing cities, famous as engines of upward mobility, to a large degree have replicated the caste and religious structure of its villages.

Our research so far does not identify the causes of these disparities. However, discriminatory provision of public facilities to MG neighborhoods has a storied history in many countries, including in India. It is perhaps unsurprising to find it also existing at the neighborhood level, but the disproportionate disadvantage of Muslim neighborhoods, even relative to SC neighborhoods, is striking.

A limitation of our work is that it is based on cross-sectional data collected in 2012–13; it is challenge to document the time path of disparity. The historical literature suggests that Scheduled Castes have been isolated at the neighborhood level for generations, but Muslim isolation has been exacerbated by Hindu-Muslim violence in the post-colonial era. Data from historical censuses could potentially shed light on changes in residential segregation over time.

That living standards are so much lower in SC and Muslim enclaves suggests that, as elsewhere, spatial concentration of marginalized groups may limit their economic opportunities. Modern India has never had the government regulations, such as redlining, that contributed to racial segregation in the United States — there are thus fewer overtly harmful policies to remove. However, housing discrimination in India's cities is widely documented and has even been explicitly tolerated by the judiciary, echoing patterns from a too recent era in the U.S..

The historic tolerance for residential segregation and unequal access to public services has had

disastrous consequences for the United States; it has prevented generations of individuals from access to opportunity, and is a central fracture in a highly polarized political system. At an earlier stage of development and with cities still rapidly growing, India has the opportunity to make a different set of choices. By highlighting segregation in India and documenting the concomitant disparities in access to public services, we hope to draw attention to the critical choices ahead.

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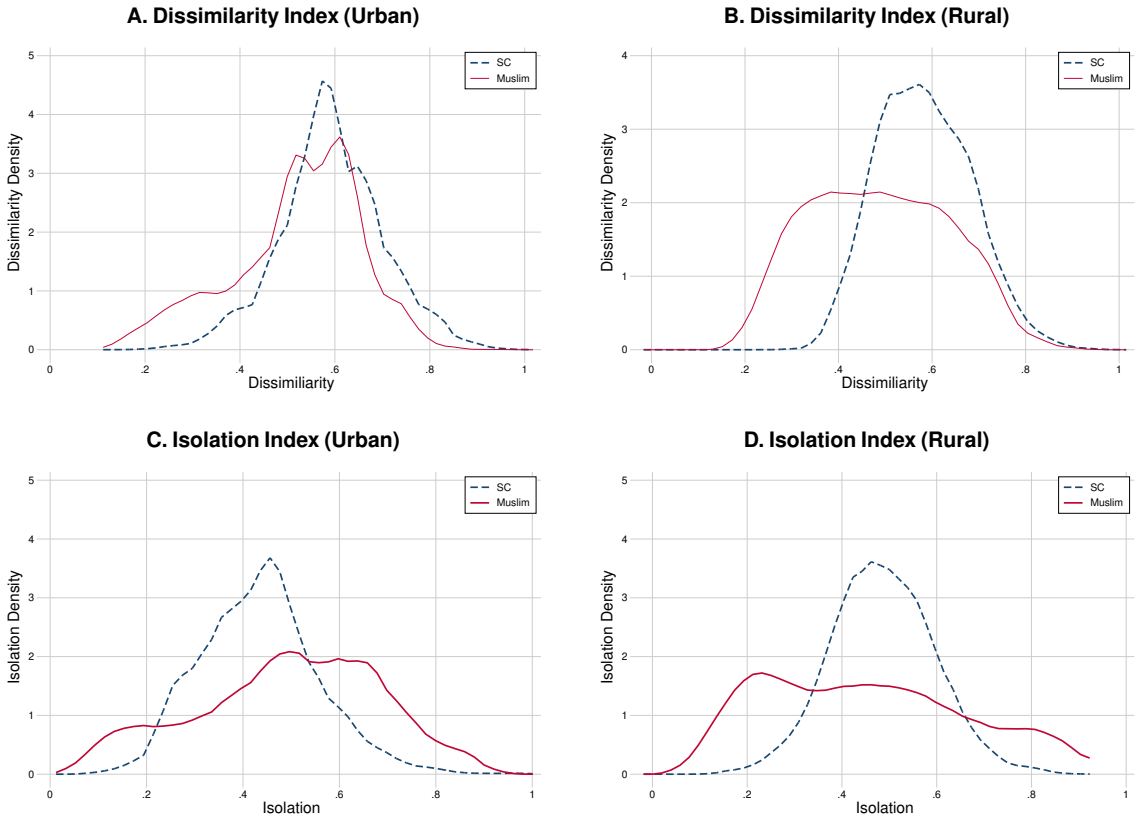
Figures

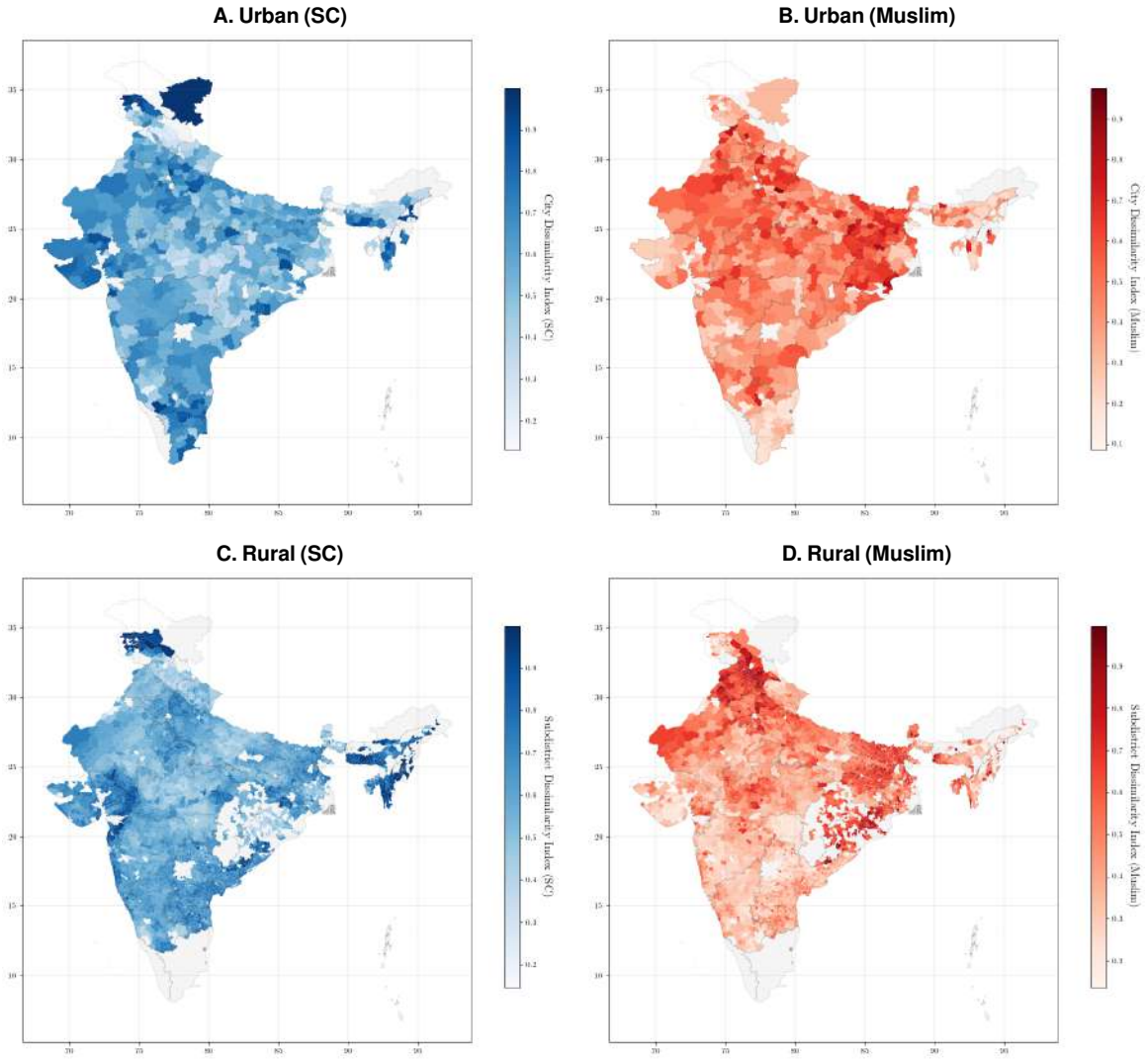
Figure 1

Distribution of Segregation of Muslims and Scheduled Castes



Notes: This figure shows the distribution of segregation across cities/towns (Panels A and C) and rural subdistricts (Panels B and D). Panels A and B show the dissimilarity index, while panels C and D show the isolation index. The SC density functions are weighted by each town/subdistrict's SC population, and the same for Muslims, such that each curve represents the experience of members of the marginalized group.

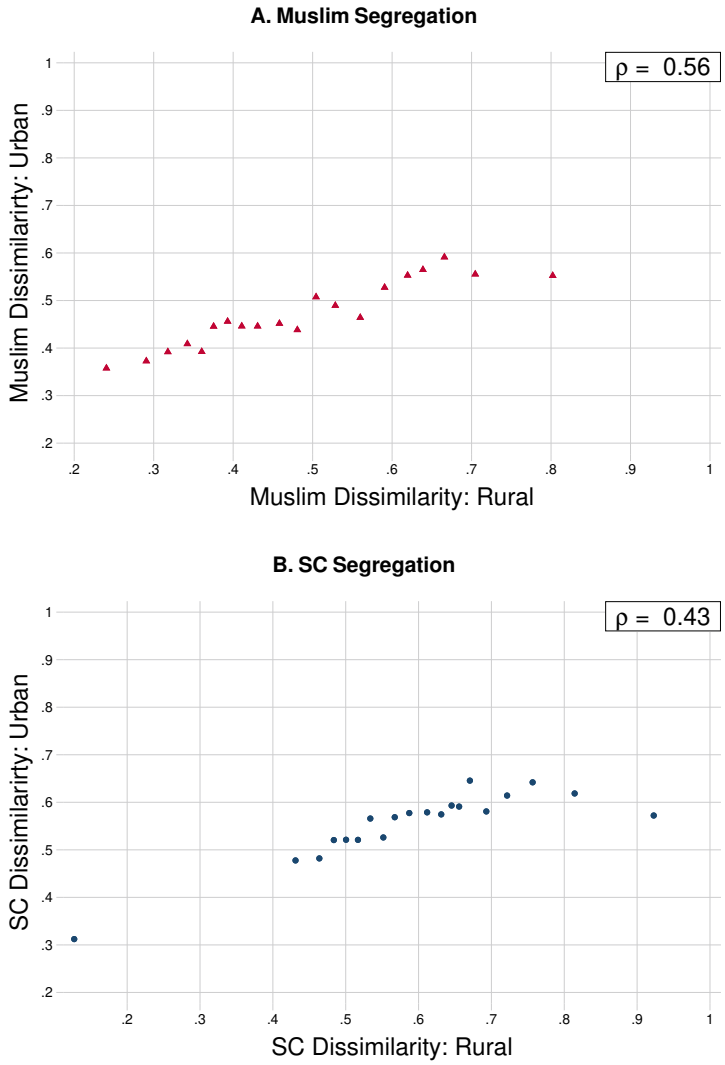
Figure 2
Segregation Maps



Notes: These maps show segregation across India. The top row presents heatmaps represent urban segregation, aggregated to the district-level for better visibility, for SCs (left) and muslims (right). The bottom row shows segregation for rural subdistricts.

Figure 3

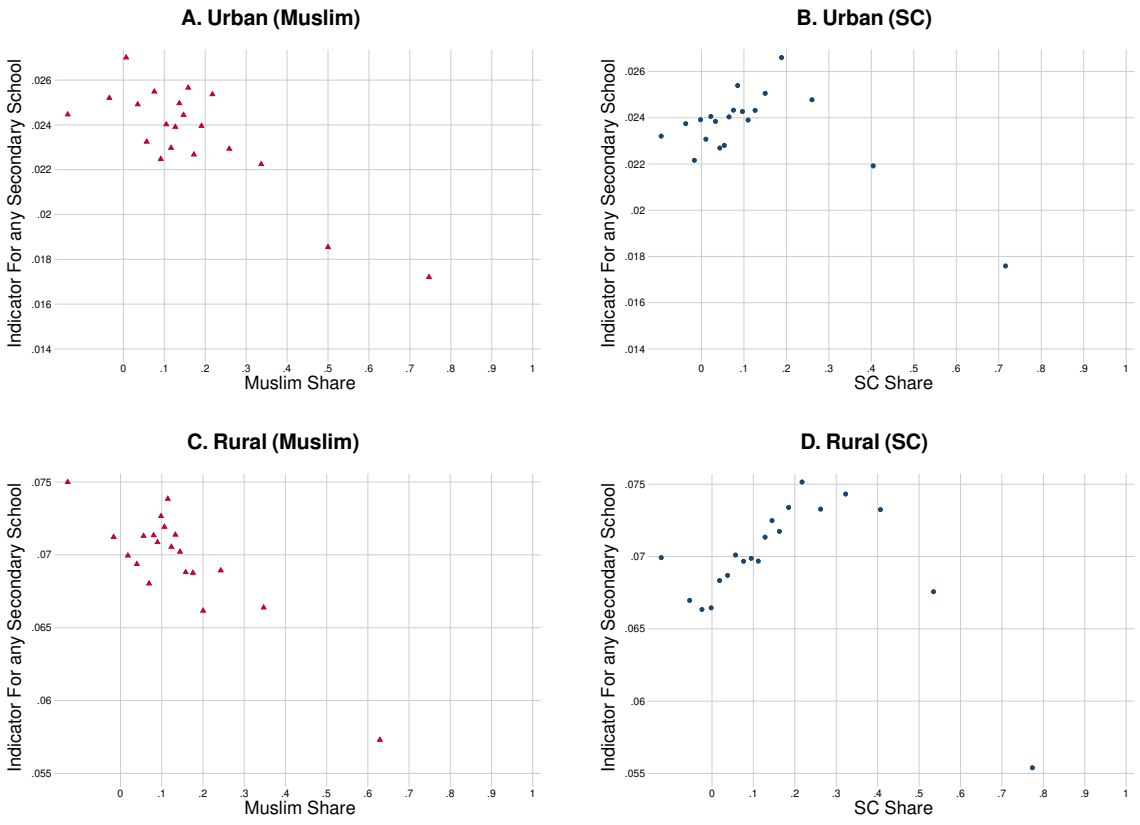
Urban vs Rural Segregation: District-level Comparisons



Notes: This figure shows a binscatter representing the district-level correlation between urban and rural segregation. It uses our standard dissimilarity measure of segregation at the town/subdistrict-level, but aggregated up to the district for comparison across urban and rural areas. Group shares and resultant dissimilarity indices come from the Socioeconomic and Caste Census.

Figure 4

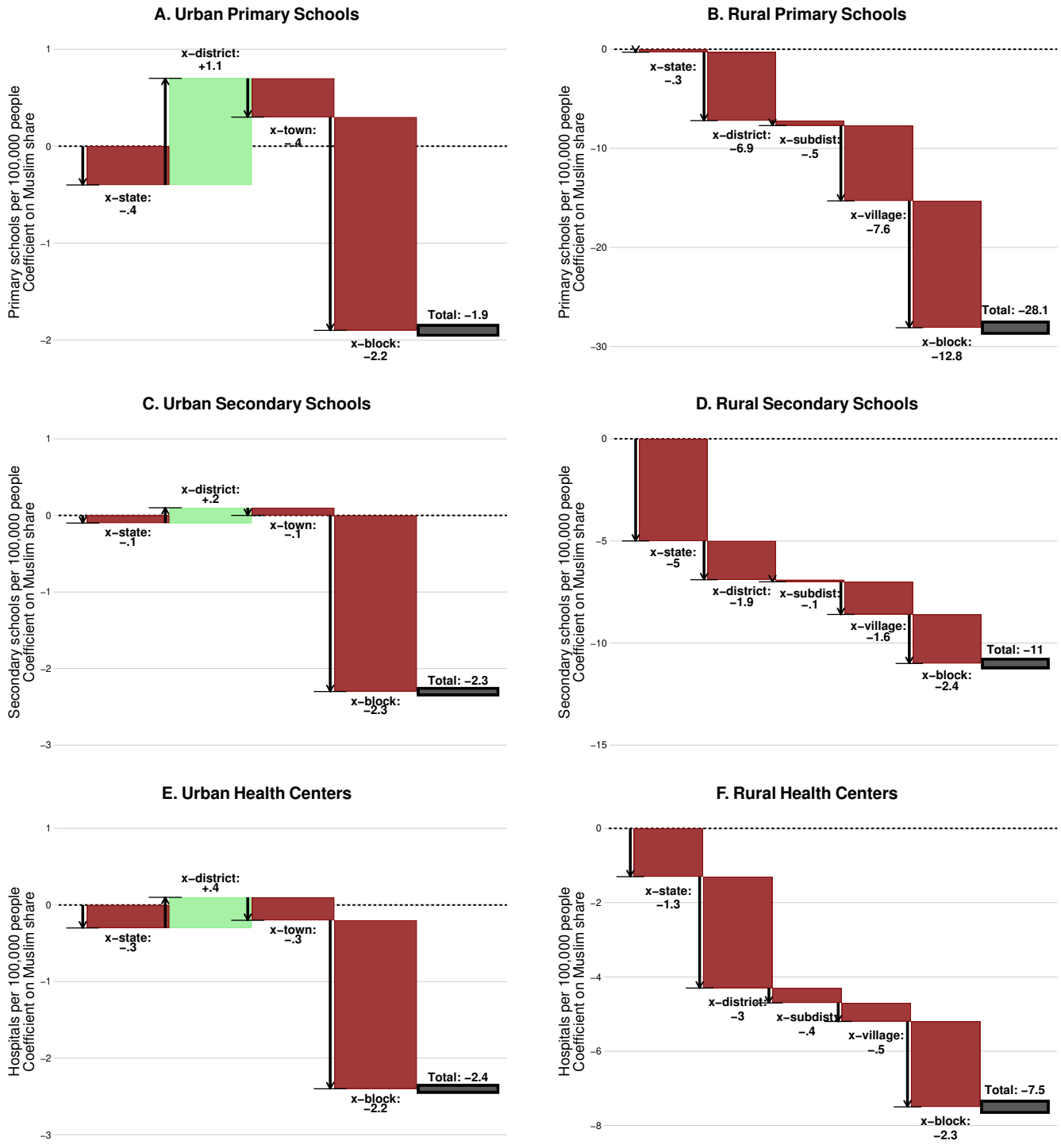
Access to Secondary Schools vs.
Neighborhood Marginalized Group Share



Notes: This figure shows binscatter plots of the percentage of neighborhoods that have a secondary school at a given level of SC/Muslim share. The data on public facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure 5

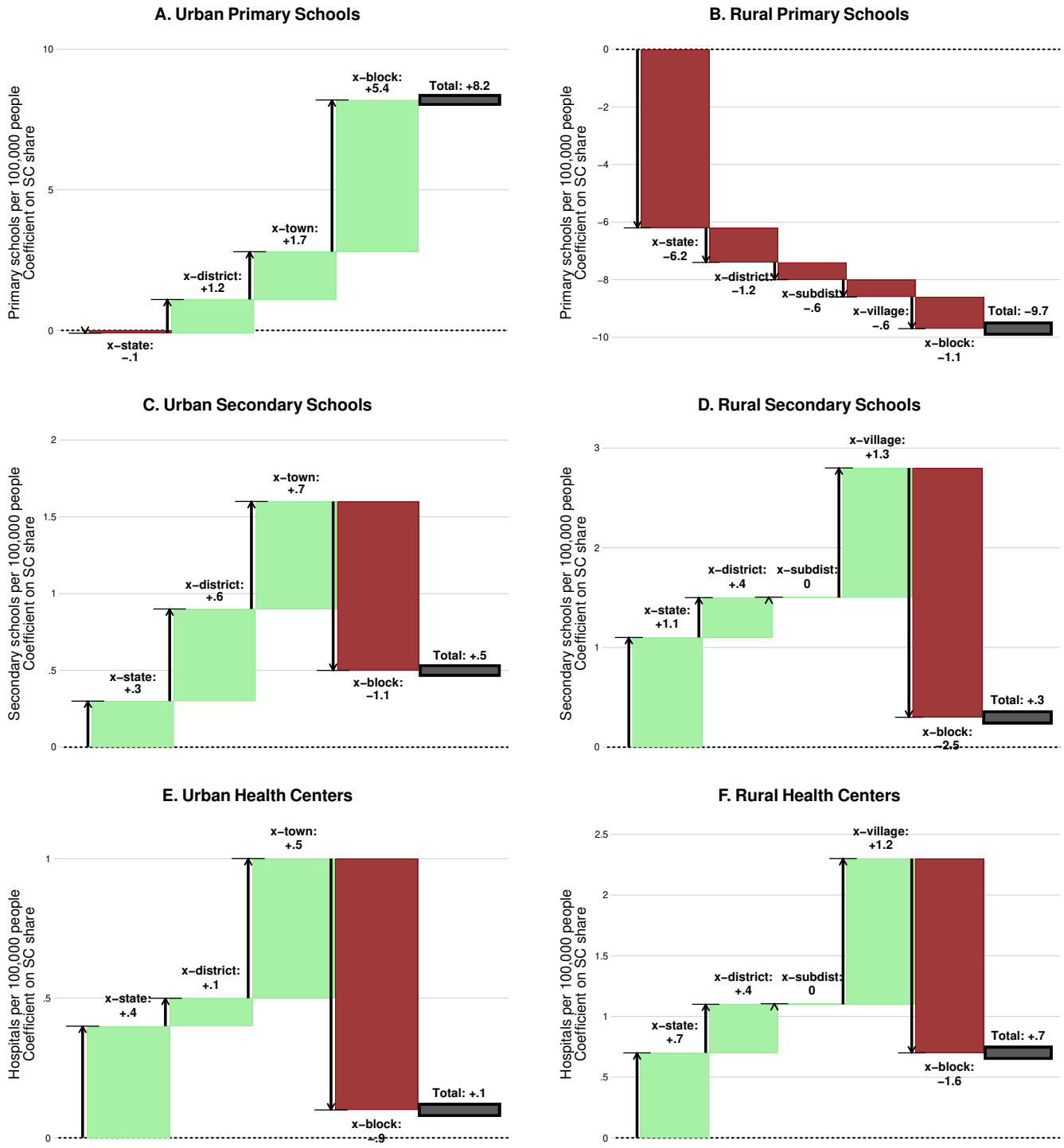
Disparities in Public Facilities as a Function of Muslim Share



Notes: This figure describes the cross-neighborhood relationship between a neighborhood's Muslim share and a neighborhood's access to public facilities: primary and secondary schools, and health centers. The dark gray box shows the coefficient of a regression of a public facility indicator on the Muslim share. The boxes to the left decompose that average effect into the effect arising at the cross-state, cross-district, cross-town/village, and cross-block levels. The outcome is the number of facilities per 100,000 people. The mean of this variable in rural areas is 74 for primary schools, 15 for secondary, and 12 for health centers. In urban areas, the means are respectively 15, 5, and 5. The data on public facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure 6

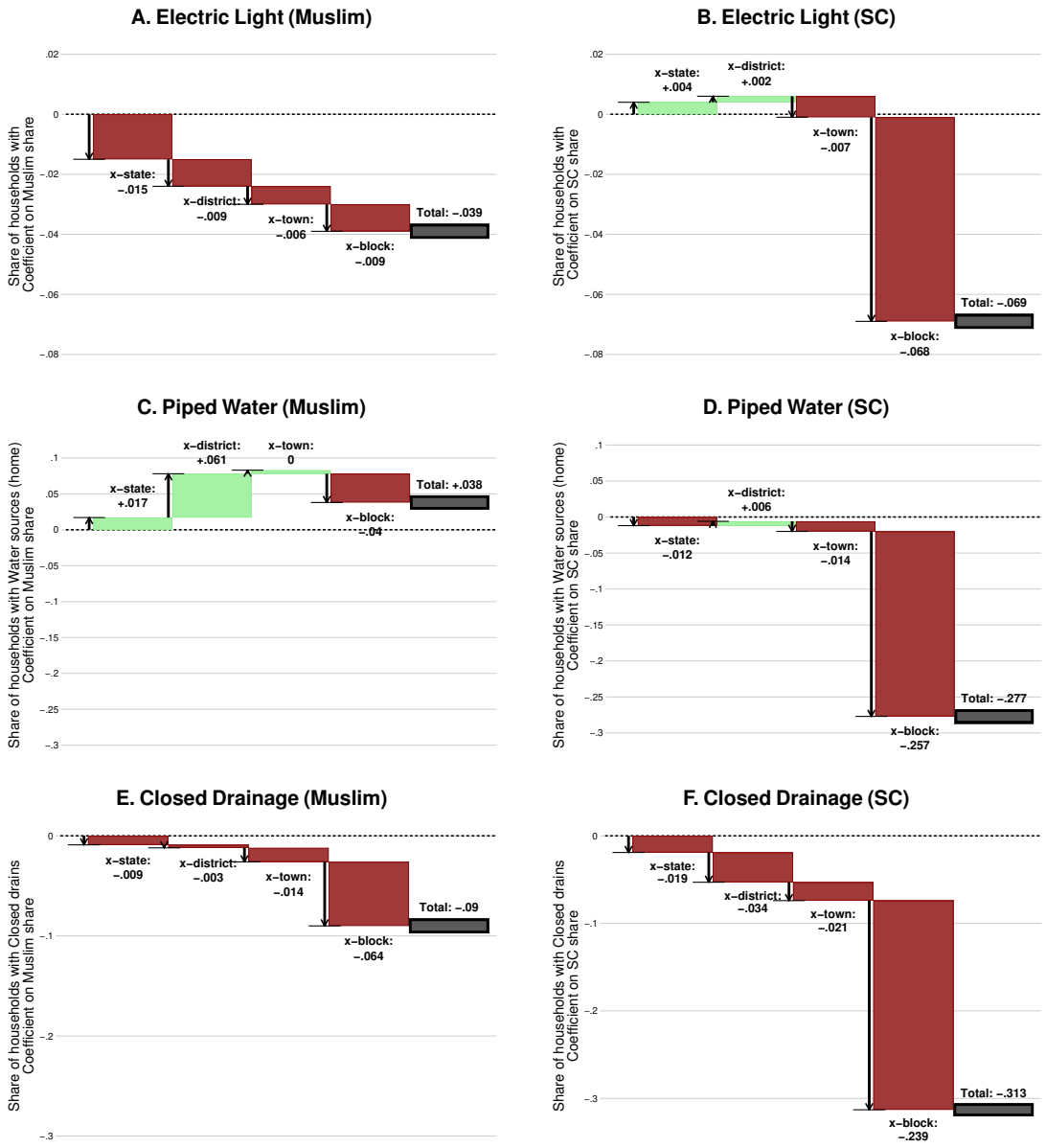
Disparities in Public Facilities as a Function of Scheduled Caste Share



Notes: This figure describes the cross-neighborhood relationship between a neighborhood's Scheduled Caste share and a neighborhood's access to public facilities: primary and secondary schools, and health centers. The dark gray box shows the coefficient of a regression of a public facility indicator on the Muslim share. The boxes to the left decompose that average effect into the effect arising at the cross-state, cross-district, cross-town/village, and cross-block levels. The outcome is the number of facilities per 100,000 people. The mean of this variable in rural areas is 74 for primary schools, 15 for secondary, and 12 for health centers. In urban areas, the means are respectively 15, 5, and 5. The data on public facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure 7

Disparities in Urban Infrastructure Access
as a Function of Marginalized Group Share



Notes: This figure describes the cross-neighborhood relationship between a neighborhood's marginalized group share (SC or Muslim) and a neighborhood's access to public infrastructure. The sample is entirely urban. Each infrastructure measure is the share of people in a neighborhood who have access to that type of infrastruture. The dark gray box shows the coefficient of a regression of the infrastructure measure on the marginalized group share. The boxes to the left decompose that average effect into the effect arising at the cross-state, cross-district, cross-subdistrict, cross-town/village, and cross-block levels. The mean of the outcomes variables are 0.95 for electric lighting, 0.73 for piped water and 0.56 for closed drainage. The data on public infrastructure comes from the 2012 Socioeconomic Caste Census.

Tables

Table 1
Summary Statistics

	Urban	Rural
Total Population	483 (165)	512 (170)
Scheduled Castes Population	56 (100)	86 (128)
Muslim Population	81 (124)	71 (117)
Scheduled Castes (Share)	0.11 (0.19)	0.17 (0.23)
Muslim (Share)	0.16 (0.23)	0.13 (0.20)
Has Public Primary School	0.07 (0.25)	0.33 (0.47)
Has Public Secondary School	0.02 (0.15)	0.07 (0.25)
Has Public Health Facility	0.02 (0.15)	0.06 (0.23)
Has Private Primary School	0.14 (0.34)	0.18 (0.38)
Has Private Secondary School	0.08 (0.27)	0.05 (0.22)
Has Private Health Facility	0.30 (0.46)	0.13 (0.33)
HH Has Closed Drains	0.56 (0.44)	NA
HH Has Electricity	0.95 (0.14)	NA
HH Has Water Source at Home	0.73 (0.34)	NA
Consumption Per Capita (SC)	30965 (17422)	16173 (8557)
Consumption Per Capita (Muslim)	27794 (14139)	15259 (7926)
Consumption Per Capita (Other)	31904 (12836)	17889 (6799)
Observations (Total)	400534	1108313

Notes: This table shows summary stats for variables from the Socioeconomic Caste Census at the neighborhood-level for urban and rural areas respectively. Semi-private goods (such as closed drains) are not measured in the SECC for rural areas.

Table 2
Sample Representativeness for Towns and Subdistricts

	Towns		Subdistricts	
	Our Sample	India (full)	Our Sample	India (full)
(Log) Population	10.31	9.87	11.51	11.39
	(1.08)	(1.03)	(0.98)	(1.20)
(Log) Area	2.33	1.99	10.34	10.25
	(1.09)	(1.10)	(0.92)	(1.08)
Scheduled Castes (Share)	0.14	0.15	0.16	0.16
	(0.09)	(0.11)	(0.10)	(0.11)
Muslim (Share)	0.18	0.19	0.09	0.09
	(0.19)	(0.22)	(0.16)	(0.16)
Town Origin Year	1947	1969		
	(42)	(43)		
Primary Schools per 100k	65.70	60.10	122.12	126.18
	(59.35)	(49.27)	(70.44)	(80.61)
Middle Schools per 100k	40.19	34.64	49.90	50.99
	(39.53)	(35.15)	(30.80)	(36.35)
Secondary Schools per 100k	22.83	20.72	19.48	19.44
	(21.66)	(21.41)	(14.91)	(15.15)
Hospitals per 100k	3.33	2.89	0.90	0.86
	(5.16)	(5.39)	(2.77)	(3.47)
Dissimilarity Index (SC)	0.59		0.58	
	(0.11)		(0.10)	
Dissimilarity Index (Muslim)	0.52		0.49	
	(0.14)		(0.15)	
Isolation Index (SC)	0.43		0.48	
	(0.13)		(0.11)	
Isolation Index (Muslim)	0.49		0.45	
	(0.20)		(0.23)	
Total Population	309,812,619	380,812,301	705,169,202	834,030,262
Observations	3504	6959	4759	5847

Notes: This table shows summary statistics at the town level (Columns 1-2) and subdistrict level (Columns 3-4) for key variables between our sample and the all India Population Census 2011 town and subdistrict directories for both urban and rural areas. Primary and Secondary Schools, and Health Centers are measured per 100,000 people. Dissimilarity is weighed by the subdistrict/town MG population. All other variables are unweighted. Standard errors in parentheses.

Table 3
Correlates of Urban Segregation

	SC Dissimilarity		Muslim Dissimilarity	
City Origin Decade	-0.007***	-0.004***	-0.009***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
SC share (town)		-0.012		-0.035
		(0.032)		(0.030)
Muslim share (town)		0.127***		0.193***
		(0.022)		(0.021)
City Population		0.012***		0.016***
		(0.003)		(0.003)
Observations	3519	3519	3519	3519
R2	0.03	0.04	0.05	0.09
Mean of Dependent Variable	0.59	0.59	0.42	0.42

Notes: This table regresses the SC Dissimilarity Index (columns 1 and 2) and Muslim Dissimilarity Index (columns 3 and 4) on town characteristics, such as the town's age and population.

Table 4
Neighborhood-level Public Facilities vs Marginalized Group Share

A. Urban Neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)
	Primary School		Secondary School		Health Facility	
	Indicator	Log Emp	Indicator	Log Emp	Indicator	Log Emp
SC Share	0.028***	0.033***	-0.005***	-0.020***	-0.004***	-0.005*
	(0.002)	(0.004)	(0.001)	(0.004)	(0.001)	(0.003)
Muslim Share	-0.004**	-0.010***	-0.010***	-0.031***	-0.009***	-0.021***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)
Observations	357975	357975	357975	357975	357975	357975
Mean of Dependent Variable	0.07	0.12	0.02	0.06	0.02	0.04
Town FE	Yes	Yes	Yes	Yes	Yes	Yes

B. Rural Neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)
	Primary School		Secondary School		Health Facility	
	Indicator	Log Emp	Indicator	Log Emp	Indicator	Log Emp
SC Share	-0.006***	-0.017***	-0.007***	-0.016***	-0.002*	-0.003*
	(0.002)	(0.004)	(0.001)	(0.003)	(0.001)	(0.002)
Muslim Share	-0.085***	-0.142***	-0.021***	-0.040***	-0.014***	-0.016***
	(0.003)	(0.005)	(0.001)	(0.003)	(0.001)	(0.002)
Observations	978635	978635	978635	978635	978635	978635
Mean of Dependent Variable	0.33	0.54	0.07	0.15	0.06	0.08
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the regression results of public facilities on marginalized group share at the neighborhood level, for towns and rural subdistricts. This is done for two different measures of public facilities: an indicator for whether or not there is the particular public facility in a neighborhood and $log(employment+1)$ in such public facilities. Columns 1 and 2 present results for primary schools, columns 3 and 4 for secondary schools, and columns 5 and 6 for health facilities. All regressions include town fixed effects and control for the log of neighborhood population.

Table 5
Neighborhood-level Private Facilities
vs Marginalized Group Share

A. Urban Neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)
	Primary School		Secondary School		Health Facility	
	Indicator	Log Emp	Indicator	Log Emp	Indicator	Log Emp
SC Share	-0.075***	-0.172***	-0.062***	-0.164***	-0.232***	-0.481***
	(0.003)	(0.006)	(0.002)	(0.006)	(0.004)	(0.007)
Muslim Share	-0.037***	-0.106***	-0.055***	-0.154***	-0.093***	-0.247***
	(0.003)	(0.006)	(0.002)	(0.006)	(0.004)	(0.007)
Observations	357975	357975	357975	357975	357975	357975
Mean of Dependent Variable	0.14	0.27	0.08	0.20	0.30	0.49
Town FE	Yes	Yes	Yes	Yes	Yes	Yes

B. Rural Neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)
	Primary School		Secondary School		Health Facility	
	Indicator	Log Emp	Indicator	Log Emp	Indicator	Log Emp
SC Share	-0.019***	-0.044***	-0.013***	-0.029***	-0.044***	-0.056***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.002)
Muslim Share	0.016***	0.014***	-0.004***	-0.011***	0.028***	0.039***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)	(0.003)
Observations	978635	978635	978635	978635	978635	978635
Mean of Dependent Variable	0.18	0.29	0.05	0.10	0.13	0.14
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the regression results of *private* facilities on marginalized group share at the neighborhood level, for towns and rural subdistricts. This is done for two different measures of facilities: an indicator for whether or not there is the particular private facility in a neighborhood and $log(employment+1)$ in such private facilities. Columns 1 and 2 present results for primary schools, columns 3 and 4 for secondary schools, and columns 5 and 6 for health facilities. All regressions include a control for the log of neighborhood population.

Table 6

Neighborhood-level Urban Infrastructure Services Facilities vs Marginalized Group Share: Urban

	Closed Drains	Water Source (Home)	Light Source (Home)
SC Share	-0.258***	-0.285***	-0.069***
	(0.003)	(0.003)	(0.001)
Muslim Share	-0.099***	-0.082***	-0.019***
	(0.003)	(0.002)	(0.001)
Observations	388559	395243	389389
Mean of Dependent Variable	0.56	0.73	0.95
Town FE	Yes	Yes	Yes

Notes: This table shows the regression results of urban infrastructure services on marginalized group share at the neighborhood level. The dependent variable is the mean of the households in the neighborhood that have the stated utility. All regressions include town fixed effects and control for the neighborhood population.

Table 7
Education Attainment of Young People
in SC and Muslim Neighborhoods: Urban

	(1)	(2)	(3)	(4)	(5)	(6)
	Son Ed	Son Ed	Son Ed	Daughter Ed	Daughter Ed	Daughter Ed
SC (Individual)	-1.132***	-0.626***	-0.126***	-1.148***	-0.632***	-0.138***
	(0.010)	(0.009)	(0.009)	(0.011)	(0.010)	(0.010)
Muslim (Individual)	-1.291***	-0.588***	-0.278***	-1.205***	-0.556***	-0.256***
	(0.010)	(0.008)	(0.008)	(0.011)	(0.009)	(0.009)
SC Share		-1.621***	-0.143***		-1.646***	-0.155***
		(0.026)	(0.023)		(0.028)	(0.025)
Muslim Share		-2.156***	-0.917***		-1.978***	-0.764***
		(0.026)	(0.023)		(0.027)	(0.025)
Father Ed			0.194***			0.190***
			(0.001)			(0.001)
Mother Ed			0.080***			0.096***
			(0.001)			(0.001)
Observations	3023922	3023922	1965454	2626264	2626264	1716267
R^2	0.15	0.16	0.33	0.16	0.17	0.34
Controls	None	None	Parent Ed + Cons	None	None	Parent Ed + Cons
Town FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results from regressions on a sample of individuals taken from the SECC 2012. We use a 2 stage random sampling strategy and take a 20% sample of neighborhoods stratified at the subdistrict level and then take a simple random sample of 50% households within those neighborhoods. Consumption controls are at the household level.

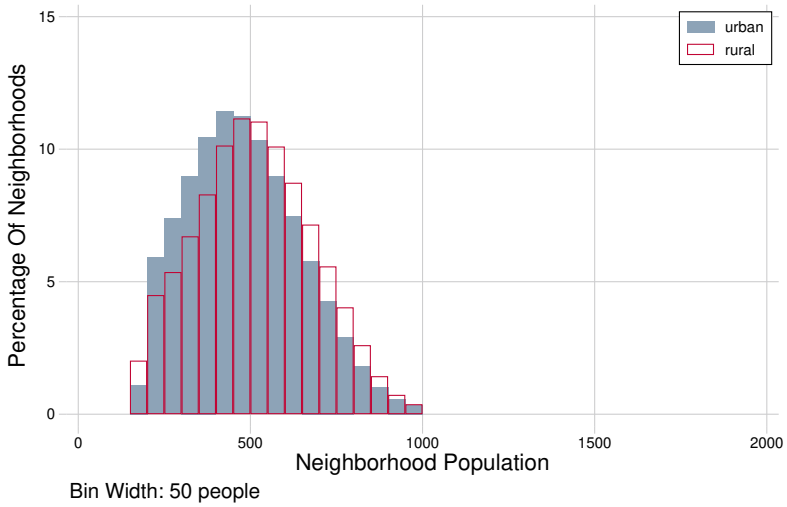
Table 8
Education Attainment of Young People
in SC and Muslim Neighborhoods: Rural

	(1)	(2)	(3)	(4)	(5)	(6)
	Son Ed	Son Ed	Son Ed	Daughter Ed	Daughter Ed	Daughter Ed
SC (Individual)	-1.151***	-1.161***	-0.316***	-1.186***	-1.213***	-0.323***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Muslim (Individual)	-1.174***	-0.749***	-0.366***	-1.132***	-0.758***	-0.373***
	(0.009)	(0.008)	(0.008)	(0.010)	(0.008)	(0.009)
SC Share		-0.001	0.028		0.050**	0.068***
		(0.020)	(0.018)		(0.021)	(0.019)
Muslim Share		-1.573***	-1.029***		-1.375***	-0.800***
		(0.026)	(0.023)		(0.028)	(0.025)
Father Ed			0.275***			0.294***
			(0.001)			(0.001)
Mother Ed			0.071***			0.116***
			(0.001)			(0.001)
Observations	4889326	4889326	3391599	4075086	4075086	2789113
R^2	0.16	0.16	0.31	0.18	0.18	0.35
Controls	None	None	Parent Ed + Cons	None	None	Parent Ed + Cons
Subdistrict FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results from regressions on a sample of individuals taken from the SECC 2012. We use a 2 stage random sampling strategy and take a 20% sample of neighborhoods stratified at the subdistrict level and then take a simple random sample of 50% households within those neighborhoods. Consumption controls are at the household level.

A Appendix A. Additional Figures and Tables

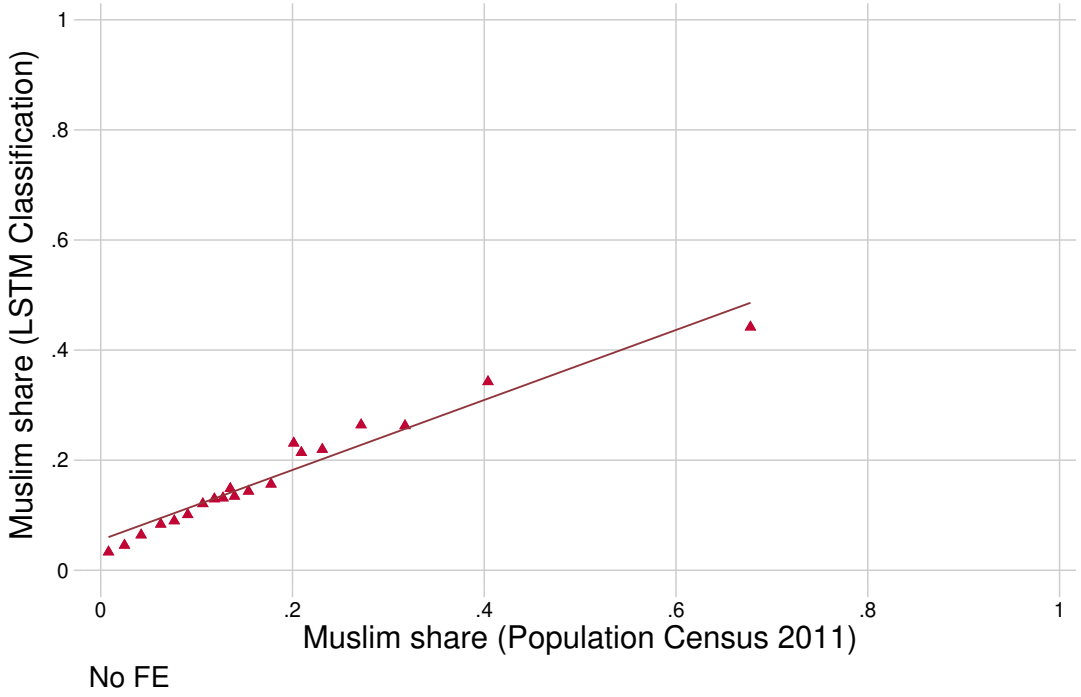
Figure A.1
Neighborhood Population Distributions



Notes: This figure shows the sample distribution of populations for neighborhoods in urban and rural areas used in our main results. Neighborhoods are excluded from the sample if they have less than 150 people or more than 1200.

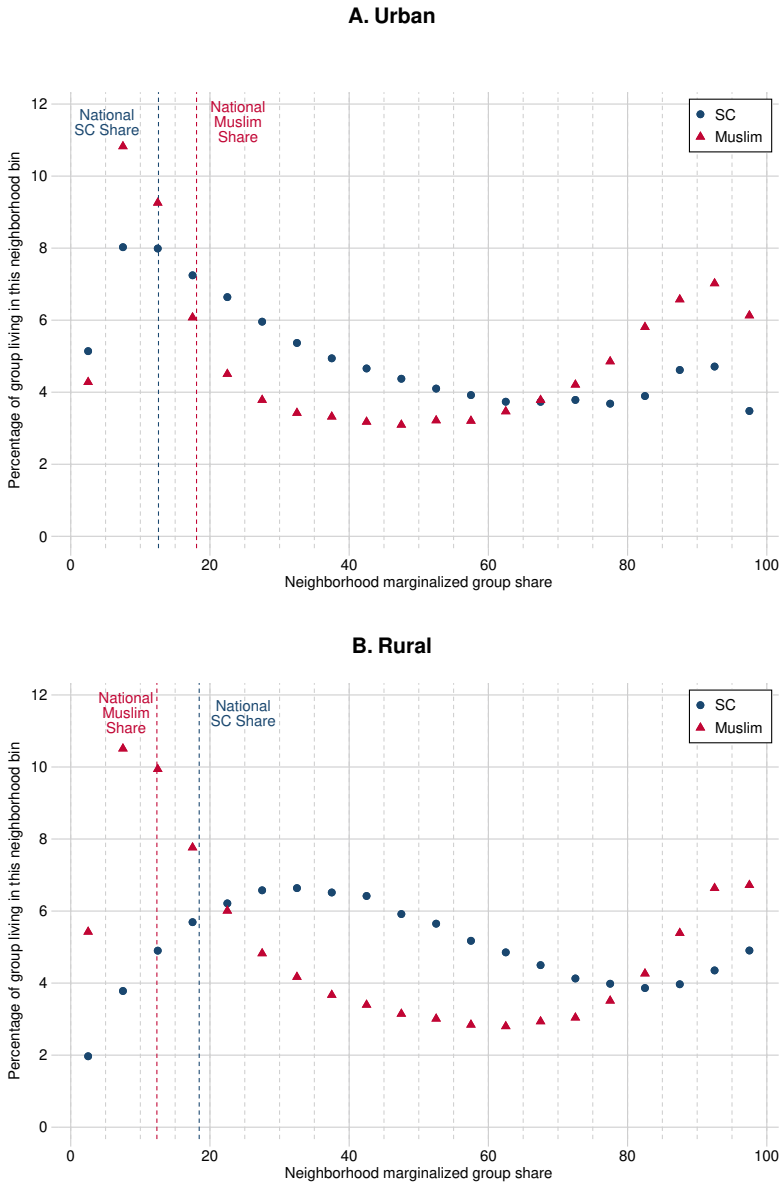
Figure A.2

Validation of Muslim Name Classification:
Subdistrict Muslim Share in SECC vs PC11



Notes: This figure is the binscatter of subdistrict-level Muslim share using our classifier of SECC names versus official 2011 Population Census Muslim share.

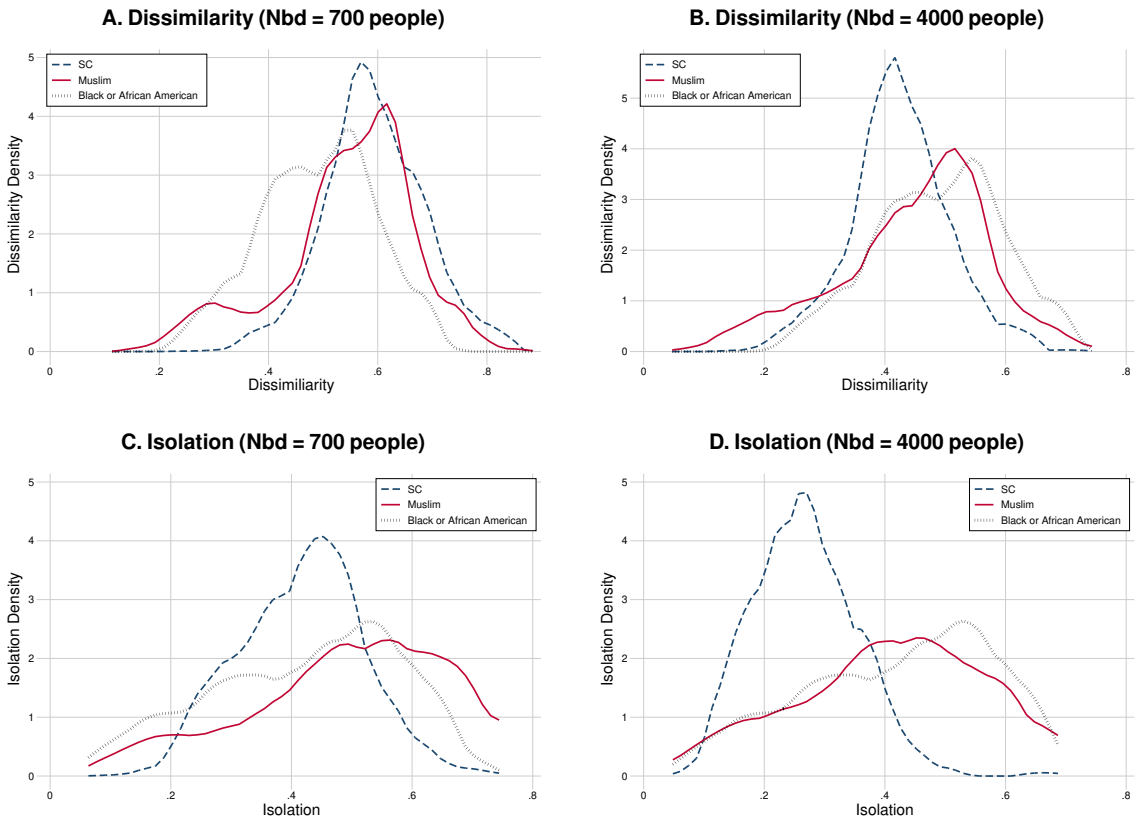
Figure A.3
Population Distribution
as a Function of Marginalized Group Share



Notes: The figure shows the distribution of Scheduled Caste and Muslim Population shares across their own neighborhood group share. For instance, the rightmost red point in Panel A reveals that 6% (Y-axis) of Muslims live in neighborhoods where the Muslim share is between 95 and 100%.

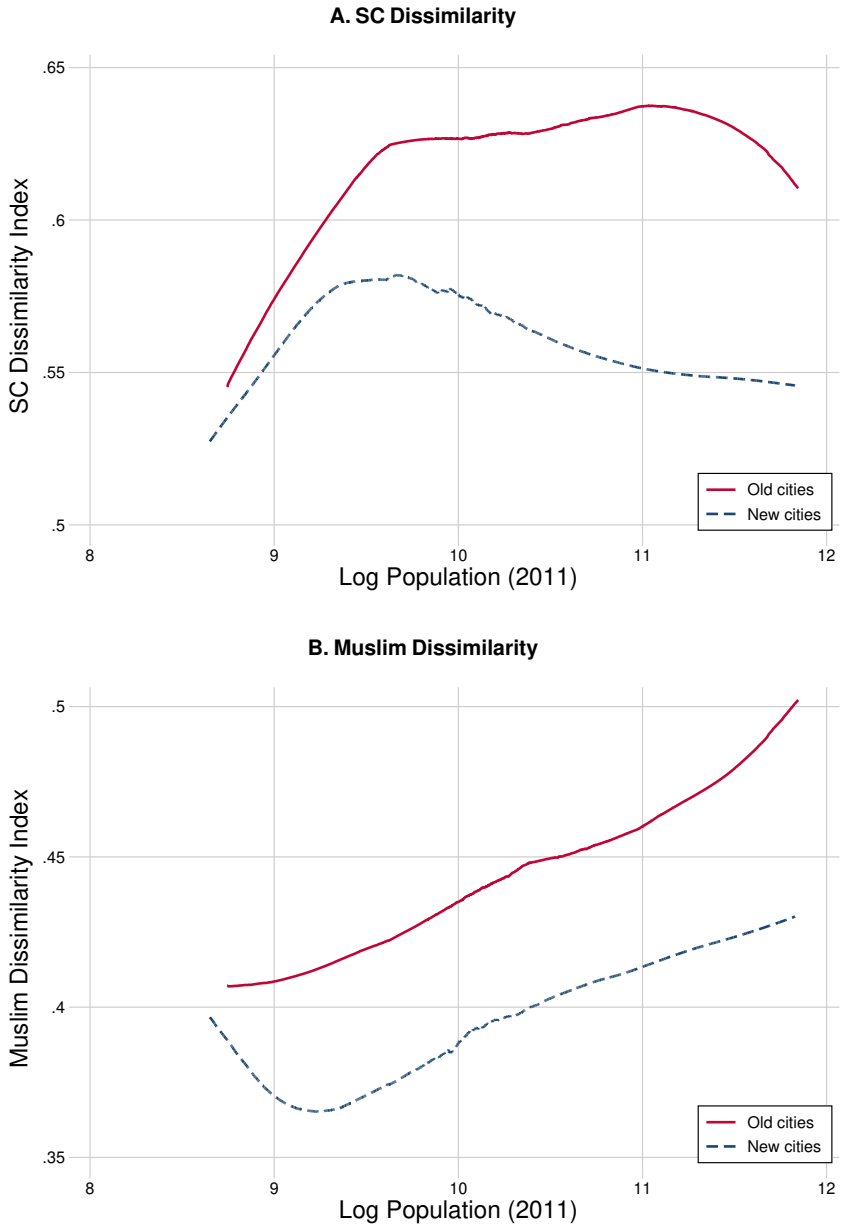
Figure A.4

Comparison of Urban Muslim/SC Segregation in India
with Urban Black Segregation in the United States



Notes: The figure shows the distribution of the dissimilarity and isolation indices of Muslim and SCs, and compares them with similar Black/White measures in the U.S. Panels A and C define neighborhoods as enumeration blocks, which is the main definition used in the paper. Panels B and D aggregate enumeration blocks to have up to 4000 people in a neighborhood, for better comparability with the U.S. measures. All plots are weighted by their respective marginalized group populations so that they reflect the experience of marginalized groups. All plots are calculated for the subset of Indian towns and American metropolitan statistical areas that have more than 100000 people, to maximize comparability.

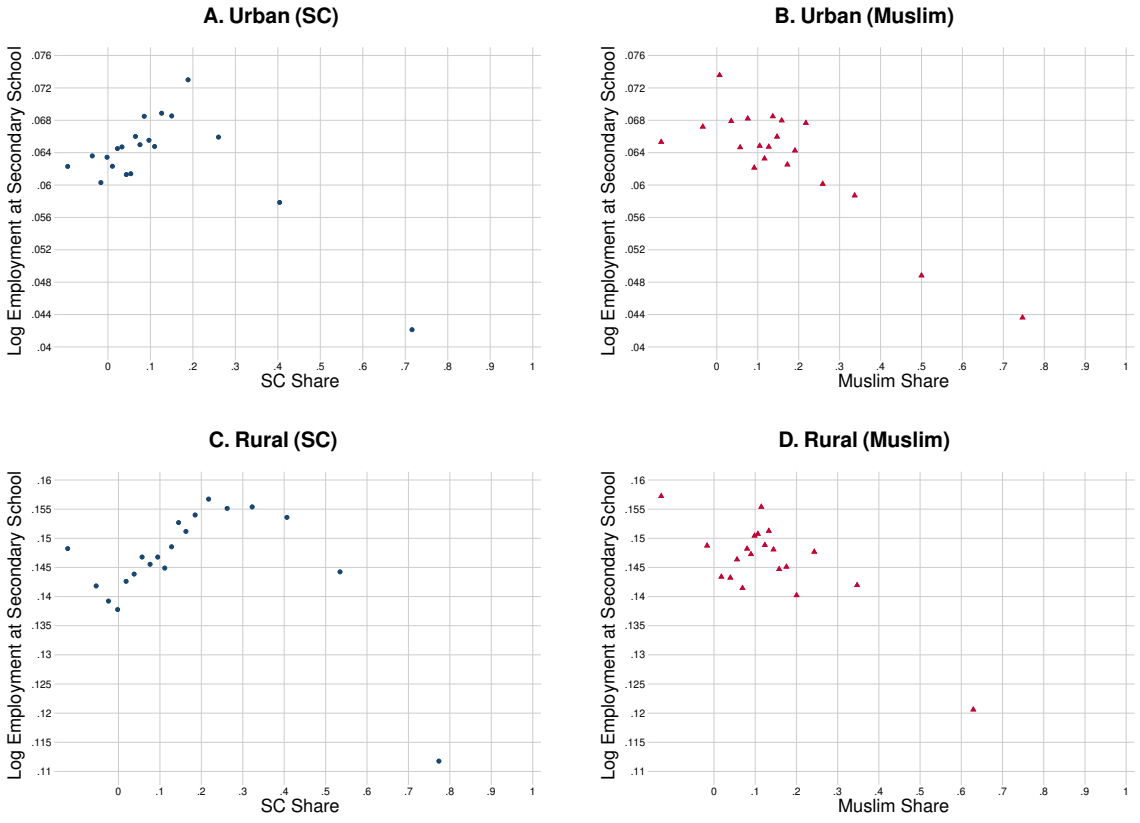
Figure A.5
Dissimilarity Indices by City Age



Notes: This figure shows lowess plots of dissimilarity measures on the log population for SCs and Muslims. Cities that are recorded in the decennial population census for the first time in 1922 or earlier are categorised as Old cities. Those that are recorded in the decennial population census after 1922, are designated to be New cities.

Figure A.6

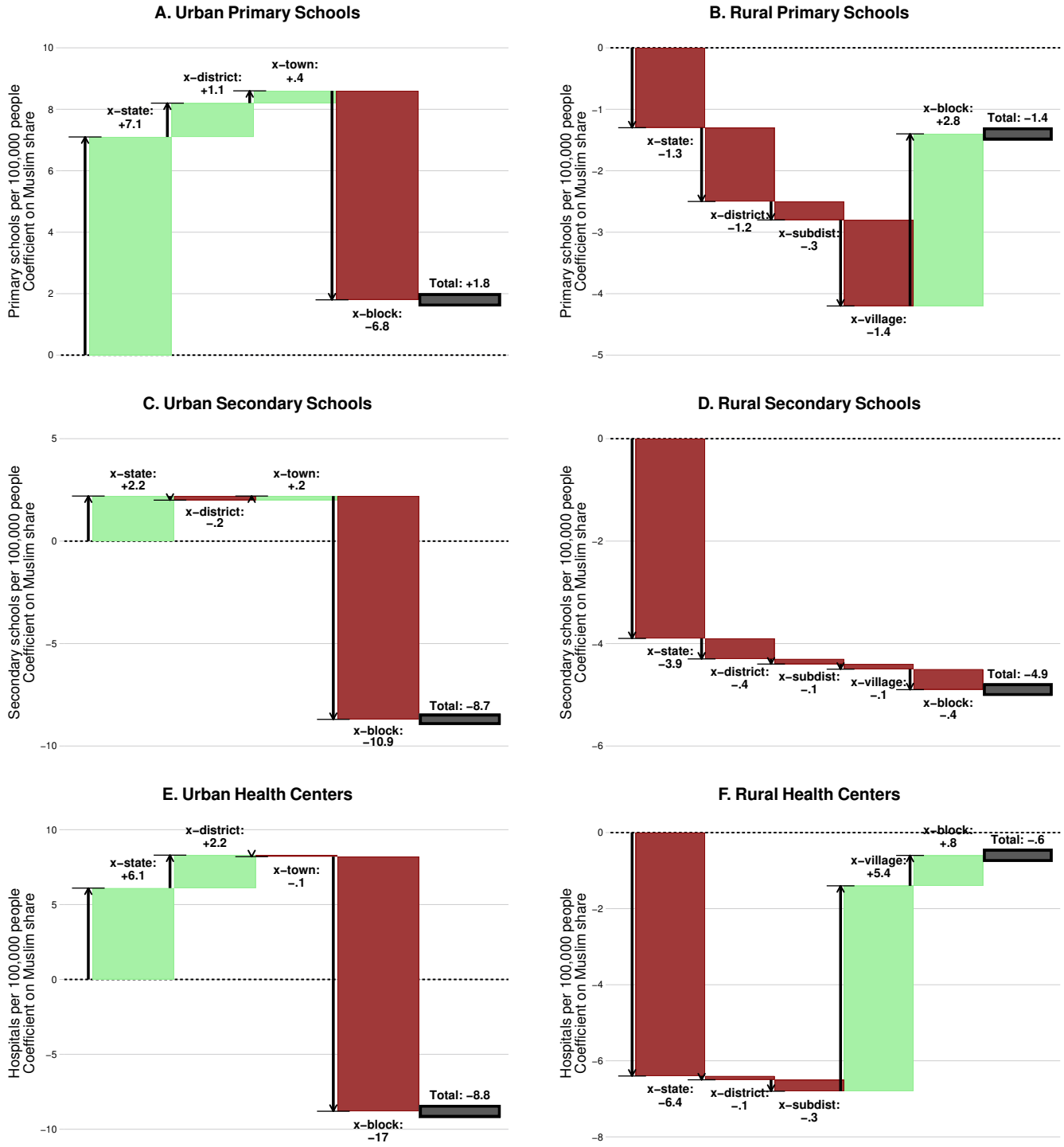
Binscatter: Log Employment at Secondary Education Facilities vs Marginalized Group Shares



Notes: This figure shows binscatter plots of the percentage of neighborhoods that have a secondary school at a given level of SC/Muslim share. The data on public facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure A.7

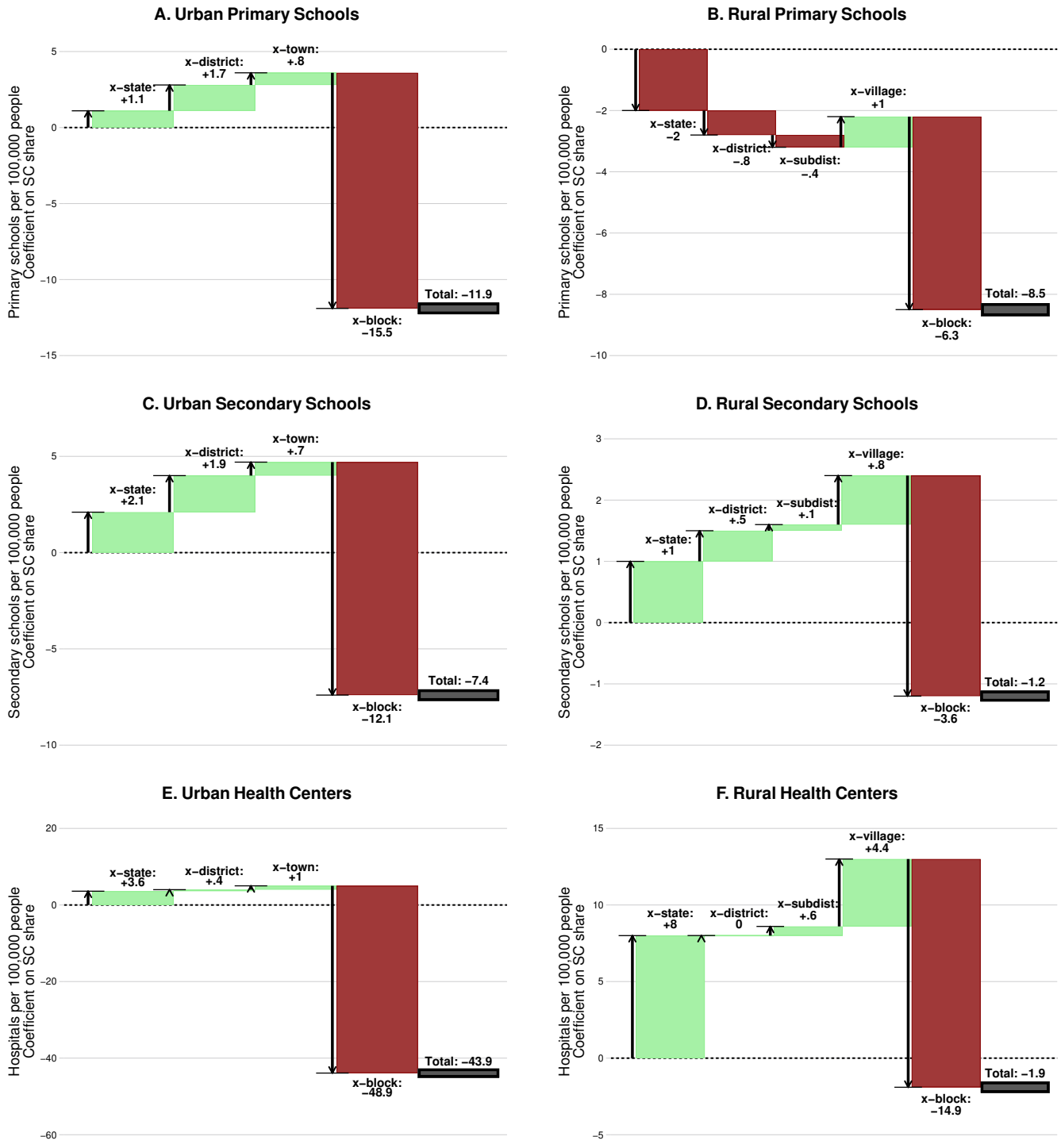
Disparities in Private Facilities as a Function of Muslim Share



Notes: This figure describes the cross-neighborhood relationship between a neighborhood's Muslim share and a neighborhood's access to private facilities: primary and secondary schools, and health centers. The dark gray box shows the coefficient of a regression of a private facility indicator on the Muslim share. The boxes to the left decompose that average effect into the effect arising at the cross-state, cross-district, cross-town/village, and cross-block levels. The outcome is the number of facilities per 100,000 people. The mean of this variable in rural areas is 38 for primary schools, 10 for secondary, and 26 for health centers. In urban areas, the means are respectively 31, 19, and 71. The data on private facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure A.8

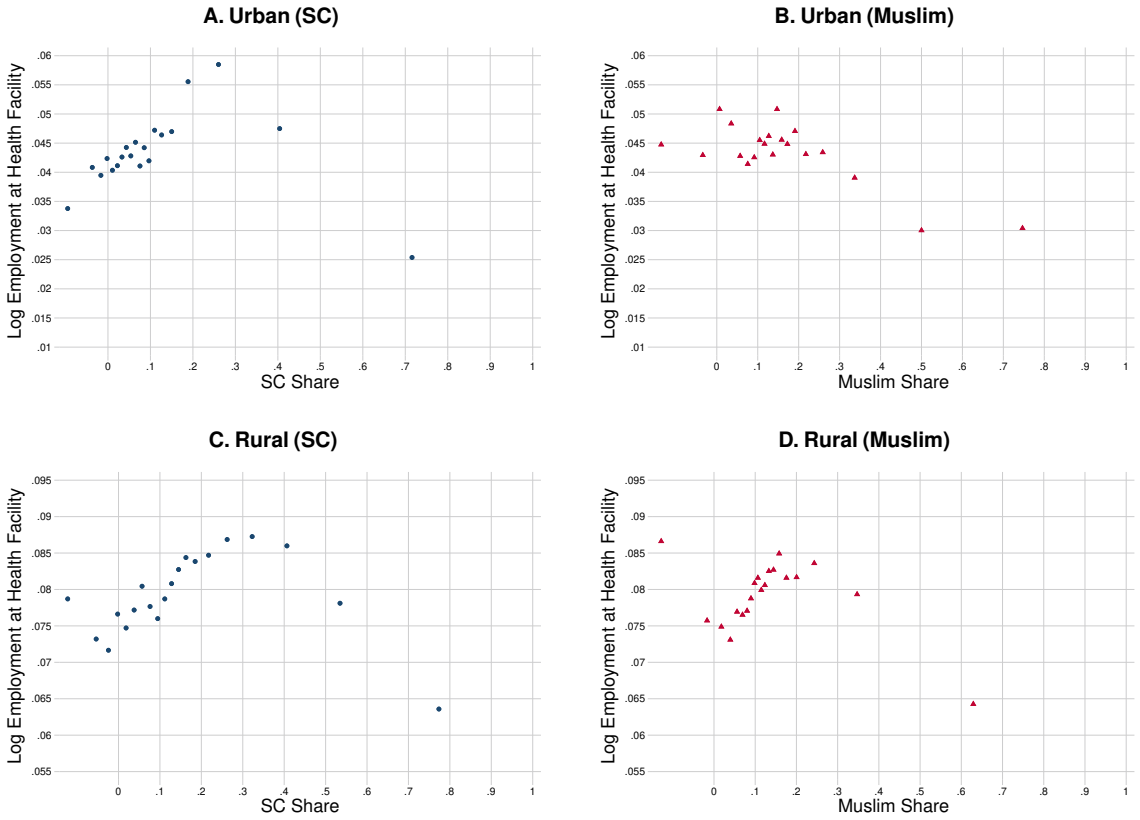
Disparities in Private Facilities as a Function of SC Share



Notes: This figure describes the cross-neighborhood relationship between a neighborhood's SC share and a neighborhood's access to private facilities: primary and secondary schools, and health centers. The dark gray box shows the coefficient of a regression of a private facility indicator on the SC share. The boxes to the left decompose that average effect into the effect arising at the cross-state, cross-district, cross-town/village, and cross-block levels. The outcome is the number of facilities per 100,000 people. The mean of this variable in rural areas is 38 for primary schools, 10 for secondary, and 26 for health centers. In urban areas, the means are respectively 31, 19, and 71. The data on private facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure A.9

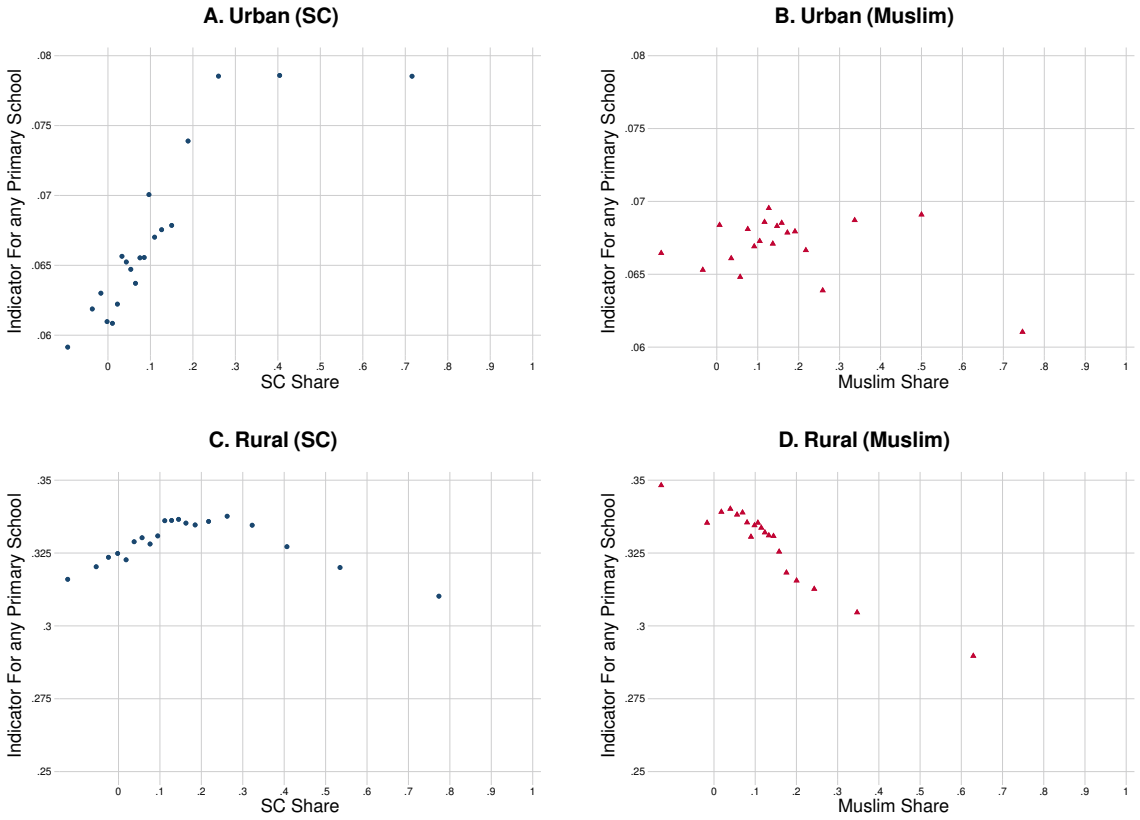
Binscatter: Log Employment at Health Facilities vs Marginalized Group Shares



Notes: This figure shows binscatter plots of the percentage of neighborhoods that have a health facility at a given level of SC/Muslim share. The data on public facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure A.10

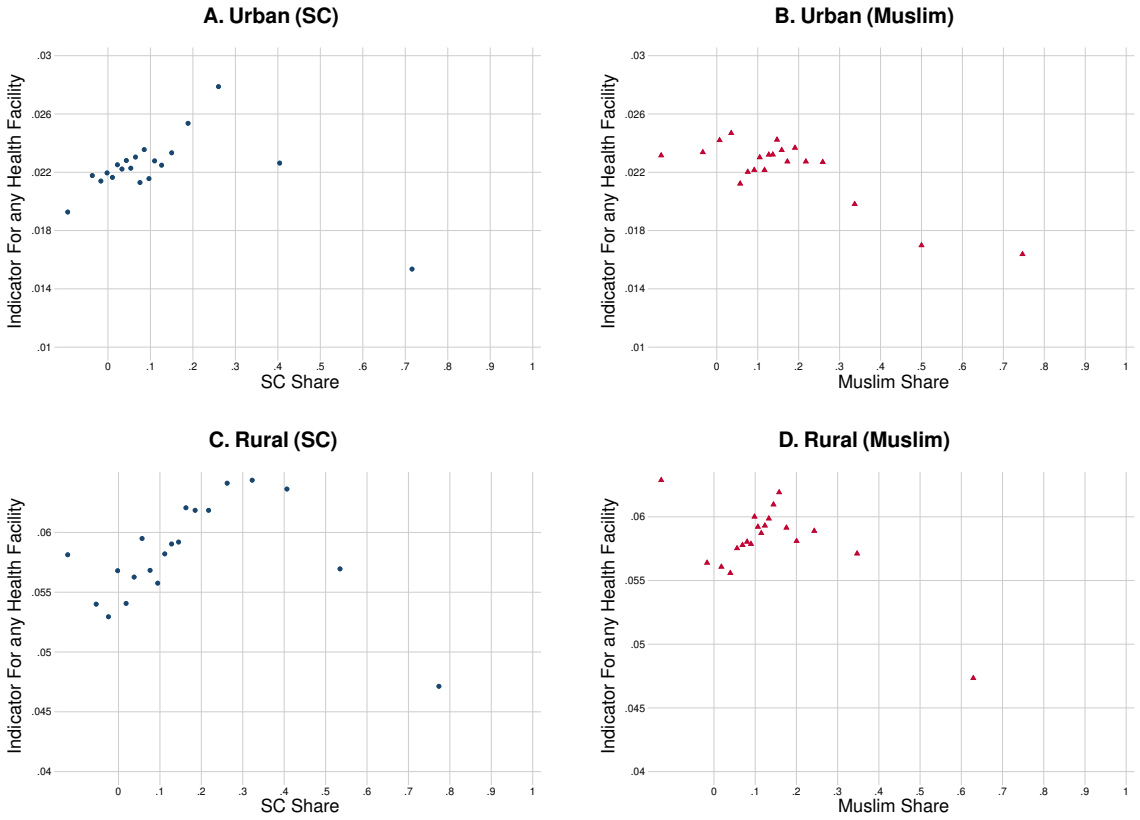
Binscatter: Primary Education Facilities vs Marginalized Group Shares



Notes: This figure shows binscatter plots of the percentage of neighborhoods that have a primary school at a given level of SC/Muslim share. The data on public facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

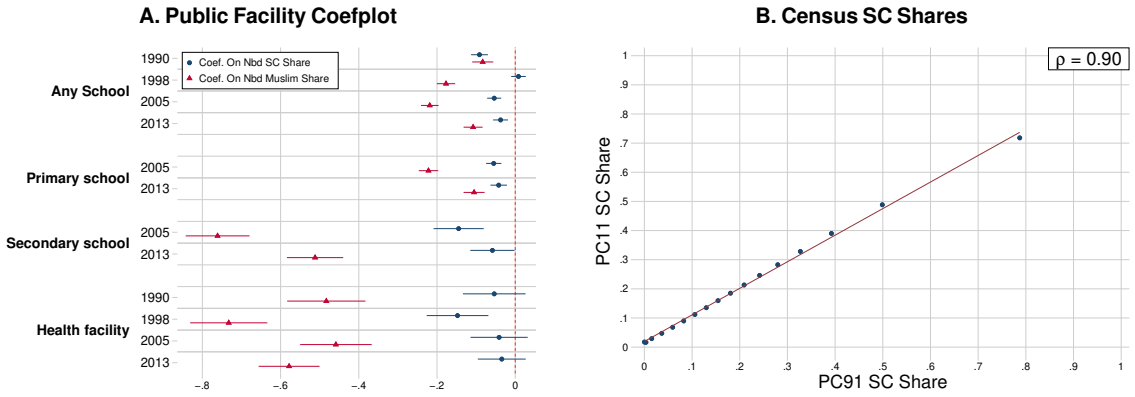
Figure A.11

Binscatter: Health Facilities vs Marginalized Group Shares



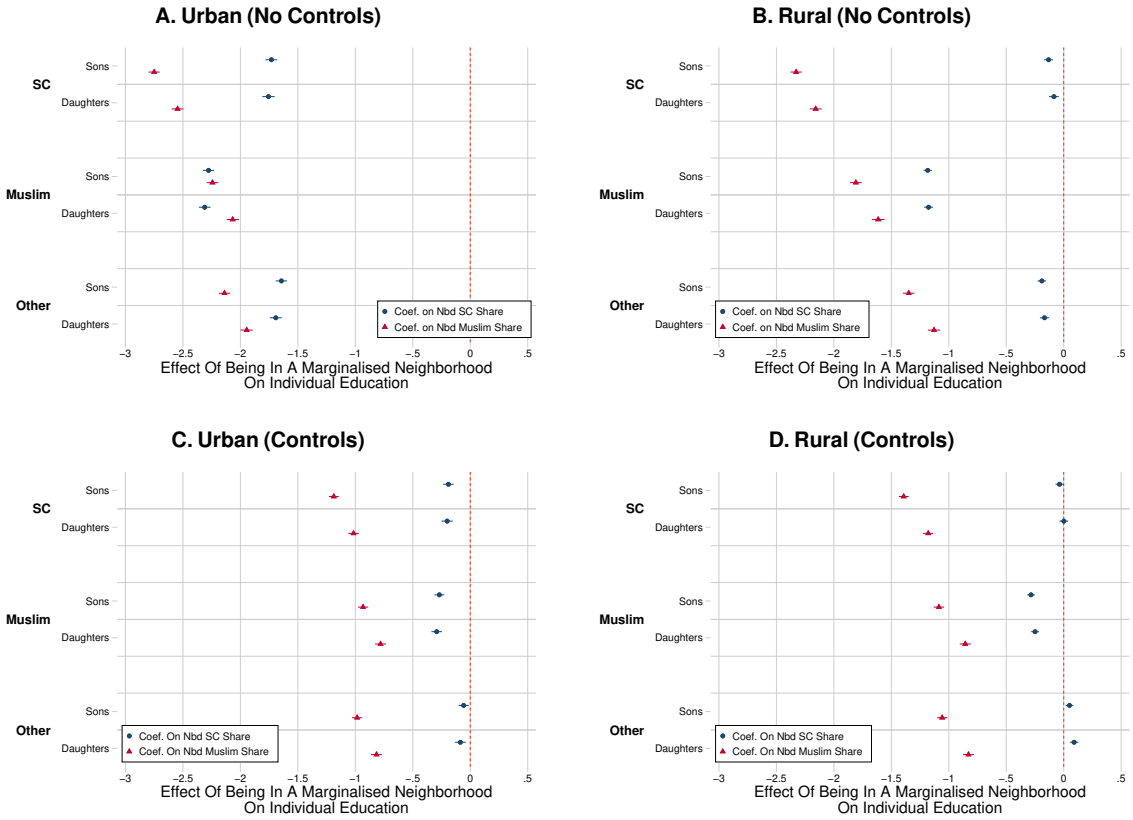
Notes: This figure shows binscatter plots of the percentage of neighborhoods that have a health facility at a given level of SC/Muslim share. The data on public facilities comes from the Economic Census 2013 and the data on shares from the Socioeconomic Caste Census.

Figure A.12
Census Village Level Results



Notes: These Figures show results similar to what we find in the SECC over time in the Census Data as well. The coefficient plot on the left hand side plots regressions of public facilities from a given economic census year on sc and muslim shares at the village level from the closest population census year. The binscatter on the right shows a high correlation among SC shares at the village level between the census rounds

Figure A.13
Educational Attainment in Marginalized Group Neighborhoods



Notes: This figure shows a coefficient plot with estimates from individual level regressions of 17–18-year-olds' education (years) on neighborhood shares of SCs and Muslims. Panels A and B control for the individual's consumption/income and parental education. All regressions include town fixed effects and control for the log of neighborhood population. Data for the public and private facilities comes from the Economic Census 2013, while the SC and Muslim shares come from the Socioeconomic Caste Census.

Table A.1
Neighborhood-level Public Facilities vs Marginalized Group Share: Controlling/Excluding Slums

	(1)	(2)	(3)	(4)	(5)	(6)
	Slum Controls			No Slum		
	Primary School	Secondary School	Health Facility	Primary School	Secondary School	Health Facility
SC Share	0.028***	-0.005***	-0.004**	0.028***	-0.005***	-0.004**
	0.002	0.001	0.001	0.003	0.001	0.001
Muslim Share	-0.004	-0.010***	-0.009***	-0.004	-0.010***	-0.010***
	0.002	0.001	0.001	0.002	0.001	0.001
Observations	356270	356270	356270	308215	308215	308215
R^2	0.067	0.024	0.022	0.064	0.023	0.022
Town FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the regression results of public facilities on marginalized group share at the neighborhood level, for towns. To measure public facilities we use an indicator for whether or not there is the particular public facility in a neighborhood. Columns 1-3 show these results with a control for whether or not the neighborhood is in a slum and Columns 4-6 show these for urban neighborhoods not in slums.

Table A.2
Individual Educational Attainment, By Social Group: Urban

A. Young Men 17–18

	(1) All	(2) SC	(3) Muslim	(4) Other	(5) All	(6) SC	(7) Muslim	(8) Other
SC Share	-1.621***	-1.996***	-1.967***	-1.401***	-0.143***	-0.590***	0.116	0.164***
	0.026	0.039	0.059	0.035	0.023	0.037	0.060	0.031
Muslim Share	-2.156***	-1.973***	-2.051***	-2.224***	-0.917***	-0.711***	-0.686***	-0.952***
	0.026	0.084	0.035	0.034	0.023	0.082	0.033	0.031
Father's Education					0.194***	0.203***	0.214***	0.178***
					0.001	0.002	0.002	0.001
Mother's Education					0.080***	0.063***	0.118***	0.076***
					0.001	0.002	0.002	0.001
Log of per capita consumption of the hh					-0.171***	-0.328**	0.170*	-0.115**
					0.035	0.104	0.078	0.043
Observations	3023922	380627	554382	2088913	1965454	249868	366217	1349369
R2	0.16	0.17	0.20	0.12	0.33	0.33	0.38	0.28
Town FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

B. Young Women 17–18

	(1) All	(2) SC	(3) Muslim	(4) Other	(5) All	(6) SC	(7) Muslim	(8) Other
SC Share	-1.646***	-2.070***	-1.950***	-1.417***	-0.155***	-0.657***	0.112	0.147***
	0.028	0.040	0.062	0.038	0.025	0.040	0.063	0.034
Muslim Share	-1.978***	-1.752***	-1.861***	-2.041***	-0.764***	-0.588***	-0.535***	-0.815***
	0.027	0.085	0.037	0.036	0.025	0.086	0.035	0.033
Father's Education					0.190***	0.199***	0.202***	0.175***
					0.001	0.002	0.002	0.001
Mother's Education					0.096***	0.074***	0.134***	0.091***
					0.001	0.002	0.002	0.001
Log of per capita consumption of the hh					-0.593***	-0.729***	-0.178*	-0.540***
					0.038	0.117	0.083	0.047
Observations	2626264	333251	513803	1779210	1716267	217380	342672	1156215
R2	0.17	0.19	0.22	0.13	0.34	0.34	0.38	0.29
Town FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results from regressions on a sample of individuals taken from the SECC 2012. We use a 2 stage random sampling strategy and take a 20% sample of neighborhoods stratified at the subdistrict level and then take a simple random sample of 50% households within those neighborhoods. Consumption controls are at the household level. Columns 1 and 5 show this for all demographic groups. Columns 2-4 and 6-8 break this up by demographic group for SC Muslim and Others respectively.

Table A.3
Individual Educational Attainment, By Social Group: Rural

A. Young Men 17–18

	(1) All	(2) SC	(3) Muslim	(4) Other	(5) All	(6) SC	(7) Muslim	(8) Other
SC Share	-0.001	-0.411***	-0.553***	0.507***	0.028	-0.331***	-0.017	0.344***
	0.020	0.030	0.044	0.026	0.018	0.029	0.044	0.023
Muslim Share	-1.573***	-0.806***	-1.539***	-1.488***	-1.029***	-0.627***	-1.033***	-0.815***
	0.026	0.065	0.036	0.037	0.023	0.064	0.033	0.033
Father's Education					0.275***	0.262***	0.299***	0.267***
					0.001	0.001	0.002	0.001
Mother's Education					0.071***	0.059***	0.113***	0.068***
					0.001	0.002	0.002	0.001
Log of per capita consumption of the hh					0.627***	0.570***	0.671***	0.601***
					0.020	0.050	0.052	0.024
Observations	4889326	852415	677549	3359362	3391599	611930	465140	2314529
R2	0.16	0.16	0.21	0.15	0.31	0.27	0.34	0.30
Subdistrict FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

B. Young Women 17–18

	(1) All	(2) SC	(3) Muslim	(4) Other	(5) All	(6) SC	(7) Muslim	(8) Other
SC Share	0.050*	-0.466***	-0.482***	0.646***	0.068***	-0.364***	0.060	0.419***
	0.021	0.032	0.048	0.029	0.019	0.031	0.047	0.025
Muslim Share	-1.375***	-0.555***	-1.319***	-1.326***	-0.800***	-0.451***	-0.750***	-0.693***
	0.028	0.071	0.039	0.040	0.025	0.070	0.036	0.036
Father's Education					0.294***	0.271***	0.300***	0.290***
					0.001	0.002	0.002	0.001
Mother's Education					0.116***	0.095***	0.164***	0.111***
					0.001	0.002	0.003	0.001
Log of per capita consumption of the hh					0.518***	0.506***	0.423***	0.528***
					0.022	0.056	0.056	0.026
Observations	4075086	685423	600899	2788764	2789113	484699	407228	1897186
R2	0.18	0.20	0.22	0.17	0.35	0.32	0.36	0.34
Subdistrict FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results from regressions on a sample of individuals taken from the SECC 2012. We use a 2 stage random sampling strategy and take a 20% sample of neighborhoods stratified at the subdipstrict level and then take a simple random sample of 50% households within those neighborhoods. Consumption controls are at the household level. Columns 1 and 5 show this for all demographic groups. Columns 2-4 and 6-8 break this up by demographic group for SC Muslim and Others respectively.

Table A.4
Individual Level Educational Attainment of Children by Age: Urban

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Son's Education				Daughter's Education			
Age	SC Share	SC Share	Muslim Share	Muslim Share	SC Share	SC Share	Muslim Share	Muslim Share
06	-0.529***	-0.263***	-0.424***	-0.245***	-0.532***	-0.262***	-0.406***	-0.217***
	(0.024)	(0.027)	(0.023)	(0.026)	(0.024)	(0.027)	(0.023)	(0.026)
07	-0.551***	-0.220***	-0.337***	-0.148***	-0.564***	-0.221***	-0.406***	-0.159***
	(0.026)	(0.028)	(0.042)	(0.029)	(0.025)	(0.028)	(0.024)	(0.026)
08	-0.562***	-0.173***	-0.348***	-0.032	-0.552***	-0.168***	-0.360***	-0.043
	(0.025)	(0.028)	(0.024)	(0.026)	(0.026)	(0.028)	(0.025)	(0.027)
09	-0.625***	-0.205***	-0.529***	-0.183***	-0.606***	-0.157***	-0.484***	-0.139***
	(0.026)	(0.028)	(0.024)	(0.026)	(0.026)	(0.029)	(0.025)	(0.027)
10	-0.727***	-0.173***	-0.752***	-0.287***	-0.705***	-0.144***	-0.660***	-0.220***
	(0.026)	(0.027)	(0.024)	(0.025)	(0.026)	(0.028)	(0.024)	(0.026)
11	-0.794***	-0.177***	-0.917***	-0.415***	-0.798***	-0.182***	-0.830***	-0.316***
	(0.025)	(0.027)	(0.025)	(0.026)	(0.026)	(0.028)	(0.025)	(0.026)
12	-0.899***	-0.146***	-1.059***	-0.410***	-0.889***	-0.143***	-0.964***	-0.358***
	(0.025)	(0.025)	(0.026)	(0.024)	(0.026)	(0.026)	(0.025)	(0.024)
13	-0.939***	-0.142***	-1.173***	-0.468***	-0.941***	-0.129***	-1.066***	-0.380***
	(0.025)	(0.025)	(0.026)	(0.024)	(0.026)	(0.026)	(0.025)	(0.025)
14	-1.160***	-0.166***	-1.489***	-0.606***	-1.124***	-0.168***	-1.290***	-0.411***
	(0.026)	(0.026)	(0.025)	(0.024)	(0.027)	(0.027)	(0.025)	(0.024)
15	-1.159***	-0.132***	-1.585***	-0.627***	-1.110***	-0.106***	-1.403***	-0.479***
	(0.026)	(0.026)	(0.026)	(0.025)	(0.027)	(0.027)	(0.026)	(0.026)
16	-1.326***	-0.141***	-1.863***	-0.776***	-1.266***	-0.129***	-1.643***	-0.597***
	(0.027)	(0.026)	(0.027)	(0.026)	(0.029)	(0.028)	(0.028)	(0.027)
17	-1.517***	-0.134***	-2.061***	-0.829***	-1.549***	-0.157***	-1.896***	-0.674***
	(0.029)	(0.028)	(0.028)	(0.027)	(0.031)	(0.030)	(0.029)	(0.028)
18	-1.728***	-0.168***	-2.261***	-0.907***	-1.740***	-0.211***	-2.070***	-0.731***
	(0.030)	(0.029)	(0.030)	(0.028)	(0.033)	(0.031)	(0.032)	(0.030)
Controls	None	Parent Ed + HH Cons	None	Parent Ed + HH Cons	None	Parent Ed + HH Cons	None	Parent Ed + HH Cons
Town FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results from regressions on a sample of individuals taken from the SECC 2012. We use a 2 stage random sampling strategy and take a 20% sample of neighborhoods stratified at the subdistrict level and then take a simple random sample of 50% households within those neighborhoods. Consumption controls are at the household level. Each estimate is from a separate regression of child educational attainment on share. Identical to table 7, except we restrict sample by age.

Table A.5
Individual Education Attainment of Children by Age: Rural

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Son's Education				Daughter's Education			
Age	SC Share	SC Share	Muslim Share	Muslim Share	SC Share	SC Share	Muslim Share	Muslim Share
06	-0.196***	-0.179***	-0.232***	-0.149***	-0.187***	-0.168***	-0.211***	-0.136***
	(0.013)	(0.014)	(0.016)	(0.017)	(0.013)	(0.014)	(0.016)	(0.017)
07	-0.188***	-0.166***	-0.260***	-0.173***	-0.194***	-0.173***	-0.254***	-0.177***
	(0.014)	(0.015)	(0.017)	(0.018)	(0.014)	(0.015)	(0.018)	(0.018)
08	-0.186***	-0.158***	-0.319***	-0.219***	-0.184***	-0.169***	-0.293***	-0.196***
	(0.015)	(0.015)	(0.018)	(0.018)	(0.015)	(0.015)	(0.020)	(0.021)
09	-0.178***	-0.161***	-0.445***	-0.315***	-0.172***	-0.144***	-0.405***	-0.306***
	(0.016)	(0.017)	(0.020)	(0.021)	(0.016)	(0.017)	(0.020)	(0.021)
10	-0.195***	-0.177***	-0.615***	-0.460***	-0.172***	-0.154***	-0.535***	-0.376***
	(0.016)	(0.016)	(0.020)	(0.020)	(0.016)	(0.016)	(0.020)	(0.019)
11	-0.117***	-0.085***	-0.749***	-0.554***	-0.098***	-0.083***	-0.686***	-0.483***
	(0.018)	(0.018)	(0.023)	(0.023)	(0.018)	(0.019)	(0.023)	(0.024)
12	-0.136***	-0.114***	-0.830***	-0.626***	-0.110***	-0.104***	-0.733***	-0.530***
	(0.017)	(0.017)	(0.022)	(0.020)	(0.018)	(0.017)	(0.022)	(0.020)
13	-0.067***	-0.044**	-1.077***	-0.800***	-0.019	-0.010	-0.893***	-0.619***
	(0.019)	(0.019)	(0.026)	(0.025)	(0.020)	(0.020)	(0.026)	(0.025)
14	-0.061***	-0.038**	-1.173***	-0.825***	-0.058***	-0.023	-1.042***	-0.705***
	(0.019)	(0.018)	(0.024)	(0.023)	(0.020)	(0.019)	(0.025)	(0.024)
15	-0.018	-0.027	-1.384***	-1.002***	-0.024	-0.003	-1.220***	-0.796***
	(0.020)	(0.020)	(0.027)	(0.026)	(0.021)	(0.021)	(0.029)	(0.027)
16	0.014	0.018	-1.500***	-1.032***	0.014	0.019	-1.335***	-0.866***
	(0.021)	(0.020)	(0.028)	(0.027)	(0.023)	(0.022)	(0.030)	(0.028)
17	0.001	0.014	-1.510***	-1.046***	0.054**	0.073***	-1.357***	-0.827***
	(0.022)	(0.021)	(0.029)	(0.027)	(0.024)	(0.023)	(0.031)	(0.029)
18	-0.003	0.029	-1.648***	-1.116***	0.045*	0.065***	-1.398***	-0.825***
	(0.023)	(0.022)	(0.030)	(0.028)	(0.026)	(0.024)	(0.033)	(0.030)
Controls	None	Parent Ed + HH Cons	None	Parent Ed + HH Cons	None	Parent Ed + HH Cons	None	Parent Ed + HH Cons
Subdistrict FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows results from regressions on a sample of individuals taken from the SECC 2012. We use a 2 stage random sampling strategy and take a 20% sample of neighborhoods stratified at the subdistrict level and then take a simple random sample of 50% households within those neighborhoods. Consumption controls are at the household level. Each estimate is from a separate regression of child educational attainment on share. Identical to 8, except we restrict sample by age.

Table A.6
Neighborhood-level Public Facilities
vs Marginalized Group Share

A. Urban Neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)
	Primary School		Secondary School		Health Facility	
	Indicator	Log Emp	Indicator	Log Emp	Indicator	Log Emp
SC Share	0.079***	0.118***	-0.013**	-0.067***	-0.012**	-0.036***
	(0.009)	(0.017)	(0.006)	(0.017)	(0.006)	(0.013)
Muslim Share	-0.020**	-0.042**	-0.047***	-0.150***	-0.046***	-0.115***
	(0.009)	(0.018)	(0.006)	(0.017)	(0.006)	(0.014)
Observations	83934	83934	83934	83934	83934	83934
Mean of Dependent Variable	0.23	0.45	0.10	0.26	0.09	0.18
Town FE	Yes	Yes	Yes	Yes	Yes	Yes

B. Rural Neighborhoods

	(1)	(2)	(3)	(4)	(5)	(6)
	Primary School		Secondary School		Health Facility	
	Indicator	Log Emp	Indicator	Log Emp	Indicator	Log Emp
SC Share	-0.005	0.000	0.001	-0.002	0.009***	0.009**
	(0.005)	(0.009)	(0.003)	(0.007)	(0.003)	(0.004)
Muslim Share	-0.053***	-0.149***	-0.063***	-0.139***	-0.053***	-0.076***
	(0.006)	(0.012)	(0.004)	(0.009)	(0.004)	(0.006)
Observations	389601	389601	389601	389601	389601	389601
Mean of Dependent Variable	0.59	1.10	0.16	0.35	0.13	0.19
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the regression results of public facilities on marginalized group share at the neighborhood level, for towns and rural subdistricts, for larger neighborhoods with at least 4000 people. This is done for two different measures of public facilities: an indicator for whether or not there is the particular public facility in a neighborhood and $log(employment+1)$ in such public facilities. Columns 1 and 2 present results for primary schools, columns 3 and 4 for secondary schools, and columns 5 and 6 for health facilities. All regressions include town fixed effects and control for the log of neighborhood population.

Table A.7
Neighborhood-level Primary Schools vs Marginalized Group Share

A. Urban Neighborhoods

	(1)	(2)	(3)	(4)	(5)
	Primary School	Primary School	Primary School	Primary School	Primary School
SC Share	0.042***	0.042***	0.036***	0.028***	0.028***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Muslim Share	0.000	0.001	-0.004*	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	357975	357975	357975	357975	357975
Mean of Dependent Variable	0.07	0.07	0.07	0.07	0.07
Fixed Effects	None	State	District	Shrid	Town

B. Rural Neighborhoods

	(1)	(2)	(3)	(4)	(5)
	Primary School	Primary School	Primary School	Primary School	Primary School
SC Share	-0.055***	-0.019***	-0.008***	-0.006**	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Muslim Share	-0.125***	-0.117***	-0.087***	-0.085***	-0.050***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Observations	978635	978635	978635	978635	978635
Mean of Dependent Variable	0.33	0.33	0.33	0.33	0.33
Fixed Effects	None	State	District	Subdistrict	Village

Notes: This table shows the regression results of public primary schools on marginalized group share at the neighborhood level, for towns and rural subdistricts. We use an indicator to measure the presence of a public primary school in a neighborhood. Column 1 has no fixed effects and Columns 2-5 successively add fixed effeects at the State, District, Subdistrict/Shrid or Town/Village level. All regressions control for the log of neighborhood population.

Table A.8
Neighborhood-level Secondary Schools vs Marginalized Group Share

A. Urban Neighborhoods

	(1)	(2)	(3)	(4)	(5)
	Secondary School	Secondary School	Secondary School	Secondary School	Secondary School
SC Share	0.002	0.000	-0.002	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Muslim Share	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	357975	357975	357975	357975	357975
Mean of Dependent Variable	0.02	0.02	0.02	0.02	0.02
Fixed Effects	None	State	District	Shrid	Town

B. Rural Neighborhoods

	(1)	(2)	(3)	(4)	(5)
	Secondary School	Secondary School	Secondary School	Secondary School	Secondary School
SC Share	-0.004***	-0.005***	-0.006***	-0.007***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Muslim Share	-0.055***	-0.030***	-0.021***	-0.021***	-0.013***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	978635	978635	978635	978635	978635
Mean of Dependent Variable	0.07	0.07	0.07	0.07	0.07
Fixed Effects	None	State	District	Subdistrict	Village

Notes: This table shows the regression results of public secondary schools on marginalized group share at the neighborhood level, for towns and rural subdistricts. We use an indicator to measure the presence of a public secondary school in a neighborhood. Column 1 has no fixed effects and Columns 2-5 successively add fixed effeects at the State, District, Subdistrict/Shrid or Town/Village level. All regressions control for the log of neighborhood population.

Table A.9
Neighborhood-level Health Facilities vs Marginalized Group Share

A. Urban Neighborhoods

	(1)	(2)	(3)	(4)	(5)
	Health Facility	Health Facility	Health Facility	Health Facility	Health Facility
SC Share	-0.000	-0.001	-0.002	-0.004**	-0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Muslim Share	-0.011***	-0.009***	-0.010***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	357975	357975	357975	357975	357975
Mean of Dependent Variable	0.02	0.02	0.02	0.02	0.02
Fixed Effects	None	State	District	Shrid	Town

B. Rural Neighborhoods

	(1)	(2)	(3)	(4)	(5)
	Health Facility	Health Facility	Health Facility	Health Facility	Health Facility
SC Share	-0.000	-0.002*	-0.002*	-0.002	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Muslim Share	-0.036***	-0.028***	-0.016***	-0.014***	-0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Observations	978635	978635	978635	978635	978635
Mean of Dependent Variable	0.06	0.06	0.06	0.06	0.06
Fixed Effects	None	State	District	Subdistrict	Village

Notes: This table shows the regression results of public health facilities on marginalized group share at the neighborhood level, for towns and rural subdistricts. We use an indicator to measure the presence of a public health facility in a neighborhood. Column 1 has no fixed effects and Columns 2-5 successively add fixed effeects at the State, District, Subdistrict/Shrid or Town/Village level. All regressions control for the log of neighborhood population.